In the name of Allah, the most gracious, the most merciful.

QUALITY OF FOOD PRODUCTS IN BANGLADESH: ANALYSIS IN THE FRAMEWORK OF QUALITY CONTROL AND ECONOMETRIC TECHNIQUES

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DEDICATION

In Memory of

My Mother

Mst. Rabeya Begum

Late December 15, 2010

—For all the sacrifices you made towards my education to ensure that I reached this far. Without your hard work, encouragement and unending support this dream would never have become a reality. I love you mum.‖

DECLARATION

I hereby declare that this thesis is the result of my own original work and has not previously been submitted to another university for the purpose of a degree. Where use has been made of the work of others, such work has been duly acknowledged in the text.

Signed _____ Date

Md. Anwar Hosssain

APPROVAL

This thesis has been submitted with our approval as University supervisors.

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Signature and Seal Date

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Signature and Seal Date

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ABSTRACT

An abstract of the thesis of Md. Anwar Hossain for the Ph.D Degree in the Department of Statistics, Biostatistics and Informatics, University of Dhaka.

Recent global increases in food contamination and adulteration have further exacerbated vulnerabilities and made it imperative to examine food products in the country. Food is identified as one of the sustainable approaches to farming and offers insights towards a paradigm shift in food and nutritional quality.

The binary logit or probit regression model is one of the popular choices to study effects on dichotomous responses. This study is designed at monitoring a definite response i.e., food acceptability result in terms of some predictors, determines the goodness of fit as well as strength of the assumptions and selecting an appropriate and more parsimonious technique there by proffer helpful suggestions and recommendations. The technique was used as a tool to representation the major factors viz. food quality characteristic (moisture, protein, fat, carbohydrate and iron etc.) and microbial (aerobic plate count, coliform etc.) that affected the acceptability of food. The fit, of the technique was illustrated with 8 (eight) types of food, 678 food samples and several physiochemical and microbial test parameters records obtained from Institute of Food Science and Technology (IFST), BCSIR, Dhaka by the method of Single Stage Cluster Sampling. This study contents some visible and numeric statistical methods for checking the level of significance of technique. The technique spotlight on assessing acceptability of statistical methods for specific food analysis variate effects. The tested technique showed best fit and performed differently depending on classification of result, sufficiency in relation to assumptions and goodness of fit.

The outcome specify that different methods for analyzing binary data are likely to vary in their presentation under the subsequent conditions: 1. the distribution of the interpreter variables follows significantly from normality, 2. the two group must have equal variances. While these conditions are by no means inclusive, the being of conditions should concern the study that the choice of a particular method should be made carefully.

Reliable with precedent studies, the presentation of logit and probit was similar under the different conditions. Hence, a selection between these two may not be significant (except in

computational cost). However, the selection among logit, probit model, Linear Discriminant Analysis and OLS is still not uncomplicated. Therefore, the study be supposed to first carry out different preliminary data study to decide the statistical properties of the forecaster variables. Possibly part of the data might be analyzed by these techniques to decide which one is most suitable. Otherwise, the study could change the data to comply with the assumptions of a particular technique.

Comparing the consequences, we observed that the Logit and Probit model outperforms other models and techniques as because they fulfill necessary assumptions as required. If in the case of normality assumptions fullfill, Discriminant analysis also yields better results. The results of one sample *t*-test and wilcoxon signed-rank/ sign test indicate that, in almost every case when the null hypothesis was false, the *t*-test performed same results with the Wilcoxon signed-rank/ sign test though the normality assumptions violated. But when H_0 was true, the Wilcoxon signed-rank test perform efficient or more power predicted probability (p-value) than the *t*-test as fullfill the assumptions.

Key words: Commercial Food; Logit and Probit model; Linear Discriminant Analysis; Single Stage Cluster Sampling, Consumer Awareness, selection of criteria of best model; *t*-test; Wilcoxon signed-rank test, Sign test.

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LIST OF ORIGINAL PAPERS

This thesis is based on the subsequent papers, referred to in the manuscript by their particular roman numerals:

i. Md. Anwar Hossain, Matiur Rahman and Md. Zillur Rahman Shabuz, 2012. Quality of Industrially Processed Fruit Juices: An Assessment Using Multivariate Framework. *Dhaka Univ. J. Sci.* 60(2): 169-173.

ii. M. Anwar Hossain, Matiur Rahman, Md. Zillur Rahman Shabuz, 2012. Assessing Maintenance of Quality Standard for Industrially Processed Biscuits in Bangladesh. *Research & Reviews: A Journal of Statistics.* 1(2):1-10.

iii. Md. Anwar Hossain, Ashish Kumar Sarker and Sahana Parveen, 2013. Physiochemical and Microbiological Quality of fortified high energy biscuits served in school of poverty areas in Bangladesh. *J Pharm Biol Sci*; 1(2): 16-20.

ACRONYMNS AND ABBREVIATIONS

AIC	Akaike Information Criterion
ANDAs	Abbreviated New Drug Applications
ANZFA	Australia New Zealand Food Authority
ARCH	Autoregressive conditional heteroskedasticity
ARCH	Autoregressive Conditional Heteroskedasticity
ARL	Average run length
BBS	Bangladesh Bureau of Statistics
BCSIR	Bangladesh Council of Scientific and Industrial Research
BDHS	Bangladesh Demographic and Health Survey
BIC	Bayesian information criterion
BSE	Bovine Spongiform Encephalopathy
BSTI	Bangladesh Standards & Testing Institution
CAC	Codex Alimentarius Commission
CDF	Cumulative Distribution Function
CFU	Colony Forming Unit
CITAC	Cooperation On International Traceability And Analytical Chemistry
CMA	Critical Material Attributes
CMC	Chemistry Manufacturing and Controls
COV	Coefficent of Variation
CPP	Critical Process Parameters
CQA	Critical Quality Attributed
CRM	Certified Reference Material
CTQs	Critical-to-quality characteristics
DA	Discriminant analysis
DALY	Disabilities Adjusted Life Years
DGHS	Directorate General of Health Services
EDF	Empirical Distribution Function
EWMA	Exponentially Weighted Moving Average Control Charts
FAO	Food and Agriculture Organization
FDA	Food and Drug Administration

FIGARCH	Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity
FPMU	Food Planning and Monitoring Unit
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GJR-GARCH	Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity
GLP	Good laboratory practice
GMO	Genetically Modified Organism
GOF	Goodness-of-fit statistics
HACCP	Hazard Analysis Critical Control Points
HEB	High Energy Biscuits
IAEA	International Atomic Energy Agency
ICDDRB	International Centre for Diarrhoeal Diseases Research Bangladesh
ICMSF	The International Commission on Microbiological Specifications for Foods
ICT	Information and Communication Technology
ICUMSA	International Commission for Uniform Methods of Sugar Analysis
IDA	Iron-Deficiency Anaemia
IDD	Iodine-Deficiency Disorders
IDF	International Dairy Federation
IFST	Institute of Food Science and Technology
IPH	Impressions Per Hour
ISO	International Organization for Standardization
K-S	Kolmogorov-Smirnov
LA	Logit Analysis
LBW	Low birth weight
LDF_s	Linear Discriminant Functions
LPM	Linear Probability Modelling
MANOVA	Multivariate Analysis of Variance
MDA	Multiple Discriminant Analysis
ME	Marginal Effects
MPN	Most probable number
NC	Nonconforming
NID	Normally and Independently Distributed

OLS	Ordinary Least Squares
PA	Probit Analysis
PCA	Process Capability Analysis
PCB	Dioxins and Polychlorinated Biphenyls
PCIs	Process capability indices
POP	Persistent organic pollutants
QA	Quality Assurance
QbD	Quality by Design
QC	Quality Control
RM	Reference Material
SPC	Standard Plate Count
SPS	Sanitary and Phytosanitary
SPSS	Statistical Package for the Social Sciences
SRS	Simple Random Sampling
STAN	Standard
TBT	Technical Barriers to Trade
TGARCH	Threshold Generalized Autoregressive Conditional Heteroskedasticity
TPP	Target product Profile
TPQP	Target Product Quality Profile
UCL/ LCL	Upper/ Lower Control Limit
UNICEF	United Nations Children's Fund
US	United States
USL/ LSL	Upper/ Lower Spec Limits
UV	Ultraviolet
V. cholerae	Vibrio cholerae
WFP	World Food Programme
WHO	World Health Organization
WSB	Wheat Soya Blend

CHAPTER 1: INTRODUCTION

In this chapter, fundamental information of this research will be introduced, such as Quality Factors of Processed Food, Food Borne Disease Load: Some evidence for Bangladesh, Situation of safety of foods of animal origin in Bangladesh, Nutrition Situation in Bangladesh, Food Safety and Public Health Issues in Bangladesh, Food Safety Practices and General Requirements, Guide to Quality in Analytical Chemistry, Rationale of the present study and Objective of the study. At the end of this chapter, an overview of the whole chapter will be provided.

1.1 Background

Food greatly influences the health of populations, therefore food quality control is an important government activity and is legislatively regulated. Food quality is a complex term that includes nutritional, sensory, hygienic-toxicological, and technological points of view. Food has to fulfill all requirements of quality, but above all it has to be safe. High quality products can be produced from high quality raw material. One can say that the raw material influences the quality of the end-products in large degree. The quality of the product is further influenced by the technological procedure used. It depends not only on the technological procedure itself but also above all on the hygienic level of the machinery used and on the total hygienic manufacturing conditions. During the technological procedure, especially at so-called critical control points, such quality parameters that most influence the total quality of the manufactured product have to be controlled. The quality of the end product has to fulfill the requirements for the given class of food. The labeling, statement concerning weight, and other data, including the date of safe usage, is important to the consumer. The producers are fully responsible for the quality of produced foods. The quality of the end food products is affected above all by the raw materials used. For this reason, close cooperation between agriculture and processing plants is needed. In many cases, farmers make agreements with the food industry not only on the quantity of produced raw materials but also on their quality. The quality of raw material (wheat, milk, eggs and so on) is evaluated, and farmers are paid accordingly. In all cases the raw material must fulfill all hygienic requirements. Great attention is paid to the presence of different kinds of contamination, such as heavy and toxic metals, toxic metabolites of microorganisms,

pesticide residue, and the presence of genetically modified organism (GMO) material and so on (Davídek, 2009).

Since the inception of human life, food has been one of the primary needs for the survival of humanity. As civilization grew, culture emerged, giving way to the development of a variety of food styles and tastes. Bangladesh is a land of rivers and crops, where farmers and fishermen worked together effortlessly to produce food to feed the nation. Healthy foods mean healthy living. So, it is very important that certain level of health standard is maintained so that safe and reliable food consumption is ensured for the general public.

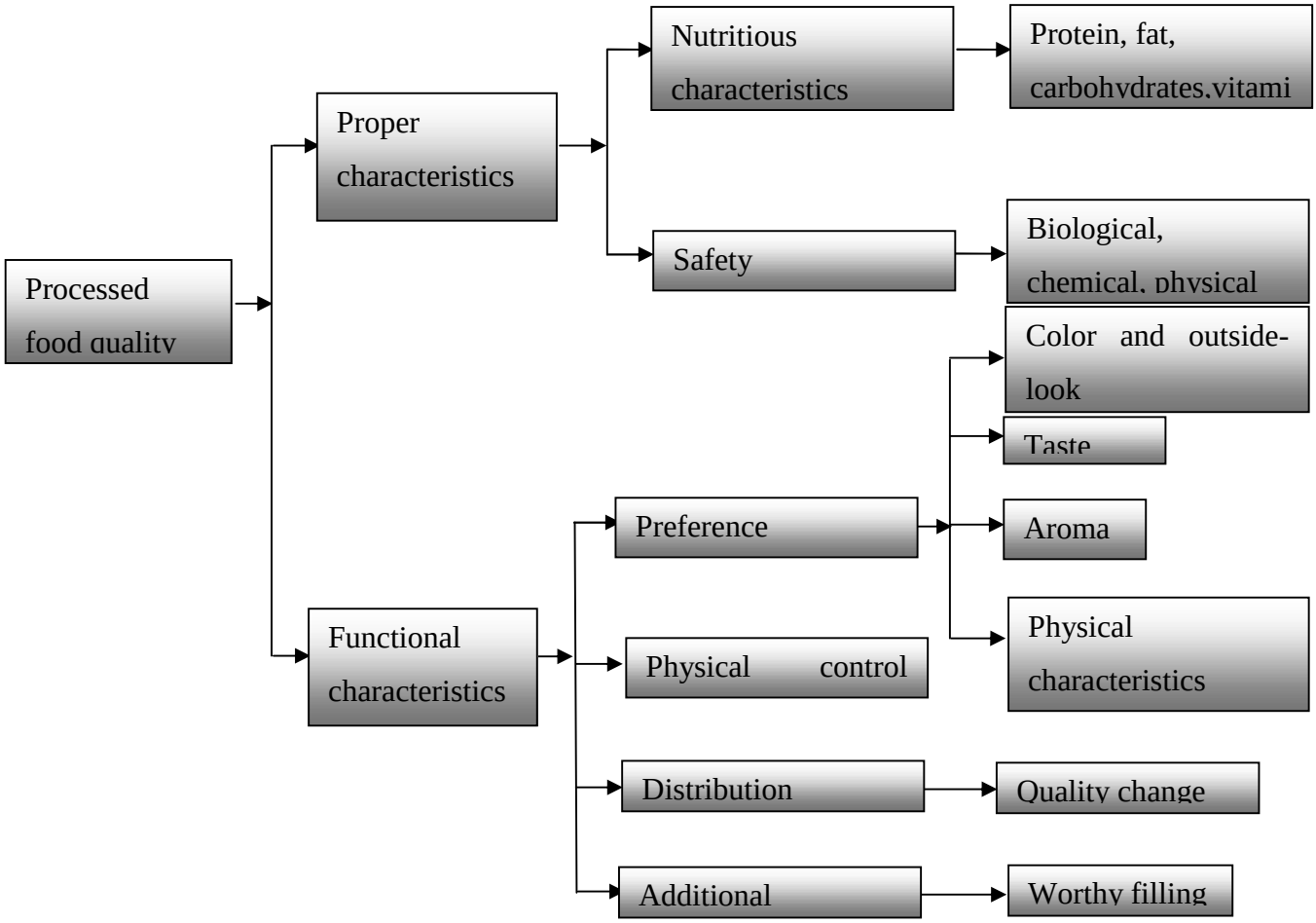
The crime or food adulteration has become a widespread problem in our local market over the past few years. As a counteraction, I want to conduct many research and experiments to demise this crime and ensure proper well being of our public health.

The ISO standard 8402 defined quality as the totality of features and characteristics of a product or service that bear on its ability to satisfy stated or implied needs. Quality control is defined as the operational activities that are used to fulfill requirements for quality (Arnold & Göb, 2003).

1.2 Quality Factors of Processed Food

The quality of processed food products is a significant requirement in the food industry in Bangladesh. Quality characteristic of food shows in Figure 1.1. This Figure shows that quality is classified into two characteristics: proper and functional. The proper characteristic consists of nutrition and safety, while the functional characteristic is related to the physiological factors and its sensitivity to humans. Of course, the nutritional aspect of food means its composition in terms of protein, fat, carbohydrates, vitamins and other elements. The safety aspect is considered the most important characteristic of all food products in Bangladesh and because of this, both the food industry and government are exhausting all efforts in ensuring food safety in all its products. Recent world news related to the BSE (bovine spongiform encephalopathy) problem, food-borne diseases such as the O157and staphylococcal enterotoxin have made consumers aware of the significance of food safety.

Figure 1. 1: Quality Factors of Processed Food.



(APO, 2002).

Food safety and sanitation are considered to be a key issue to ensure overall food security inBangladesh.Food is the major source of human exposure to pathogenic agents, both chemical and biological (viruses, parasites, bacteria), from which no individual is spared. The importance of food safety stems from: (1) food being the primary mode of transmission of infectious disease; (2) the intricate linkage with development- governs individual and community health, national productivity, and promotes export potential & thus earn foreign exchange; (3) emerged as prominent sources of conflict in international agricultural trade.Biotechnology has raised some food safety concerns as new scientific methods to assess the safety of food derived from biotechnology have yet to be developed and agreed upon internationally.In Bangladesh more than 90 % tube wells of 61 districts (out of 64) are contaminated with arsenic.Urban population are gradually shifting from cereal-based diets and would likely generate a demand for fish, livestock, horticultural, forest produce as well as

processed items, in turn necessitating safety load of associated transport, storage and marketing infrastructure.

Potential risks in food, A wide range of food borne diseases (endemic----hyperendemic---epidemic---pandemic) is encountered in Bangladesh.

Naturally occurring toxins, such as mycotoxins, marine biotoxins, cyanogenic glycosides andtoxins occurring in poisonous mushrooms, periodically cause severe intoxication.

Bovine Spongiform Encephalopathy (BSE, or "mad cow disease"), are suspected to cause new variant Creutzfeldt-Jakob Disease in humans. Recently occurring “bird flue” disease in poultrycaused by avian viruses is also a threat.

Persistent organic pollutants (POPs): Dioxins and Polychlorinated Biphenyls (PCBs) exist in theenvironment and in the human body, which are carcinogenic.

Metals, such as lead and mercury, cause neurological damage in infants and children. Exposure tocadmium can also cause kidney damage, usually seen in the elderly (FAO/WHO, 2004).

Food Standards: So far, Bangladesh had adopted 40 Codex standards as national standards. Bangladesh had developed standards for food safety. Much emphasis had been put on safety of food. Bangladesh also had adopted HACCP standards for domestic food processing and exporting industries. Bangladesh had maderegulations for mandatory certification of 54 food products in 1985 by an ordinance. Manufacturers and importers of these 54 items were to follow the mandatory standards which were in line with Codex standards (FAO/WHO, 2005).

1.3 Food Borne Disease Load: Some evidence for Bangladesh

Diarrhoea diseases are one of the major public health problems in Bangladesh around 70% of which are food and water borne. A UNICEF study in 2000 revealed that prevalence of diarrheal diseases among fewer than five children is 16.7% (Organization, 2000). A Report of the Directorate General of Health Services (DGHS, 2001) showed that the diarrheal diseases is the most prevailing one among all age groups including 5.9 % deaths (1997) (FAO/WHO, 2004; MALEK, 2013).

Prevalence of Food Borne Diseases: Food borne diseases are very common in Bangladesh, mainly attributable to poor water and environmental sanitation status. Diarrhoeal disease is

one of the major public health problems, particularly among infants and young children, around 70% of which are food and water borne. Impacts of diarrhoeal disease are enormous, beginning from high disability due to nutrient loss from the body to death. In Bangladesh high disability rates are resulting in 5.7 million disabilities adjusted life years (DALY), 61% of total DALYs. Past data from the government epidemic surveillance system reported a total of 16,57,381 cases and 2,064 deaths from acute diarrhea in 199816, excluding post flood (1998) diarrhoea (14,86,197 cases and 1,836 deaths). Hygiene related diseases in Bangladesh cost US $80 million each year for treatment alone.The prevalence of diarrhoea among children under 5 years markedly increased from 16.7% in 2000 to 23.9% in 2003. More recent estimates are however characterized by high discrepancies (e.g. BDHS estimates a prevalence rate of 9.8% for 2007 while a recent study from IPH suggests a rate as high as 44% (FPMU, 2010; UNICEF & others, 1998).

Salmonella infections (typhoid): It is highly endemic in Bangladesh and is an important cause high morbidity and economic loss,which are known to cause a wide spectrum of disease syndromes in man and animals likegastroenteritis, enteric fever, bacteremia, focal abscess or as an asymptomatic infection i.e. carrier state. However, data on salmonellae in Bangladesh remain scantyand limited to few clinical reports andSalmonella Meningitis.

Cholera: In Bangladesh, cholera outbreaks occur regularly twice a year, both before and after monsoon (ICDDR, 1998). Case-control studies have shown that, in Bangladesh, the rate of contamination of household water with *V. cholerae* 01 is significantly higher in water used for cooking than in water used for drinking. However, only 0.13% of the food samples cultured were contaminated with *V. cholerae*01. indicating the risk of food-borne transmission of cholera during the non-epidemic season. Nevertheless, *V. cholerae*01 has been isolated from aquatic flora and fauna in this region, including blue- green algae (reservoir of *V. cholerare*01. Transmission of cholera through contaminated foods served by street vendors and restaurants should be considered: in Dhaka, there were two outbreaks of cholera in 1974 and 1975 (FAO/WHO, 2004).

1.4 Situation of safety of foods of animal origin in Bangladesh

Food safety situation in Bangladesh is very much precarious. Consumers in Bangladesh become victims of serious adulteration in food. Here food safety laws, regulations and administration are rather ineffective. Food safety administration and inspection does not include the monitoring of the entire chain of production and transaction. The country has although set some goals for domestic consumption and increasing export of fresh and processed foods, but adequate food safety control has not yet been achieved to gain access to the European and Global markets. It is agreed that to ensure quality and safety of foods in this country 'from farm to table' pre-harvest and post-harvest hygienic functions are very much neglected. The primary prevention 'on-farm' exposure to food-borne hazards due to pathogens and residue producing chemicals persisting in the food chain is not given due importance.

We know that "Open Dating" on a food product is a quality date stamped on the package of a product to help the store management determine how long to display the product for sale. In Departmental food shops in Bangladesh sometimes packaged perishable foods are found, but "Open Dating" is rarely found primarily on perishable foods such as meat, poultry, eggs, and dairy products. According to latest information from internet, more than 35 percent of meat available in the local market in Bangladesh goes to domestic households as well restaurants. Some of the elite society's elegant restaurants in the capital are selling local beef in the name of 'California Beef' or 'Texas Beef', but Bangladesh Customs confirms the fact that, in past two years, no cow meat was ever imported by anyone in Bangladesh. So, it is understood that, those so-called imported beef is nothing but very much local one, which the shrewd restaurant owners are selling at exorbitant price to the customers with false tag.

In recent years we experience complex changes in production, processing, storage, distribution, marketing and serving of foods. High standards of hygiene at abattoir, improved dressing procedures and sophisticated quality control for holding meat foods under cold chain and refrigeration for extended period are established in many developed countries to assure food safety and consumers' protection. Prime cuts of meats are now packaged to specification to local needs and of overseas customers. These are transported and chilled in air-tight bags of multilayer polyethylene and plastic to prevent spoilage. In comparison to the above facilities the scenario of our home country is very primitive. Food control activities are

implemented in a disorganized form. There is a lack of consumer/public awareness program. Both producers and consumers are lacking in knowledge regarding food safety laws, regulations and standards. Proper enforcement of laws, regulations and standards are absent. Food laws and regulations do not embody recent international developments. It is not up to date with recommendation by CAC (Codex Alimentarius Commission Act, 1961), SPS (Sanitary and Phytosanitary) Agreement, TBT (Technical Barriers to Trade) Agreement and HACCP (Hazard Analysis Critical Control Point) System. The Government of Bangladesh is however encouraging the private sector to put the food processing and marketing into the context of industrial standard keeping in view the cost effectiveness and public health issues, so that we can enter the global trade. In recent years a modern abattoir namely Bengal Meat Ltd has been established to offer consumers wholesome meat. The situation of food safety needed in relation to hygiene and production of foods of animal origin in Bangladesh is briefly narrated below (Kabir & Mufizur Rahman, 2012).

1.5 Nutrition Situation in Bangladesh

This section discusses determinants of malnutrition among pregnant and lactating women and young children in Bangladesh and several important risk factors that are particularly relevant to this.

1.5.1. Dietary pattern

Cereals, largely rice, are the main food in Bangladesh. Nearly two-thirds of the daily diet consists of rice, some vegetables, a little amount of pulses and small quantities of fish if and when available. Milk, milk products and meat are consumed only occasionally and in very small amounts. Fruit consumption is seasonal and includes mainly papaya and banana which are cultivated round the year. The dietary intake of cooking oil and fat is meagre. The typical rural diet in Bangladesh is, reportedly, not well balanced (Jahan & Hossain, 1998).

Traditional dietary habits often do not meet good nutritional requirements, with a preference for polished rice and leafy vegetables of poor nutritional quality. In addition, cultural norms dictate a better diet for males over females with the male head of the household getting the best meal portions. Persistent poverty, inadequate nutrition information and gender inequity cause pervasive malnutrition among women, especially pregnant women and lactating mothers.

While food habits vary at regional and even individual household levels, in general, food preparation methods result in significant nutrient loss. Minerals and vitamins, especially B-complex vitamins are lost (40 percent of thiamine and niacin) even during the washing of rice before cooking. Boiling rice and then discarding the water results in even more nutrient losses. The manner of washing and cooking vegetables leads to considerable loss of vitamin C and B-complex vitamins.

Household food consumption studies show that cereals make up the largest share (62 percent) of the diet, followed by non-leafy vegetables, roots and tubers, which together comprise more than four-fifths of the rural people's total diet. Protein and micronutrient-rich foods like fish, meat, eggs, milk, milk products, fats and oils account for less than 10 percent of the rural person's diet, and the consumption of vegetables and fruits is declining steadily (Jahan & Hossain, 1998).

Rural consumption of leafy and non-leafy vegetables has remained more or less the same over the past two decades after increasing over the preceding 30 years. Fruit consumption has declined in rural areas after more than doubling in the 1970s. With an average national per capita consumption of 23 g of leafy vegetables, 89 g of non-leafy vegetables and 14 g of fruit, the average Bangladeshi eats a total of 126 g of fruit and vegetables daily. This is far below the minimum daily consumption of 400 g of vegetables and fruit recommended by FAO and the World Health Organization (Who & Consultation, 2003).

1.5.2. Nutritional status

Despite considerable improvement in the national rural health status, the nutritional well-being of rural people continues to be neglected. Children and women in Bangladesh suffer from high levels of malnutrition and micronutrient deficiencies such as low birth weight (LBW), undernutrition (underweight, stunting and wasting), vitamin A deficiency, iodine-deficiency disorders (IDD) and iron-deficiency anaemia (IDA). At the same time, new health problems related to over-nutrition such as obesity are emerging (White, 2005).

Maternal undernutrition (body mass index less than 18.5 kg/m^2) in non-pregnant women in the country, while declining from 54 percent in 1996–1997 to 38 percent in 2003, is still very

high. Undernutrition, both before and during pregnancy, causes intrauterine growth retardation and is one of the major reasons for the high LBW (36 percent) prevalence in the country (Mitra, Al-Sabir, Saha, & Kumar, 2001).

Low birth weight is more common among adolescent mothers. Marriage at very young age has serious consequences for pregnancy, future survival, health, growth and development. When combined with positive energy balance (adequate energy intake) in later life, LBW increases the risk of obesity, diabetes, high blood pressure and coronary heart disease. Between 1990 and 2004, underweight levels among children fell from 67 to 48 percent and child stunting fell from 66 to 43 percent but the levels are still unacceptably high (BBS, 1989-1990) (Mitra, Al-Sabir, Saha, & Kumar, 2004).

The consumption of vitamin A-rich foods is still low, suggesting that the underlying causes of vitamin A deficiency require further attention. The diets of pregnant women in low-income groups are deficient not only in micronutrients but also in energy. Anaemia is a severe public health problem affecting pre-school children (49 percent) and pregnant women (47 percent), and a moderate public health problem among non-pregnant women (33 percent) and adolescents (29 percent). Anaemia caused by iron deficiency impairs the growth and learning ability of children, lowers resistance to infectious diseases and increases the risk of maternal death and LBW. Children are malnourished by inadequate dietary intake or infectious diseases (Wardlaw, 2004).

The underlying causes include (i) household food insecurity resulting from inability to grow or purchase a nutritionally adequate amount and variety of food; (ii) lack of dietary diversity; (iii) inadequate maternal and child care due to inappropriate hygiene, health and nutrition; (iv) low rates of exclusive breast feeding; (v) inadequate access to quality health services; (vi) poor environmental hygiene and sanitation along with low levels of income and maternal formal education. Malnutrition early in life has long-lasting and negative effects on overall growth, morbidity, cognitive development, educational attainment and adult productivity (UNICEF & others, 1998).

Because of this, the nutritional status of children, particularly below five years of age, is seen as one of the most sensitive indicators of a country's vulnerability to food insecurity and overall socio-economic development. Women of child-bearing age are also highly vulnerable

to nutritional deficiencies because of increased need for food and nutrients during pregnancy and lactation (Bhattacharjee, Saha, & Nandi, 2007).

1.6 Food Safety and Public Health Issues in Bangladesh

In Bangladesh, most of the foodstuffs, be it manufactured or processed, are unsafe for consumption or adulterated in varying degrees. This problem persists at every level of food from preparation to consumption. Food manufacturers, processors, restaurants, fast food outlets and so forth are all involved in one way or another in this corrupt practice of adulteration. Foods are adulterated by using various harmful chemicals and toxic artificial colours on the one hand; and rotten perishables turning to be poisonous foods are stored, sold and served to consumers in an unhygienic atmosphere on the other. This unsafety of food is contributing to the public health seriously with numerous chronic and non-chronic diseases. Despite different reasons for this unsafety and adulterations of foodstuffs in Bangladesh, this study will concentrate on the regulatory failures to combat the current food safety problems persisting in Bangladesh (Ali, 2013).

1.7 Food Safety Practices and General Requirements

The Food Act 1984 requires all food business operators and food handlers to comply with the Food Safety Standards. Food Safety Practices and General Requirements sets clear requirements for food businesses to make sure that food does not become unsafe or unsuitable.

This Standard sets the requirements for all food handling activities within your business such as; the receipt of food, storage, processing, display, packaging, transporting, disposal and recall of food.

The Food Safety Standards are enforceable under the Food Act 1984 and all food premises and food handlers must comply with these Standards. There are other accepted ways of meeting some of these standards, however the business must be able to show that the food will still be safe and suitable.

Food Handling Skills and Knowledge: Food businesses must make sure that all food handlers, and people who supervise food handlers, have the right skills and knowledge in

food safety and food hygiene for the work they do. Refer to the 'Food Handlers Food Safety Training' fact sheet.

Notification: Requires you to notify Council of details about your business. This is covered by your registration (*food-safety-standards*, n.d.).

Food handling controls: Food handling controls related to the receipt, storage, processing, display, packaging, transportation, disposal and recall of food. Other requirements relate to the skills and knowledge of food handlers and their supervisors, the health and hygiene of food handlers and the cleaning, sanitising and maintenance of the food premises and equipment within the premises. If complied with, these requirements will ensure that food does not become unsafe or unsuitable (*Standard 3.2.2 – Food Safety Practices and General Requirements*, n.d.).

Temperature control: Generally the Standards require that potentially hazardous food is kept under temperature control which means below 5°C and above 60°C. Businesses need to limit the amount of time that potentially hazardous foods are kept in the 'danger zone' - temperatures between 5°C and 60°C.

Food receipt: Food businesses must make sure that all food that they receive is safe and suitable. This means that you must make sure that:

food is protected from contamination;

food can be identified traced back to its supplier;

food is at the correct temperature (below 5°C and above 60°C or frozen) (*food-safety-standards*, n.d.).

Food storage: During storage you must make sure that the safety and suitability of the food is kept. This means that:

Food must be protected from contamination;

Food must be stored under correct environmental conditions eg lighting and humidity;

Potentially hazardous food must be stored under correct temperature (below 5°C and above 60°C or frozen).

Food processing: Businesses must make sure that when processing food:

Only safe and suitable food is processed;

Food must be protected from contamination;

There are no organisms present that can cause illness when the food is ready to eat.

Some processing steps have clear requirements for example:

Cooking: Food must be cooked correctly and thoroughly to make sure that the food poisoning bacteria is killed and the food is safe to eat. Food that is cooked must be cooked to a temperature of at least 75°C.

Cooling: Any potentially hazardous food that is hot must be cooled to 5°C as quickly as possible to ensure that the food is safe. Cool food within two hours from 60°C to 21°C and within a further four hours from 21°C to 5°C.

Thawing: When thawing frozen food make sure that the food does not reach 5°C or warmer. The ideal method of thawing food is in the refrigerator.

Reheating: Reheating of potentially hazardous food must be done quickly. Use a method that rapidly heats the food to 60°C or above.

Food display: Businesses must make sure that when displaying food:

Food must be protected from contamination, for example barriers, covering ready to eat foods such as cakes and muffins that are on counters and supervision.That potentially hazardous food is either kept under temperature control or time is used as the control to keep the food safe.

As a guide, the 2 hour/4 hour rule is summarised below:

If less than 2 hours the food must either be refrigerated or used immediately;

For longer than 2 hours, but less than 4 hours, must be used immediately;

For a total of 4 hours or longer, must be thrown out;

If using the 2 hour/4 hour rule the business must be able to provide evidence of the times, e.g. tags with times marked.

Food packaging: Food businesses must make sure that when packaging food:

the packaging material used is safe for food;

the packaging material used is not likely to contaminate the food;

the food is not contaminated during the packaging process.

Food transportation: Businesses must make sure that food being transported is:
protected from contamination and thatPotentially hazardous food must be transported at the correct temperature (below 5°C and above 60°C or frozen).

Food disposal/recall: Food that is recalled or that may not be safe or suitable, (refer to 'Your Legal Requirements' fact sheet), must be labelled and kept separate from the other food on the premises until such time that it can be dealt with correctly. Wholesale suppliers, manufacturers and importers must have a written recall system for the recall of unsafe food (*food-safety-standards*, n.d.).

Health and Hygiene requirements: A food handler is anyone who works in a food business and handles food, or surfaces that are likely to come into contact with food (e.g. cutlery, plates). A food handler may be involved in food preparation, production, cooking, display, packing, storage or service (Clark & Associations, 2004).

Food businesses must:

inform the food handlers about their health and hygiene responsibilities;

make sure that the food handlers do not handle food if they are unwell with an illness such as gastro, or other illnesses that can be passed on through food;

provide sufficient handwashing facilities, refer to 'Food Safety Standards Premises and Equipment' fact sheet;

make sure that food handlers on the premises do not contaminate food.

Food handlers requirements: Food handlers must do everything they can to make sure that they do not contaminate food. They must wash their hands with soap and running warm water in the hand wash basin provided and then dry them using either a paper towel or air drier. Hand washing before handling food must be done regularly and whenever there might be the

risk of contaminating food. They must not behave in any way that could cause contamination of food, for example smoking in food handling areas.

Food handlers must inform their supervisor if they are suffering from; diarrhoea, vomiting, a sore throat with fever, fever or jaundice, any infected skin wound or discharges from their ears, nose, or eyes as these conditions could contaminate food.

Cleaning, Sanitising and Maintenance: Businesses must make sure that the food premises and vehicles are kept clean. Food contact surfaces, ie- chopping boards and preparation benches, must be cleaned and sanitised regularly or in between tasks to make sure that contamination of food does not occur. This also applies to the eating and drinking utensils. Sanitising can be achieved by; using hot water (77°C at least), using a food grade sanitiser or diluted bleach.

The premises, fittings and equipment must be kept clean and in a state of good repair. Chipped, cracked or broken utensils must not be used. Garbage must not be left to build up and must be removed regularly.

Miscellaneous: Temperature measuring devices:
Businesses that handle potentially hazardous food must have a probe thermometer that accurately measures to +/-1°C. Some sections of your Food Safety Program will require you to take temperatures and record them.

Single use items: These include items that should be used only once such as; paper cups, straws, disposable gloves, take away containers etc. The Standard requires the business to make sure that single-use items:

do not contaminate food;

do not pass on any illness; andare not reused.

The main ways to make sure that food is kept safe using single-use items includes:

protecting the single use item with packaging or a container;

using dispensers that will allow only the customer who will use the single use item to touch it;

storing the single use item away from chemicals, in food storage areas;

throw away the single-use item if it has been used, damaged, touched or in any way contaminated.

Animals and pests: Premises and vehicles must be kept free of animals and pests. No animals are allowed in food handling areas apart from live seafood. Assistance animals, such as guide dogs, are the only animals allowed in dining and drinking areas.

You can meet these requirements by completing the records, found in your Food is Safe (Authority, 2001; *food-safety-standards*, n.d.).

1.8 Guide to Quality in Analytical Chemistry

1.8.1 Definitions and Terminology

There are a number of important terms used in quality management and conformity assessment whose meaning may vary according to the context in which they are used. It is important to understand the distinction between the various terms. A few are presented here (ISO9000, 2000; ISO, 1996).

Quality: Degree to which a set of inherent characteristics fulfils requirements (ISO9000, 2000).

Accreditation: 'Procedure by which an authoritative body gives formal recognition that a body or person is competent to carry out specific tasks' (ISO/IEC Guide 2) (Program, 2015).

Certification: 'Procedure by which a third party gives written assurance that a product, process or service conforms to specified requirements' (ISO/IEC Guide 2). Certification, (sometimes known as registration) primarily differs from accreditation in that technical competence is not specifically addressed.

Quality Assurance (QA): QA describes the overall measures that a laboratory uses to ensure the quality of its operations. Typically this might include:

A quality system;

Suitable laboratory environment;

Educated, trained and skilled staff;

Training procedures and records;

Equipment suitably maintained and calibrated;

Quality control procedures;

Documented and validated methods;

Traceability and measurement uncertainty;

Checking and reporting procedures;

Preventative and corrective actions;

Proficiency testing;

Internal audit and review procedures;

Complaints procedures;

Requirements for reagents, calibrants, measurement standards & reference materials.

Quality Control (QC): 'The operational techniques and activities that are used to fulfill requirements for quality'. Quality control procedures relate to ensuring the quality of specific samples or batches of samples and include:

Analysis of reference materials/measurement standards;

Analysis of blind samples;

Use of quality control samples & control charts;

Analysis of blanks;

Analysis of spiked samples;

Analysis in duplicate;

Proficiency Testing.

Audit and Review: In practice quality audits take two forms. An audit carried out by an independent external body as part of the accreditation process is more usually known as an assessment. "Quality audits" carried out within the laboratory, are sometimes subdivided into audit, often called 'internal audit', (which checks that the quality procedures are in place, and fully implemented) and review (which checks to ensure that the quality system is effective and achieves objectives. The review is carried out by senior management with responsibility for the quality policy and work of the laboratory. In this guide the term audit refers to internal audit; assessment refers to external audit.

Standard: This word has a number of different meanings in the English language. In the past it has been used routinely to refer firstly to written standards, i.e. widely adopted procedures, specifications, technical recommendations, etc., and secondly, to chemical or physical standards used for calibration purposes. In this guide, to minimise confusion, standard is used only in the sense of written standards. The term measurement standard is used to describe

chemical or physical standards, used for calibration or validation purposes, such as: chemicals of established purity and their corresponding solutions of known concentration; UV filters; weights, etc. Reference materials are one (important) category of measurement standards.

Reference Material (RM): 'Material or substance one or more of whose property values are sufficiently homogeneous and well established to be used for the calibration of an apparatus, the assessment of a measurement method, or for assigning values to materials'(I. Guide, 1992).

Certified Reference Material (CRM): 'Reference material, accompanied by a certificate, one or more of whose property values are certified by a procedure, which establishes its traceability to an accurate realisation of the units in which the property values are expressed, and for which each certified value is accompanied by an uncertainty at a stated level of confidence'("E lemental A nalysis M anual," n.d.; I. Guide, 1992).

Traceability: Property of the result of a measurement or the value of a standard whereby it can be related to stated references, usually national or international standards, through an unbroken chain of comparisons all having stated uncertainties.

Measurement Uncertainity: a parameter associated with the result of a measurement that characterises the dispersion of the values that could reasonably be attributed to the measurand(Eurachem, 2002).

1.8.2 Analytical Strategy

i. All analytical work should be adequately planned. Such a plan may, in its most basic form, be simply a notebook entry. More detailed plans will be appropriate for larger, more complicated tasks. For work carried out under GLP, there is a specific requirement that the work be performed to documented study plans.
ii. Plans will typically indicate the starting and intended finishing point of the particular task together with the strategy for achieving the desired aims. Where, during the course of the work, it is appropriate to change the strategy, the plan should be amended accordingly.

1.8.3 Computers and Computer Controlled Systems

i. In chemical testing laboratories, computers have a wide variety of uses, including:

- control of critical environmental conditions;
- monitoring and control of inventories;
- calibration and maintenance schedules;
- stock control of reagents and measurement standards;
- design and performance of statistical experiments;
- scheduling of samples and monitoring of work throughput;
- control chart generation;
- monitoring of test procedures;
- control of automated instrumentation;
- capture, storage, retrieval, processing of data, manually or automatically;
- matching of sample and library data;
- generation of test reports;
- word processing;
- communication (C. E. Guide, 2001; Singer, Stefan, & van Staden, 2005).

1.9 Rationale of the present study

It is expected that the results obtained from the present research will provide the information about the quality of energy biscuit, chips, carbonated soft drink, juices and chocolate etc. in Bangladesh.

Using harmful chemical for human body as an ingredient of carbonated beverage has found in India and also in Canada. In Bangladesh, most of the formulas of processing of soft drinks are foreign origin. So there is a possibility of existence of harmful elements in soft drink, in Bangladesh, which may affect health of large number of people. The results of the study will provide information about the hazardous chemicals and will help alert consumer or stakeholder.

The quality of fruit juices is strictly maintained in developed countries under some law and regulation but in many developing and under developed countries the manufacturers are not concerned about the microbiological safety and hygiene of fruit juices because of negligence of law. Thus the transmission of some human diseases through juice and other drinks are

considered a serious problem in recent years (Hossain, Rahman, & Shabuz, 2012). The result will provide information about the snacks quality available in Dhaka.

Due to illiteracy there is a tendency to use non-permitted food colours, artificial sugar and other additives in snacks, which sometimes cause of death of consumer. The result of the study will provide the information about the chemicals that will be helpful to alert consumer or stakeholder. The result of the study will help to establish the fundamental principle of 'Food Safety'. It will help to establish 'Consumer Protection Act'.

The study will provide information about the quality of energy biscuit, chips, carbonated soft drink, juices and chocolate etc. those are available in Bangladesh and it will also help to raise the consciousness of both the producer and the consumer. At the end of the analysis, it will be possible to know about the hazardous chemicals, present in snacks that are used during preparation.

1.10 Objective of the study

To evaluate quality of industrially processed packed food products such as fortified high energy biscuit, chips, carbonated soft drink, corn flakes, weetabix, juices and chocolate etc. in Bangladesh by measuring several parameters i.e. protein, fat, acidity, aflatoxin, iron, sugar, SPC, coliform etc. including pesticides for compliance of the BSTI/WFP/ICMSF standard in the framework of quality control technique and econometric tools.

To statistical analyse different health hazardous/non-permitted chemicals data present in food products as identified in the laboratory by physiochemical analysed and to explore overall quality of this food items.

To use econometric model and quality control techniques to assess quality of industrially processed food products with especial reference to physiochemical and microbial analysis information for researcher or stakeholder awareness buildup.

Furthermore, the application of the econometric model and quality control techniques to physiochemical characteristics of different processed food products that examines whether the food products are acceptable or not on the basis of the norms as prescribed by the national or international food standard organization.

The overall objective of the study is to model economic aspects of food production and analysis systems, understanding physiochemical analysis report and concern stakeholder awareness for food products. Specifically the study will pursue the following objectives: (i) to describe the physiochemical analysis of data characteristics of food products; (ii) establish the determinants of food decision to accept in food products distinguishing between the fully-accepted food and unaccepted; (iii) elicit producer risk preferences and empirically analyze producer sources of risk and risk management strategies; (iv) explore consumer or stakeholder awareness, perceptions and attitudes regarding food products; and (v) identify the factors that affect the consumer‘s preference and consumption of food products. The outcome of which will help make policy recommendations that have an implication on technology adoption, increase small holders capacity to bear risk and enable government and other role players have a clear understanding of consumers' food purchase decisions.

1.11Outline of the thesis

Chapter 1 of this thesis presents the background to the study, quality factors of processed food, Food Borne Disease Load: Some evidence for Bangladesh, Situation of safety of foods of animal origin in Bangladesh, Nutrition Situation in Bangladesh, Food Safety and Public Health Issues in Bangladesh, Guides to Quality in Analytical Chemistry. The chapter proceeds to sets out the rationality for the present study as well as the objectives of the study.

Chapter 2 is a review of the literature, historical perspective of quality-contributions by W.A. Shewhart, Process Capability Indices, Limited Dependent Variable Modeland autoregressive conditional heteroskedasticity (ARCH) model. The chapter proceeds to present the status of application of above mentioned model and the role of statistics in the Bangladeshfood quality.

Chapter 3 presents process of data collection, Model Development, Data Sources, Sampling and data collection, Quality Control using Econometric Techniques, Process Capability Methodology, Measures of the central tendency and description of the data, Data analysis Models and Conditional Heteroscedasticity: ARCH-GARCH Models. The variables are specified in this section as is the background on the empirical data analysis models used in the study.

The research findings and analysis of results are presented in **chapters 4, 5, 6, 7, 8 and 9.** These chapters present the findings on on food products quality, assessment of food quality data as well as the consumer and researchers awareness and market potential for food respectively. This commences with the descriptive statistics of the data of the food quality. The results of the statistical quality control chart, process capability analysis, binary logit and probit model, discriminatrory analysis and autoregressive conditional heteroskedasticity (ARCH) model that identifies the determinants of food quality is presented and discussed in this chapter with findings by studies.

Chapter 10 concludes with the summary of the study and the policy implication of this study. Areas of further research are suggested.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Food and nutritional quality remain an issue of major concern globally and especially in developing countries (Obi, 2014). The role of food products as a sustainable approach to address these issues is hence. This chapter gives an overview of the global food and food products quality that the response to the food and food products quality at the global, national and local levels. The chapter concludes with a review of issues around the consumer as well as researcher awareness and knowledge as well as preference and purchase of food products.

This section discusses the relevant literature on the adoption of food safety and quality assurance systems by firms. A review is provided of the regulatory debate in the food safety literature and of the incentives to adopt food safety and quality practices. A brief summary of the literature on the impact of the adoption of food safety and quality practices on firms' performance is given (Hassan, Green, & Herath, 2006a).

In general, consumer awareness and demand for various food quality attributes (nutritional, packaging and labeling, animal welfare) are increasing (Caswell, Bredahl, & Hooker, 1998). At the same time, there is an increasing demand forimprovements in food safety attributes involving food-borne pathogens, pesticideresidues, and food additives. Factors contributing to this growing demand for saferfood products include an ever-increasing knowledge of food-borne diseases, changingfood consumption habits, and the increasing global availability of food products (Huf & Owen, 1999; L. Unnevehr & Roberts, 2002). More importantly, unlike otherfood quality attributes, food safety poses a unique challenge due to its direct andperceptible impact on the morbidity and the mortality of consumers. The regulatoryresponses to ensure safer food products are becoming increasingly stringent globally,particularly in the developed world (Henson & Caswell, 1999).

In response to the pressures for greater intervention in food safety and quality,mandatory regulations are being proposed; however, their efficiency in achieving thedesired level of food safety and quality is being debated (Antle, 1995; Henson & Caswell, 1999; T. Roberts, Buzby, & Ollinger, 1996; Segerson, 1999). This regulatory debate has focused on two major aspects. The first relates to the need for measuring thecost and benefits of a given food safety

regulation to ensure that benefits are greaterthan costs (Antle, 1999; Caswell, 1998; MacDonald & Crutchfield, 1996; T. Roberts et al., 1996). The perceived costs are those of compliance borne by thefirms, while the perceived benefit is the avoidance of economic losses due to foodbornediseases.

The second aspect deals with the notion of equi-marginal gains for publicspending. The efficiency of allocating public funds for achieving societal benefits (e.g., reducing the risk of statistical death) through various regulatory interventions,including regulations on different safety attributes of food products, requires suchbenefits to be equal to the last dollar spent on these regulations. (Antle, 1995) states that "the current emphasis in food safety regulations on the prevention ofcancer from chemical residues represents a wildly inefficient allocation of publicfunds." When the potential for societal benefits from a set of regulatory responses isdistinctly different, then both the benefit cost analysis of a given regulation and thefood safety attribute that warrants the intervention are important in the regulatorydebate (Antle, 2001; L. J. Unnevehr, 2000).

There is a consensus among researchers that regulations can only partly explainfirms' commitments and incentives to adopt food safety and quality practices. Thomsenand (Thomsen & McKenzie, 2001) suggest that firms are willing to spend resources to provide alevel of safety, not only because consumers demand it, but also because, as profitmaximizers, they want to avoid the costs associated with the recall and the disposal ofcontaminated food, as well as liability claims. Also, firms work very hard to avoid theconsequences of negative publicity and lost market share when an outbreak of illnessrelated to food contamination occurs. (Buzby & Frenzen, 1999) indicate that a combinationof product liability, governmental regulations, and market forces determinethe current level of food safety. (Caswell et al., 1998) observe, however, that the literature is scanty when it comes to analyzing the adoption andperceived effects of voluntary and quasi-voluntary meta-systems such as HACCP and ISO 9000.

Why is the knowledge of firms' adoption behavior so important? In understanding firms' adoption behavior, public agencies would be able to channel the limited available resources more efficiently, thus achieving the objective of enhanced food safety and quality, as well as

increased consumer confidence in the country's food systems (Hassan, Green, & Herath, 2006b; Huf & Owen, 1999; Woteki, 2000).

The literature review is divided into several sections. In the section, we present the previous research on quality control charts and Process Capability Analysis (PCA). Binary logistic regression model, Binary probit regression model, Discriminant analysis (DA) and Autoregressive conditional heteroskedasticity (ARCH) models.

2.2 Historical Perspective of Quality – Contributions by W.A. Shewhart

Quality initiatives began to develop in the early 1930s. Walter Shewhart made a significant contribution to the philosophy of quality improvement with his book "Economic Control of Quality of Manufactured Products" (W A Shewhart, 1939). (W A Shewhart, 1939) with a stroke of a pen developed the control chart, which relied on probability and statistical theory to define common-cause and special-cause variation of manufactured products (Wheeler, Chambers, & others, 1992). Shewhart's work provided the statistical basis for many quality improvement initiatives of the 20th century (W A Shewhart, 1939; Walter Andrew Shewhart, 1931).

Shewhart's quality improvement philosophy represented a significant departure from the Scientific Management manufacturing philosophy of the 1930s and earlier. Even though Shewhart's views were being practiced within Bell Laboratories, most manufacturers of this era adopted the ideas and concepts of Scientific Management promoted by Frederick Taylor (F. W. Taylor, 1947). Taylor is associated with the extreme division of labor and with using time and motion studies to turn people into mindless automatons. Scientific Management had four basic principles: (1) Find the most efficient way to do a job; (2) Match people to tasks; (3) Supervise, reward and punish; and (4) Use staff to plan and control. Many feel that Taylorism led to the birth of managers and collective bargaining (Hayes, Wheelwright, & Clark, 1988). A statistician's view of Taylorism may find one serious shortcoming, i.e., Taylorism does not attempt to define the natural variation of a process (E. Deming, 1986; W. E. Deming, 1993; Walter Andrew Shewhart, 1931; F. W. Taylor, 1947).

Shewhart continued to enhance his quality improvement philosophy in his second book titled, "Statistical Methods from the Viewpoint of Quality Control" (Walter Andrew Shewhart & Deming, 1939). Shewhart's second book introduced his colleague W. Edward Deming to

many readers interested in quality control and improvement. The general theme conveyed by Shewhart and Deming in the book was that quality and productivity can be continually improved, i.e., "as quality improves, costs decrease and productivity increases" (W A Shewhart, 1939). They introduced the notion of the "customer" and they felt the role of the manufacturer was to deliver a product to the customer that not only met their quality needs but also exceeded their expectations (E. Deming, 1986; W. E. Deming, 1993; Walter Andrew Shewhart & Deming, 1939). Deming believed, "A satisfied customer is not enough. Business is built on the loyal customer, one who comes back and brings a friend" (E. Deming, 1986; W. E. Deming, 1993).

Controlling and reducing variation in manufacturing reduces defective products and rework. Shewhart's philosophy as related to the control chart identifies and quantifies process and product variation. By collecting time ordered data the process can be constantly monitored. The Shewhart control chart defines variation as being either common-cause variation (natural system variation) or special-cause variation. Shewhart defined common-cause variation as variation that is inherent to the manufacturing system. Common-cause variation is caused by day-to-day machinery variation, operator to-operator variation, supplier variation, etc. Shewhart defined special-cause variation as variation that occurs from an event in the manufacturing process. The event may be due to downtime, start-up, a new supplier, motor-stop, tool-wear, etc. Shewhart observed that variation due to common-causes exhibited a symmetric or normal distribution whereas variation due to special-causes goes beyond natural variation and does not follow typical statistical laws (Walter Andrew Shewhart, 1931; Walter Andrew Shewhart & Deming, 1939).

Shewhart stated "a process will be in control when through the use of past experience, we can predict, at least within limits, how the process will behave in the future" (Walter Andrew Shewhart, 1931). Special-cause variation is unpredictable and indicates the process is out of statistical control (Walter Andrew Shewhart, 1931; Walter Andrew Shewhart & Deming, 1939; Wheeler, 1993). The benefit to manufacturers from using Shewhart control charts comes from the ability to predict the future, i.e., if the process is in a state of statistical control, the limits can be extended out in to the future (E. Deming, 1986; W. E. Deming, 1944, 1993; Williams, 2001).

The paper deals with one of the significant parts of the concept related to controlling production quality, which is the analysis of production quality stability done for the following production procedure regulation aimed at the food manufacturing industry. The proposed methodology (respecting the change of location and variability of the food quality characteristics) will be introduced on the milk quality regulation. Also, there is the frequent problem solved out here in the report that relates to food quality measuring – their self-regulation by using the statistical calculation of self-regulation higher classes' coefficients and also using the functional statement taken from the differential description (Hron, Macak, & others, 2009).

2.3 Process Capability Indices

The science of process capability analysis, first introduced by Juran began as a comparison of the process output distribution with the product tolerances (S Kotz & Lovelace, 1998). Frequency histograms, log plots and control charts were used to compare process data to product tolerances. Process capability indices were born out of the need for an index that could relate information from the various plots into a single value. Pearn, Kotz and Johnson discussed the distributional properties of the three basic indices, C_p, C_{pk} and C_{pm} and their estimators. A new index C_{pmk} was proposed, which was more sensitive to the departure of the process mean from the target value and thus able to distinguish between off-target and on-target processes (Pearn, Kotz, & Johnson, 1992).

Quality by Design (QbD) refers to a holistic approach towards drug development. QbD has become the answer to assist both industry and FDA to move towards a more scientific, risk based, holistic and proactive approach to pharmaceutical development. The concept promotes industry's understanding of the product and manufacturing process starting with product development, basically building quality in, not testing it. Under this concept of QbD during designing and development of a product, a company needs to define desire product performance profile [Target product Profile (TPP), Target Product Quality Profile (TPQP)] and identify critical quality attributed (CQA). On the basis of the information company then design the product formulation and process to meet the product attributes. This leads to understand the impact of raw materials [critical material attributes (CMA)], critical process parameters (CPP) on the CQAs and identification and control sources of variability. As results of all understanding, a company can continually monitor and update its manufacturing

process to assure consistent product quality. This systematic approach to product development and manufacturing has received a great deal from traditional approach, which was extremely empirical. Implementation of QbD is enabling transformation of the chemistry, manufacturing, and controls (CMC) review of Abbreviated New Drug Applications (ANDAs) into a modern, science and risk based pharmaceutical quality assessment (Roy, 2012).

2.4 Limited Dependent Variable Model

Over the years, failure prediction or financial distress models have been much discussed in accounting and credit management literature. From the late 1960s, when Beaver (BEAVER, 1967) and (E. I. Altman, 1968) published their first failure prediction model, an enormous number of academic researchers from all over the world have been developing good failure prediction models based on various modelling techniques. Moreover in many papers some attention has been paid to the comparison of different scoring techniques (for example logit analysis, neural networks and decision trees) on the same dataset have been published or to the performance of different types of failure prediction models (Mossman, Bell, Swartz, & Turtle, 1998). However most of researches have focused, from both a theoretical and empirical point of view with reference to the private sector. This study aims to contribute, from an empirical point of view, in this field of research with reference to local governments.

(Beaver, 1968) was the pioneer in building a corporate failure prediction model with financial ratios. He was the first researcher to apply a univariate model – a "univariate Discriminant analysis model" – on a number of financial ratios of a paired sample of failing and non-failing companies in order to predict company failure. In his studies Beaver demonstrated the predictive ability of accounting data (Beaver, 1966; Beaver, Kennelly, & Voss, 1968). Univariate analysis is a very simple technique that classifies a company as healthy if the value assumed by an accounting index is above the critical value, also called the cut off point; on the contrary, if its value is below the cut off point the company is considered at risk (Lachenbruch, 1975).

The cut off, in other words the critical point that determines the company's classification, corresponds, therefore, to the equidistant value between the averages of the two groups. This methodology provides the same results as those obtained through a multiple linear regression,

in which the dependent variable assumes a dichotomous value (1 in the case of a company crisis and 0 for the healthy company).

Moreover the Univariate analysis is based on the stringent assumption that the functional form of the relationship between a measure or ratio and the failure status is linear. This assumption is often violated in practice, where many ratios show a non-linear relationship with the failure status (Keasey & Watson, 1991). Moreover, firm classification can only occur for one ratio at a time, which may give inconsistent and confusing classifications results for different ratios on the same firm (E. I. Altman, 1968; Zavgren, 1983). In 1968, (E. I. Altman, 1968) introduced the Multiple Discriminant Analysis (MDA) which is "a statistical technique used to classify an observation into one of several a priori groups dependent upon the observation's individual characteristicsattempts to derive a linear [or quadratic] combination of these characteristics which 'best' discriminates between the groups (E. I. Altman, 1968)". In his study he estimated a model called the 'Z-score model' used in an enormous volume of studies. After the 1980s, the MDA method is frequently used as a 'baseline' method for comparative studies (E. I. Altman, Haldeman, & Narayanan, 1977).

An MDA model consists of a linear combination of variables, which provides the best distinction between the group of failing and the group of non-failing firms. For example, Altman's Z-score model is a linear combination of the following ratios: working capital/ total assets, retained earnings/ total assets, earnings before interest and taxes/ total assets, market capitalization/ total debts and sales/ total assets (E. I. Altman, 1968).

In most studies, a low discriminant score indicates a poor financial health. In 1980s MDA method has been replaced by conditional probability models' (Zavgren, 1983) as logit analysis (LA), probit analysis (PA) and linear probability modelling (LPM). (Ohlson, 1980) pioneered in using logit analysis on financial ratios in order to predict company failure.

On the theoretical the logistic regression is a more appropriate instrument than linear regression, since it allows to define two distinct classes (good and bad risks) (Hand & Henley, 1997). In this study, it allows you to define two distinct classes: local authorities with financial risk and local authorities with no financial risk. In the author's opinion, logit and probit models can be successfully employed in the analysis of the risk of insolvency of local

authorities, because they allow researchers to estimate the probability that a crisis occurs, given the values of the account variables, that constitute the explanatory variables of the model, i.e. X.

The econometric methodology of the logit analysis was also chosen to avoid some know problems associated with the Multivariate Discriminant Analysis (MDA). Some of the problems of this technique are: 1) there are some statistical requirements imposed on the properties of the distribution of predictors: for example, the variance-covariance matrix of the predictors should be the same for both groups (failed and no-failed firms); 2) the requirement of normally distributed predictors certainly reduces the use of binary independent variables (Eisenbeis, 1977; Joy & Tollefson, 1975). The MDA approach has long been the leading method for predictions of business failure. The main drawback is certainly the assumption of normally distributed regressors: since generally the financial ratios are not normally distributed, the maximum likelihood methods and in particular the logit and probit were the most frequently used (Demirgüç-Kunt, 1989; Lennox, 1999; Martin, 1977; Trussel & Patrick, 2009). There are also some problems with the "matching procedures" that are generally used in the MDA: the failed and no-failed firms are matched based on criteria such as size and sector, and these tend to be somewhat arbitrary (Ohlson, 1980). The use of logit analysis, instead, avoids essentially all of the problems discussed in relation to MDA. The fundamental problem of the estimate may be reduced simply to the following statement: “as the company belong to a prespecified population, what is the probability that the company failed within a prespecified period of time?” With logit analysis no assumptions should be made regarding the prior probability of failure and/or distribution of the predictors. These are the main advantages compared to discriminant analysis (Ohlson, 1980).

Conditional probability models allow to estimate the probability of company failure conditional on a range of firm characteristics by a non-linear maximum likelihood estimation. The models are based on a certain assumption concerning the probability distribution. The logit models assume a logistic distribution (Hosmer & Lemeshow, 1989; Maddala, 1977), while the probit models assume a cumulative normal distribution (Theil, 1971). In the linear probability models, the relationship between the variables and the failure probability is assumed to be linear (E. Altman, Eisenbeis, & Sinkey, 1981; Gloubos & Grammatikos, 1988). Both logit and probit models provide the probability of occurrence of an outcome

described by a dichotomous (or polytomous) dependent variable using coefficients of the independent variables (Vranas, 1992; Zavgren, 1985). The main difference between logit and probit analysis is that the former uses the cumulative logistic probability function, while the latter is based on the cumulative standard normal distribution function. A significant advantage of these models over discriminant analysis is that they do not require the independent variables to be multivariate normal (Keasey & Watson, 1991). Furthermore, they provide much more useful information to the financial/credit analysts in bankruptcy prediction, since except for the classification of the firms into bankrupt and non-bankrupt ones, they also provide the probability of failure of a firm. Besides the fact that logit analysis has no assumptions concerning the distribution of the independent variables and the prior probabilities of failure, there are some other important advantages of LA. First, the output of the LA model, the logit score, is a score between zero and one, which immediately gives the 'failure probability' of the company (Ohlson, 1980; Ooghe, Joos, & De Vos, 1993). Second, the estimated coefficients in a LA model can be interpreted separately as the importance or significance of each of the independent variables in the explanation of the estimated failure probability (Mensah, 1984; Ohlson, 1980; Zavgren, 1985), provided that there is no multi-collinearity among the variables. Third, LA models allow for qualitative variables with categories rather than continuous data. In this case, dummies are used (Joos, Vanhoof, Ooghe, & Sierens, 1998; Keasey & Watson, 1987; Ohlson, 1980).

The linearity that ensures the linear model is easy to use can also be its major drawback, however. These models run into problems of inference, and the assumptions of normality/homoschedasticity of the errors are violated (i.e., the remainders are dichotomous and heteroschedastic) (Stock & Watson, 2005).

The linear model is probably the easiest to use and read, but fails to capture the nonlinear nature of the true regression function of the population. The logit and probit regressions model the nonlinearity in probability. The classic static-econometric methods can be considered the most commonly used methods for developing business models to forecast failure. In addition to these traditional statistical methods, academic researchers are beginning to use several alternative methods to analyze and predict business failure(Balcaen & Ooghe, 2004).

The best-known alternative models that have produced a considerable number of studies on the prediction of business failure are the survival analysis, decision trees and neural networks (Balcaen & Ooghe, 2004).

There are several different methods that can be used when forecasting business cycles. In thesis used a model closely related to the binary probit model in which the probability of an event occurring is calculated with the help of different predictors. When choosing this model take into account the findings of (Chin, Geweke, & Miller, 2000) and (Estrella & Mishkin, 1998) who state that a probit model is the most appropriate model to use when predicting business cycle turning points. According to Chin, Geweke and Miller the probit model has a clear advantage over the usual standard methods in that it predicts turning points directly instead of indirectly through the estimation of future GDP, generally resulting in a higher degree of accuracy. The model actually used in this thesis is, as mentioned above, not the probit model but a closely related version called the logistic-regression model. This model has the same basic implications as the probit but with the advantage of being somewhat more intuitive and easier to compute (Gujarati, 2003). More specifically we use what is called a binary logistic regression where binary means that the dependent variable can take only one of two values, “0” or “1”. In our case, a time period classified as an expansion is labeled “0” and a contraction is labeled “1” (Hamberg & Verständig, 2009).

The above is the development and mainstream of the research approaches for exploring the determinants of credit participation and credit demand. Other models and methods are also applied for estimating the factors affecting credit demand in different lending sectors. (Holly Wang, Turvey, Kong, & Huo, 2010) use the binary logistic regression against four binary dependent variables to estimate the results of the factors influencing borrowing from informal and formal credit sectors and take general linear method regression to measure the factors affecting credit amount borrowed. (Doan, Gibson, & Holmes, 2010) employ the multinomial Logit estimates to examine the factors influencing the probability of specified credit market participation; the purpose of the model is to compare each outcome probability with the base outcome of non-borrower group. (Tang, Guang, & Jin, 2010) explore the rural credit demand simultaneously through a multinomial Probit model given the fact that the farmers are facing three exclusive choices, the choice of informal credit is set as the base to compare with the choices of formal credit and non-borrowing.

In short, the existing researches are mainly focused on the credit demand of the households in all the segmented credit sectors and normally the real credit market participation is determined by the credit demand and credit access (Zheng, 2012). (E. I. Altman, 1968) is the first researcher who used discriminant analysis to predict the failures of firm from different industries.

2.5 Autoregressive Conditional Heteroskedasticity (ARCH)

To large extent, Economists have already captured the changes in financial data over a long time. From the paper of (Franses & McAleer, 2002), it can be seen many financial economists are very concerned about how to estimate the volatility of assets' returns better. They also do much try and explore many researches which made a possible is that almost every price series exhibits the same characteristics, so we have to find some approximate volatility models to fit these features. This was pointed out early by (French, Schwert, & Stambaugh, 1987) and (Bollerslev, 1986) and is especially clear in some of the surveys of empirical work from (R. Engle, 2002).

This first model is Autoregressive Conditional Heteroskedasticity (ARCH) which was early introduced in the (R. F. Engle, 1982), it aimed to capture the conditional variance that is why it became the most popular way of describing the unique feature. Later on, for making this model better (Bollerslev, 1986) and (S. J. Taylor, 1986) put forward, independently of each other, a generalization of this model, called Generalized ARCH (GARCH). And this model have been certificated not only to catch volatility clustering but also to contain fat tails from the volatility data. These are common features about the financial data. Even though the GARCH model is already the extension of the ARCH model, it still has some drawbacks. The main point is that the GARCH model is symmetric, so it has a poor performance in reflecting the asymmetry. Because a fact on an interesting feature of financial volatility data is that bad news seems to have a more significant effect on the fluctuation compared to good ones. In other words, positive and negative information generate different degrees of influence to the changes of financial data. So this asymmetric phenomenon is leverage effect. Considering the stock data, it always exist a strong negative correlation between the current return and the future conditional variance. That is why some advanced GARCH model will be introduced later. Such as exponential-GARCH model, (Nelson, 1991) and GJR-GARCH model,

(Glosten, Jagannathan, & Runkle, 1993), are proposed. Except these models, there still have many other extension GARCH models, such as TGARCH model—threshold ARCH—attributed to (Rabemananjara & Zakoian, 1993) and (Glosten et al., 1993), FIGARCH model—introduced by (Baillie, Bollerslev, & Mikkelsen, 1996) IGARCH model—proposed by (R. F. Engle & Bollerslev, 1986) and so on (Bollerslev, 2008).

2.6 Statistical Technique used in Quality of diffrent Food Products

There were a greater variety of statistical tests chosen to determine quality of food products in publication. Major groups of analyses prevailed: (1) using Parametric Test (2) using ANOVA or variations etc. The most popular tests were the Post Hoc Tests and the Analysis of Variance test (ANOVA used in 13 out of 20 studies, Bold highlight in Table 2.1). Most studies did not perform for normality as well as goodness of fit test before choosing a appropriate statistical test. Almost all the tests used were for parametric distributed data. With the exception of Parvan, K., Zamanzadeh, V., & Hosseini, F. A. (2012)., distributional assumptions were stated. But it was evident by the testing that all performed a hypothesis test with a point null hypothesis of the means/medians between groups being equal. All of the studies reviewed are summarized in Table 2.1.

Table 2. 1: Food Quality Assessments Involving Statistical Analysis

Author	Monitoring matter	Distribution Assumption	Publication Name	Test Used
Kader, Abdul, et al. (2015)	Quality of Milk	None stated (NS)	Food Science and Technology	One-sample *t*-test
Siddiqui, A. A., & Chowdhury, M. N. A. (2013)	Quality Assessment of Wheat Flour	NS	journal of substance abuse treatment	**One-way ANOVA and Duncan's multiple range tests**
Islam, Md Serajul, et al. (2014)	Properties of Litchi Honey	NS	Journal of Entomology and Zoology Studies	**Analysis of variance (ANOVA) and Duncan's Multiple Range Test (DMRT)**
Nayak, N. K., et al. (2015).	Quality of Carrageenan	NS	Livestock Research International	**Analysis of Variance (ANOVA) and Duncan's multiple range test (DMRT)**
Kapute, Fanuel, et al. (2012)	Quality assessment of tilapia	NS	Internet Journal of Food Safety	Simple *t*-tests
Obaroh, I. O., Haruna, M. A., & Ojibo, A. (2015).	**C**omposition of Clarias gariepinus	NS	European Journal of Basic and Applied Sciences	**ANOVA**
Kale, S. J., et al. (2015)	Characteristics of Basmati Rice.	NS	Rice Science	**Duncan's multiple range tests**
Asghar, A., and M. Abbas. (2015).	Properties of cake	NS	American Journal of Scientific and Industrial Research	**Duncan's Multiple Range Test**

Author	**Monitoring matter**	**Distribution Assumption**	**Publication Name**	**Test Used**
Latifa, Gulshan Ara, et al. (2014)	Quality of Fish Species	NS	American Journal of Food and Nutrition	SPSS Software
Khuntasom, M., & YONGSAWATDI GUL, J. (2014).	Inhibitory activity of protein hydrolysates fromThai panga skin.	NS	ACS AGFD – ACS ICSCT Symposium on Agricultural and Food Chemistry	**Duncan's multiple range test (DMRT)**
Akhter, M. S., Mannan, D. M. A., & Ghosh, S. (2012).	Characteristics of papaya germplasms	NS	International Research Journal of Applied Life Sciences	**Duncan's Multiple Range Test (DMRT)**
Normah, I., and I. Muhammad Fahmi. (2015).	Characteristics of sutchi catfish gelatin	NS	International Food Research Journal	**Analysis of variance (ANOVA)**
Jesús, Marcelo Nunes de, et al. (2013)	characteristics of desserts prepared with egg products	NS	Food Science and Technology	**Analysis of variance and Tukey's test**
Akissoe, Noël, et al. (2011).	quality of yam products	NS	LWT-Food Science and Technology	Anova and general linear model (GLM) procedures, Newmane Keuls mean comparisons, correlation and linear multiple regression models.
Gil, María I., Encarna Aguayo, and Adel A. Kader. (2006)	Quality of fruits	NS	Journal of Agricultural and Food chemistry	**Analysis of variance (ANOVA) and least significant difference test (LSD).**
Hoseinzadeh, Edris, et al. (2013)	Quality of the Central Restaurant Food	NS	Thrita Journal of Medical Science.	SPSS software
Bach, V. (2012).	Quality of culinary preparations of root crops.	NS	Aarhus University, Department of Food Science.	Multivariate data analysis
Karami, B., et al. (2013)	Quality of Red Tilapia	NS	Iranian Journal of Fisheries Sciences	**Two and one way analysis of variance (ANOVA)**
Mashak, Z., H. Sodagari, and B. Moradi. (2014)	Microbiological and Chemical Quality of Sohan: An Iranian Traditional Confectionary Product.	NS	Journal of food quality and hazards control	**Analysis of variance (ANOVA) and Tukey test.**
Parvan, K., Zamanzadeh, V., & Hosseini, F. A. (2012).	Assessment of professional values	Stated	Thrita Journal of Medical Science.	Mann-Whitney and Kruskal-Wallis tests, Bonferroni adjustment method

CHAPTER 3:MATERIALS AND METHODS

In this chapter an overview of the materials and methods used in the thesis is presented. The samples and Statistical Analytical Procedures are also describe.

3.1 Data

The Institute of Food Science and Technology (IFST) started functioning as an Institute of Bangladesh Council of Scientific and Industrial Research (BCSIR). At present Institute has a total of 78 scientists. This Institute has been examining the qualitative different different parameters of food products which are imported and developed by different entrepreneurs in Bangladesh. The food products analyzed by following national and international acceptable method and procedures. Food products analysis data has been collected from Institute of Food Science and Technology (IFST), BCSIR with permission of the authority. The variable name of study are microbial count (SPC, Coliform, Mold, Yeast, E.Coli, Salmonella etc.), physical properties (Broken, Damaged, Moisture, Ash, Milling degree, Paddy etc.), chemical properties (Protein, Fat, Fibre, Carbohydrate, Energy, Acidity, Sugar etc.) and toxicity (Aflatoxin) and relevant data have been collected from the adhoc analysis report of different food prodcts which are previously analysed by respective scientist of IFST.

3.2 Methods of Data Collection

Data collection methods were non-participant observation of organization included in the study. Archival research included hard-copy issues of reports of analytical documents.

We sought to collect each data over the five year period from 2007 to 2012 on a Single Stage Cluster Sampling basis. Each variable is discussed in detail in the below:

Table 3. 1: Variables in the food products.

Sl. No.	Description of food Products	Number of observations	Name of variables (unit)	Level of measurement
1.	Fortified High Energy Biscuits	310	Moisture (%)	Ratio scale
			Protein (%)	
			Fat (%)	
			Sugar (%)	
			Total Carbohydrate (%)	

Sl. No.	Description of food Products	Number of observations	Name of variables (unit)	Level of measurement
	Fortified High Energy Biscuits		Iron (mg/100g)	Ratio scale
			Vitamin A (µg/100g)	
			Mesophyllic aerobic bacteria (cfu/g)	
			Coliforms (MPN/g)	
			Escherichia coli (MPN/g)	
			Salmonella spp.	
			Staphylococcus (cfu/g)	
			Bacillus cereus (cfu/g)	
			Enterobacter sakazakii (cfu/g)	
			Yeast and moulds (cfu/g)	
2.	Complan Nutritional Drink	19	Energy (kcal/100g)	Ratio scale
			Moisture (%)	
			Protein (%)	
			Fat (%)	
			Total Carbohydrate (%)	
3.	Soft Drinks	57	pH	Ratio scale
			Total Soluble Solid (%)	
			Reducing Sugar (%)	
			Total Sugar (%)	
			Acidity (%)	
			Standard Plate Count (cfu/ml)	
			Coliform (MPN/ml)	
			Mold (cfu/ml)	
			Yeast (cfu/ml)	
			Alcohol (%)	
			Vitamin C (mg/100ml)	
			Gas Pressure (lb/in^2)	
4.	Milk	32	Moisture, %	Ratio scale
			Protein, %	
			Milk Fat, %	
			Total Ash (on dry basis), %	
			Tritratable Acidity (as lactic acid), %	
			Solubility , %	
			Total Milk Solid, %	
			Melamine (ppm/100g)	
			Lactose, %	
			Standard Plate Count, cfu/g	
			Total Coliform, MPN/g	
5.	Parboiled Rice	18	Broken (%)	Ratio scale
			Moisture (%)	
			Damaged/Discoloured (%)	
			Yellow Kernels (%)	

Sl. No.	Description of food Products	Number of observations	Name of variables (unit)	Level of measurement
	Parboiled Rice		Red and Streaked (%)	
			Chalky grain (%)	
			Paddy per Kg	
			Other Varieties (%)	
			Milling Degree	
			SPC(cfu/g)	
			Total Coli Form (MPN/g)	
			Total Fungi (cfu/g)	
			Aspergillus flavus (cfu/g)	
			Aflatoxin (B1, B2, G1, G2)	
6.	Wheat Soya Blend (WSB)	36	Moisture (%)	Ratio scale
			Protein (%)	
			Fat (%)	
			Sugar (as sucrose) (%)	
			Total Carbohydrate (%)	
			Vitamin A (IU/100g)	
			Iron (mg/100g)	
			Standard Plate Count (cfu/g)	
			Total Coliform (MPN/g)	
			E. Coli (MPN/g)	
7.	Yellow Split Peas	30	Moisture (%)	Ratio scale
			Purity (%)	
			Whole peas (%)	
			Heat damage (%)	
			Other damage (%)	
			Foreign matter (%)	
			Other colour (%)	
			Insect damage (%)	
			Broken (%)	
8.	White Sugar	176	Moisture, %	Ratio scale
			Sulphated Ash, %	
			Colour of the solution, in ICUMSA units	
			Sucrose, %	
			Sulphur dioxide, ppm	
			Hydrogen Peroxide, ppm	
			Hydrose, ppm	

Sample:

Total 678 food sample analysed observations from different food products as Fortified High Energy Biscuits 310, Complan Nutritional Drink 19, Soft Drinks 57, Rice 18, Milk 32, Wheat

Soya Blend (WSB) 36, Yellow Split Peas 30 and White Sugar 176 Samples analysis report of which 83 analytical tests parameter were surveyed.

Samples of previously analyzed food specimen data were collected by the method of Single Stage Cluster Sampling from Institute of Food Science and Technology (IFST), BCSIR, Dhaka. Here we define each section as cluster in the study, then select 7 (seven) clusters out of 16 (sixteen) clusters in the population with simple random sampling (SRS) strategy. All units (elements) in the sampled clusters are selected for the study.

3.3 Model Development

Selection and grouping of food quality as a starting point, the following groups of attributes are considered in evaluation:

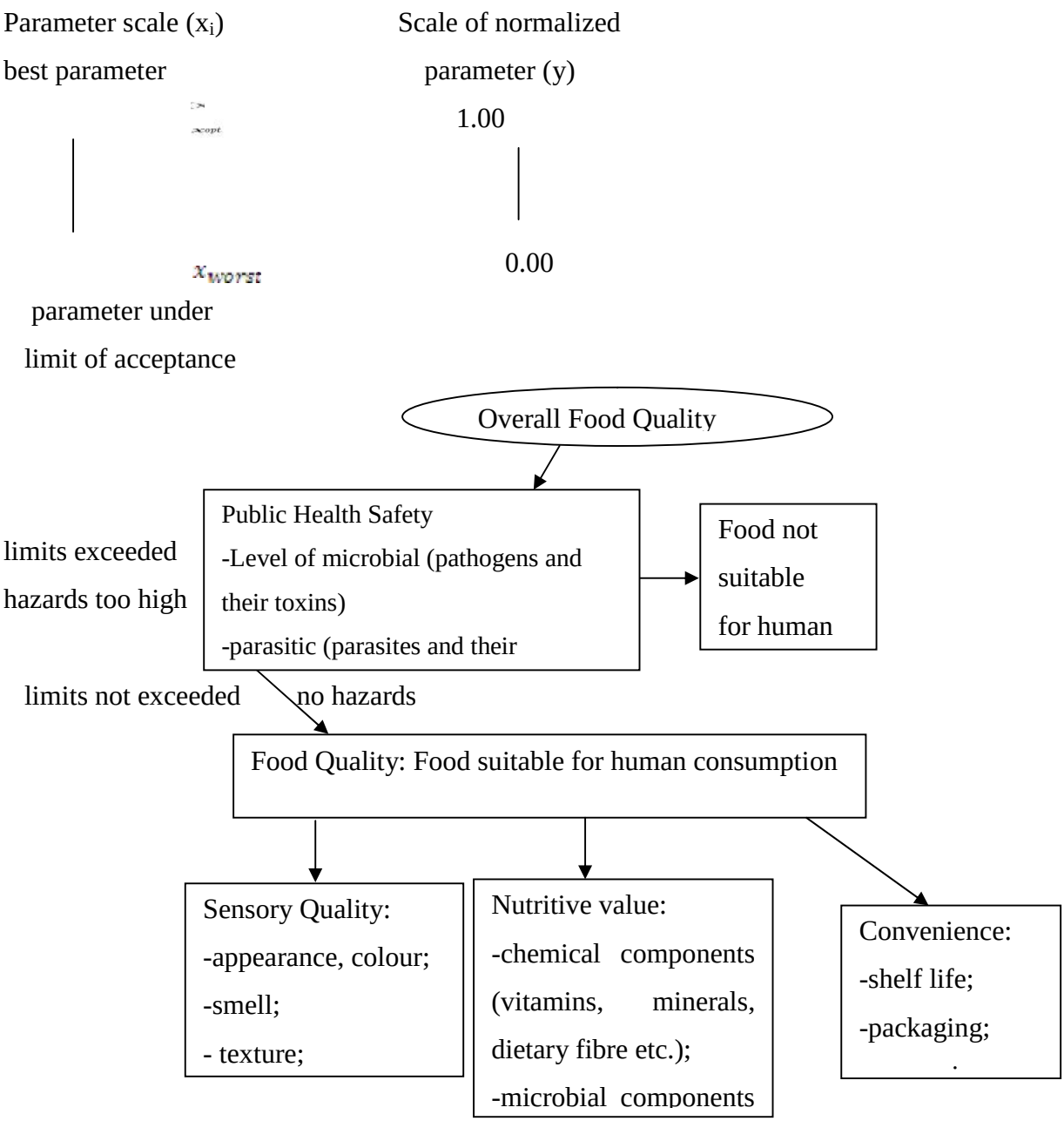
i. Chemical composition and physical properties;
ii. Microbiological contaminants;
iii.Toxicological contaminants.

Within a group of properties, the type of product determines the attributes to be selected for consideration, based primarily on prior consultation with experts. This technical judgment is of importance even if mathematical methods are used to identify attributes. It is advisable to link the statistical methods used in identifying attributes to the determination of the weighting factors for the selected attributes.

3.3.1 Possibilities of parameter normalization

In accordance with the evaluation methods, the range of parameters involved in the evaluation should be between 0 and 1. It is recommended that the limit values are chosen so as to have a ‘sudden jump’ in product quality at these values. The parameter ascribed to zero indicates food products below the limit of acceptance and/or greatly differing from product specification. The optimum (best) value of the product parameter is ascribed to 1. The theoretical normalization model of measured parameter is as follows:

Figure 3. 1: Definition and description of food quality



The relationship between the normalized and the original values $y = f(x_i)$ which may be linear or nonlinear (Molnar, 1995).

Dependent Variable (Z)

=Quality characteristic of food products

(Acceptable vs. Unacceptable)

Independent Variables (X_i) are

Moisture content;

Protein content;

Fat content;

Total Carbohydrate content etc.

Computation statistical software in statistical analysis:

- Specialised statistical software, Stata;
- Statistical Package for the Social Sciences, SPSS;
- Both are statistical and chemo-metric software;
- Powerful statistical and graphical Software, Minitab.

Principally two analytical tools namely, statistical Quality Control Techniques and Econometric Modellings will be adopted for performing the present research. We elaborate the conceptual framework of six Statistical Analytical Procedures below.

1. Quality Control Charts;
2. Process Capability Methodology;
3. Binary Logistic Model;
4. Binary Probit Model;
5. Discriminant Analysis Model and
6. Autoregressive Conditional Heteroskedasticty (ARCH) Model.

3.4 Quality Control using Econometric Techniques

3.4.1 Historical Background

Statistical quality control comparatively new, the science of statistics itself belongs to two to three centuries ago. Moreover, it is the greatest development has taken place during the 20th century.The notion of using sampling and statistical analysis techniques in a production started in 1920 and applied effectively to quality control as a result of the development of sampling theory.

The first who applied the newly discovered statistical methods to the problem of quality control was Walter A. Shewhart (1891–1963) in the Bell Telephone Laboratories. He issued a memorandum on (May 16, 1924) that featured a sketch of modern quality control chart to control and detect non-stochastic variation in the process of a production. For the first time

statistical methods applied to the problem of quality control by Walter Shewhart and he kept improving and working on this scheme, in 1926–1927 published three papers on the (Quality Control and Control chart). Therefore, for the first time after publishing these papers in the Journal of (American statistical society), he used control chart in Bell Telephone Laboratories. This marked the beginning of statistical quality control (Besterfield, 1986; Montgomery, 2007; Walter A Shewhart & Deming, 1967).

In 1931 W.A. Shewhart published a book on statistical quality control under the title of (Economic Control of Quality of Manufactured Product), published by (Van Nostrand in New York). He gave some lectures on statistical methods in production and control charts at the University of London in 1932 and invited Shewhart by Deming in 1938, to present seminars on control charts at the U.S. Department of Agriculture Graduate School (Del Castillo, 2002; Runger & Testik, 2003).

From 1942 to 1946, the training courses on statistical quality control were given to industry. And more than fifteen quality societies are formed in North America, such as (American society for quality control) formed on 16/2/1946. This organization, through its publication, conference and training session, has promoted the use of quality control for all types of production and service (Besterfield, 1986; Bisgaard, Hunter, & Pallesen, 1984).

In 1950 W. Edward Deming (1900–1993), who had worked with Shewhart at Bell Telephone Laboratories, gave a series of lectures on statistical method to Japanese Engineers and on quality responsibility to top management (Besterfield, 1986).

The British statistician, (E.S.Page) in 1954, when he was in the statistical laboratory at the Cambirg University, introduced a new control chart in the name of CUSUM (Cumulative Sum) control chart. This is a draw of Cumulative Sum of error of observations (Page, 1954). In 1959 statistician, Barnard introduced a V-Mask, for making the decision with CUSUM-chart (Barnard, 1959; Montgomery, 2007).

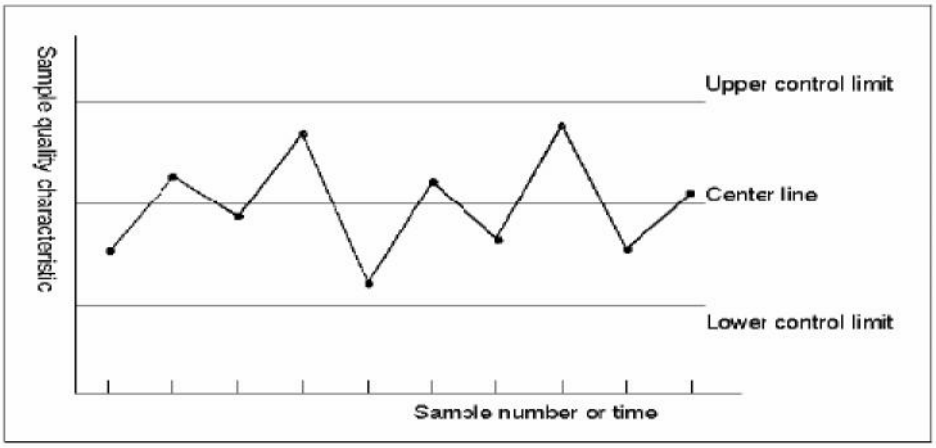
The statistician S.Roberts introduced 3-new control charts. The first was based on Moving Average (1958), the second was the Moving Range (1958) and the third was based on Geometric Moving Average (1959). The decision about the production process for these three

charts are depending on the past data as well as the current data, therefore the decision is not based on a single plotted data (MacGregor & Harris, 1993; Steiner, 1999; Testik & Borror, 2004). (Hamada, 2003), proposed the use of Beta-content tolerance intervals as the basis for control limits and more precisely probability control limits (Montgomery, 2005).

3.4.2 Quality Control Charts

Control charts are widely used in industry as a tool to monitor output process. Different types of control charts may be used depending upon the type of the data that is measured or computed from samples. A control chart always has a centerline for the average value of the quality characteristic, and two other horizontal lines, an upper line called the upper control limit (UCL) and a lower line for the lower control limit (LCL), are shown on the Fig. 3.3. The control limits are chosen because if the process in control means that all of the plotted points will fall between them, and no action is necessary. If a point falls outside one of the control limits, this would be an indication that the process is out of control. Then, an action should be taken, and this is to search for assignable causes (or non-stochastic cause or causes).

Figure 3. 2: General control chart.



The control limits usually are set at (±3σ) from the centerline.

(UCL, LCL) = T ±3σ

where:

T = target value (centerline)

σ = standard deviation

The quality control charts are divided into two main types, which are variable quality control chart and attribute quality control chart. The terms variable and attribute are associated with

the type of data being collected from the production line of the process (Spiegel Murray & Stephens Larry, 1999).

3.4.3 Variable Quality Control Charts

A quality characteristic that is measured on a numerical scale is called a variable; and includes dimensions such as length or width, temperature; time and volume (can be measured in fraction or decimals). When dealing with a quality characteristic that is of variable type, it is usually preferable to monitor both the mean level of the quality characteristic and its variability.

The variable quality control charts are divided into two types:

(i). Shewhart variable quality control charts;

(ii). Non-Shewhart variable quality control charts(Montgomery, 2005).

3.4.4 Shewhart Control Charts

The familiar shewhart control charts are:

$\overline{\overline{X}}$ -chart (Average-chart or Mean–chart);

R-chart (Range–chart);

σ-chart (Standard deviation chart);

Exponentially Weighted Moving Average Control Charts (EWMA).

1. $\overline{\overline{X}}$ -Chart: $\overline{\overline{X}}$ -chart for variables data, (data that is both quantitative and continuous in measurement, such as a measured dimension or time).

The aim of using the $\bar{x}$ -chart is to control the mean level of the output of a process.

The point plots on this chart are the average ($\bar{x}$) of subgroups data, calculate from:

$$\bar{x}_j = \frac{\sum_{i=1}^{n} x_i}{n} \quad \text{……(3. 1)}$$

The centerline of the $\bar{x}$ -chart is ($\overline{\overline{X}}$) calculate from:

$$\overline{\overline{X}} = \frac{\sum_{j=1}^{m} x_i}{m} \quad \text{……..……(3. 2)}$$

The control limits of the $\overline{\overline{X}}$ -chart are established at three-standard deviation (±3σ) from the target value and calculate by the formulas:

$$UCL_{\bar{x}} = \overline{\overline{X}} + 3\pounds_{\bar{x}} \quad \text{.....(3. 3)}$$

$$LCL_{\bar{x}} = \bar{\bar{X}} - 3\hat{\sigma}_{\bar{x}} \quad \text{.....(3. 4)}$$

In practice the calculations are simplified by using (for n < 10)

$$UCL = \bar{\bar{X}} + A_2\bar{R} \quad \text{.....(3. 5)}$$

$$LCL = \bar{\bar{X}} - A_2\bar{R} \quad \text{.....(3. 6)}$$

where:

$$\hat{\sigma} = \frac{\bar{R}}{d_2} \quad \text{……..……..……..(3. 7)}$$

$\bar{R}$ = average of the subgroup range

But for (n ≥ 10) the control limits are:

$$UCL = \bar{\bar{X}} + A_3\bar{S} \quad \text{.....(3. 8)}$$

$$LCL = \bar{\bar{X}} - A_3\bar{S} \quad \text{.....(3. 9)}$$

where:

$\bar{S}$ = average of the subgroups (or samples) standard deviations.

The constants (A_1) and (A_2) are quality control factors given in the table (Hamada, 2003; Montgomery, 2005).

2. R-Chart (Range Chart): The R-chart is developed from the range of each subgroup data. The aim of using Range chart is to control the variation in the output of a process. The point plots on this chart are the range (R) of subgroup data, calculate from:

$R_j = \text{Max}\{x_1, x_2, \ldots, x_n\} - \text{Min}\{x_1, x_2, \ldots, x_n\}$ …….……(3. 10)

When subgroup sizes are less than (10), both (R-chart and S-chart) will graphically portray the same variation, however, as subgroup sizes increase to (10) or more, extreme values have an undue influence on the R-chart. Therefore, at larger subgroup sizes the S-chart (σ-chart) is used.

If the sample size is relatively small, (n < 10) it is preferable to use R-chart.

The centerline for the R-chart is ($\bar{R}$), calculate from:

$$\bar{R} = \frac{\sum_{j=1}^{m} R_j}{m} \quad \text{..... (3. 11)}$$

The control limits for the control chart, calculate by the formulas:

$UCL = \bar{R} + 3\pm_R$ ..... (3. 12)

$LCL = \bar{R} - 3\pm_R$ ..... (3. 13)

In practice, the calculations are simplified by using the formulas:

$UCL = D_4\bar{R}$ ..... (3. 14)

$LCL = D_3\bar{R}$ .....(3. 15)

Remark:

In general the (R-chart) is not symmetric around target line, because for (n =2, 3, ..., 6), the $D_3 = 0$. The constant D_3 and D_4 are the quality control factors given in the table (Besterfield, 1986; Montgomery, 2005).

3. σ-Chart: The aim of using (sigma–chart) is to control the variation of the output in the quality of a process. The point plots on this chart are (σ) or standard deviation of sample.

The centerline of sigma-chart is ($\pm\bar{}$) and calculated as:

$$\pm\bar{} = \frac{\sum_{j=1}^{m} \pm_j}{m} \text{ .....(3. 16)}$$

If s is unknown, then it would be estimated from the data.

$$\pm\hat{} = \frac{\bar{R}}{d_2} \text{ ..... (3. 17)}$$

The action lines are:

$UCL_{\pm} = \pm\bar{} + 3\pm_{\pm} = B_4\pm\bar{}$ .....(3. 18)

$LCL_{\pm} = \pm\bar{} - 3\pm_{\pm} = B_3\pm\bar{}$ .....(3. 19)

The constants d_2, B_3 and B_4 are quality control factors given in the table (Besterfield, 1986; Montgomery, 2007).

4. Cumulative Sum Control Charts: The Cumulative Sum (Cusum) control chart is an alternative to the Shewhart-type chart, which can be used in the same context. It was first introduced by E.S. Page in 1954 and has been studied by a number of authors (Ewan, 1963; Gan, 1991; HAWKINS, 1993; Page, 1954; Woodall & Adams, 1993).

Cusum charts are generally used to detect small process shifts. Since they combine information from several samples, they are more effective than Shewharttype charts, even in the case of subgroups of size n= 1. They can detect process shifts of *0.5σ* to 2*σ* in about half the time of a Shewhart chart with the same sample size, but they are slower in detecting large shifts (Montgomery, 1996).

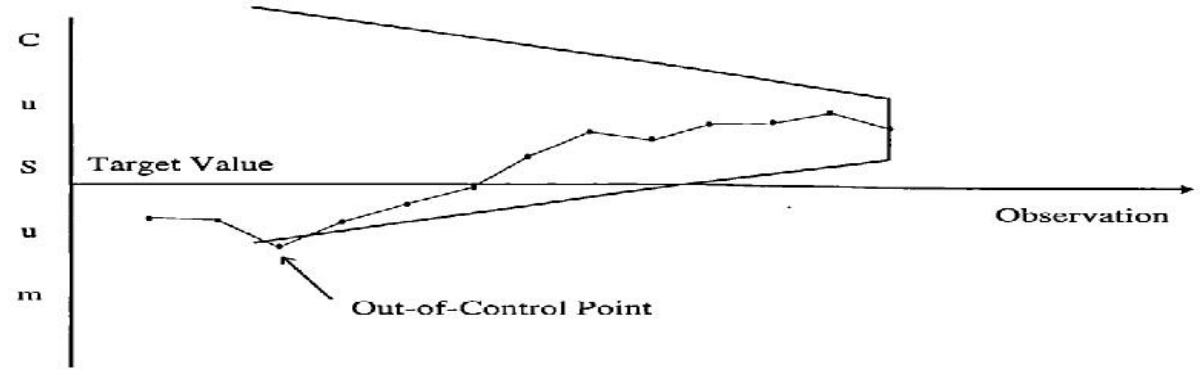
A Cusum chart uses all the information in a sequence of values of a statistic by plotting the cumulative sums of their deviations from a target value. Suppose that rational subgroups of size n≥1 are collected from a process and that the average $\bar{X}_i$ of each rational subgroup is calculated. If $\mu_0$denotes the target for the process mean, then the Cusum control chart is formed by plotting the statistic:

$$C_i = \sum_{j=1}^{i}(\bar{X}_j - \mu_0) \quad \text{(3. 20)}$$

against the rational subgroup number i. A typical Cusum control chart is presented in Figure 3.3 (Hawkins & Olwell, 1997).

The control limits are usually calculated using the *V-mask* procedure (Barnard, 1959; Johnson, 1961). The out-of-control signal in a Cusum control scheme is given when the sample statistic C_i exceeds the control limits. Note that, re-initialization of the Cusum statistic to target value is required after taking corrective action. A detailed discussion of the calculation of the ARL in Cusum control charts can be found in (Montgomery, 1996).

Figure 3. 3: A cumulative sum control chart



(Papazoglou, 1998).

5. Exponentially Weighted Moving Average Control Charts (EWMA): An alternative to the Shewhart-type control chart, especially when one wants to detect small and moderately-

sized sustained process shifts, is the Exponentially Weighted Moving Average (EWMA) control chart. It was introduced by S.W. Roberts in 1959. Comprehensive descriptions of EWMA are provided by many authors (Crowder, 1989; Davis & Woodall, 1994; Lucas & Saccucci, 1990; Montgomery, 1996; S. Roberts, 1959). The EWMA statistic is defined as:

$$z_i = \text{a}\bar{x}_i + (1-\text{a})z_{i-1} \quad \text{.....(3. 21)}$$

or by recursive substitution as:

$$z_i = \text{a}\sum_{j=0}^{i-1}(1-\text{a})^j \bar{x}_{i-j} + (1-\text{a})^i z_0 \quad \text{.....(3. 22)}$$

Where, $\bar{x}_i$ denotes the average of the i-th rational subgroup, λ is a weighting factor ($0 < \lambda \leq 1$) and z_0 is the starting value of the statistic under study (first sample at i=l), which is usually taken to be equal to the population mean of the statistic (μ_0):

$$z_0 = «_0 \quad \text{.....(3. 23)}$$

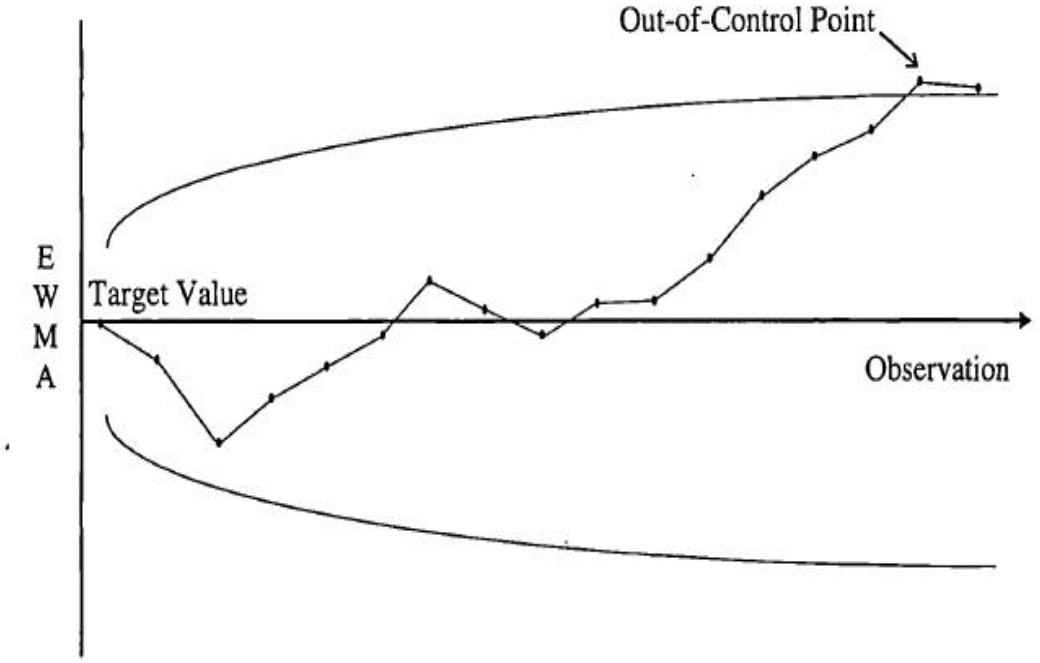
The control limits for the EWMA control chart can be calculated based upon the assumption that the observations x_i that comprise the collected rational subgroup, are independent random variables:

$$CL_{EWMA} = «_0 \pm L\pm \sqrt{\frac{\text{a}}{(2-\text{a})}[1-(1-\text{a})^{2i}]} \quad \text{..... (3. 24)}$$

Where, L is a factor defining the width of the control limits and is the standard deviation of the sample under study.

EWMA can be viewed as a weighted average of all past and current observations. Specifically, a new moving average is formed each time a new sample is collected by calculating a weighted average of the new value and the previous moving average. A typical example of a EWMA control chart is illustrated in Figure 3.4. The performance of the EWMA control chart is approximately equivalent to that of the Cusum chart, although EWMA charts is easier to set-up and operate. Furthermore, EWMA charts can be used to smooth the effects of known but uncontrollable noise in the data by appropriate choice of the weighting factor λ. Many chemical process with day-to-day fluctuations, fit into this category. Moreover, a modified EWMA control chart can be used for auto-correlated processes with a slowly drifting process mean (Mastrangelo & Montgomery, 1995). Issues including the Average run length (ARL) in EWMA control charts are discussed in (Montgomery, 1996).

Figure 3. 4: EWMA control chart



(Papazoglou, 1998).

3.5 Process Capability Methodology

Process capability analysis (PCA) methodology occupies important places in quality and process improvement initiatives. As a fundamental technique in any production, quality and process improvement efforts, PCA is used to improve processes, products or services to achieve higher levels of customer satisfaction. In order to measure process capability numerically, process capability indices (PCIs) have been developed (Antony, Kumar, & Tiwari, 2005).

Process: Process is defined as a combination of materials, methods, equipments and people engaged in producing a measurable output. As a matter of fact, all processes have inherent statistical variability, which can be identified, evaluated and reduced by statistical methods.

The source and amount of variability should always be considered by organizations. In order to satisfy customer requirements, organizations must improve the quality by reducing variance in production processes. The less variation the system has, the better quality it

provides. Thereby, the variability of critical-to-quality characteristics (CTQs) is a measure of the uniformity of outputs. When the variation is large, the numbers of products that are nonconforming are large. Nonconforming (NC) is the failure of meeting specification limits whereas specifications are the desired measurements for a quality characteristic.

Process capability: In particular, process capability deals with the uniformity of the process. Variability of CTQs in the process is a measure of the uniformity of outputs. Here, variability can be thought in two ways: one is inherent variability in a CTQ at a specified time, and the other is variability in a CTQ over time. It should be considered that process capability study frequently measures functional parameters or CTQs on the product. It does not measure the process itself (Montgomery, 2009). Process capability compares inherent variability in a process with the specifications that are determined according to the customer requirements. In other words, process capability is the proportion of actual process spread to the allowable process spread, which is measured by six process standard deviation units. Process capability compares the output of a process that is an in-control state to the specification limits by using PCIs. To sum up, a capable process is the one where almost all the measurements fall inside the specification limits and process capability study can be conducted to indicate the extent to which the process can meet these specifications.

In a true process capability study, when there is direct observation of the process, inferences can be made about the stability of the process over time by directly controlling or monitoring data collection activity and understanding the time sequence of the data. However, when there is no direct observation of the process, only sample units of product are known, in this case, the study is called product characterization. In a product characterization study, distribution of the product quality characteristic or the fraction that conforms to specifications, which is referred to as process yield, can only be estimated, notably information about stability or dynamic behavior of the process cannot be given (Montgomery, 2009).

3.6 Process Capability Analysis (PCA)

PCA involves statistical techniques, which are useful throughout the product cycle. Generally, PCA is used in development activities prior to manufacturing process, in

quantification of process variability, in analysis of this variability relative to specifications and in elimination or reduction of the process variability (Montgomery, 2009).

As a fundamental technique in any production, quality and process improvement efforts, PCA is used to improve processes, products or services to achieve higher levels of customer satisfaction. PCA has become widely adopted as the measure of performance to evaluate the ability of a process to satisfy customer requirements in terms of specification limits(English & Taylor, 1993; Şenvar & Tozan, 2010). The output of a process is expected to meet specifications, which can be determined according to the customer requirements. PCA is a prominent technique that is used to determine how well a process meets to these specification limits. PCA is based on a sample of data taken from a process and often produces: an estimate of the dpmo (defects per million opportunities), one or more capability indices, an estimate of the sigma quality level at which the process operates. The sigma quality level of a process can be used to express its capability that means how well it performs with respect to specifications.

PCA is often used to estimate the process capability. The estimate of process capability can be in the form of a distribution that has parameters of shape, center (mean) and spread (standard deviation). In this case, PCA can be performed without regard to specifications of the quality characteristic. Here, process capability can be expressed as a percentage outside of specifications (Montgomery, 2009). For PCA, the following techniques can be used:

Histograms: In statistics, histograms are defined as graphical displays of frequencies. In the quality applications, histograms are well-known as one of the seven basic tools of quality control. Histograms are very useful in estimating process capability and for visualizing process performance. Hence, histograms can be used to determine the reason for poor process performance, instantaneously. As quality characteristics are often assumed to have normal distribution, histogram along with the sample mean and sample standard deviation can provide information about process capability as it is possible to estimate the process capability independent of the specifications. Here,normality assumption can be investigated by looking at the shape of the histogram. If the histogram is fairly skewed, then the normality assumption might be a concern and estimate of the process capability is unlikely to be correct. On the other hand, there are some drawbacks of using histograms. Fundamentally, it

is necessary to divide the range of a variable into classes. Also, histograms cannot be used for small samples, for this reason, at least hundred observations are needed. Essentially, in order to have reliable estimate of process capability, these observations must be moderately stable (Montgomery, 2009).

Control Charts: Control charts are very useful for establishing a baseline of the process capability or process performance. Control charts can be used as monitoring devices to show effects of changes in the process on process performance. Basically, control charts can determine whether a manufacturing or business process is in a state of statistical control or not. They show systematic patterns in process output, as well. In particular, before using PCIs, there is a need for establishment of a state of statistical control. That is, if a control chart indicates that the process is currently under control, then it can be used with confidence to predict the future performance of the process. In the contrary, if a control chart indicates that the process being monitored is not in control, the pattern it reveals can help to determine the source of variation to be eliminated in order to bring the process back into control. Concisely, the control chart allows significant change to be differentiated from the natural variability of the process. This is shown to be the key for effective process control and improvement. Control charts are effective in displaying potential capability of the process by performing the issue of statistical control, for this reason, they should be regarded as the primary technique of PCA. In PCA, both variables and attributes control charts can be used (Montgomery, 2009).

3.7 Process Capability Indices (PCIs)

In the literature, process capability indices (PCIs) are also called process capability ratios (PCRs). PCIs are used as tools for characterizing the process quality. In order to measure the process capability numerically, PCIs have been developed. PCIs use process specifications as well as process variability, in this regard, the use of PCIs is important as they are statistical indicators of the process capability. PCIs are also defined as the quantitative indicators that compare the behavior of process or product characteristic to the specifications. In other words, PCIs are used to determine how well the process performs with respect to specifications and they express the ability of the process to meet these specifications, as a unique value quantitatively. There are several statistics that can be used to measure the capability of a process. Frequently used measures of performance are the PCIs, which relate

the natural tolerance limits of a process to the specification limits (English & Taylor, 1993). In practice, Cp, Cpk (Cpl, Cpu), Cpm are some of the widely used PCIs. In next sections, process capability indices: Cp, Cpk (Cpl, Cpu), Cpm, Cpmk will be explained(Şenvar & Tozan, 2010).

Process Capability index, Cp: In the literature, Cp index is also called process potential index, or process capability ratio, or inherent capability index, and two-sided PCI for two-sided specifications, that is, process is having both lower and upper specification limits. Cp is frequently used in industrial environment in order to express process capability in a simple quantitative way. When the parameters are known, that is, in that case, when process standard deviation σ is known, PCI Cp is computed as follows:

$$Cp = \frac{USL - LSL}{6\pm} \quad \text{..... (3. 25)}$$

where LSL and USL are lower and upper specification limits, respectively. The percentage of the speciation band used up by the process can be calculated in the following way:

$$P = \left(\frac{1}{Cp}\right) * 100 \quad \text{..... (3. 26)}$$

In practice, it is often impossible to know parameters. Generally, it is suitable to use sample standard deviation s to estimate process standard deviation σ. Thus, when the parameters are unknown, that is, in that case, when process standard deviation σ is unknown, by replacing sample standard deviation s to estimate process standard deviation σ, the formula used for estimating Cp is given below:

$$\hat{Cp} = \frac{USL - LSL}{6s} \quad \text{..... (3. 27)}$$

where LSL and USL are lower and upper specification limits, respectively.

A Cp value less than 1 indicates that the process variation exceeds the specifications and a significant number of defects are made. A Cp value equal to 1 indicates that the process is exactly meeting the specifications. At least 3% defects would be made. However, if the process is not centered on the target value (off-center), more defects are expected to be made. A Cp value greater than 1 indicates that the process variation is less than the specifications. However, if the process is not centered on the target value (off-center), more defects are expected to be made. A Cp value greater than 1.67 indicates that the process is highly capable.

Process Capability index, Cpk: In the literature, for one-sided specifications, Cpk is defined as one-sided PCI for specification limit nearest to the process mean. When the parameters are known, that is, in that case, when process mean μ and process standard deviation σ are known, PCI Cpk is computed as follows:

$$Cpk = \frac{1}{3\pm}\min(USL - «, « - LSL) = \min(Cpu, Cpl) \quad \text{..... (3. 28)}$$

where LSL and USL are lower and upper specification limits, respectively. In practice, it is often impossible to know parameters. Generally, it is suitable to use sample mean x to estimate process mean μ and sample standard deviation s to estimate process standard deviation σ. When the parameters are unknown, that is, in that case, when process mean μ and process standard deviation σ are unknown, by replacing sample mean x and sample standard deviation s to estimate process mean μ and process standard deviation σ, respectively, the formula used for estimating Cpk is given below:

$$\hat{C}pk = \frac{1}{3s}\min(USL - \bar{x}, \bar{x} - LSL) = \min(Cpu, Cpl) \quad \text{.....(3. 29)}$$

Where, LSL and USL are lower and upper specification limits, respectively.

(Montgomery, 2009) defined Cp as the measurement of the potential capability in the process. As a matter of fact, Cp does not consider where the process mean is located relative to the specification limits. Cp only measures the spread of the specifications relative to the six sigma spread in the process. Cp does not deal with the case of a process with mean μ that is not centered between the specification limits. On the other hand, he defined Cpk as the measurement of the actual capability in the process. Cpk takes process centering into account. In other words, Cpk deals with the case of a process with mean μ that is not centered between the specification limits. The magnitude of Cpk relative to Cp is the direct measure of how off-center the process is operating. (Montgomery, 2009) examined several cases, which can explain the relationship between Cp and Cpk, are given below:

- If Cp=Cpk, the process is centered at the midpoint of the specification limits.
- If Cpk<Cp, the process if off-centered. This can be accepted as lower capability than the case that the process is centered. The reason is that it is not operating at the midpoint of the interval between the specification limits.
- If Cpk=0, the process mean is exactly equal to one of the specification limits.

- If Cpk<0, the process mean lies outside the specification limits, that is for μ>USL or μ<LSL, Cpk<0.
- If Cpk<-1, the entire process lies outside the specification limits. It should be noted that some authors define Cpk to be nonnegative so that values less than zero are defined as zero.
- 1<Cpk<1.33 means that the process is barely capable. Automotive industry uses Cpk=1.33 as a benchmark in accessing the capability of a process (AIAG, 2002).

Process Capability index, Cpm: In the literature, Cpm is referred to as Taguchi index. Simply, Cpm is defined as the ability of the process to be clustered around the target or nominal value, which is the measurement that meets to exact desired value for the quality characteristic. Actually, Cpm was developed because Cpk is observed to be inadequate measure of process centering although Cpk was developed to deal with the case of a process with mean μ that is not centered between the specification limits wheras Cp is inadequate in process centering. As a matter of fact, when μ is in the interval of the specification limits, LSL and USL, Cpk depends inversely on process standard deviation σ and becomes large as process standard deviation σ gets closer to zero. Keeping these features in mind, it is possible to say that Cpk is not convenient as a measure of centering. This means a large value of Cpk does not actually give any information about the location of the mean in the interval of the specification limits, LSL and USL. In that case, process capability index Cpm, which is a better indicator of process centering, would be much more convenient (Montgomery, 2009). Consequently, the PCI Cpm is intended to account for variability from the process mean and deviation from the target value T and Cpm is shown to be useful in process centering. When the parameters are known, that is, in that case, parameters of process mean μ and process standard deviation σ are known, PCI Cpm is computed as follows:

$$Cpm = \frac{USL - LSL}{6\tau} \quad \text{……..……..……..(3. 30)}$$

where τ is the square root of expected squared deviation from target T. The target value T, which is the measurement that meets to exact desired value for the quality characteristic, is known to be the midpoint of the specification interval. Target T is evaluated as follows:

$$T = \frac{1}{2}(LSL + USL) \quad \text{…….……..…(3. 31)}$$

The formula for process variation around desired process target is given below:

$$\tau^2 = E[(x-T)^2] = E[(x-\mu)^2] + (\mu - T)^2 = \sigma^2 + (\mu - T)^2 \quad \text{……..(3. 32)}$$

Computation of Cpm can also be performed with the following way:

$$Cpm = \frac{USL - LSL}{6\sqrt{\pm^2 + (« - T)^2}} = \frac{Cp}{\sqrt{1 + \left(\frac{« - T}{\pm}\right)^2}} \quad \text{……..……(3. 33)}$$

Cpm approaches zero asymtotically as $|\mu - T| \rightarrow \infty$. When the parameters are unknown, that is, in that case, when process mean μ and process standard deviation σ are unknown, by replacing sample mean $\bar{x}$ and sample standard deviation s to estimate process mean μ and process standard deviation σ, respectively, the formulas used for estimating PCI Cpm is given below:

$$\hat{C}pm = \frac{\hat{C}p}{\sqrt{1 + V^2}} \quad \text{……..……..……... (3. 34)}$$

Where; $V = \frac{\bar{x} - T}{s}$.

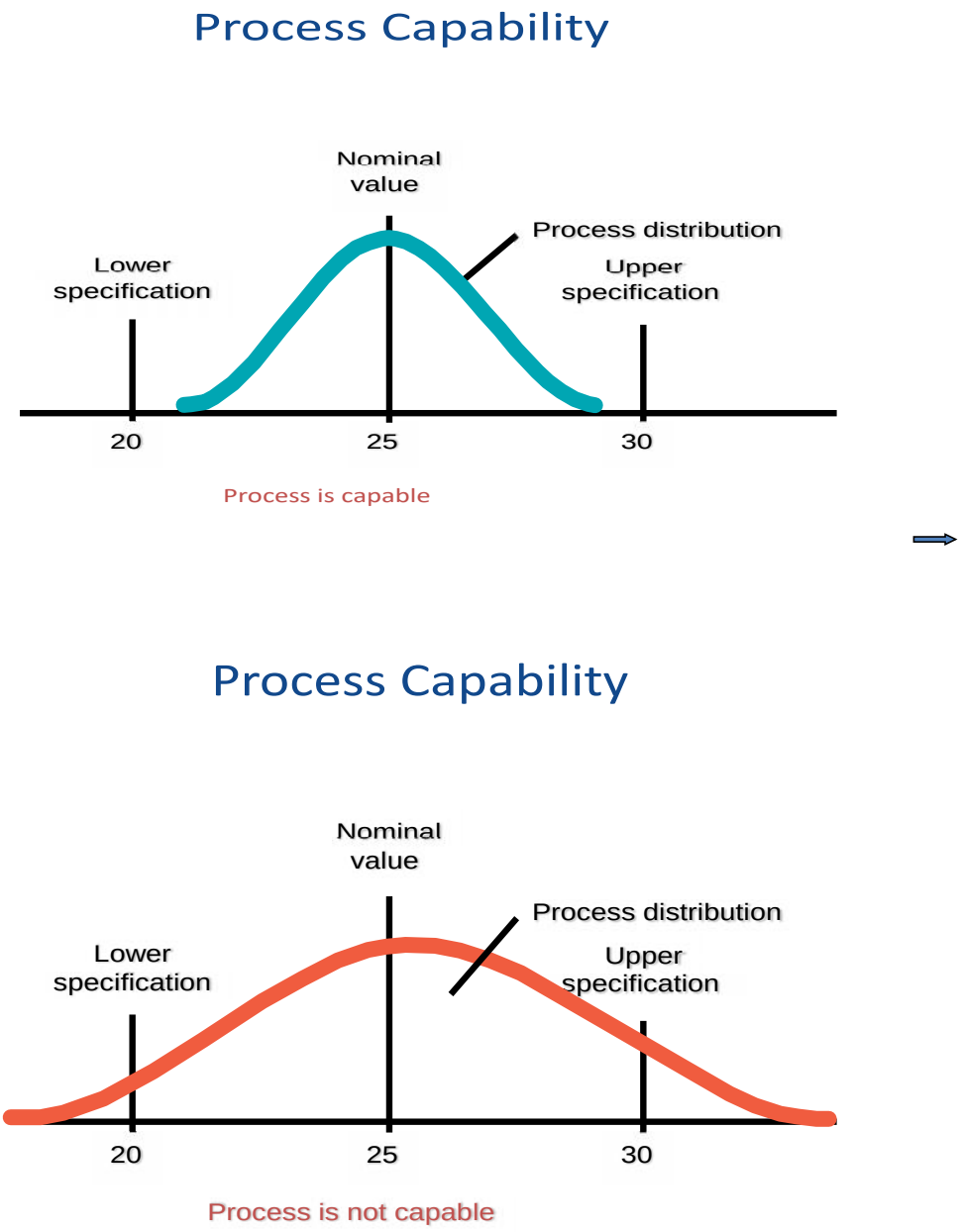
Process Capability index, Cpkm: The motivation of Cpkm is increased sensitivity to departures of the process mean μ from the desired target value T. Cpkm is known as a third generation PCI, since it is derived from the second generation PCIs Cpk and Cpm, in the same way that the PCIs, Cpk and Cpm are derived from the first generation PCI Cp. Computation of Cpkm is as follows:

$$Cpkm = \frac{Cpk}{\sqrt{1 + \left(\frac{« - T}{\pm}\right)^2}} \quad \text{……...…….……..(3. 35)}$$

At the end of this section, it has to be emphasized that PCIs can measure expected future performance. Industrial use of PCIs concentrates on evaluating and interpreting the point estimates of the desired quantities of PCIs, which are utilized to measure the ability of a process to meet the specification limits. It must be noted that point estimates of PCIs are simply point estimates and they are subject to statistical fluctuation. In other words, since point estimates of PCIs are subject to variability, alternatively, researchers recommend practitioners to use confidence intervals for estimating PCIs. There is a recent focus on hypothesis testing and confidence intervals on PCIs that are used as the basis for establishing the process capability (English & Taylor, 1993). For details about hypothesis testing and

confidence intervals on PCIs, interested readers are referred to (Montgomery, 2009; Şenvar & Tozan, 2010).

Figure 3. 5: Process Capability



Comparisons between, PCIs: In the review paper of (Samuel Kotz et al., 2002), Cp is ascribed to Juran, Cpk to Kane, and Cpm for the most part to Hsiang and Taguchi. Kotz and Johnson emphasized that it is necessary to distinguish the features of PCIs and the features of

their estimators. Apart from this, the relationship between these PCIs are defined as; "$Cp \geq Cpk$ and $Cp \geq Cpm$". Also, researchers realize that Cpk and Cpm coincide with Cp when $\mu=T$ and decrease as μ moves away from target T, wheras $Cpk<0$ for $\mu<LSL$ or $\mu>USL$.

(Spring, Cheng, Yeung, & Leung, 2002) highlighted that both Cp and Cpk are related to expected proportion of nonconforming items or defects. In other words, Cp and Cpk are related to marginal expected value of ppm (parts per million). On the other hand, Cpm does not arise from examining the number of nonconforming product in the process. Therefore, Cpm is unreliable if the expected proportion of nonconforming is regarded as the most important feature. Unlike the other PCIs, Cpm is not distributionally sensitive.

In industrial practice, it should be noticed that the motivation of Cp, Cpl, Cpu, Cpk are the most extensively used PCIs, while Cpm is seldomly being used. According to (Bothe, 2002), Cpk seems to have the greatest degree of acceptability among the PCIs. It is important to emphasize that Cpk is not suitable for product features with asymmetric tolerances. Even all the assumptions are satisfied, a higher Cpk does not represent a higher level of quality for customers. On the other hand, Cpm is related to Taguchi quadratic loss function because Cpm is defined as the ability of the process to be clustered around the target. Furthermore, Cp, Cpl, Cpu, Cpk are interpreted as the measure of nonconforming. Any change in the magnitude of these indices, under the constraint of holding customer requirements constant, is due to changes in the distance between the specification limits and the process mean. Cpk does not in itself say anything about distance between μ and T and it only measures the process yield (Şenvar & Tozan, 2010; Spring et al., 2002).

Assumptions, Conditions and Precautions: Capability indices described here strive to represent with a single number the capability of a process. Much has been written in the literature about the pitfalls of these estimates. Following are some of the precautions the readers should exercise while calculating and interpreting process capability:

1. The indices for process capability discussed are based on the assumption that the underlying process distribution is approximately bell shaded or normal. Yet in some situations the underlying process distribution may not be normal. For example, flatness, pull strength, waiting time, etc., might naturally follow a skewed distribution. For these

cases, calculating Cpk with the usual way might be misleading. Many researchers have contributed to this problem (Clements, 1989).

2. The process / parameter in question must be in statistical control. It is experience that there is tendency to want to know the capability of the process before statistical control is established. The presence of special causes of variation makes the prediction of process capability difficult and the meaning of Cpk unclear.

3. The data chosen for process capability study should attempt to encompass all natural variations.

   For example, one supplier might report a very good process capability value using only ten samples produced on one day, while another supplier of the same commodity might report a somewhat lesser process capability number using data from longer period of time that more closely represent the process. If one were to compare these process index numbers when choosing a supplier, the best supplier might not be chosen.

4. The number of samples used has a significant influence on the accuracy of the Cpk estimate. For example, for a random sample of size n = 100 drawn from a know normal population of Cpk = 1, the Cpk estimate can vary from 0.85 to 1.15 (with 95 % confidence). Therefore smaller samples will result in even larger variations of the Cpk statistics. In other words, the practitioner must take into consideration the sampling variation's influence on the computed Cpk number (Bissell, 1990; “Measuring Your Process Capability - processcapability.pdf,” n.d.).

3.8 Measures of the central tendency and description of the data

Normal distribution is important because many statistical tests are applicable and the inference made from them is valid only, if the data follows such distribution. The exact shape of the normal distribution, graphically represented by the well known "bell curve", is defined by a function, which has only two parameters: mean and standard deviation.

Another procedure that produces a large amount of summary information about a single sample is the Descriptive Statistics procedure. While it is not as focused on hypothesis testing, it contains many additional descriptive statistics, including minimum, maximum,

range, counts, trimmed means, sums, mode, variance, Skewness, Kurtosis, coefficient of variation, coefficient of dispersion, percentiles, additional normality tests, and a stem-and-leaf plot (Details, n.d.).

Problems may occur or wrong conclusions are made when a test based on the normal distribution is applied to a set of data, which does not follow this type of distribution. In such situations there are two alternatives to solve the problem. First, we can use some alternative non-parametric test or the so-called "distribution-free test". However, such tests are less powerful and the conclusions they would provide may not be definitive. Alternatively, in many cases one can still use the normal distribution-based test if the size of the sample is large enough. As the sample size increases, the shape of the sampling distribution approaches to a normal shape, even if the distribution of the variable in question is not normal.

In rigour, therefore, it is required that the first step in a statistical analysis should be to examine if the data to be analysed follow a normal distribution. There are several statistical tests, which can be used to determine whether the distribution of the data is normal(Iaea, 2003).

Parametric assumptions

Normality has always been an important assumption when dealing with parametric methods of data analysis. This assumption is crucial for the correct implementation of the methods. Realizing the importance of this assumption, many statisticians have put their effort on the modification or improvement of the original tests of normality as well as developing a new test. This is proven by numerous amount of test of normality available in the statistical literature. Some of the common tests were discussed by Farrel and Stewart (Farrell & Rogers-Stewart, 2006) and Oztuna, Elhan and Tuccar (Öztuna, Elhan, & Tüccar, 2006). Among the tests discussed include those commonly available in most statistical packages; Shapiro-Wilk (SW), Kolmogorov-Smirnov (KS), Lilliefors (LF) and Anderson-Darling (AD) tests (Razali, Shamsudin, Maarof, Ismail, & others, 2012).

The Kolmogorov-Smirnov (K-S) test and Shapiro-Wilk test are commonly used to test the normality of the data. The K-S test is based on the empirical distribution function (EDF), which is defined as a set of N independent observations x_1, x_2 …x_n with a common

distribution function F(x). The Shapiro-Wilk W is the ratio of the best estimator of the variance to the usual corrected sum of squares estimator of the variance. The statistic is positive and less than or equal to one. Being close to one indicates normality. The nine identified questions used in the survey were first treated with both Kolmogorov-Smirnov and Shapiro-Wilk tests to confirm the normality of the data. Data obtained through the survey were analyzed using SPSS software package (Version 22) in 5 percent level of significance (Shekhar & Raveendran, 2013).

Relationship between two sets of data: In analytical chemistry it is essential to validate a given analytical method to determine its applicability, reproducibility, repeatability and the accuracy of the data obtained. The analyst should establish some basis to prove that the method is working for its intent use. Normally, the amount of data is rather small and the so-called ***Student t distribution*** should be used.

Hypothesis Testing: Setting up and testing hypotheses is an essential part of statistical inference. In order to formulate such a test, usually some theory has been put forward, either because it is assumed to be true or because it is to be used as a basis for argument, but has not been proved, for example, claiming that acceptability of food products comply with acceptable range as prescribed by world food programme (WFP)/ other same organization or not.

One-Sample Test: This procedure provides several reports for making inference about a population mean based on a single sample. These reports include confidence intervals of the mean or median, the *t*-test, the *z*-test, and non-parametric tests including the randomization test, the quantile (sign) test and the Wilcoxon Signed-Rank test. Tests of assumptions and distribution plots are also available in this procedure (Details, n.d.).

Wilcoxon Signed Rank Test : This is another test that is a non-parametric equivalent of a 1-Sample *t*-test. The Wilcoxon Signed Rank procedure assumes that the sample we have is randomly taken from a population, with a symmetric frequency distribution. The symmetric assumption does not assume normality, simply that there seems to be roughly the same number of values above and below the median. The Wilcoxon procedure computes a test statistic W_{STAT} that is compared to an expected value. W_{STAT} is computed by summing the

ranked differences of the deviation of each variable from a hypothesized median above the hypothesized value (N. U. Tests et al., 2002).

The 1-sample Wilcoxon test is a nonparametric alternative of the 1-sample *t*-test because it does not require the data to come from a normally distributed population, as the *t*-test does. However, the 1-sample Wilcoxon test also assumes the data comes from a symmetric distribution, such as the uniform or Cauchy distributions. If you cannot verify this assumption of symmetry, use the nonparametric 1-sample sign test, which does not assume a symmetric distribution ("Why should I use a 1-sample Wilcoxon test?," n.d.).

One-Sample *z*-test and confidence interval estimate for a population mean:

1. Many basic statistics textbooks present a large-sample/small-sample approach to the one-sample test for a mean when sigma is unknown. The appropriate test statistic for conducting this test when the population distribution is normal is

   t = (\bar{X} - mu)/(S/\sqrt{n})……..……(3. 36)

The authors of many basic statistics textbooks suggest conducting this test when n >= 30 by using the formula in (3.36), but replacing the t critical value with a z critical value. This is presented in most of these textbooks by modifying formula (3.36) to

z = (\bar{X} - mu)/(S/\sqrt{n})…….(3. 37)

This provides a means for conducting the test for sample sizes of 30 or more without having to acquire a t critical value.

2. It appears that about half the authors of basic statistics textbooks disregard the large-sample/small-sample distinction and use the t-test regardless of sample size. They rely on studies showing that the t-test is reasonably robust against the violation of the normality assumption for large sample sizes, except for extremely skewed populations (Bartlett, 1935; Bradley, 1980; Geary, 1947; Pearson & Please, 1975; Pocock, 1982; Scheffe, 1959; Subrahmaniam, Subrahmaniam, & Messeri, 1975). On the other hand, (Pocock, 1982) established that for an extremely skewed, L-shaped population, t does not converge to normality until the sample size is very large, and (Geary, 1947; Pearson & Please, 1975) found that parental skewness had an effect on Type I error rates for one-sided tests. However, our extensive review of literature did not uncover any research that compares

the use of t and z critical values when conducting a one-sample test for a mean (sigma unknown) for various sample sizes when parent distributions are not normal.

3. Because so many textbooks simply replace the t statistic with a z statistic when n >= 30, it follows that many students of elementary statistics are taught or learn from a textbook that the t statistic is appropriate when n <30, and a z statistic is appropriate when n>= 30. In reality, for samples from the normal distribution, the z critical value is an approximation to the t critical value when n >=30, but the distribution remains a t.
4. Moreover, when using the computer to conduct this test, t is used regardless of the sample size, making the z approximation irrelevant. With the expanding use of statistical software, a discrepancy is developing between what is learned in some classrooms or stated in some textbooks and what is done in practice.
5. Should the large-sample/small-sample distinction continue to be taught in basic statistics courses? It would seem from the above discussion that the answer would be no, if considering only the case where the population distribution is normal. What remains to be determined is whether there is any advantage to using the z critical value when the population is non-normal. The following questions will be answered in this study.
    1. For non-normal parent distributions, are there particular sample sizes for which there is an advantage in using either the t or z critical value when conducting this test?
    2. Is replacing the t critical value with z more appropriate for non-normal parent distributions than for the normal parent distribution?(Rhiel & Chaffin, 1996)

Study mean of one population assume that a random sample from a normal population with known variance, or a relatively large (>30) random sample (if variance is unknown, it can be approximated by sample variance) (I. S. Tests, Hypotheses, & Rule, n.d.).

6. While the one-sample *t*-test is the most commonly used statistic when you want to compare the population mean to a constant value, you can also use a one-sample *Z*-test if you know the population standard deviation and do not need to estimate it based on the sample data.

The one-sample *Z*-test is more powerful than the one-sample *t*-test (meaning that it is more likely to detect diferences between the estimated mean and the comparison value), but is not often used because people rarely have access to the population standard deviation. A one-sample *Z*-test is performed as a hypothesis test with the following characteristics.

- $H_0 : \mu = X_0$

  $H_a : \mu \neq X_0$

Notice that these are the same hypotheses examined by a one-sample *t*-test. Just like the one-

sample *t*-test, you can also test a one-tailed hypothesis if you change H_a to be either $\mu < X_0$ or $\mu > X_0$.

- The test statistic is

$$z = \frac{\bar{X} - X_0}{\frac{\sigma_X}{\sqrt{n}}}, \quad \text{(3. 38)}$$

  where σ_X is the population standard deviation of the variable you are measuring.
- The p-value for the test statistic *Z* can be taken from the standard normal distribution. Notice that there are no degrees of freedom associated with this test statistic. A table containing p-values for the *Z* statistic can be found inside the front cover of (Moore & McCabe, 2003).
- This test assumes that X follows a normal distribution (DeCoster, 2006).

3.9 Data analysis Models

The different models used in the analysis are presented below. These are the binary logistic, binary probit, discriminant analysis model, Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH).

3.9.1 Model Specification

Popular methods used to analyze binary response data include the probit model, discriminant analysis, and logistic regression. Probit regression is based on the probability integral transformation. A major drawback of the probit model is that it lacks natural interpretation of regression parameters. Discriminant analysis is computationally simpler than the probit model. It assumes that predictor variables are normally distributed and that variables jointly assume a multivariate normal distribution. Because many variables in regression analysis are dichotomous or discrete, discriminant analysis assumptions are often violated. Furthermore, because discriminant analysis examines the distribution of X in terms of Y, it is dependent on Bayes theorem to extract the variable of primary interest. In contrast, the logistic regression model makes no assumption about the variable distribution. It is a direct probability model because it is stated in terms of Pr{Y = 1|X}. Another advantage of the logit model is its ability to provide valid estimates, regardless of study design (Hailpern & Visintainer, 2003; Harrell, 2001; Newton et al., 2010).

3.9.1.1 The Binary logistic model

This section presents the background to the binary logistic model as well as its application in the study and the mathematical representation of the model. The binary logistic regression is used to determine the factors affecting the stakeholders awareness of food products.

Background: Logistic regression was chosen for this analysis because it is known to be quite flexible relative to alternative methods such as Linear regression modeling which is not suitable for the dichotomous data utilized in this study as it allows for the dependent variable to take values less than zero and greater than one while a scale of probability can lie only between zero and one. The principle of the Binary logistic regression model is that independent variable data can be analyzed so as to determine which are 'most responsible' for initiating a positive dependent outcome. The significance of the independent variable data therefore affects the output of the model, for example to model many parameters of no great significance produces a meaningless model. The aim is to identify and utilize independent parameters that significantly affect the occurrence. The section is an outline of how the independent variables discussed earlier can be assessed so as to identify which influence the dependent variable outcome (Lawther, 2008).

Independent parameter data (x_1, x_2, x_3 ….. x_n) are stored in a database relative to the dichotomous dependent sample which are divided between acceptable limit (0) and unacceptable limit (1) of food analysis parameter. Regarding a susceptibility assessment, the inherent benefit of binary logistic regression modeling relative to other multivariate statistical techniques is that predicted values (probability) lie between 0 and 1 (David & Mitchel, 1994). The logistic regression model is a type of generalized linear model that extends the linear regression model by linking the range of real numbers to the 0-1 range. It utilizes the independent variables in a linear combination so as to explain the variation in the dependent variable relative to its dichotomous state of failure/non-failure (F. Dai & Lee, 2003).The purpose of which is to develop the 'best fit' model of the relationship between the dependent variable and the set of independent parameters (Ohlmacher & Davis, 2003).

Furthermore it facilitates the modeling of a broad range of parameters as it is feasible to use both continuous and categorical independent variables within the same regression. Unlike linear regression, it is neither necessary that data are normally distributed (dichotomous data

have unique distributional assumptions) and it is therefore that logistic regression analysis is utilized as opposed to more common techniques applied to continuous or ordinal data, such as linear regression. Furthermore, logistic regression analysis has a steady history of application within a broad range of subjects and in recent years it has been utilized within several worthwhile publications concerning landslides and slope instability (Ayalew & Yamagishi, 2005; F. C. Dai, Lee, Li, & Xu, 2001; F. Dai & Lee, 2002).

3.9.1.1.1 Modeling Dichotomous Outcome Variables

Logistic regression analysis is one of the most frequently used statistical procedures, and is especially common in medical research (King & Ryan, 2002). The technique is becoming more popular in social science research. Ordinary least squares (OLS) regression, in its various forms, is the most common linear model analysis in the social sciences. If a dependent variable is a binary outcome, an analyst can choose among discriminant analysis and OLS, logistic or probit regression. OLS and logistic regression are the most common models used with binary outcomes.

Logistic regression estimates the probability of an outcome. Events are coded as binary variables with a value of 1 representing the occurrence of a target outcome, and a value of zero representing its absence. OLS can also model binary variables using linear probability models (Menard, 1995). OLS may give predicted values beyond the range (0,1), but the analysis may still be useful for classification and hypothesis testing. The normal distribution and homogeneous error variance assumptions of OLS will likely be violated with a binary dependent variable, especially when the probability of the dependent event varies widely. Both models allow continuous, ordinal and/or categorical independent variables(Pohlman & Leitner, 2003).

The dependent variable in logistic regression is usually dichotomous, that is, the dependent variable can take the value 1 with a probability of success θ, or the value 0 with probability of failure $1-\theta$. This type of variable is called a Bernoulli (or binary) variable. Although not as common and not discussed in this treatment, applications of logistic regression have also been extended to cases where the dependent variable is of more than two cases, known as multinomial or polytomous (Tabachnick & Fidell, 1996).

As mentioned previously, the independent or predictor variables in logistic regression can take any form. That is, logistic regression makes no assumption about the distribution of the independent variables. They do not have to be normally distributed, linearly related or of equal variance within each group. The relationship between the predictor and response variables is not a linear function in logistic regression, instead, the logistic regressionfunction is used, which is the logit transformation of θ:

$$\boldsymbol{\theta} = \frac{e^{(\alpha+\beta_1 x_1+\beta_2 x_2+\cdots\beta_k x_k)}}{1+e^{(\alpha+\beta_1 x_1+\beta_2 x_2+\cdots\beta_k x_k)}} \quad \text{(3. 39)}$$

Where α = the constant of the equation and, β = the coefficient of the predictor variables.

An alternative form of the logistic regression equation is:

$$\boldsymbol{logit}[\boldsymbol{\theta}(\boldsymbol{x})] = \boldsymbol{log}\left[\frac{\boldsymbol{\theta}(\boldsymbol{x})}{\boldsymbol{1-\theta}(\boldsymbol{x})}\right] = \boldsymbol{\alpha} + \boldsymbol{\beta_1 x_1} + \boldsymbol{\beta_2 x_2} + \cdots \boldsymbol{\beta_k x_k} \quad \text{(3. 40)}$$

The goal of logistic regression is to correctly predict the category of outcome forindividual cases using the most parsimonious model. To accomplish this goal, a model is created that includes all predictor variables that are useful in predicting the response variable. Several different options are available during model creation. Variables can be entered into the model in the order specified by the researcher or logistic regression can test the fit of the model after each coefficient is added or deleted, called stepwise regression (“Logistic Regression,” n.d.).

Stepwise regression is used in the exploratory phase of research but it is not recommended for theory testing (Menard, 1995). Theory testing is the testing of apriori theories or hypotheses of the relationships between variables. Exploratory testing makes no a-priori assumptions regarding the relationships between the variables, thus the goal is to discover relationships.

Backward stepwise regression appears to be the preferred method of exploratoryanalyses, where the analysis begins with a full or saturated model and variables are eliminated from the model in an iterative process. The fit of the model is tested after the elimination of each variable to ensure that the model still adequately fits the data.When no more variables can be eliminated from the model, the analysis has been completed.

There are two main uses of logistic regression. The first is the prediction of groupmembership. Since logistic regression calculates the probability or success over the

probability of failure, the results of the analysis are in the form of an odds ratio. For example, logistic regression is often used in epidemiological studies where the result of the analysis is the probability of developing cancer after controlling for other associated risks. Logistic regression also provides knowledge of the relationships and strengths among the variables (e.g., smoking 10 packs a day puts you at a higher risk for developing cancer than working in an asbestos mine).

The process by which coefficients are tested for significance for inclusion or elimination from the model involves several different techniques. Each of these will be discussed below.

Wald Test: A Wald test is used to test the statistical significance of each coefficient (β) in the model. A Wald test calculates a *Z* statistic, which is:

$$z = \frac{\hat{B}}{SE} \quad \text{.....(3. 41)}$$

This z value is then squared, yielding a Wald statistic with a chi-square distribution. However, several authors have identified problems with the use of the Wald statistic. (Menard, 1995) warns that for large coefficients, standard error is inflated, lowering the Wald statistic (chi-square) value. (Agresti, 1996) states that the likelihood-ratio test is more reliable for small sample sizes than the Wald test.

Likelihood-Ratio Test: The likelihood-ratio test uses the ratio of the maximized value of the likelihood function for the full model (L_1) over the maximized value of the likelihood function for the simpler model (L_0). The likelihood-ratio test statistic equals:

$$-2\log\left(\frac{L_0}{L_1}\right) = -2[\log(L_0) - \log(L_1)] = -2(L_0 - L_1) \quad \text{..... (3. 42)}$$

This log transformation of the likelihood functions yields a chi-squared statistic. This is the recommended test statistic to use when building a model through backward stepwise elimination (Agresti, 1996; Interval & Ratio, 2008).

3.9.1.2 The Binary probit model

This section presents the background to the binary probed model as well as the mathematical representation of the model. The binary probit model is used to identify the determinants of food products decision to be accepted or unaccepted according to acceptable range as prescribed by WFP, Dhaka.

3.9.1.2.1 Application of model

While Linear Probability Model (LPM) has a number of shortcomings that make it unsuitable; it is can generate probability values that lie below zero or above one, which would be unrealistic. LPM also leads to questionable values of R^2 as a measure of goodness of fit (Gujarati, 2003). This study assumes a normal cumulative distribution function and hence the choice of probit.

Binary response models are used when the number of alternatives that can be chosen is more than one. They are developed to describe the probability of each of the possible outcomes as a function of personal or alternative specific characteristics (Verbeek, 2008). Binary response models are applied where there exists a binary or logical ordinal of the alternatives. In this case it is assumed that there exists an underlying latent variable that drives the choice between the alternatives (Verbeek, 2008). The results in this case will be sensitive to the way in which the alternatives are numbered. The modeling methodology used to establish the determinants of the quality of food products status is the binary probit model.

The binary probit is suitable for modeling with a categorical dependent variable (in this study the acceptable range of physiochemical analysis of food products status). Multivariate modeling is an especially useful and informative approach for understanding the accepted or unaccepted food products decision on their physiochemical analysis status. This is because multiple factors contribute to their decision on whether to be fully accepted or unaccepted. Binary probit is especially appropriate in this study because like Ordinary Least Square (OLS) it identifies the statistical significant relationships between the explanatory variables and the dependent variable. Unlike the OLS regression, binary probit discerns unequal differences between binary categories in the dependent variable (Greene, 2003; McKelvey & Zavoina, 1975).

3.9.1.2.2 Mathematical representation of the binary probit model

In this study, the dependent variable of the physiochemical analysis of food products status was placed in two categories. The food products are classified as fully accepted or unaccepted. A binary probit model is used to determine the qualitative acceptability of food products status. Based on this, the model is estimated as follows

Accepted or unaccepted food products status = f (physiochemical and microbial analyzed parameters of food products) ……..….....(3. 43)

The food products status is modeled using the binary probit model with the model outcomes:

$S_i = 0$ (fully accepted) and

$S_i = 1$ (unaccepted).

The decision on food products status is unobserved and is denoted by the latent variable s_i*. The latent equation below models how s_i* varies with physiochemical analyzed parameter characteristics and is represented as:

$$s_i^* = X_i'\sim + £_i \quad \text{……...……..} \quad (3.\ 44)$$

Where, the latent variable s_i* measures the difference in utility derived by individual i from either being fully-certified accepted or unaccepted. (i= 1, 2, 3…….n) n represents the total number of food products samples. Each individual i belongs to one of the two groups.

X_i is a vector of exogenous variables,

α is a conformable parameter vector and the error term ε_i is independent and identically distributed as standard normal, that is $\varepsilon_i \sim NID(0, 1)$.

The observed variable (S_i) relates to the latent variable (s_i*) such that

$$S_i = \begin{cases} 1 if\ s_i^* \le 0 \\ 0 if\ s_i^* > ¥ \end{cases} \quad \text{……..….....} \quad (3.\ 45)$$

Taking the value of 0 if the individual was fully-certified acceptable and 0 if the individual was unacceptable. The implied probabilities are obtained as:

$$\Pr\{S_i = 1 | X_i\} = \Pr\{s_i^* \le 0 | X_i\} = c\ (-X_i'\sim),$$

$$\Pr\{S_i = 3 | X_i\} = \Pr\{s_i^* > ¥ | X_i\} = 1 - c\ (¥ - X_i'\sim)$$

and

$$\Pr\{S_i = 2 | X_i\} = c\ (¥ - X_i'\sim) - c\ (-X_i'\sim) \quad \text{…….....} \quad (3.\ 46)$$

Where γ is the unknown parameter that is estimated jointly with α. Estimation is based upon the maximum likelihood where the above probabilities enter the likelihood function. The interpretation of α coefficient is in terms of the underlying latent variable model in equation (3.46).

The probability of the food products being fully-certified acceptable can be written as

$$\Pr(S_i = 1) = c\ (X_i'\sim_1)) \quad \text{…..……..……...} \quad (3.\ 47)$$

Where Φ(.) is the cumulative distribution function (cdf) of the standard normal (Obi, 2014; Verbeek, 2008).

3.9.1.3 Discriminant analysis model

This section presents the background of the discriminant model as well as its application in the study and the mathematical representation of the model.

Discriminant analysis is a statistical technique designed to investigate the differences between two or more groups of cases with respect to several underlying variables. This technique is more appropriate than commonly used measures (correlation, regression, etc) because the variables being predicted are categorical. It provides a more rigorous test than one based on univariate comparison of means and results in a unit of analysis, predicted category membership that is more useful in evaluating instructional interventions. Its goal is to classify cases into one or several mutually exclusive groups based on their values for a linear combination of predictor variables (Manly, 1986). In this study, the foods are classified into two main groups: those that have never acceptable range of food products and those that have considered acceptable range of food products depending on their physiochemical analysis of food products status.

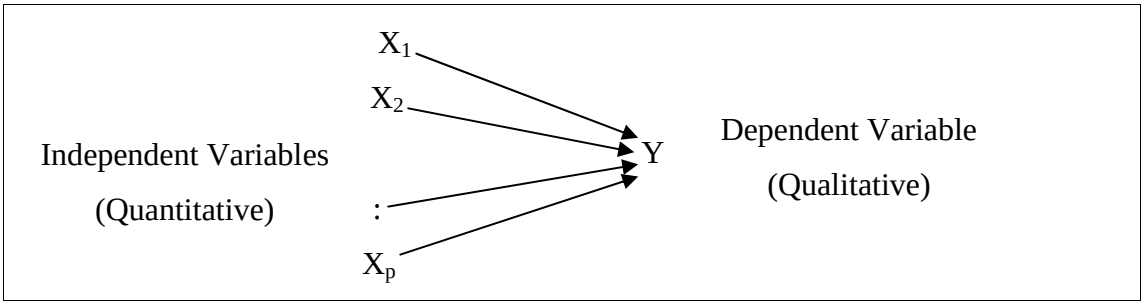
Since there are two groups, the number of unique functions that can be extracted is equal to (g-1), where g is the number of groups, or, p, the number of discriminant variables, whichever is less. In this study a Linear Discriminant Functions (LDF_s) are computed. The analysis assumes that the discriminant function scores (D_{km}) are normally distributed for each group and that the groups have equal variance covariance matrices for the discriminating variables. In practice these conditions are seldom applied strictly as the technique is very robust to departures from these assumptions (Klecka, 1980).

In multiple linear regression, the objective is to model one quantitative variable (called the dependent variable) as a linear combination of others variables (called the independent variables). The purpose of discriminant analysis is to obtain a model to predict a single qualitative variable from one or more independent variable(s). In most cases the dependent variable consists of two groups or classifications, like, high versus normal blood pressure, loan defaulting versus non defaulting, use versus non use of internet banking etc. The choice

between three candidates, A, B or C in an election is an example where the dependent variable consists of more than two groups.

Discriminant analysis derives an equation as linear combination of the independent variables that will discriminate best between the groups in the dependent variable. This linear combination is known as the discriminant function. The weights assigned to each independent variable are corrected for the interrelationships among all the variables. The weights are referred to as discriminant coefficients.

The model:



The discriminant equation:

$F = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \varepsilon$…….. (3. 48)

where, F is a latent variable formed by the linear combination of the dependent variable, X_1, X_2 ,… X_p are the p independent variables, ε is the error term and β_0, β_1 , β_2 ,…, β_p are the discriminant coefficients.

The objective discriminant analysis is to test if the classifications of groups in a variable Y depend on at least one of the X_i's.

Assumptions: The assumptions of discriminant analysis are the same as those for MANOVA. The analysis is quite sensitive to outliers and the size of the smallest group must be larger than the number of predictor variables.

- The variables X_1, X_2, …, X_p are independent of each other.
- Groups are mutually exclusive and the group sizes are not grossly different.
- The number of independent variables is not more than two less than the sample size.
- The variance-covariance structures of the independent variables are similar within each group of the dependent variable.

- Errors (residuals) are randomly distributed.
- For purposes of significance testing, the independent variables follow a multivariate normal distribution.

There are several purposes for MDA:

- To investigate differences among groups.
- To determine the most parsimonious way to distinguish among groups.
- To discard variables which are little related to group distinction.
- To classify cases into groups.
- To test theory by observing whether cases are classified as predicted (Data, Using, & Lesson, n.d.; Garson, 2009).

3.10 Conditional Heteroscedasticity: ARCH-GARCH Models

The analysis of chemical analysis data has received considerable attention in the literature over the last 20 years. Several models have been suggested for capturing special features of this data and most of these models have the property that the conditional variance (or the conditional scaling) depends on the past. One of the best known and most often used is the autoregressive conditionally heteroscedastic (ARCH) process introduced by (R. F. Engle, 1982). The theoretical results on ARCH and related properties have played a special role in empirical work in the analysis of data on rates, prices and in inflation rate data to mention but a few (Ngailo, 2011).

3.10.1ARCH model

ARCH (Auto-regressive Conditional Heteoskedastic Model) is the first and the basic model in stochastic variance modeling and is proposed by (R. F. Engle, 1982). The key point of this model is that it already changes the assumption of the variation in the error terms from constant $Var(\varepsilon_t) = \sigma^2$ to be a random sequence which depended on the past residuals ($\{\varepsilon_1 \dots \varepsilon_{t-1}\}$). That is to say, this model has changed the restriction from homoscedastic to be heteroscedasticity. This breakthrough is explained by (Baillie & Bollerslev, 1989). And this is an accurate change to reflect the volatility data's features. Let ε_t as a random variable that has a mean and a variance conditionally on the information set I_{t-1}, The ARCH model of ε_t has the following properties. Come from (Terasvirta, 2006).

First,

$E(\varepsilon_t | I_{t-1}) = 0$

And second, conditional variance

$\sigma_t^2 = E(\varepsilon_t^2 / I_{t-1})$

is a positive valued parametric function of I_{t-1}. The sequence $\{\varepsilon_t\}$ may be observed directly,or it may be got from the following formula. In the latter case, I can get

$\varepsilon_t = y_t - \mu_t(y_t)$

Where y_t is observed value and $\mu_t(y_t) = E(y_t | I_{t-1})$ is the conditional mean of $y_t$given I_{t-1}, (R. F. Engle, 1982) application was of this type. In what follows, the ε_t could beexpressed as another way on parametric forms of σ_t^2.

So, here ε_t is assumed as follows:

$\varepsilon_t = z_t \sigma_t$

Where $\{z_t\}$ is a sequence of independent, identically distributed (iid) random variables with zero mean and unit variance. This implied:

$\varepsilon_t \sim D(0,\sigma_t^2)$,

So the ARCH model of order q is like this:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_q \varepsilon_{t-q}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \quad \text{..... (3. 49)}$$

Where $\alpha_0 > 0$, and $\alpha_i \geq 0$, $i > 0$. To assure $\{\sigma_t^2\}$ is asymptotically stationary random sequence, I can assume that $\alpha_1 + \ldots + \alpha_q < 1$. This is the ARCH model.

With the generation of ARCH model, it already can explain many problems in many fields, for instance, interest rates, exchange rates and trade option and stock index returns. (Bollerslev, Chou, & Kroner, 1992) already used these models to achieve a variety of applications in their survey. It's different between forecasting the conditional variance of these series and forecasting the conditional mean of them because the conditional variance cannot be observed. So how to measure the conditional variance should be considered from (Andersen & Bollerslev, 1998).

3.10.2 GARCH Model

Because of some drawbacks and limitation on ARCH model, it has been substituted by the so-called generalized ARCH (GARCH) model that (Bollerslev, 1986) and (S. J. Taylor, 1986) proposed independently of each other. Based on the ARCH model has been raised, it

adds the lagged conditional variance term (σ_{t-j}^2) as a new term in the GARCH model. The improved ARCH model (GARCH model) also reduces the number of estimated parameters. In this model, the conditional variance is still a linear function of its own lags and error terms, it has the following form:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad \ldots\ldots (3.\ 50)$$

where constants are non-negative.

Here, I need to explain this function, q represent the order of ε_t^2 and the p represents the order of the σ_t^2, in order to acquire the positive value, a sufficient condition for the conditional variance is $\alpha_0 > 0$; $\alpha_i \geq 0$; j = 1, . . .,q; $\beta_j \geq 0$; i = 1, . . .,p, The GARCH(p , q) process is weakly stationary if and only if $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$, and the GARCH model keeps not only all the characteristics of the ARCH model but also a linear function of lagged conditional variance. So the GARCH model is an extension of ARCH model. In my paper, I just use the most basic GARCH (1, 1), a sufficient condition of GARCH (1, 1) model for the conditional variance to be positive with probability one is $\alpha_0 > 0$; $\alpha_1 \geq 0$ $\beta_1 \geq 0$. The model which I need to use in the paper is given by (Alexander & Lazar, 2006):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad \ldots\ldots (3.\ 51)$$

The more complicated higher-order GARCH models are mentioned in the paper of (Nelson & Cao, 1992). In addition to this, this paper also describes the necessary and sufficient conditions for positive value of the conditional variance in higher-order GARCH models. The GARCH (2, 2) case has been studied in detail by (He & Terasvirta, 1999).

GARCH model has greater applications in some areas, but it also has some limitations in estimating the volatility asset pricing. From the article of (Enocksson & Skoog, 2012), the GARCH model generally has two limitations. First, it cannot measure the leverage effect. The GARCH model treats the influence which comes from positive and negative information in a series equally, but it’s not reasonable in many cases. The negative information of stock price always has pronounced effect on the fluctuation than the positive information, thus the symmetric GARCH model does not capture this kind asymmetry performance, see (Dennis,

Mayhew, & Stivers, 2006). Second, it's also difficult to achieve all the parameters are assumed larger than zero in GARCH models.

In order to solve these series of problems, the GARCH model has been improved further. For measuring the negative impact of leverage effect in the volatility models, (Nelson, 1991) proposed the EGARCH model. (Glosten et al., 1993) proposed GJR-GARCH model (W. Jiang, 2012; Wei, 2012).

3.10.3 Parameter estimation

There are several available methods for estimating the unknown parameters α_0, α_1, β_1 of the conditional variance processes above. Referring to (R. Engle, 1995), the ordinary least squares method could be used, however maximum likelihood is more efficient for estimation of the parameters.

The following loglikelihood function, l, could be maximized in order to estimate α_0, α_1 for ARCH(1) model and α_0, α_1, β_1 for GARCH(1,1) model.

$$l = \ln L = \ln(f(£_1, £_2, ..., £_n | R_{t-1})) = \ln(\prod_{t=1}^{n} f(£_t | R_{t-1})) \quad \text{..... (3. 52)}$$

Assumed the process (3.49) with μ=0 and also assumed normal distribution of the conditional errors $\varepsilon_t \quad R_{t-1} \quad N(0,\sigma_t)$, the loglikelihood function is as follows:

$$l = -\frac{n}{2}\ln(2®) - \frac{1}{2}\sum_{t=1}^{n}\ln ±_t^2 - \frac{1}{2}\sum_{t=1}^{n}\frac{R_t^2}{±_t^2} \quad \text{..... (3. 53)}$$

Taking into consideration the definitions of the conditional variances it gives us

$$l_{ARCH(1)} = -\frac{n}{2}\ln(2®) - \frac{1}{2}\sum_{t=1}^{n}\ln(~_0 + ~_1 R_{t-1}^2) - \frac{1}{2}\sum_{t=1}^{n}\frac{R_t^2}{(~_0 + ~_1 R_{t-1}^2)} \quad \text{..... (3. 54)}$$

Maximization of the functions above is to be done numerically with the inequality constrains (Kostavelis, 2012).

3.10.4 Properties of unconditional error terms

Recalling the fact that the unconditional mean value is equal to zero and the unconditional variance is not changing over time based on the law of iterated expectations

E[Y]=E[E[Y/X]]..... (3. 55)

where Y is a random variable and X is relevant known data. Assuming stationarity of the process, we can state for ARCH(1).

$$\sigma^2 = Var(\varepsilon_t) = E[\varepsilon_t^2] = E[E[\varepsilon_t^2 | R_{t-1}]] = E[\alpha_0 + \alpha_1 \varepsilon_{t-1}^2] = \alpha_0 + \alpha_1 E[\varepsilon_{t-1}^2] = \frac{\alpha_0}{1-\alpha_1} \quad \text{……} \quad (3.\ 56)$$

and also for GARCH(1,1) the unconditional variance could be expressed similarly

$$\sigma^2 = Var(\varepsilon_t) = E[\varepsilon_t^2] = E[E[\varepsilon_t^2 | R_{t-1}]] = \frac{\alpha_0}{1-\alpha_1-\beta_1} \quad \text{………………………………..……} \quad (3.\ 57)$$

(Kostavelis, 2012).

3.10.5 Residual Test/ ARCH LM Test

This is a Lagrange multiplier (LM) tests for autoregressive conditional hetroskedasticity (ARCH) in the residuals. The test statistic is computed by an auxiliary regression as follows.

$$P_t = \alpha_1 P_{t-1} + u_t \Rightarrow u_t = P_t - \alpha_1 P_{t-1} \quad \text{……………………………………………………} \quad (3.\ 58)$$

To test the null hypothesis that there is no ARCH up to order q in the residuals, the following regression is run.

$$u_t^2 = \lambda_0 + \left(\sum_{s=1}^{q} \lambda_s u_{t-s}^2 \right) + v_t \quad \text{……………………………………………………………………} (3.\ 59)$$

Where u_t is the residual. This is a regression of the squared residuals on a constant and lagged squared residuals up to order q. The null hypothesis is that, $\lambda_s=0$ in the absence of ARCH components.

In a sample of T residuals under the null hypothesis of no ARCH errors, the LM test statistic equals number of observations*R-square (TR^2). The test statistic TR^2 follows Chi (χ^2)-distribution with q (lag length) degrees of freedom. If TR^2 calculated is greater than the chi-square table value (TR^2 critical), we would reject the null hypothesis in favour of the alternate hypothesis. Hence there is ARCH effect in the GARCH model (Kuwornu, Mensah-Bonsu, & Ibrahim, 2011).

3.10.6 Unit Root Test

In the case of time series analysis, unit root tests are important. Unit root tests help to identify the stationarity and non-stationarity of time series data used for the study. A stationary time series has three basic properties. First, it has a finite mean. This means that a stationary series

fluctuates around a constant long run mean. Second, a stationary time series has a finite variance. This means that variance is time invariant and third, a stationary time series has a finite (auto) covariance. This reflects that theoretical autocorrelation decay fast as lag length increases. Regressions run on non-stationary time Series produce a spurious relationship. Hence, to avoid a spurious relationship, there is a need to perform a unit root test on variables (Hye & Ali, 2009). This thesis uses Dickey–Fuller (DF) test for performing unit root tests.

Dickey – Fuller (DF) has been widely used to check the stationarity and presence of unit root of a process. TheDickey – Fuller test is valid only for AR(1). We usethe DF test when the residual are not autocorrelated. Dickey – Fuller considered theestimation of the parameter α from the models.

1. $y_t = \alpha y_{t-1} + e_t$(pure random walk)
2. $y_t = \mu+\alpha y_{t-1} + e_t$ (drift + random walk)
3. $y_t = \mu+bt+\alpha y_{t-1} + e_t$ (drift + linear trend)

It assumes that $y_0=0$ and e_t ~i.i.d $(0, \sigma^2)$

The null and alternative hypotheses are:

H_0: α=1 (α(z)=0 has a unit root)

H_1: |α |<1 (α(z)=0 has root outside unit circle) (Mahadeva & Robinson, 2004; Pantelis & Zehtabchi, 2008). Using non-stationary time series data in financial models produces unreliable and spurious results and leads to poor understanding and forecasting ("Introduction To Stationary And Non-Stationary Processes | Investopedia," n.d.).

3.11 Model Selection

Methods such as forward, backward and stepwise selection are available, but, in logistic as in other regression methods are not to be recommended. They give incorrect estimates of the standard errors and p-values; can discard variables that are important to be included in the model (Harrell, 2001). It is much better to compare models based on their results, reasonableness, and fit as measured, by the Information Criterion (Flom, 2005).

The Akaike Information Criterion (AIC) is one of the best possible ways to select a model from a set of models. This approach is based on information theory and select a model that minimizes the Kullback-Leibler distance between the estimated and the true models. Let L be the likelihood function, then the AIC is defined as

$$AIC = -2 \ln(L) + 2p, \quad \ldots\ldots (3.60)$$

Whre, p is the number of parameters in the model. Generally, AIC trade off between accuracy and complexity of the model. In statistics, the Bayesian information criterion (BIC) or Schwarz criterion ($BIC_{Schwarz}$) is another criteria which mainly considers likelihood function, and it is closely related to Akaike information criterion (AIC). The BIC ($BIC_{Schwarz}$) is defined as

$BIC_{Schwarz} = - 2 \ln(L) + p \ln(n)$..... (3. 61)

When fitting a model, it is possible to increase the likelihood by adding parameters, but doing so the result may overfit the model. However, the BIC resolves this issue by introducing a penalty term for the number of parameters in the model. The penalty term is larger in BIC than in AIC and depends on the number of observations. In both cases, a smaller the value the better the model (Akaike, 1974; F. Jiang, 2013; Schwarz, 1978).

Pearson goodness-of-fit test: Let M be the total number of covariate patterns among the N observations. View the data as collapsed on covariate patterns j = 1, 2, …, M, and define m_j as the total number of observations having covariate pattern j and y_j as the total number of positive responses among observations with covariate pattern j. Define p_j as the predicted probability of a positive outcome in covariate pattern j.

The Pearson χ^2 goodness-of-fit statistic is

$$i^2 = \sum_{j=1}^{M} \frac{(y_j - m_j p_j)^2}{m_j p_j (1 - p_j)} \quad \text{..... (3. 62)}$$

This χ^2 statistic has approximately (M – k) degrees of freedom for the estimation sample, where k is the number of independent variables, including the constant. For a sample outside the estimation sample, the statistic has M degrees of freedom (Archer & Lemeshow, 2006; StataCorp, 2005).

CHAPTER 4:HIGH ENERY (HEB) BISCUITS

4.1 Introduction

This chapter describes the High Energy Biscuits (HEB) for product description and analysis for the study. A description of prducts includes the following sub sections: product purpose, miller companies list of Bangladesh, main ingredients, school feeding in poverty prone areas. The resulting data were employed in different levels of analysis. The chapter concludes by giving the empirical specification and estimation procedures for the fitted models.

4.2 Product Description

WFP High Energy Biscuits (HEB) are biscuits (small baked bread or cakes) that are supplemented with a premix of vitamins and minerals. This ready to eat food participates to the covering of urgent needs in the acute phase of an emergency situation during which population is not able to cook due to a lack of access to basic facilities (clean water, cooking equipment…). Their use is also extended to a complement food ration (use as snacks) to provide vitamins and minerals in regions/population where diet is subjected to nutritional deficiencies. HEB can be used also to prevent micronutrients deficiency of young children and school age children (Value, Fsc, & Food, n.d.).

Miller Companies list of Bangladesh: Complete lists of mills and food processing factories can easily be found at the divisional level (contacting the local Chambers of Commerce, for eample) or by contacting the professional organizations or trade-unions. The lists here under are the suppliers short listed by WFP.

S.L. No.	Suppliers of Biscuits- Bangladesh
1.	New Olympia Biscuit Factory
2.	Masafi Bread & Biscuit Industries Ltd.
3.	Resco Biscuit & Bread factory (PVT) Ltd.
4.	Central Marketing Company (CMC) (Alauddin Food & Chemical Industries Ltd)
5.	Mona Food Industries
6.	Olympic Industries Limited
7.	Romania Food&Beverages Ltd.

(*Bangladesh Milling assesment additional info*, n.d.).

Main ingredients: HEB must be manufactured from fresh and good quality, free from foreign materials, substances hazardous to health, excessive moisture, insect damage and fungal contamination and must comply with all relevant national food laws and standards (Van Hoan, 2013).

Requirements for the main ingredients are:

Wheat flour must conform toCodex STAN 152 (Standard, 1995).

Sugar must conform to Codex STAN 212-1999 (Stan, n.d.).

Shortening must be prepared from oil that conform to Codex STAN 210-1999, must be free from trans fatty acids and must contain only antioxidants that comply with Codex and relevant regulations (CODEX, n.d.).

Skimmed milk powder must conform to Codex STAN 207-1999.It must be accompanied by a 'melamine-free' certificate (Alimentarius, 1993).

Maximum level aflatoxin M1: < 0.5 mcg/kg milk (recommended methods ISO 14501/IDF 171:2007 (Reybroeck, Ooghe, Saul, & Salter, 2014) or ISO 14674/IDF 190:2005 ("ISO 14674:2005(en), Milk and milk powder — Determination of aflatoxin M1 content — Clean-up by immunoaffinity chromatography and determination by thin-layer chromatography," n.d.; Van Hoan, 2013).

Key achievements in 2010: School Feeding Program for Poverty Prone Areas in Bangladesh.

- Provided school feeding to 1,170,719 preprimary and primary school children (51 percent girls) in 9,965 schools.
- Each child received an average of 182 feeding days during the year, amounting to 8,191mt of high energy biscuits.
- Established 375 school gardens to demonstrate good homestead gardening practices and to deliver food and nutrition security messages.
- Increased female representation in School Management Committees from 18 percent in 2009 to 37 percent in 2010 (Report, 2010).

4.3 Preliminary analysis of the data

After collecting data, the first task for a researcher is to organize and simplify the data so that it is possible to get a general overview of the results. One method for simplifying and organizing data is to construct a frequency distribution ("HANDOUTS," n.d.).

Table 4. 1: Frequency distribution results for physiochemical analysis of Fortified High Energy Biscuits.

Proximate Variable		Frequency	Percentage
Moisture (%)			
	Acceptable Range	302	99.0
	Not Acceptable Range	3	1.0
Protein (%)			
	Acceptable Range	250	80.9
	Not Acceptable Range	59	19.1
Fat (%)			
	Acceptable Range	130	42.3
	Not Acceptable Range	177	57.7
Sugar (%)			
	Acceptable Range	295	97.0
	Not Acceptable Range	9	3.0
Total Carbohydrate (%)			
	Acceptable Range	188	62.3
	Not Acceptable Range	114	37.7
Vitamin A (mcg/100g)			
	Acceptable Range	128	44.6
	Not Acceptable Range	159	55.4
Iron (mg/100g)			
	Acceptable Range	129	43.9
	Not Acceptable Range	165	56.1

Frequency distribution presented in Table 4.1 obtained by using accepted level of requirement as prescribed by World Food Productrs (WFP), Dhaka indicates that only Moisture (%) and Sugar (%) contains are reasonably acceptable (>95%) and in case of other variables remarkable number of cases are unacceptable range were compared to the standard value prescribed by WFP, Dhaka.

Table 4. 2: Frequency distribution results for microbial analysis of Fortified High Energy Biscuits.

Microorganisms Variable		Frequency	Percentage
Mesophyllic aerobic bacteria (cfu/g)			
	Acceptable Range	88	100
	Not Acceptable Range	0	0
Coliforms (MPN/g)			
	Acceptable Range	88	100
	Not Acceptable Range	0	0
Escherichia coli (MPN/g)			
	Acceptable Range	90	100
	Not Acceptable Range	0	0
Salmonella			
	Acceptable Range	90	100
	Not Acceptable Range	0	0
Staphylococcus (cfu/g)			
	Acceptable Range	88	100
	Not Acceptable Range	0	0
Bacillus cereus (cfu/g)			
	Acceptable Range	88	100
	Not Acceptable Range	0	0
Enterobacter sakazakii (cfu/g)			
	Acceptable Range	86	97.7
	Not Acceptable Range	2	2.3
Yeast and moulds (cfu/g)			
	Acceptable Range	88	97.8
	Not Acceptable Range	2	2.2

Frequency distribution presented in Table 4.2 indicates that microorganisms contains are reasonably acceptable range (>95%) were compared to the standard value prescribed by WFP, Dhaka.

4.4 Descriptive Statistics of Fortified High Energy (HEB) Biscuits

Statistics are a set of tools for obtaining insight into a psychological phenomenon. Descriptive statistics summarise the data, making clear any trends, patterns etc. which may be lurking within

them; they consist of visual displays such as graphs, and summary statistics such as means (Hole, 2000).

Table 4. 3: Descriptive Statistics results for proximate analysis of Fortified High Energy Biscuits.

Proximate Variables	Minimum	Maximum	Mean	Std. Deviation
Moisture (%)	0.96	7.81	2.96	0.77
Protein (%)	1.31	14.44	10.27	1.44
Fat (%)	7.33	21.29	14.71	2.07
Sugar (%)	9.10	24.07	13.58	2.18
Total Carbohydrate (%)	63.31	78.63	70.40	2.80
Iron (mg/100g)	1.91	89.00	11.70	7.63
Vitamin A (µg/100g)	0.00	5785.00	426.00	760.51

The mean, standard deviation and other descriptive statistics for proximate analysis are displayed in Table 4.3. Here Total Carbohydrate (%), Iron (mg/100g) and Vitamin A (µg/100g) are high standard deviation (SD>2).

Table 4. 4: Descriptive Statistics results for microbiological analysis of Fortified High Energy Biscuits.

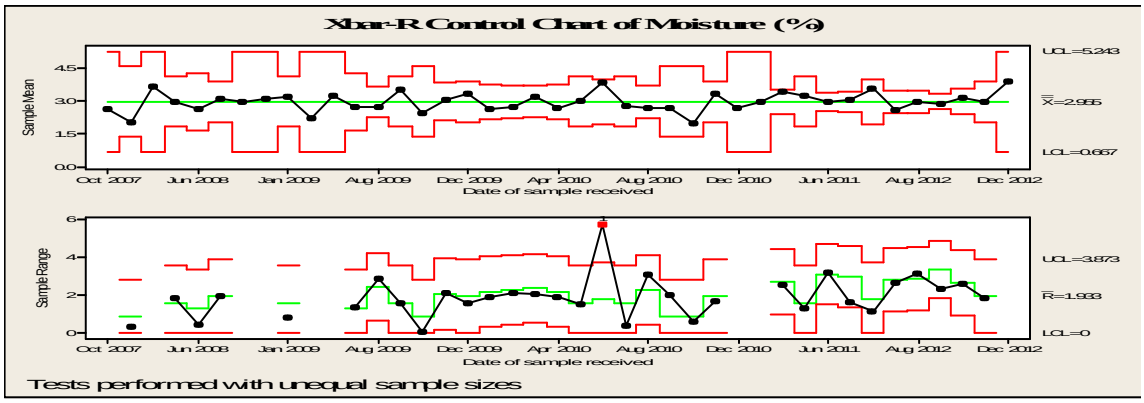
Microorganisms Variables	Minimum	Maximum	Mean	Std. Deviation
Mesophyllic aerobic bacteria (cfu/g)	0.00	7280.00	310.57	1302.49
Coliforms (MPN/g)	0.00	0.00	0.00	0.00
Escherichia coli (MPN/g)	0.00	0.00	0.00	0.00
Salmonella spp.	0.00	0.00	0.00	0.00
Staphylococcus (cfu/g)	0.00	1.00	0.01	0.11
Bacillus cereus (cfu/g)	0.00	9.99	0.57	2.33
Enterobacter sakazakii (cfu/g)	0.00	9.99	0.23	1.50
Yeast and moulds (cfu/g)	0.00	9500.00	111.67	1001.03

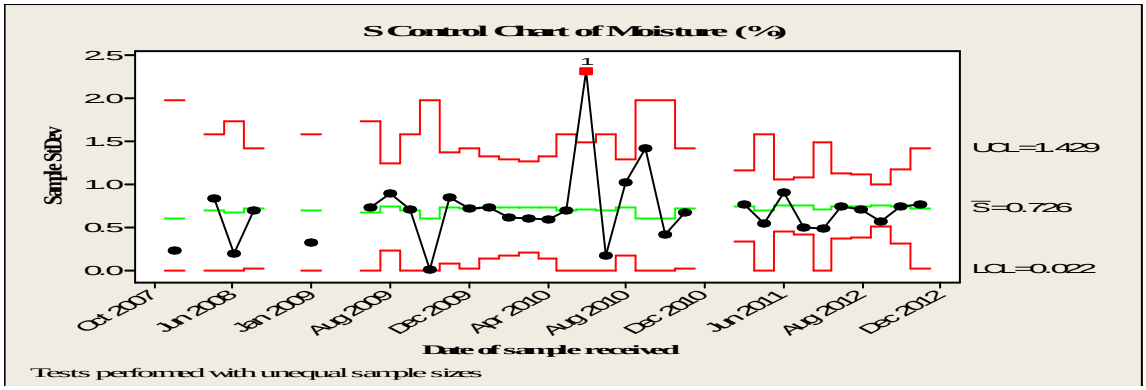
The mean, standard deviation and other descriptive statistics for microbiological analysis are displayed in Table 4.4. Here Mesophyllic aerobic bacteria (cfu/g) and Yeast and moulds (cfu/g) are highly standard deviation (SD>2).

4.5 Application of control charts on Fortified High Energy (HEB) Biscuits

In order to clarify whether the food products were under acceptable condition of quality or not we have adopted following control chart for fortified high energy biscuit.This section illustrates graphical chart of control charts and for showing their visual clarity.

Quality characteristic: Moisture





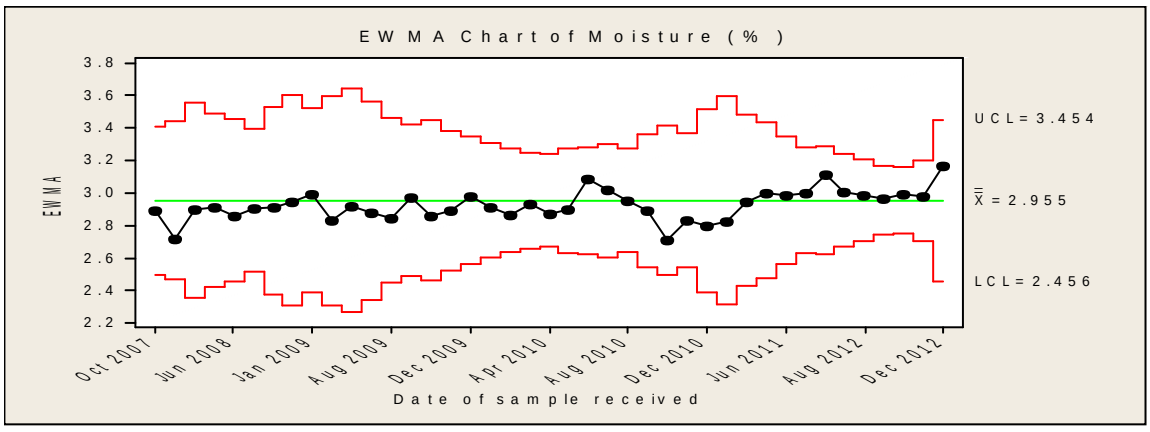


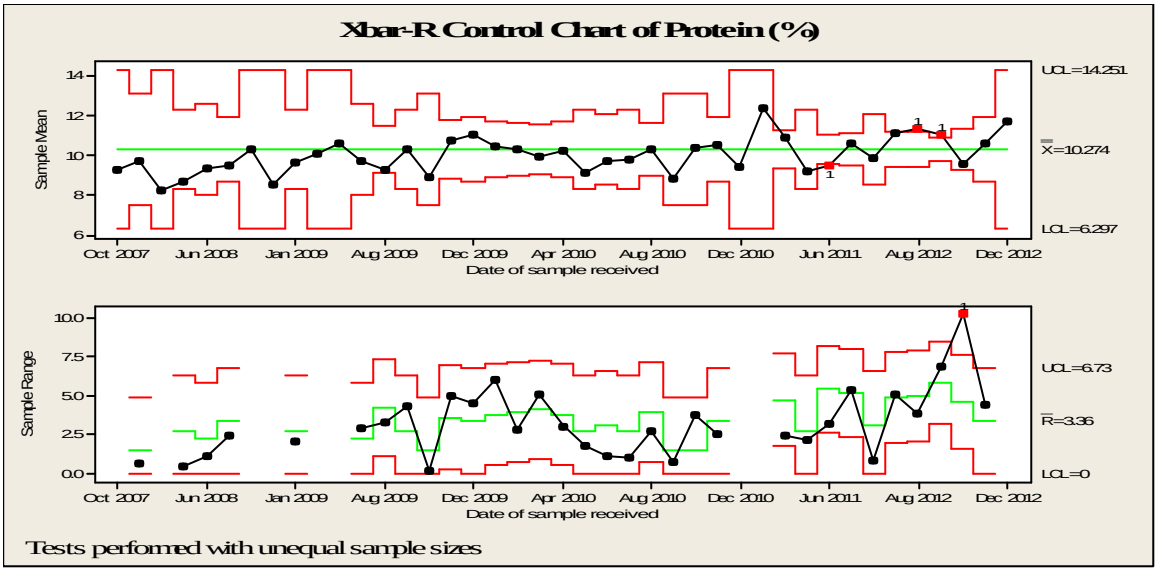
Figure 4. 1: X-bar, R, S and EWMA Charts for Moisture (%) of Biscuit (High Energy Fortified Biscuit, 2007-2012).

The first control chart given as output is the chart for the mean. This chart, which is pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control.

The second and third control chart is for the range and standard deviation and it is clear that, as far as range and standard deviation are concerned, the process is also in control except only one point are out of control on both chart. The fourth control is for the EWMA (Exponentially Weighted Moving Average) chart and it can be seen, the chart doesn't contain points out of control in Moisture (%) of biscuits in (Figure 4.1).

The Range and Standard deviation chart give alarming indication that there is lack of smooth functioning of the analysis of biscuits.

Quality Characteristic: Protein



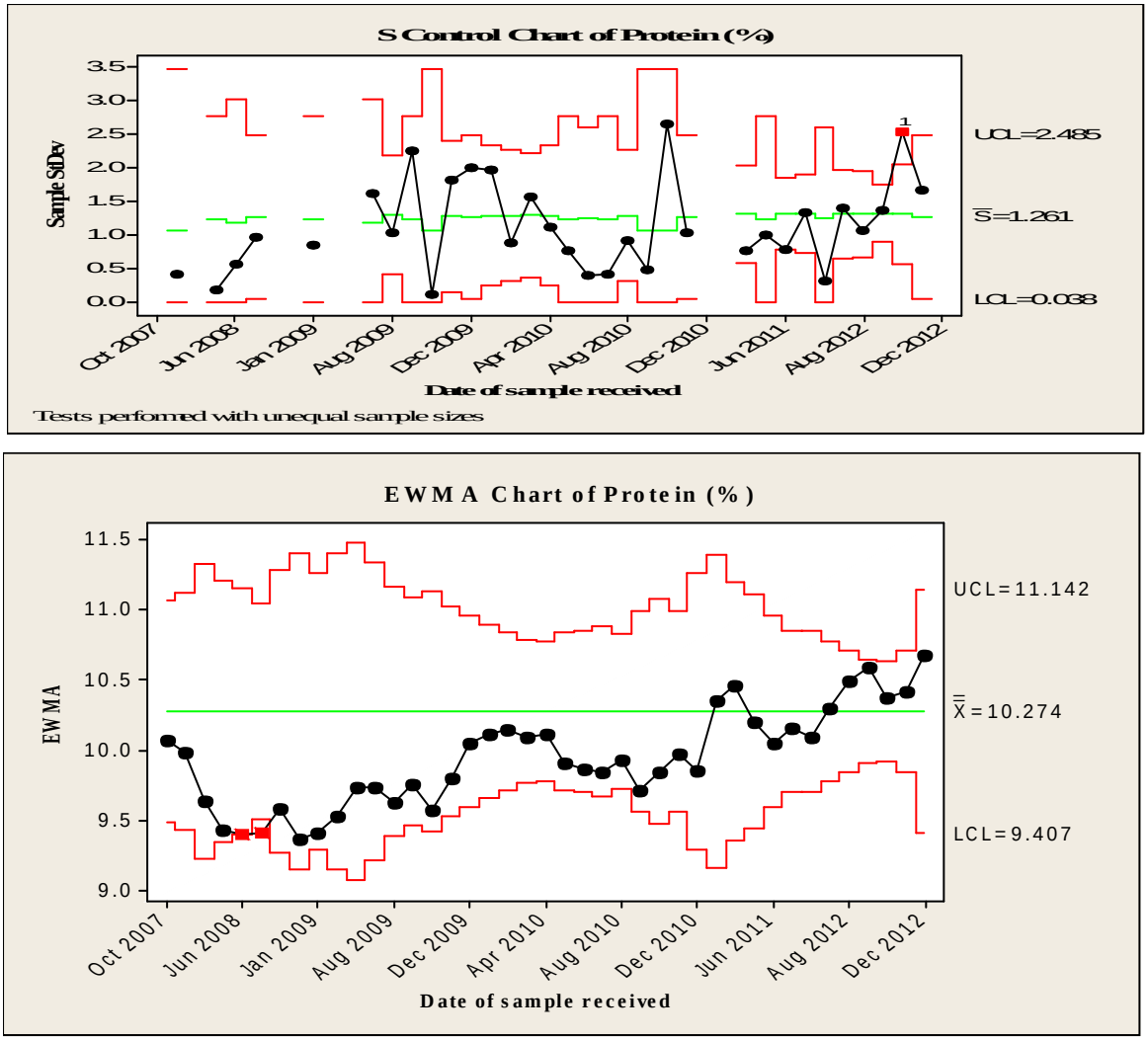


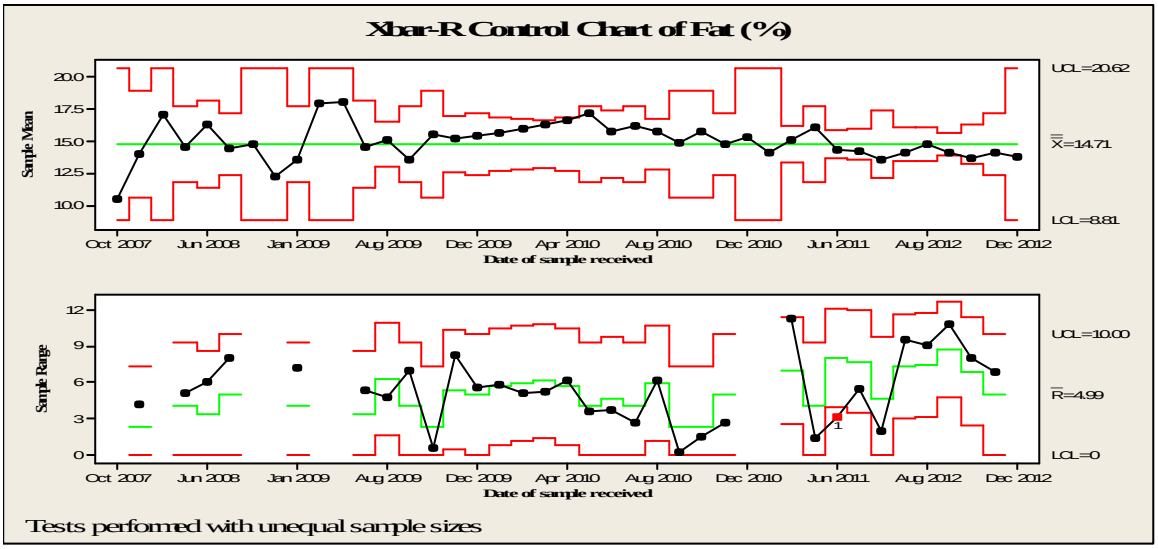
Figure 4. 2: X-bar, R, S and EWMA Charts for Protein (%) of Biscuit (High Energy Fortified Biscuit, 2007-2012).

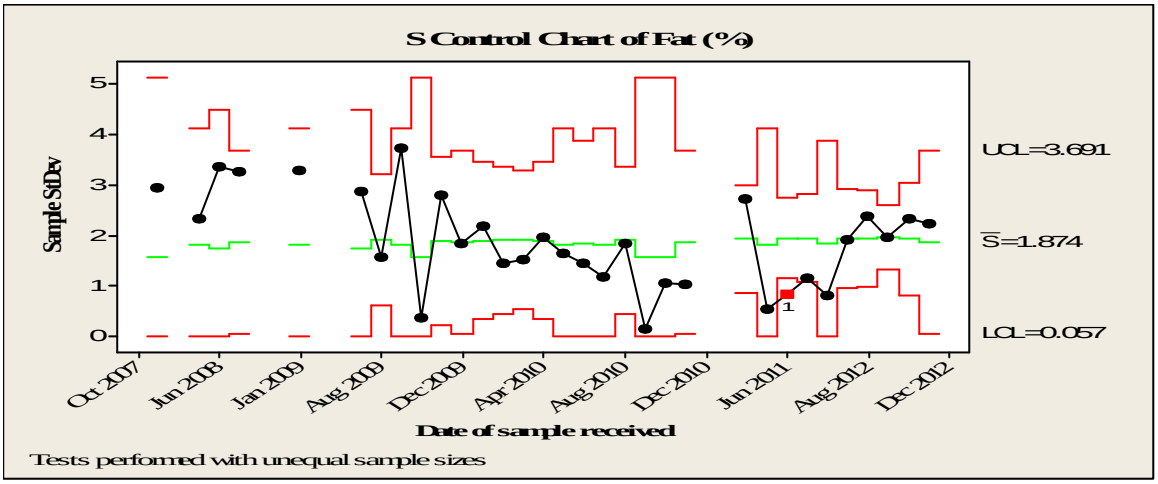
The first control chart given as output is the chart for the mean. This chart, which is pretty much self-explanatory, clearly shows the date wise sample means along with the unspecified (UCL and LCL) control limits. It is clear that the process is out of control after period June 2011.

The second and third control chart is for the range and standard deviation and it is clear that, as far as range and standard deviation are concerned, the process is in control except only one point are out of control for R chart and S chart respectively. The fourth control is for the EWMA (Exponentially Weighted Moving Average) chart and it can be seen from the graphic analysis of EWMA carried in July, 2008 is noticed two consecutive points out of control (Figure 4.2) in Protein (%) of biscuits.

For protein content of High Energy Fortified Biscuit, there is a problem about maintaining the average, range, standard deviation and EWMA chart quality level.

Quality Characteristic: Fat





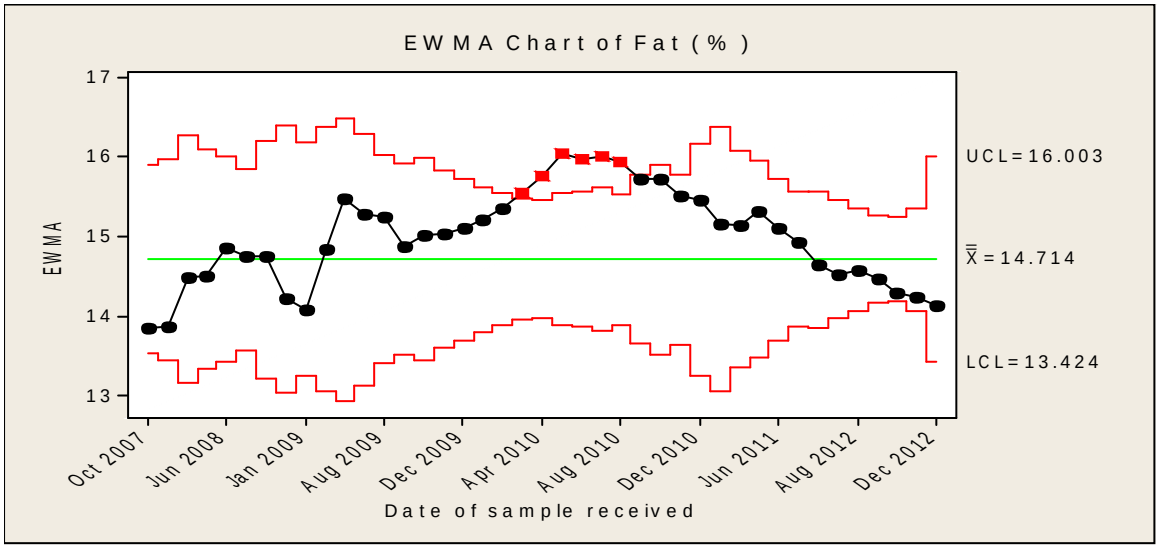


Figure 4. 3: X-bar, R, S and EWMA Charts for Fat (%) of Biscuit (High Energy Fortified Biscuit, 2007-2012).

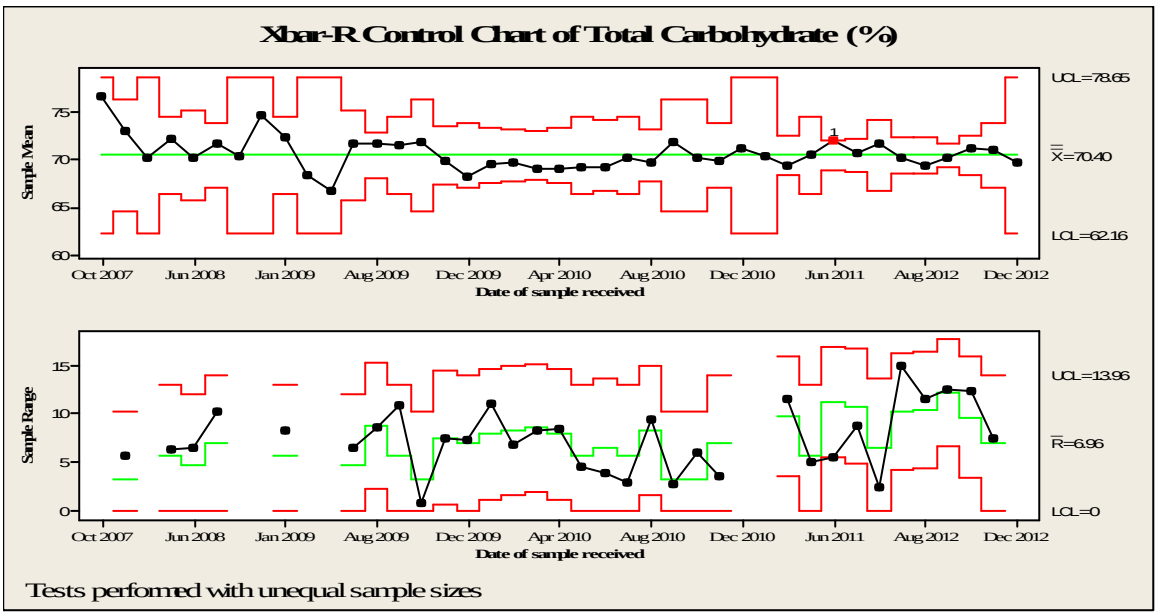
The first control chart given as output is the chart for the mean. This chart, which is pretty much self-explanatory, clearly shows the date wise means along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control.

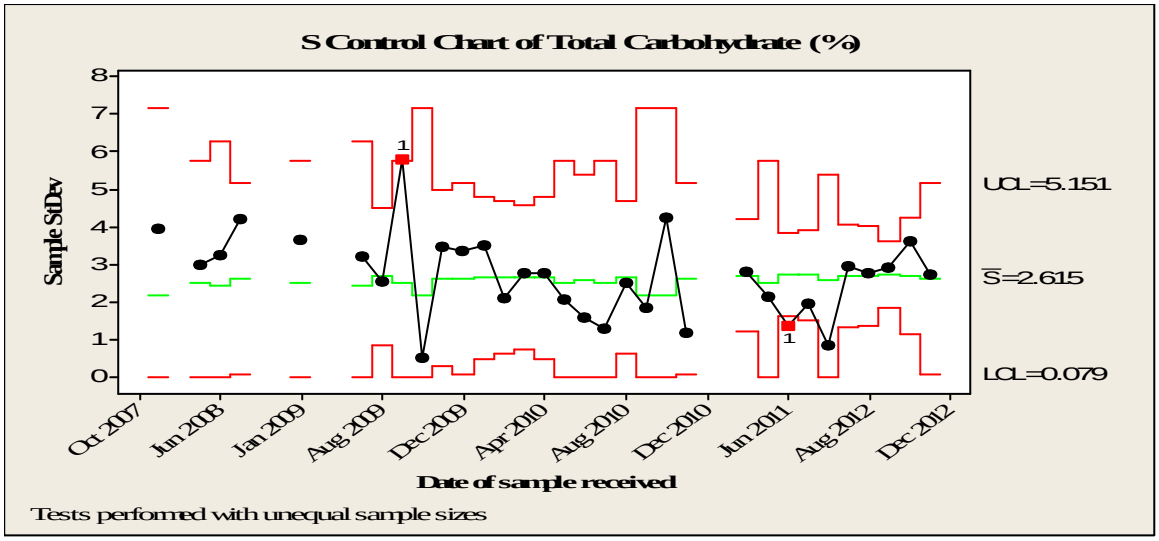
The second and third control chart is for the range and standard deviation and it is clear that, as far as range and standard deviation are concerned, the process is in control except only one point out of control on both charts.

The EWMA (Exponentially Weighted Moving Average) chart and it can be seen from the graphic analysis of EWMA carried in March, 2010 to August, 2010 that noticed six consecutive points are out of control (Figure 4.3) in Fat (%) of biscuits.

Regarding fat content of High Energy Fortified Biscuit the problem is still more serious except for mean chart.

Quality Characteristic: Total Carbohydrate





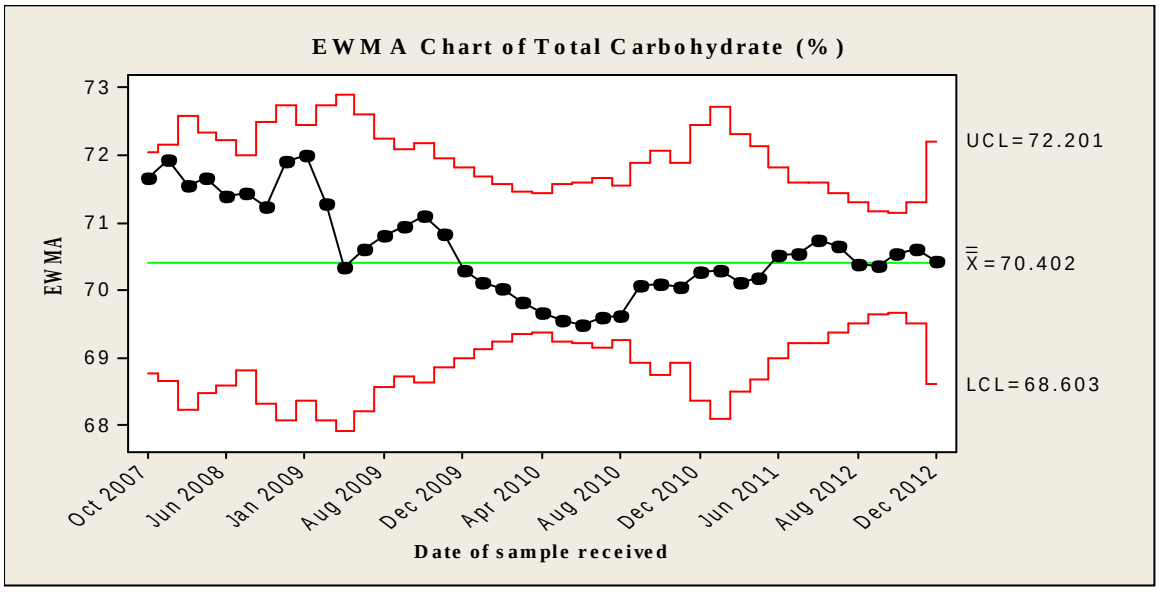


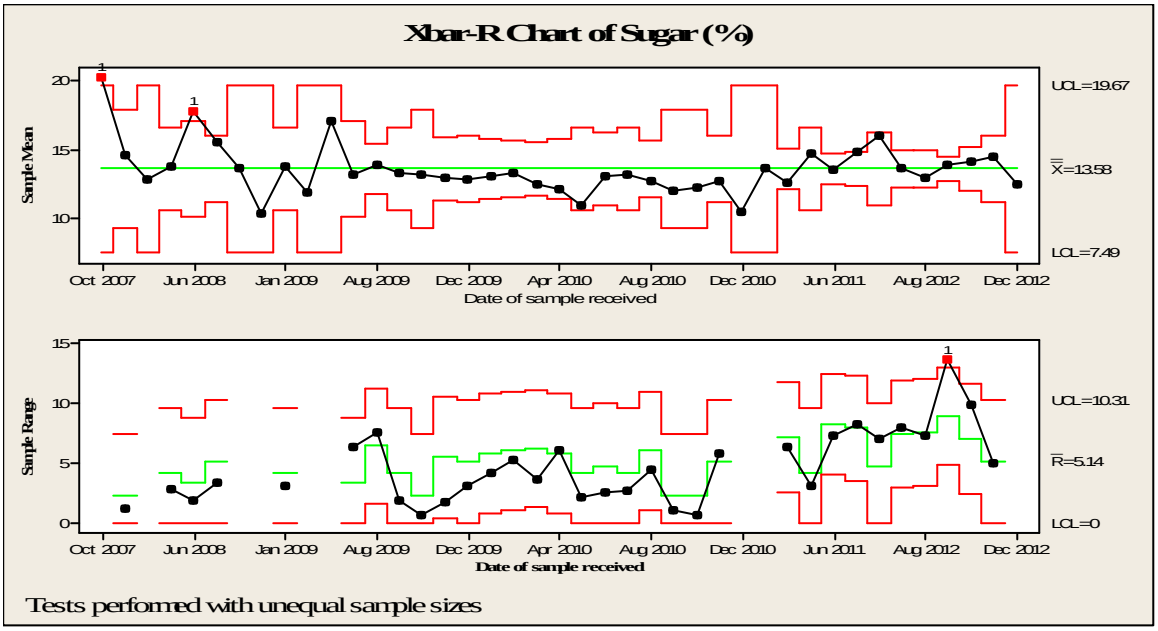
Figure 4. 4: X-bar, R, S and EWMA Charts for Total Carbohydrate (%) of Biscuit (High Energy Fortified Biscuit, 2007-2012).

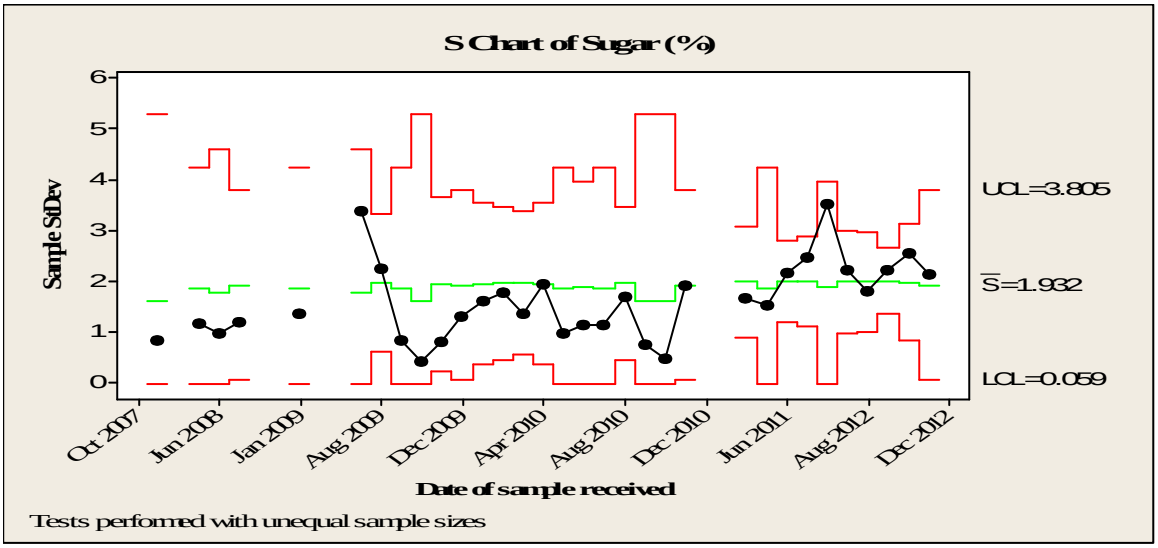
The first control chart given as output is the chart for the mean. This chart, which is pretty much self-explanatory, clearly shows the date wise sample means along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control where one points are out of control.

The second control chart is for the range and it is clear that, as far as range is concerned, the process is in control. The third control chart is for the standard deviation and it is clear that, as far as standard deviation is concerned, the process is out of control on two points. The fourth one is for the EWMA (Exponentially Weighted Moving Average) chart and it can be seen, the chart doesn't contain points out of control in Total Carbohydrate (%) of biscuits in (Figure 4.4).

Regarding Carbohydrate content of High Energy Fortified Biscuit both mean and standard deviation chart give alarming indication that there is lack of smooth functioning of analysis of biscuits.

Quality Characteristic: Sugar





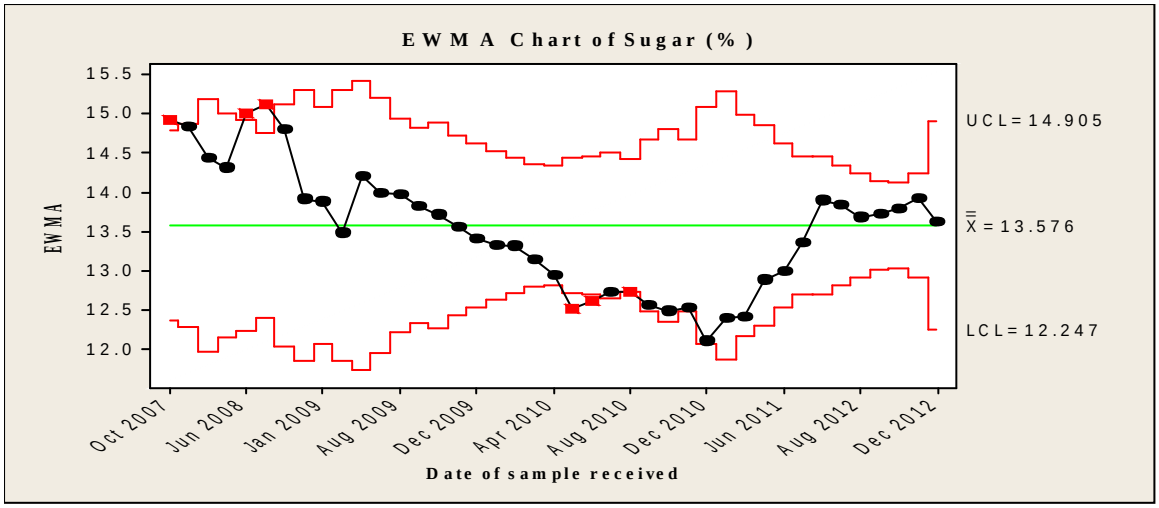


Figure 4. 5: X-bar, R, S and EWMA Charts for Sugar (%) of Biscuit (High Energy Fortified Biscuit, 2007-2012).

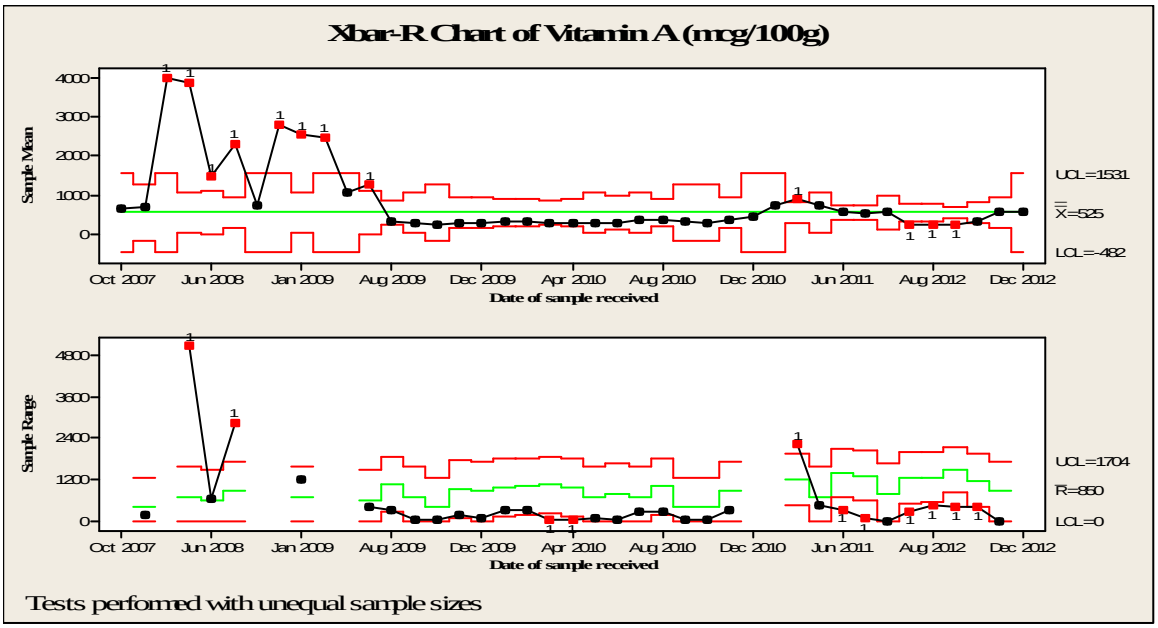
The first control chart given as output is the chart for the mean. This chart, which is pretty much self-explanatory, clearly shows the date wise sample means along with the unspecified (UCL and LCL) control limits. It is clear that the process is out of control for two points of period October, 2007-June, 2008.

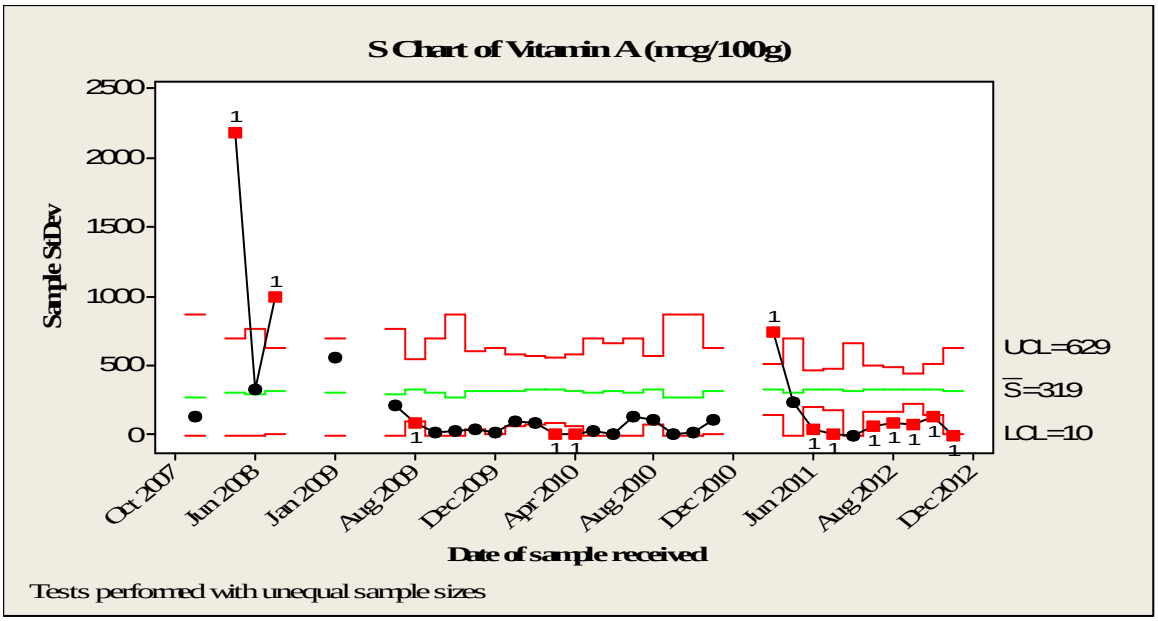
The second control chart is for the range and it is clear that, as far as range is concerned, the process is out of control on one points. The third control chart is for the standard deviation and it is clear that, as far as standard deviation is concerned, the process is in control.

The fourth control is the EWMA (Exponentially Weighted Moving Average) chart and it can be seen from the graphic analysis of EWMA carried in October, 2007 at one point, June-July, 2008 at two consecutive points and May-August, 2010 are found to be three points out of control (Figure 4.5) in Sugar (%) of biscuits.

In the case of sugar content of Fortified High Energy Biscuit, the average, range and EWMA chart give alarming indication that there is lack of smooth functioning of the analysis of biscuits.

Quality Characteristic: Vitamin A





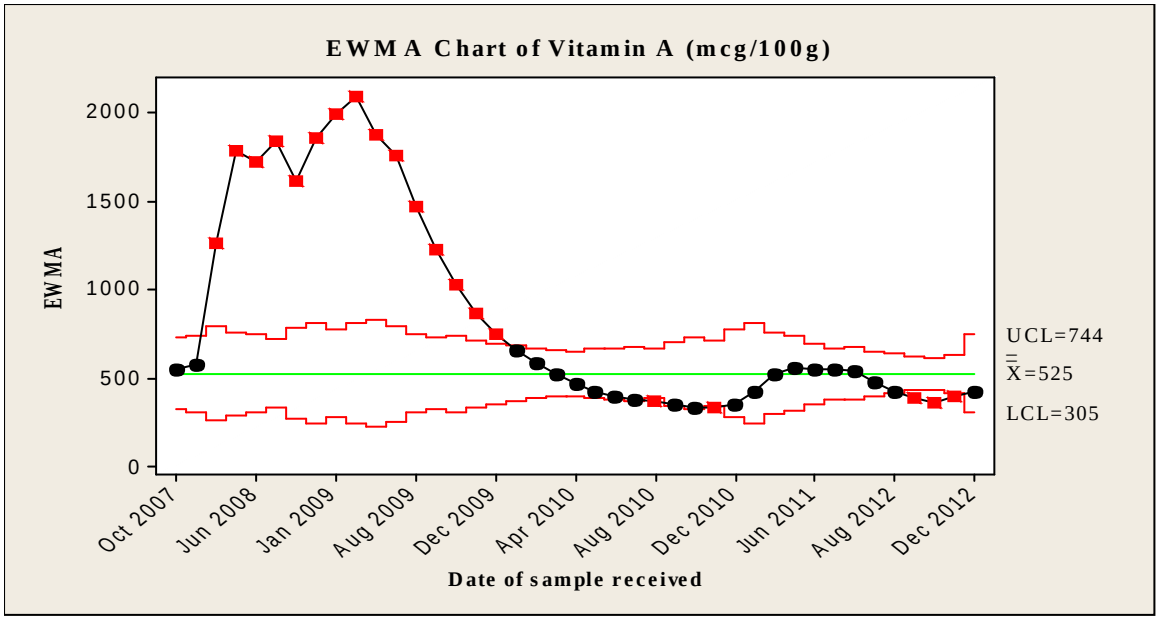


Figure 4. 6: X-bar, R, S and EWMA Charts for Vitamin A (µg/100gm) of Biscuit (High Energy Fortified Biscuit, 2007-2012).

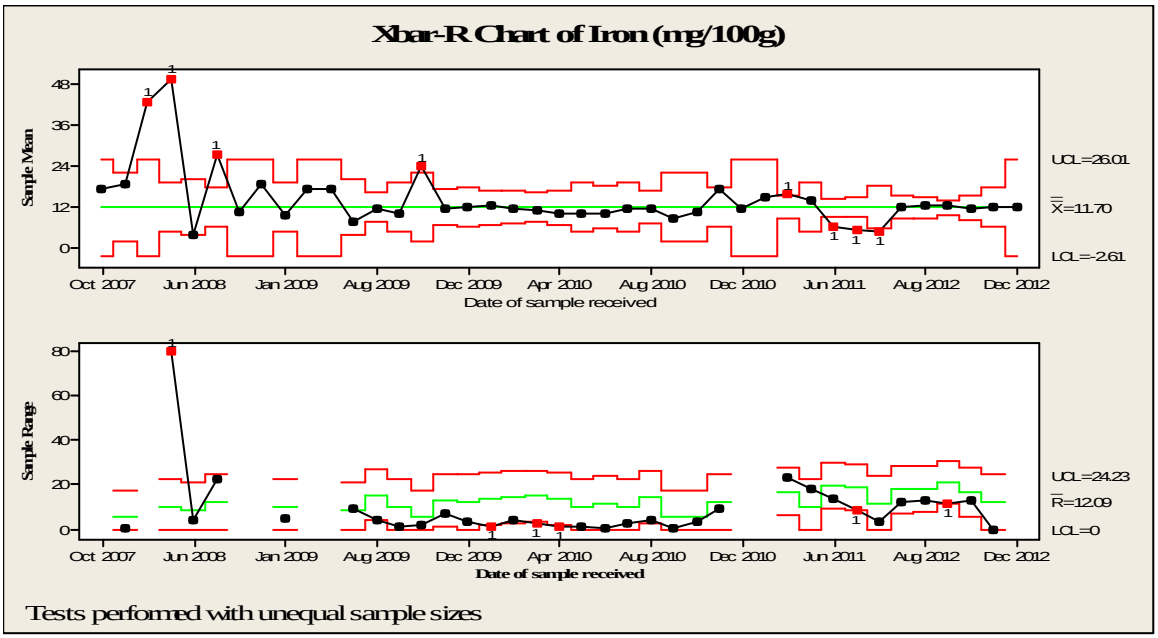
The first control chart is for the mean. This chart, which is pretty much self-explanatory, clearly shows the industry means along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control of most of the points.

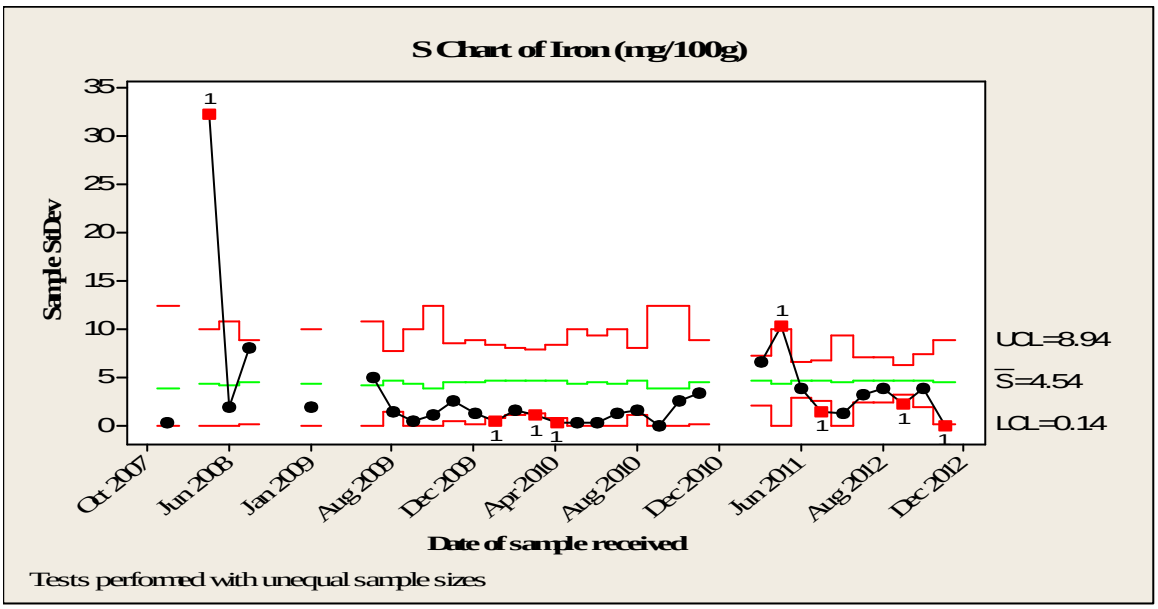
The second and third control chart is for the range and standard deviation and it is clear that, as far as range and standard deviation is concerned, the process is out of control for most of the points.

The fourth control is the EWMA (Exponentially Weighted Moving Average) chart and it can be seen from the graphic analysis of EWMA carried for December, 2007 to December, 2009 that fifteen consecutive points are out of control. Also for august, November, 2010 two points and for September to November, 2012 three consecutive points are out of control in case (Figure 4.6) of Vitamin A (µg/100gm) of biscuits.

Regarding Vitamin A content of High Energy Fortified Biscuit the problem is still more serious. The quality of variability and EWMA level in it shows out of control.

Quality Characteristic: Iron





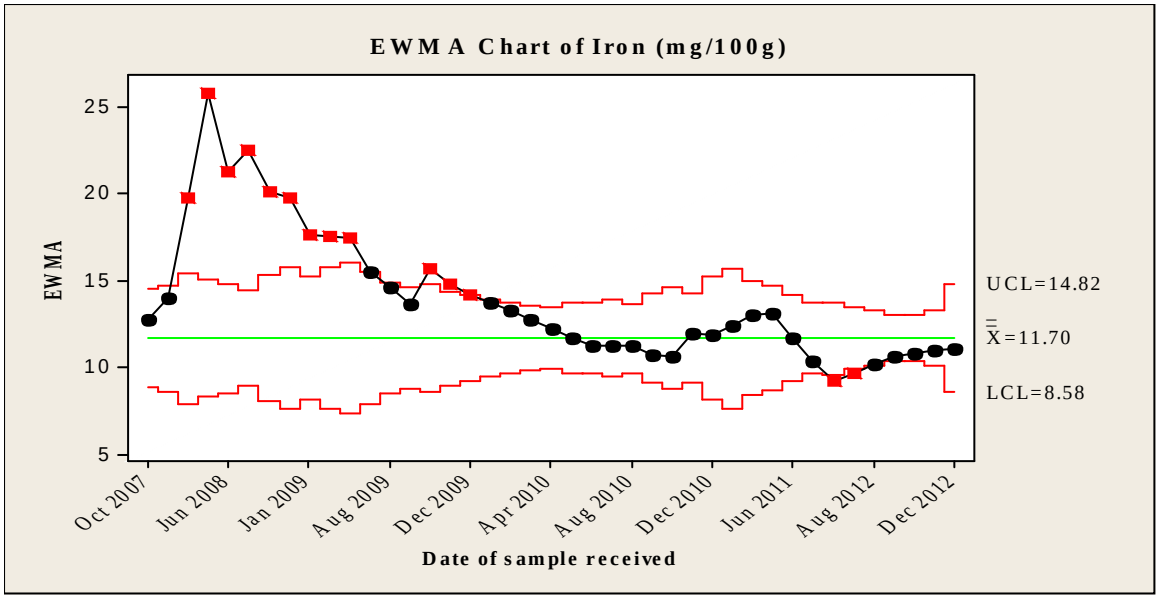


Figure 4. 7: X-bar, S and EWMA Charts for Iron (mg/100gm) of Biscuit (High Energy Fortified Biscuit, 2007-2012).

The first control chart given as output is the chart for the mean. This chart, which is pretty much self-explanatory, clearly shows the date wise means along with the unspecified (UCL and LCL) control limits. It is clear that the process is out of control on most of the points.

The second and third control chart is for the range and standard deviation and it is clear that, as far as range and standard deviation is concerned, the process is out of control on also more of the points of both charts.

The fourth is the EWMA (Exponentially Weighted Moving Average) chart and it can be seen from the graphic analysis of EWMA carried for the period December, 2007 to June, 2009 it's found that nine consecutive points are out of control. Also for October to December, 2009 three consecutive points and August, 2011 to July, 2012 two consecutive points are out of control in case (Figure 4.7) of Iron (mg/100gm) content of biscuits.

Regarding the content of Iron of Fortified High Energy Biscuit the problem is still serious. Neither the quality level nor the variability in it shows controlled analysis of biscuits.

4.6 Process Capability Analysis (Using Normal Distribution Curve)

In this case, we want to assess the analysis of food products quality capability for different industries producing certain fortified high energy biscuits. The proximate analysis of the biscuits is of concern. The specification limits on the biscuits are in given appendix 1. There has been a consistent problem with meeting the specification limits and the some process produces a high percentage of rejects.

The histogram of the data shows that proximate analysis of biscuits follow a normal distribution or approximately normal distribution. The variation from biscuittobiscuit can be estimated using the within group standard deviation. Since the process is stable and the measurements are normally or approximately normality distributed, the normal distribution option of process capability analysis can be used.

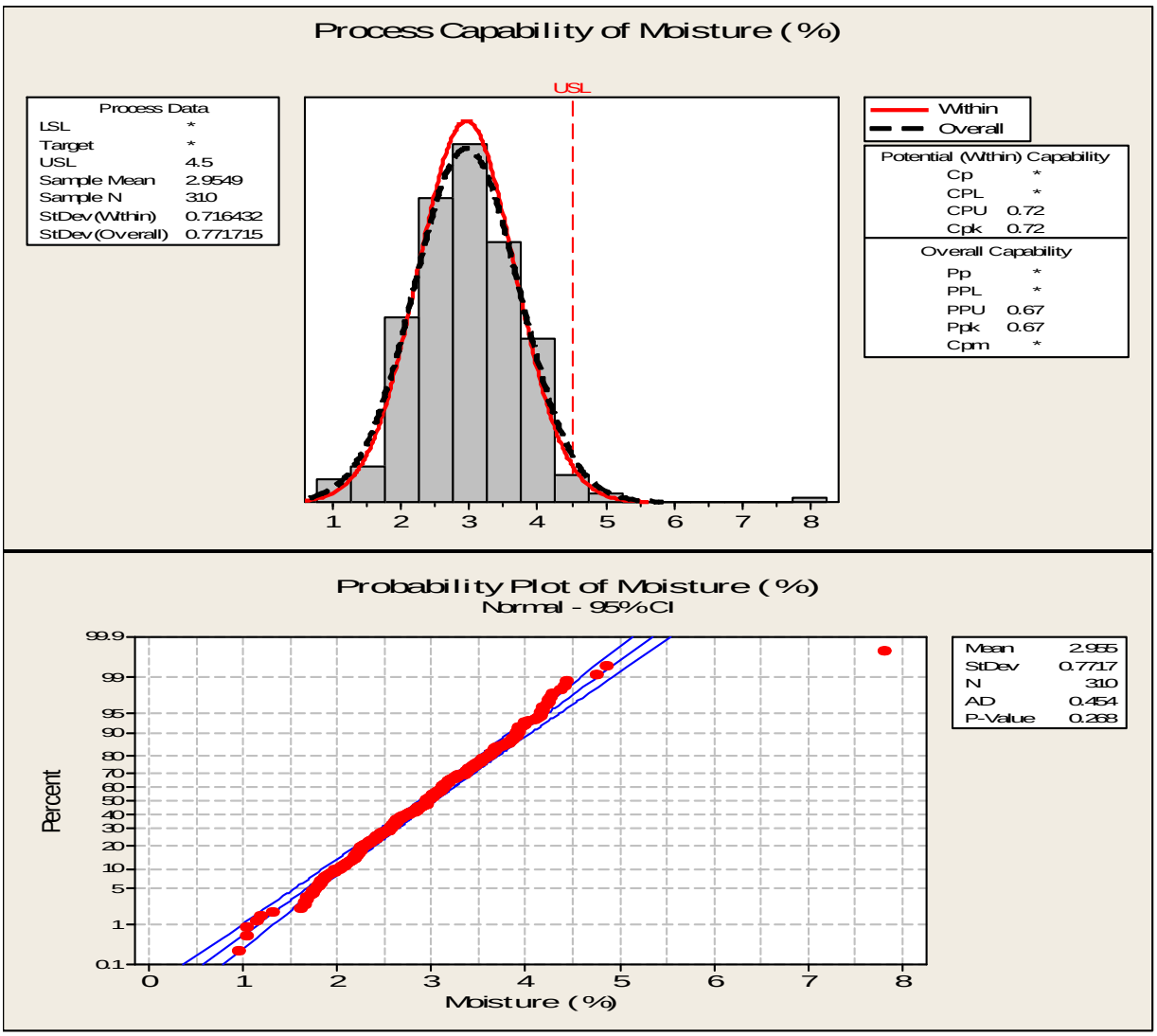


Figure 4. 8: Process Capability Report of Moisture (%).

The above left box reports the analysis data including the lower specification limit and the upper specification limit. These values were provided by the Minitab statistical package program. The calculated values are the sample mean and the estimates of within standard deviations.

The report in Figure 4.8 shows the histogram of the data along with normal curves overlaid on the histogram. A normal curve with a solid line. The biscuit products of Moisture analysis report by this process exceed the upper specification limit (USL). Here also notice that insignificant percentage of the Moisture of biscuit are outside of Upper Specification Limit.

Note that the DF test exhibits a p-value greater than 0.05 (in this case, the p-value = 0.268 as shown in Figure 4.8) and there are no serious deviations from linearity in the Normal probability plot. We may therefore reasonably conclude that (i) the process is in statistical control and (ii) the data can be assumed to approximately follow a Normal distribution(B. K. M. Bower, 2000). Thenecessary assumptions appear to have been fulfilled and we may investigate the capability of this process, as shown in Figure 4.8.

The potential or within process capability of the process is reported on the right hand side. Cpk =0.69 is less than 1.00. This means that the process is offcentered.

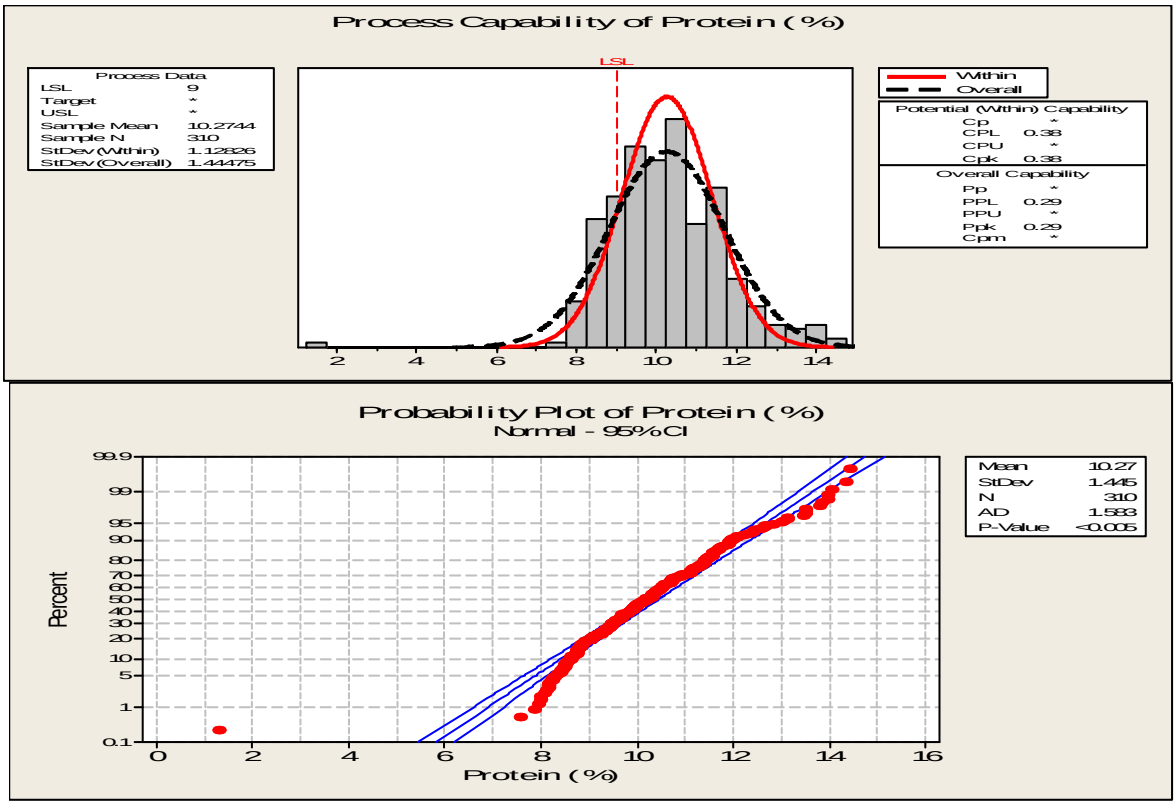


Figure 4. 9: Process Capability Report of Protein (%).

The above left box reports the process data including the lower specification limit and the upper specification limit. These values were provided by the minitab program. The calculated values are the analysis sample mean and the estimates of within standard deviations.

The report in Figure 4.9 shows the histogram of the data along with normal curves overlaid on the histogram. The products of biscuit of Protein analysis report by this process exceed the lower specification limit (LSL). A significant percentage of the Protein of biscuits is outside of Lower Specification Limit.

From the Normal probability plot graph in Fig. 4.9, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level(Bangphan, Bangphan, & Boonkang, 2014). This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.38 is less than 1 means that the process is off centered and not capable.

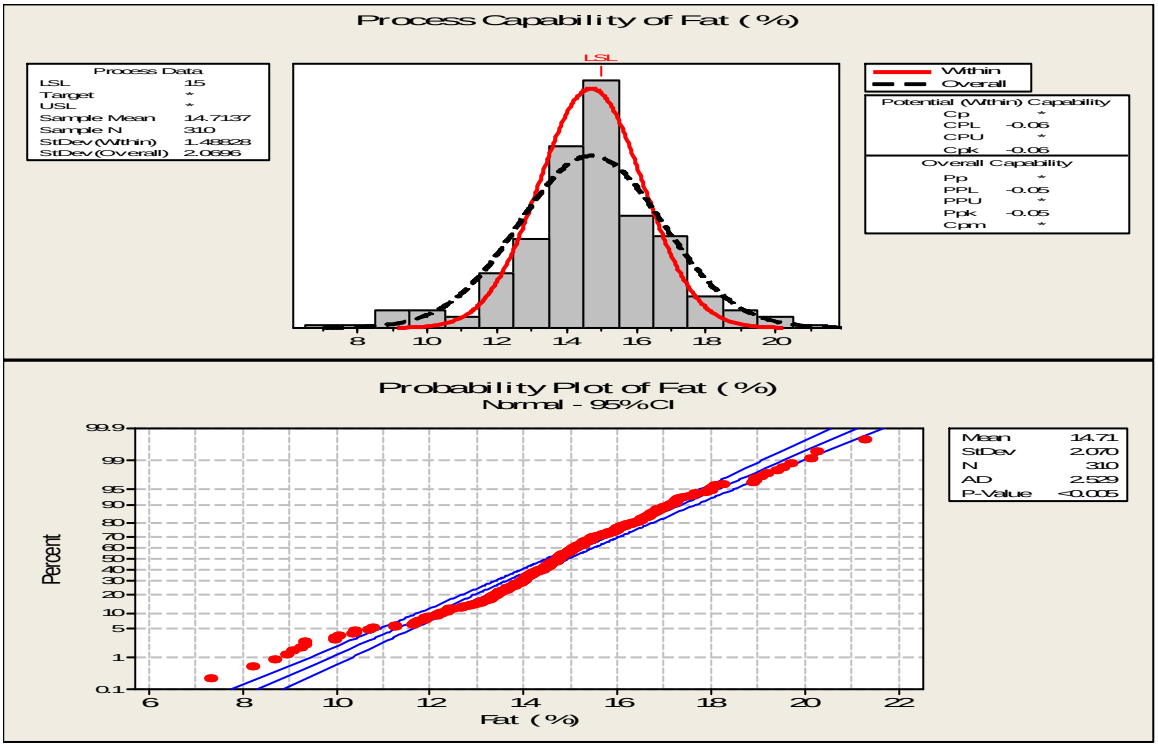


Figure 4. 10: Process Capability Report of Fat (%).

The upper left box reports the analysis data including the lower specification limit and the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 4.10 shows the histogram of the data along with normal curves overlaid on the histogram. A normal curve with a solid line. The biscuit products of Fat analysis report by this process exceed the lower specification limit (LSL). A significant percentage of the Fat of biscuits is outside of Lower Specification Limit.

From the Normal probability plot graph in Fig. 4.10, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level(Bangphan et al., 2014). This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-0.06 is less than 1 means that the process is off centered and capable.

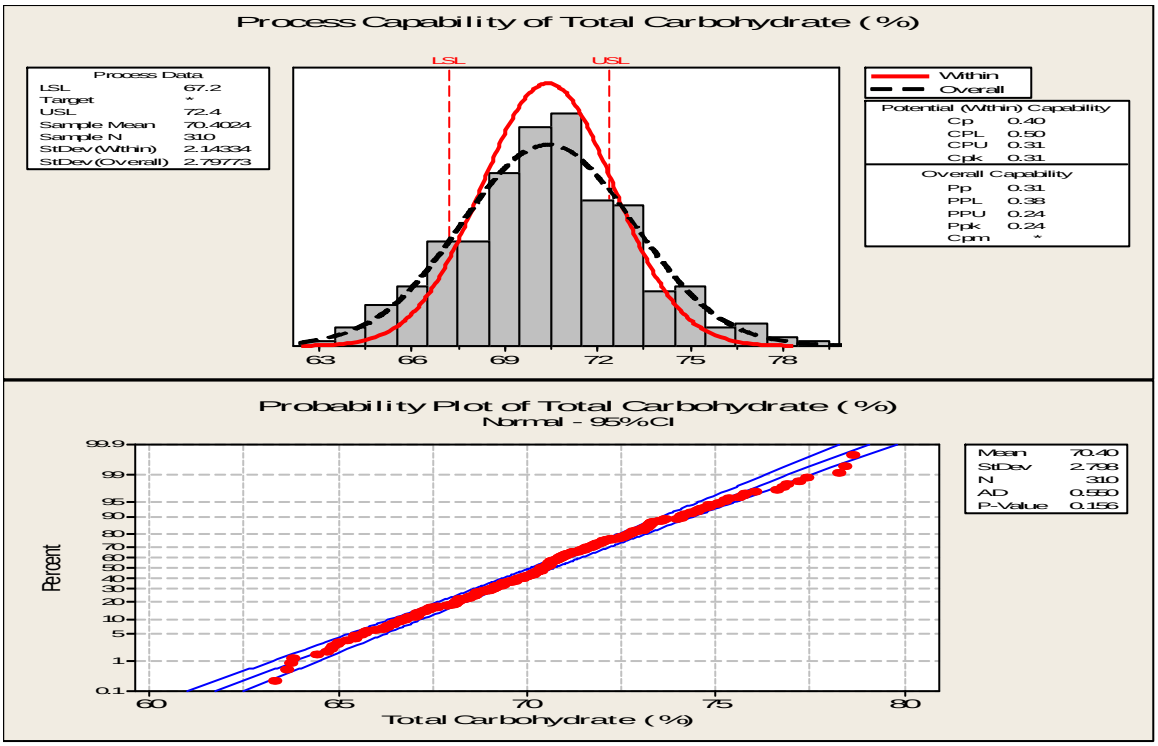


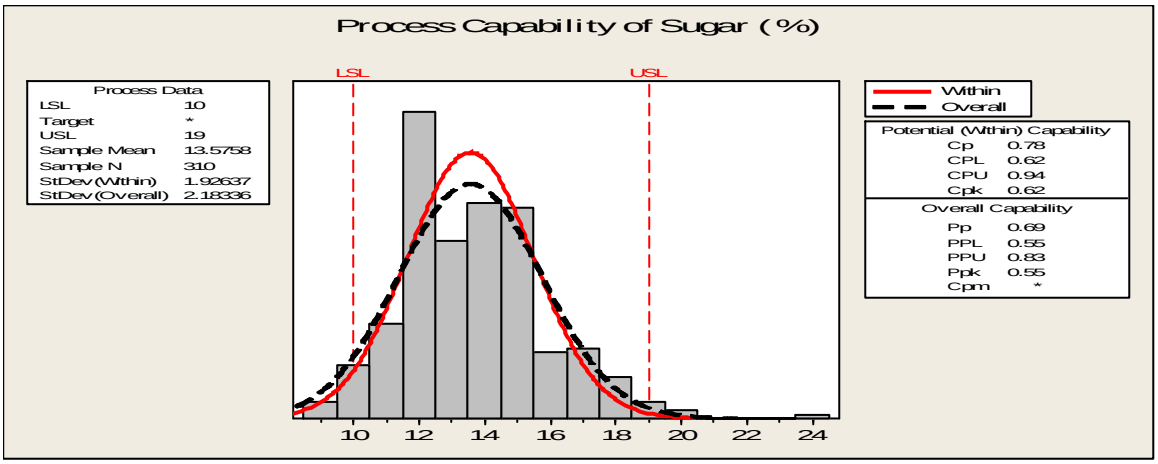
Figure 4. 11: Process Capability Report of Total Carbohydrate (%).

The above left box reports the analysis data including the lower specification limit and the upper specification limit. These values were provided by the Minitab program. The calculated values are the sample mean and the estimates of within standard deviations.

The Figure 4.11 shows the histogram of the data along with normal curves overlaid on the histogram. A normal curve with a solid line. The histogram and the normal curves can be used to check visually if the process data are normally distributed. To interpret the process capability, the normality assumption must hold. The biscuit products of Total Carbohydrate analysis report by this process exceed the lower and upper specification limit (LSL & USL). A significant percentage of the Total Carbohydrate of biscuit are outside of Lower and upper Specification Limit.

The DF test exhibits a p-value greater than 0.05 (in this case, the p-value = 0.156 as shown in Figure 4.11) and there are no serious deviations from linearity in the Normal probability plot.We may therefore reasonably conclude that (i) the process is in statistical control and (ii)
the data can be assumed to approximately follow a Normal distribution(B. K. M. Bower, 2000). Thenecessary assumptions appear to have been fulfilled and we may investigate thecapability of this process, as shown in Figure 4.11.

The potential or within process capability of the process is reported on the right hand side. The value of Cp=0.37 indicates that the process is not capable (Cp < 1). Also, Cpk =0.28 is less than Cp=0.37. This means that the process is off centered.



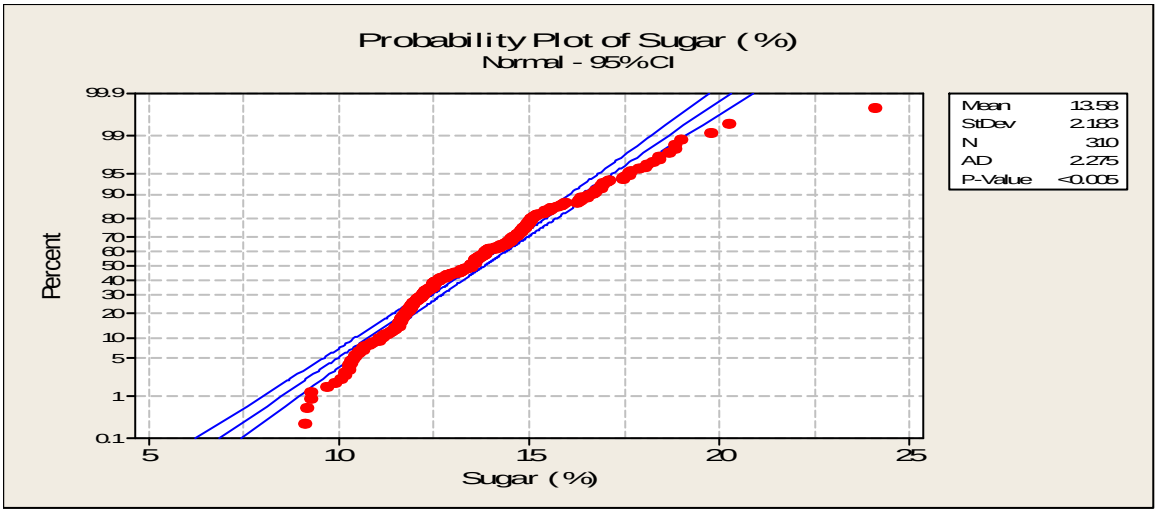


Figure 4. 12: Process Capability Report of Sugar (%).

The above left box reports the process data including the lower specification limit and the upper specification limit. These values were provided by minitab program. The calculated values are the sample mean and the estimates of within standard deviations.

The report in Figure 4.12 shows the histogram of the data along with normal curves overlaid on the histogram. A normal curve with a solid line. The histogram and the normal curves can be used to check visually if the process data are normally distributed. To interpret the process capability, the normality assumption must hold. The biscuit products of sugar analysis report by this process exceed the lower and upper specification limit (LSL & USL). A significant percentage of the sugar of biscuits is outside of Upper and Lower Specification Limit.

From the Normal probability plot graph in Fig. 4.12, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level (Bangphan et al., 2014). This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cp=0.78 indicates that the process is not capable (Cp < 1). Also, Cpk =0.62 is less than Cp=0.78. This means that the process is off centered.

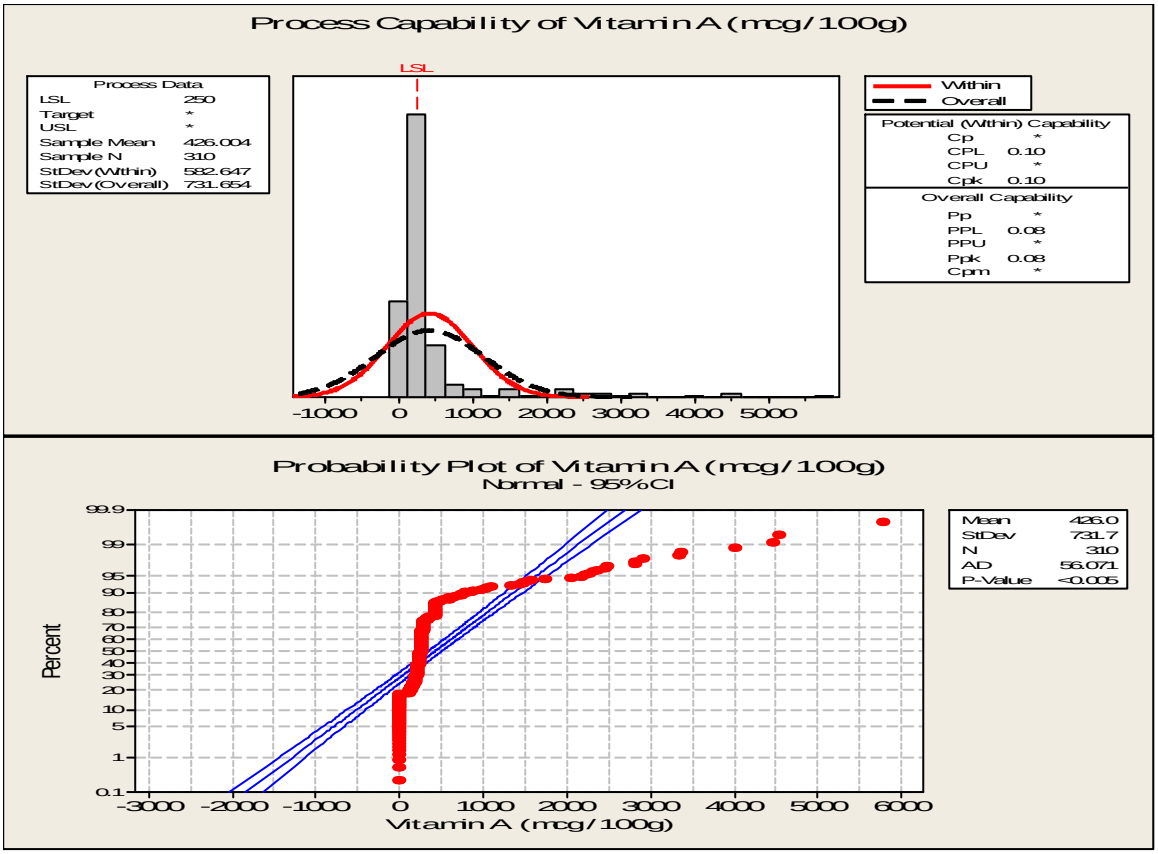


Figure 4. 13: Process Capability Report of Vitamin A (mcg/100g).

The upper left box reports the process data including the lower specification limit, target and the upper specification limit. These values were provided by the Minitab Statistical program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 4.13 shows the histogram of the data along with normal curves overlaid on the histogram. A normal curve with a solid line. The histogram and the normal curves can be used to check visually if the process data are normally distributed. To interpret the process capability, the normality assumption must hold. The biscuit products of vitamin A analysis report by this process exceed the lower specification limit (LSL). A significant percentage of the Vitamin A of biscuits is outside of lower specification limit.

From the Normal probability plot graph in Fig. 4.13, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level (Bangphan et al., 2014). This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.10 is less than 1 means that the process is off centered and not capable.

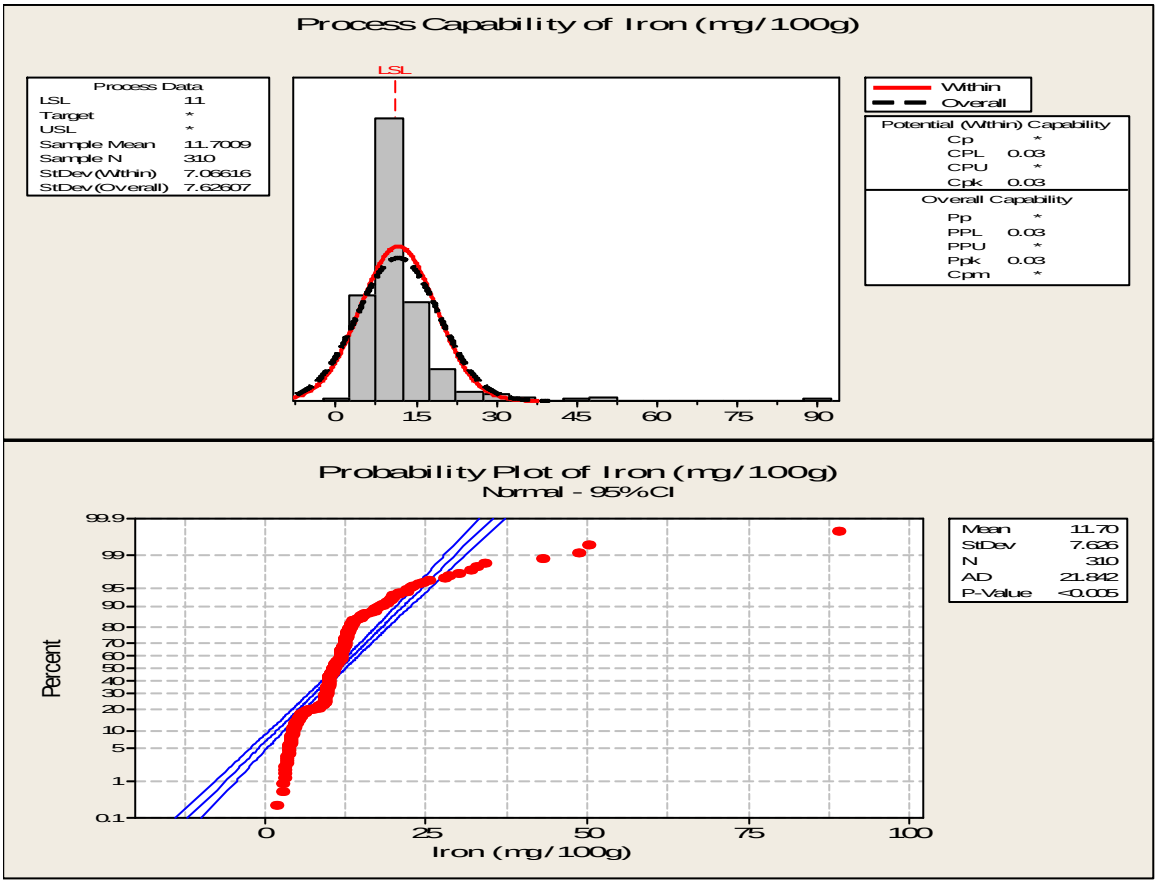


Figure 4. 14: Process Capability Report of Iron (mg/100g).

The upper left box reports the process data including the lower specification limit, target and the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 4.14 shows the histogram of the data along with normal curves overlaid on the histogram. A normal curve with a solid line. The histogram and the normal curves can be used to check visually if the process data are normally distributed. To interpret the process capability, the normality assumption must hold. The biscuit products of Iron analysis report by this process exceed the lower specification limit (LSL). A significant percentage of the Iron of biscuits is outside of lower and upper specification limit.

From the Normal probability plot graph in Fig. 4.14, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level (Bangphan et al., 2014). This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-0.03 is less than 1 means that the process is off centered and not capable.

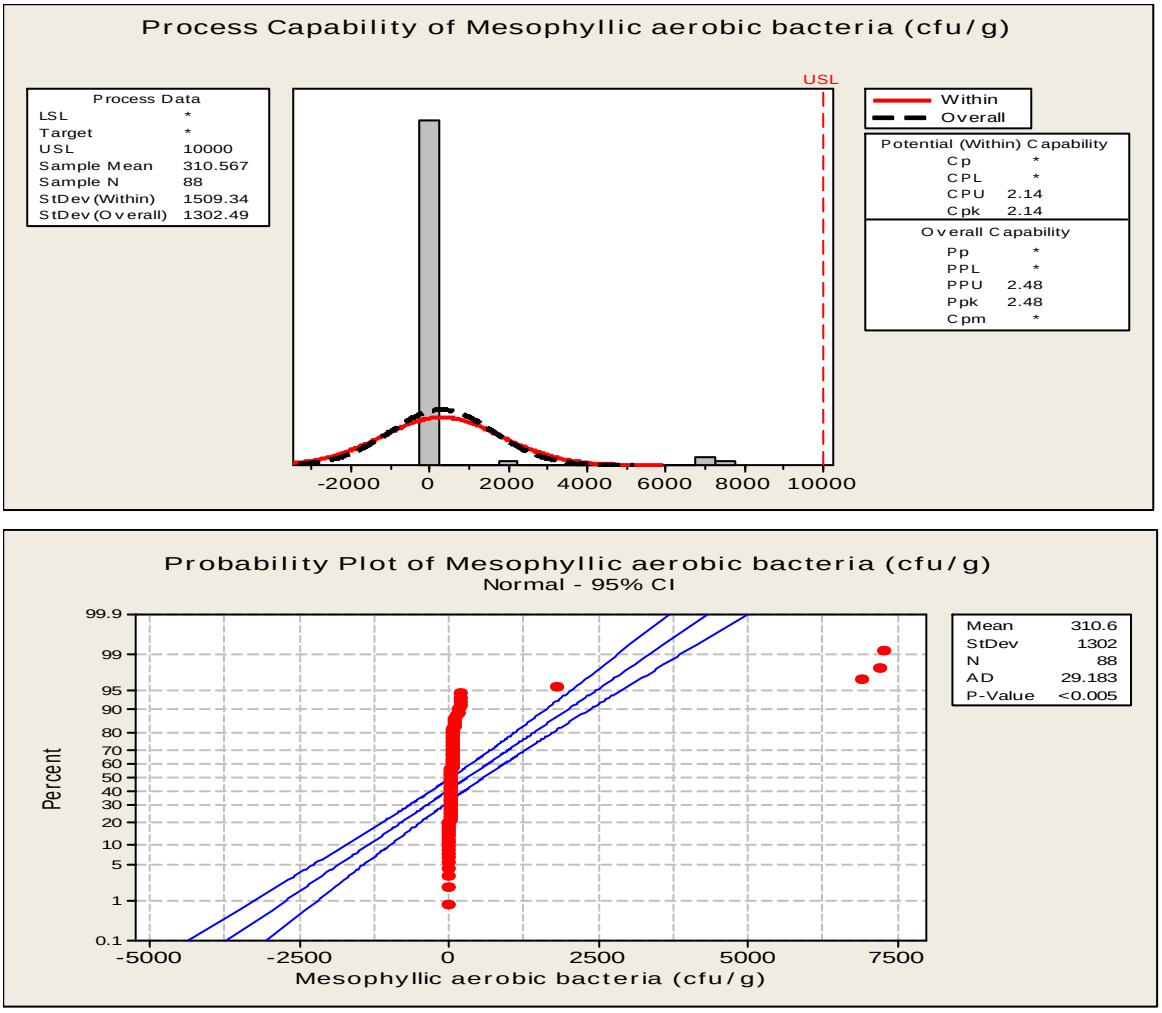


Figure 4. 15: Process Capability Report of Mesophyllic aerobic bacteria (cfu/g).

The Figure 4.15 shows the histogram and Probability Plot of the data along with normal curves overlaid on the histogram. The histogram and the Probability Plot can be used to check visually if the process data are normally and symmetrically distributed. From the Fig. 4.15, shows that data wan not follow a Normal distribution as well as symmetric distribution.

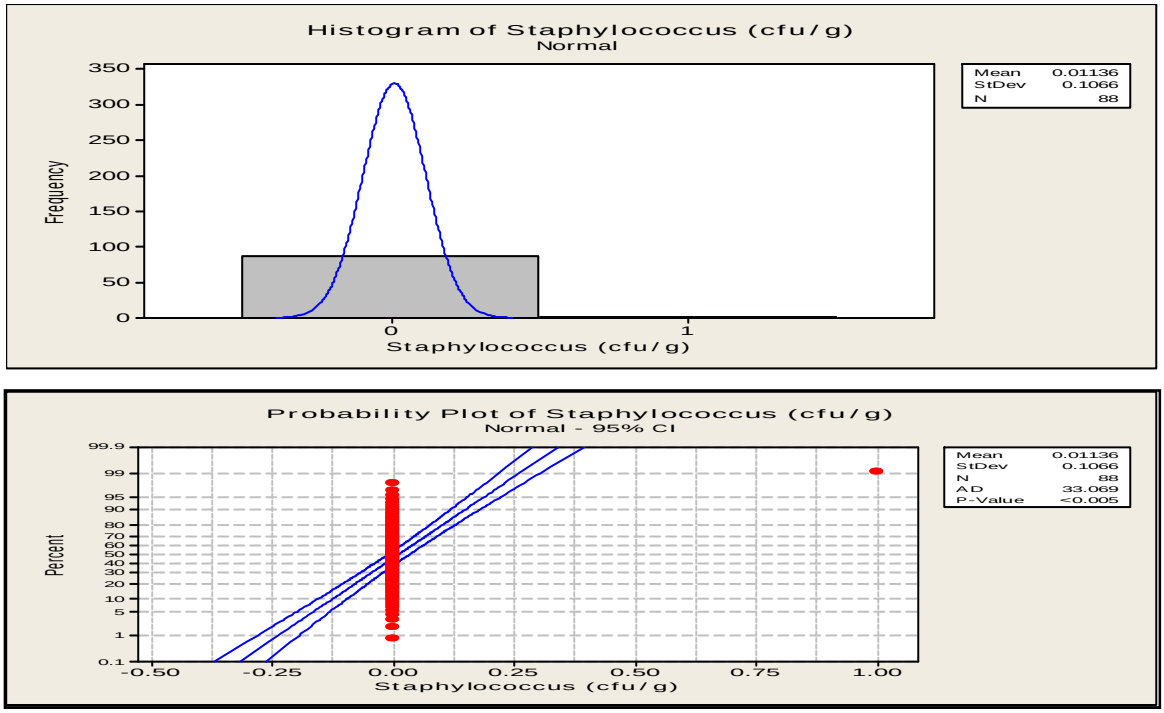


Figure 4. 16: Probability plot of Staphylococcus (cfu/g).

The Figure 4.16 shows the histogram and Probability Plot of the data along with normal curves overlaid on the histogram. The histogram and the Probability Plot can be used to check visually if the process data are normally and symmetrically distributed. From the Fig. 4.16, shows that data wan not follow a Normal distribution as well as symmetric distribution.

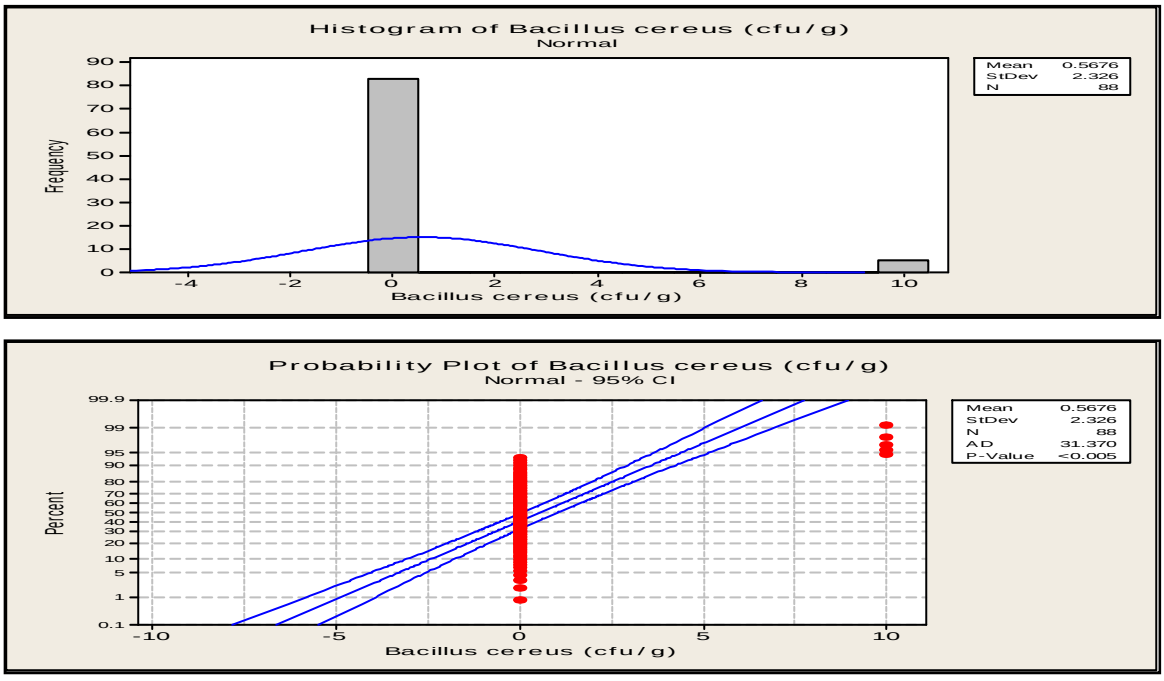


Figure 4. 17: Probability plot of Bacillus cereus (cfu/g).

The Figure 4.17 shows the histogram and Probability Plot of the data along with normal curves overlaid on the histogram. The histogram and the Probability Plot can be used to check visually if the process data are normally and symmetrically distributed. From the Fig. 4.17, shows that data wan not follow a Normal distribution as well as symmetric distribution.

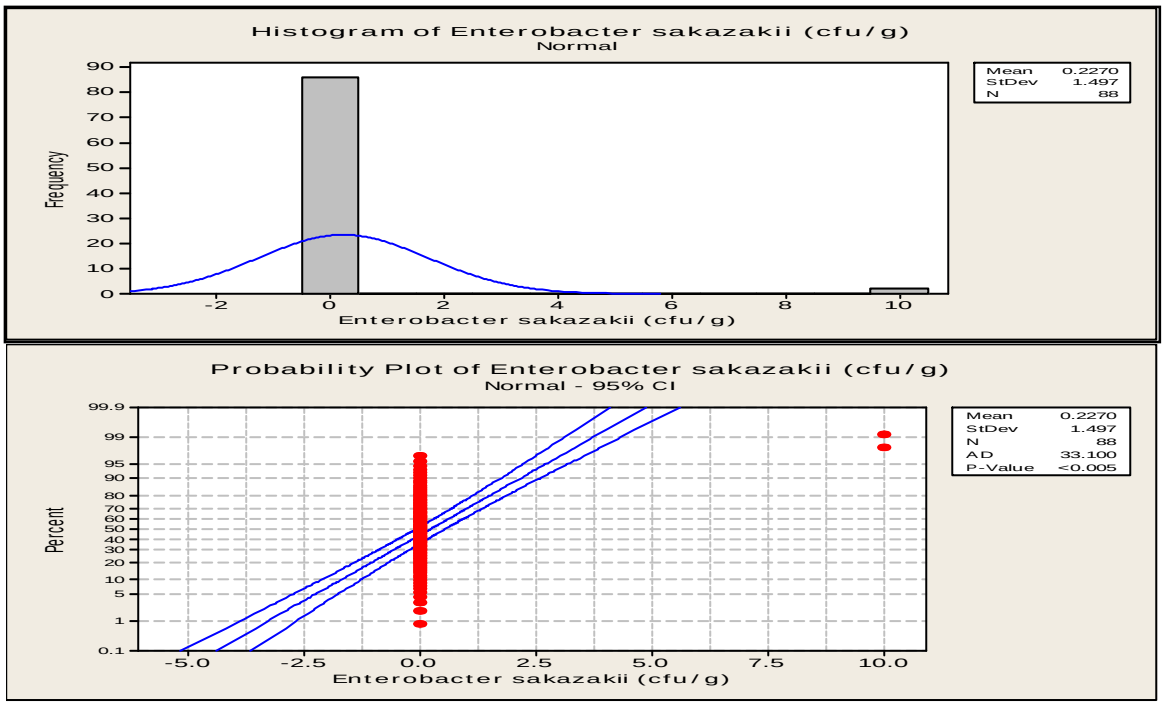
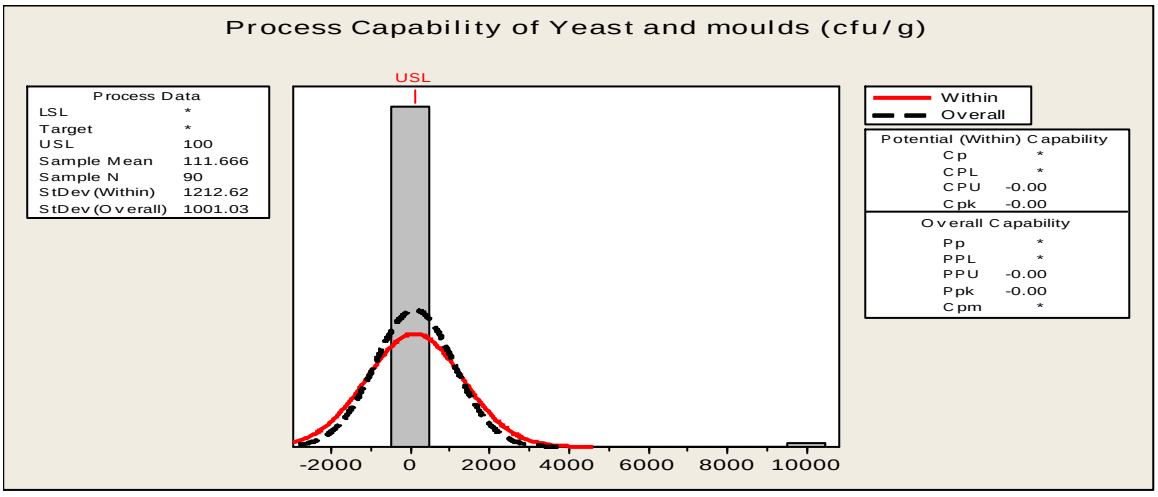


Figure 4. 18: Probability plot of Enterobacter sakazakii (cfu/g).

The Figure 4.18 shows the histogram and Probability Plot of the data along with normal curves overlaid on the histogram. The histogram and the Probability Plot can be used to check visually if the process data are normally and symmetrically distributed. From the Fig. 4.18, shows that data wan not follow a Normal distribution as well as symmetric distribution.



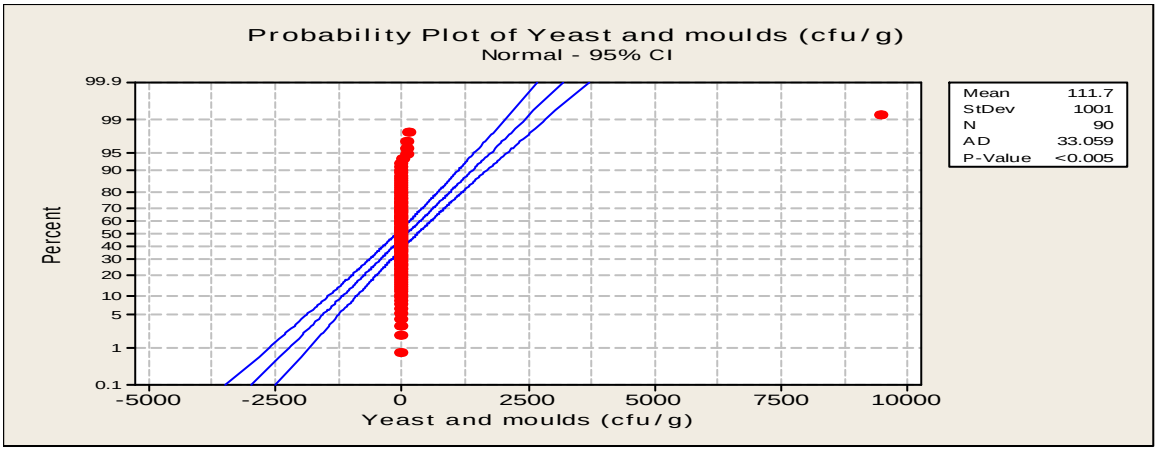


Figure 4. 19: Process Capability Report Yeast and moulds (cfu/g).

The Figure 4.19 shows the histogram and Probability Plot of the data along with normal curves overlaid on the histogram. The histogram and the Probability Plot can be used to check visually if the process data are normally and symmetrically distributed. From the Fig. 4.19, shows that data wan not follow a Normal distribution as well as symmetric distribution.

4.7 Comparison of parametric and non-parametric test

In analytical chemistry it is essential to validate a given analytical method to determine its applicability, reproducibility, repeatability and the accuracy of the data obtained. The analyst should establish some basis to prove that the method is working for its intent use. Normally, the amount of data is rather small and the so-called Student *t* distribution should be used (IAEA, 2003).

(Doane & Seward, 2007) indicated that the Wilcoxon signed-rank test is robust to non-normal, and somewhat asymmetrical, population shapes. In fact, the assumptions underlying the *t*-test are violated in every situation because there is neither an underlying normal distribution nor an interval level of measurement (Meek, Ozgur, & Dunning, 2007).

Table 4. 5: Comparison of one sample parametric and non-parametric test for chemical analysis of Fortified High Energy Biscuits according to their acceptable range as prescribed by WFP, Dhaka.

Variables	Wilcoxon /Sign test	P-value	Z test	P-value	KS* test	P-value
Moisture (%)	323.0	1.000	-35.04	1.000	0.032	>0.150
Protein (%)	43741.5	1.000	15.56	1.000	0.048	0.087
Fat (%)	19889.5	0.010	-2.42	0.008	0.076	<0.010

Vitamin A (µg/100g)	Sign test	0.043	3.92	1.000	0.377	<0.010
Iron (mg/100g)	20826.0	0.279	1.58	0.942	0.226	<0.010
Mesophyllic aerobic bacteria (cfu/g)	Sign test	1.000	-69.79	1.000	0.488	<0.010
Staphylococcus (cfu/g)	Sign test	1.000	-851.83	1.000	0.531	<0.010
Bacillus cereus (cfu/g)	Sign test	1.000	-37.98	1.000	0.540	<0.010
Enterobacter sakazakii (cfu/g)	Sign test	0.250	1.42	0.078	0.538	<0.010
Yeast and moulds (cfu/g)	Sign test	1.000	0.11	0.456	0.482	<0.010

*Kolmogorov-Smirnov test

This study also investigated the behavior of the one sample *Z*-test for Fortified High Energy Biscuits samples for large sample in Table 4.5. Fat (%) was significant compared with acceptable range as Prescribed by WFP, Dhaka. While other variables are insignificant.

For the above test, where $\alpha = 0.05$, given that $p > \alpha$ for the Moisture (%) and Protein (%), we would conclude that only two Variable (test parameter) are normally distributed. Therefore, the assumption of normality has been met for this few variables.

Even so, the results indicate that, in almost every case when the null hypothesis was false, the *Z*-test performed similar results with the non-parametric Wilcoxon signed-rank/ Sign test though violate the normality assumpton. But when the null hypothesis was true, non-parametric Wilcoxon signed-rank/ Sign test performed as efficient or more power than the parametric *Z* test. There were a total of 4 cases in which the non-parametric test predicted probability (p-value) results more power than the parametric-test when H_0 was true.

4.8 Binary logistic regression analysis of High Energy Biscuits

A stata software was performed to identify fortified biscuits quality parameters appropriate for inclusion in a logistic regression model to predict the accepted/ unaccepted as prescribed acceptable range by WFP, Dhaka in a biscuits sample.

Logistic regression was used to assess the impact of a physiochemical analysis of biscuit parameter to identify the quality of fortified high energy biscuit which was supplied by some biscuits sample produced industries. The model contained a independent variables Moisture (%) and 8 (eight) dependent variables as acceptability of Protein (%), Fat (%), Sugar (%), Total Carbohydrate (%), Iron (mg/100g), Vitamin A (mcg/100g), Enterobacter sakazakii (cfu/g) and Yeast and moulds (cfu/g). But we were not include variables acceptabilty of Coliforms (MPN/g),

Escherichia coli (MPN/g), Salmonella spp., Staphylococcus (cfu/g) and Mesophyllic aerobic bacteria (cfu/g) against one independent due to not availability of unaccepted case of which parameters as presented in table 4.6.

Table 4. 6: Logistic Regression Analysis of acceptancey for Proximate Analysis of Fortified High Energy Biscuits of their moisture (%).

Dependent Varible	Independent Variable	Coeff. (OR)	Std. Err.	z-value	P-value	AIC	BIC	GOF
Protein (%)	Moisture (%)	-0.325 (0.722)	0.198	-1.64	0.101	297.96	305.40	0.112
Fat (%)		0.231 (1.260)	0.154	1.50	0.133	417.23	424.68	0.522
Sugar (%)		0.641 (1.899)	0.337	1.90	0.057	81.92	89.34	0.164
Total Carbohydrate (%)		-0.013 (0.987)	0.154	-0.09	0.932	403.39	410.80	0.115
Iron (mg/100g)		-0.201 (0.818)	0.153	-1.31	0.189	402.59	409.95	0.273
Vitamin A (mcg/100g)		-0.241 (0.786)	0.157	-1.54	0.123	392.83	400.14	0.460
Enterobacter sakazakii (cfu/g)		0.011 (1.012)	1.094	0.01	0.992	23.09	28.05	0.999
Yeast and moulds (cfu/g)		-2.247 (0.106)	1.570	-1.43	0.152	20.29	25.24	0.988

Note: Coeff.= Coefficient of the model, OR=Odds Ratio, Std. Err.= Standard Error, AIC= Akaike Information Criterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

The full model containing a variable Moisture (%) was statistically insignificant with P>0**.**05 according to accepted range of test parameter as prescribed by WFP, Dhaka. Indicating that the model was able to distinguish between fortified biscuits samples which reported having and not having accepted range as prescribed by WFP, Dhaka. The *p*-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in Table 4.6 with insignificant (P>0.05).

The test parameter Protein (%), Total Carbohydrate (%), Iron (mg/100g), Vitamin A (mcg/100g) and Yeast and moulds (cfu/g) were found to have negative association with Acceptable Range as Prescribed by WFP, Dhaka while positive association were found in rest of the test parameter.

The odds ratio for Protein (%) shows that in acceptability of biscuits increases by a factor of 0.722. The odds ratio for Fat (%) shows that in acceptability of biscuitsincreases by a factor of 1.260 and so on.

4.9 Binary probit regression analysis

To determine the factors influencing the decision to acceptable in food products a probit model were used. The decision to use probit is based on the fact that the decision variable is discrete and dichotomous (one either acceptable of high energy biscuit (HEB) as prescribed by WFP, Dhaka or not), discrete decisions are analyzed using qualitative response models one of which is probit.

Collecting (HEB) analysis data findings revealed that Fortified High Energy Biscuits analysis data can be classified into two classes; acceptable and non acceptable according to WFP prescribed range. A probit regression was used to determine the factors that influence the decision to analysis value among food producer or analyzer operators.

Table 4. 7: Binary Probit/Normit regression of acceptancey for Proximate Analysis of Fortified High Energy Biscuits of their moisture.

Dependent Varible	Independent Variable	Coef. (M.E.)	Std. Err.	z-value	P-value	AIC	BIC	GOF
Protein (%)	Moisture (%)	-0.181 (-0.049)	0.111	-1.63	0.103	298.00	305.44	0.112
Fat (%)		0.144 (0.056)	0.096	1.51	0.131	417.23	424.68	0.522
Sugar (%)		0.317 (0.019)	0.171	1.86	0.063	81.67	89.10	0.083
Total Carbohydrate (%)		-0.008 (-0.003)	0.094	-0.08	0.933	403.39	410.80	0.115
Iron (mg/100g)		-0.124 (-0.049)	0.094	-1.32	0.186	402.60	409.96	0.273
Vitamin A (mcg/100g)		-0.151 (-0.059)	0.098	-1.55	0.122	392.83	400.14	0.460
Enterobacter sakazakii (cfu/g)		0.005 ($2.85e^{-04}$)	0.477	0.01	0.991	23.09	28.05	0.999
Yeast and moulds (cfu/g)		-1.098 (-0.023)	0.770	-1.43	0.154	19.99	24.94	0.996

Note: Coeff.= Coefficient of the model, M.E.= Marginal Effects, Std. Err.= Standard Error, AIC= Akaike Information Criterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

The full model containing a variable Moisture (%) was statistically insignificant with P>0.05 according to accepted range of test parameter as prescribed by WFP, Dhaka. Indicating that the model was able to distinguish between fortified biscuits samples which reported having and not having accepted range as prescribed by WFP, Dhaka. The p-values for pearson chi-square ($\chi 2$) test of the goodness-of-fit statistics presented in Table 4.7 with insignificant (P>0.05).

Th test parameter Protein (%), Total Carbohydrate (%), Iron (mg/100g), Vitamin A (mcg/100g) and Yeast and Moulds (cfu/g) were found to have negative association with Acceptable Range as Prescribed by WFP, Dhaka while positive association were found in rest of the test parameter.

For instance one unit increase in Moisture (%)from the baseline, the probability of qualityacceptabilityof proteinfor biscuitsdecreases by 4.9%. Similarly one unit increase in the Moisture (%) of the biscuits from the baseline increases the probability of acceptability of fatfor biscuits by 5.6 % and so on.

To find correct estimates of standard errors and p-values it is necessary to choose better model. To select the model, here, we consider two information criteria used to compare models. In general, “smaller is better”: given two models, the one with the smaller AIC fits the data better than the one with the larger AIC. As with the AIC, a smaller BIC indicates a better-fitting model (Samples, n.d.).

We fit a model explaining the quality of high energy biscuit products has on the basis of Moisture (%) against the acceptability of Protein (%), Fat (%), Sugar (%), Total Carbohydrate (%), Iron (mg/100g), Vitamin A (mcg/100g), Enterobacter sakazakii (cfu/g) and Yeast and moulds (cfu/g). The goodness-of-fit criteria for comparing these two model results are found in table 4.6 and 4.7. AIC and BIC were determined by logit and probit regression of the predicted values obtained in the fit to the true model equation. For the test parameter studied in Table 4.6 and 4.7; based on the AIC and BIC criterion were approximated same using a Logistic and probit model.

4.10 Discriminant function analysis

The discriminant analysis to Fortified High Energy Biscuits under Acceptable Range as Prescribed by WFP, Dhaka, with the test to determine classify groups of acceptabilitybetween

the groups using Wilks' Lambda revealed that the diverse parameters yielded a statistical significance at a level of 0.05.

Table 4. 8: Discriminant Function Analysis results of chemical analysis of Fortified High Energy Biscuits.

Dependent Varible	Independent Variable	Wilks' Lambda	P-value	goodness-of-fit test	
				Box's M	P-value
Protein (%)	Moisture (%)	0.991	0.102	0.102	0.751
Fat (%)		0.993	0.132	0.163	0.687
Sugar (%)		0.988	0.054	0.259	0.618
Total Carbohydrate (%)		1.000	0.932	16.931	0.000
Iron (mg/100g)		0.994	0.187	0.182	0.670
Vitamin A (mcg/100g)		0.992	0.121	4.925	0.027
Enterobacter sakazakii (cfu/g)		1.000	0.992	0.385	0.596
Yeast and moulds (cfu/g)		0.973	0.125	6.667	0.021

Box's M test tests the assumption of homogeneity of covariance matrices. This test is very sensitive to meeting the assumption of multivariate normality. Discriminant function analysis is **robust** even when the homogeneity of variances assumption is not met, provided the data do not contain important outliers (Bian, n.d.). For our data except the test parameter acceptability of Total Carbohydrate (%) and Yeast and moulds (cfu/g), we achieve that groups homogeneity in their covariance matrices, fit an assumption of discriminant analysis. When n is large, small deviations from homogeneity will be found significant, which is why Box's M must be interpreted in conjunction with inspection of the log determinants (Bian, n.d.).

The Wilk‘s lambdais a measure of the overall statistical significance of the Linear Discriminant Functions and is statistically insignificant results at the 5 percent level of probability for the LDF 1 of Moisture (%) against the acceptability range of test parameter (refer to Table 4.8). This implies that the group means for the independent variables are different on the discriminating function and that the differences in the mean discriminant score are greater than can be attributed to non-sampling error. While other parameters are within acceptable range as prescribe acceptable rang by WFP, Dhaka.

4.11 ARCH-LM test

To detect the presence of ARCH effect in the mean equation of Fortified High Energy Biscuits we use the ARCH-LM (Lagrange multiplier) test.

Table 4. 9: ARCH-LM and DF test analysis results of chemical analysis of Fortified High Energy Biscuits.

Variable	LM test for autoregressive conditional heteroskedasticity (ARCH)		Dickey-Fuller test for unit root	
	Chi-square Statistic	P-value	Test Statistic, Z(t)	P-value
Moisture (%)	0.255	0.6136	-16.497	0.000
Protein (%)	3.706	0.0542	-15.953	0.000
Fat (%)	0.380	0.5377	-16.910	0.000
Sugar (%)	0.047	0.8283	-15.074	0.000
Total Carbohydrate (%)	0.332	0.5644	-17.445	0.000
Iron (mg/100g)	62.038	0.0000	-7.515	0.000
Vitamin A (mcg/100g)	158.344	0.0000	-6.167	0.000
Mesophyllic aerobic bacteria (cfu/g)	7.708	0.0055	-6.911	0.000
Bacillus cereus (cfu/g)	0.309	0.5786	-9.992	0.000
Enterobacter sakazakii (cfu/g)	0.046	0.8296	-9.612	0.000
Yeast and moulds (cfu/g)	0.012	0.9142	-9.403	0.000

In our analysis the different value for different variables of above parameters of the ARCH-LM test; the lags included in the test are only 1. The corresponding P-Value is <0.05, which is very low for Iron (mg/100g), Vitamin A (mcg/100g) and Mesophyllic aerobic bacteria (cfu/g). So we have no difficulty to reject the null hypothesis of no ARCH error, and conclude that there is an ARCH error in the analysis series. This confirms that the order of the ARCH error is three variables for analysis of biscuit food products. Others parameters are insignificant that means no ARCH effects of the models. The estimation results are given in the table 4.9.

Table 4.9 shows that the values of DF test for all variables p-value <0.05 at 5%, level of significance which implies that the variables series is stationary. An outcome of DF test confirms that the physiochemical analysis variables series is stationary.

4.12 Spike Behaviour of ARCH(1) and GARCH(1,1) model estimations

The presence of extreme spikesin our analysis of biscuit products that is a bad characteristic of food products.

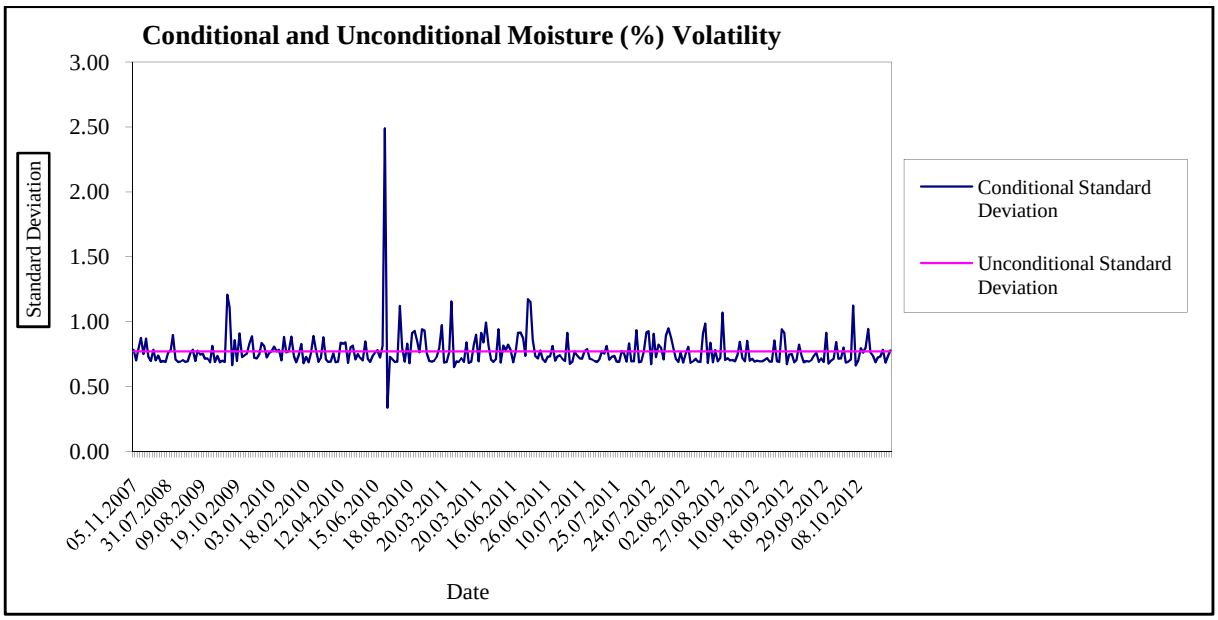


Figure 4. 20: Moisture (%) content of biscuit products for the Period November 2007 to November 2012.

Figure 4.20 shows the conditional and unconditional standard deviation of Moisture (%) content over the period November 2007 to November 2012. Conditional standard deviations are over 0.33 during the sample period. The results indicate that the standard deviation almost stable among 2007 to 2012 and in spike behaviour in 2010. However, volatility in deviations is very low in this time period.

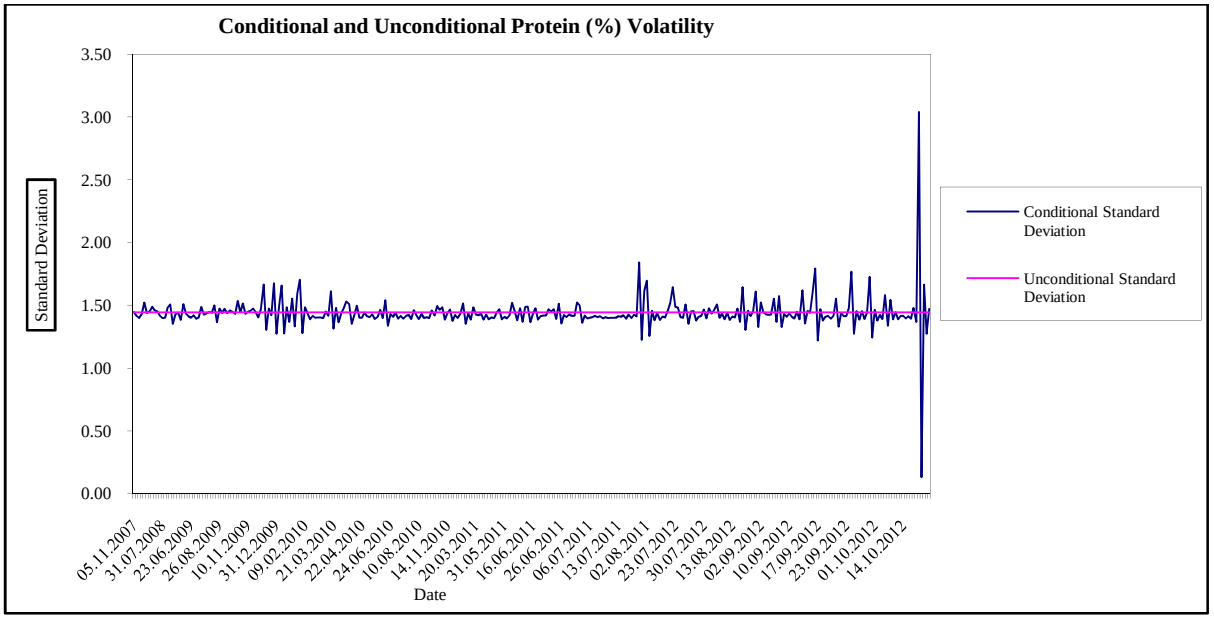


Figure 4. 21: Protein (%) content of biscuit products for the Period November 2007 to October 2012.

Figure 4.21 shows the conditional and unconditional standard deviation of Protein (%) content over the period November 2007 to October 2012. Conditional standard deviations are over 0.12 during the sample period. The results indicate that the deviations increased significantly between 2010 and 2012 and decreased between 2007-2009 and 2010-2011 and also in spike behaviour at the end of 2012. However, volatility in deviation is low in this time period.

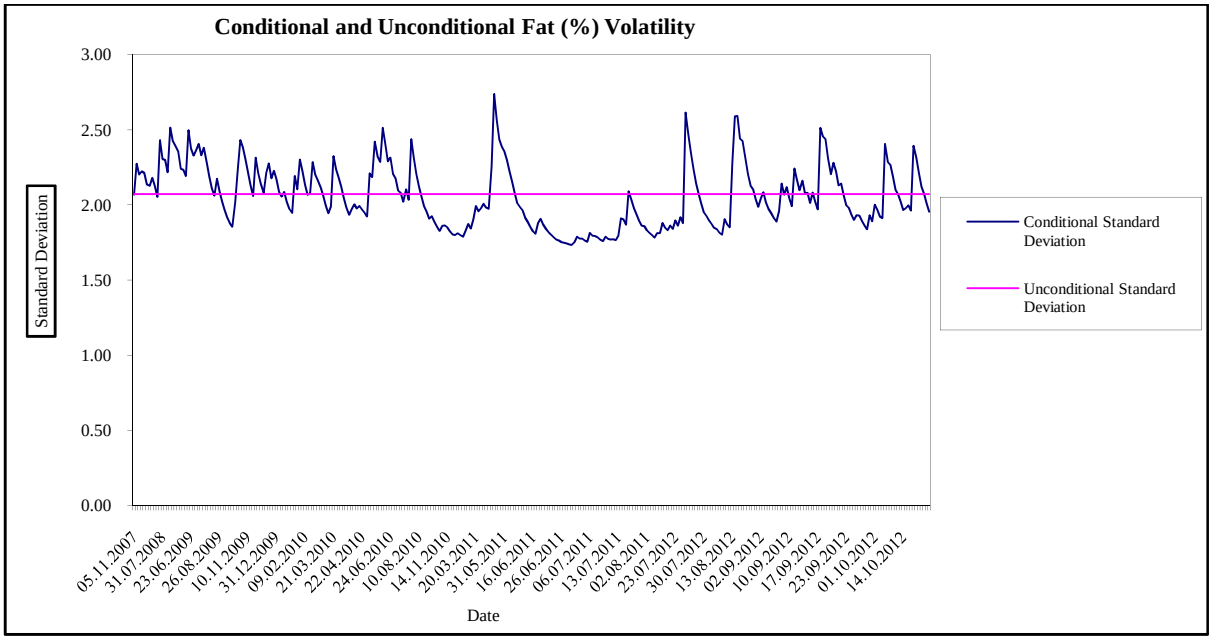


Figure 4. 22: Fat (%) content of biscuit products for the Period November 2007 to October 2012.

Figure 4.22 shows the conditional and unconditional standard deviation of Fat (%) content over the period November 2007 to October 2012. Conditional standard deviations are over 1.5 during the sample period. As can be seen in Fig. 4.22, the deviation has an increasing trend between 2011 and relatively stable at the end of period 2012. However, volatility in deviation is low in this time period.

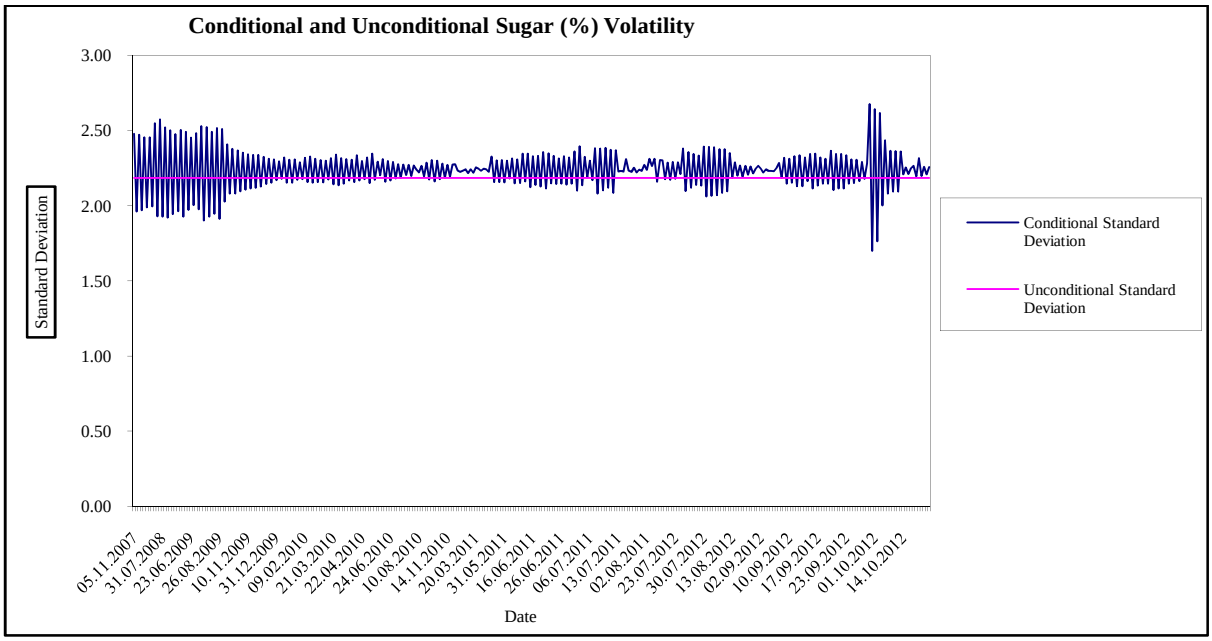


Figure 4. 23: Sugar (%) content of biscuit products for the Period November 2007 to October 2012.

Figure 4.23 shows the conditional and unconditional standard deviation of Sugar (%) content over the period November 2007 to October 2012. Conditional deviations are over 1.5 during the sample period. The results indicate that the deviations decreasing trend between 2007 -2012 and also increasing at the end of 2012. However, volatility in deviations is low in this time period. The deviations are spike behaviour during the period 2007-2009 and at the end of 2012.

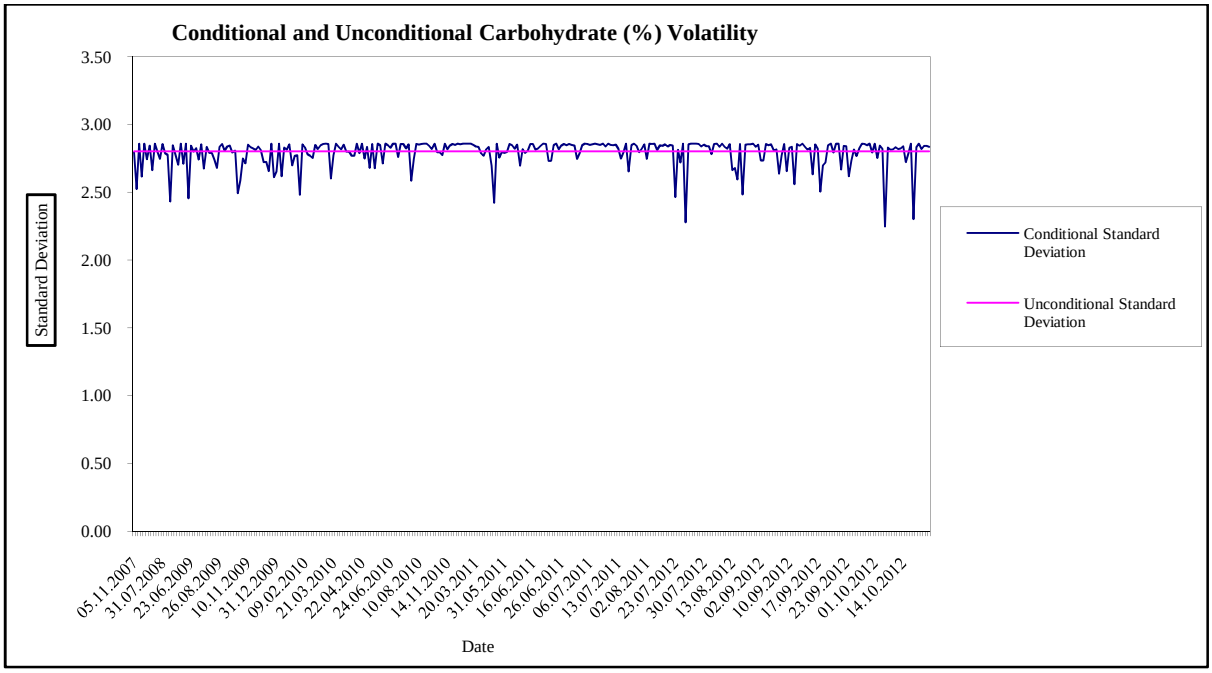


Figure 4. 24: Total Carbohydrate (%) content of biscuit products for the Period November 2007 to October 2012.

Figure 4.24 shows conditional and unconditional standard deviation of Total Carbohydrate (%) content over the period November 2007 to October 2012. Conditional deviations are over 2.00 during the sample period. As can be seen in Fig. 4.24, the deviation has relatively stable during sample period. However, volatility in deviation is low in this time period. The deviation is spike behaviour during the period 2007–2012.

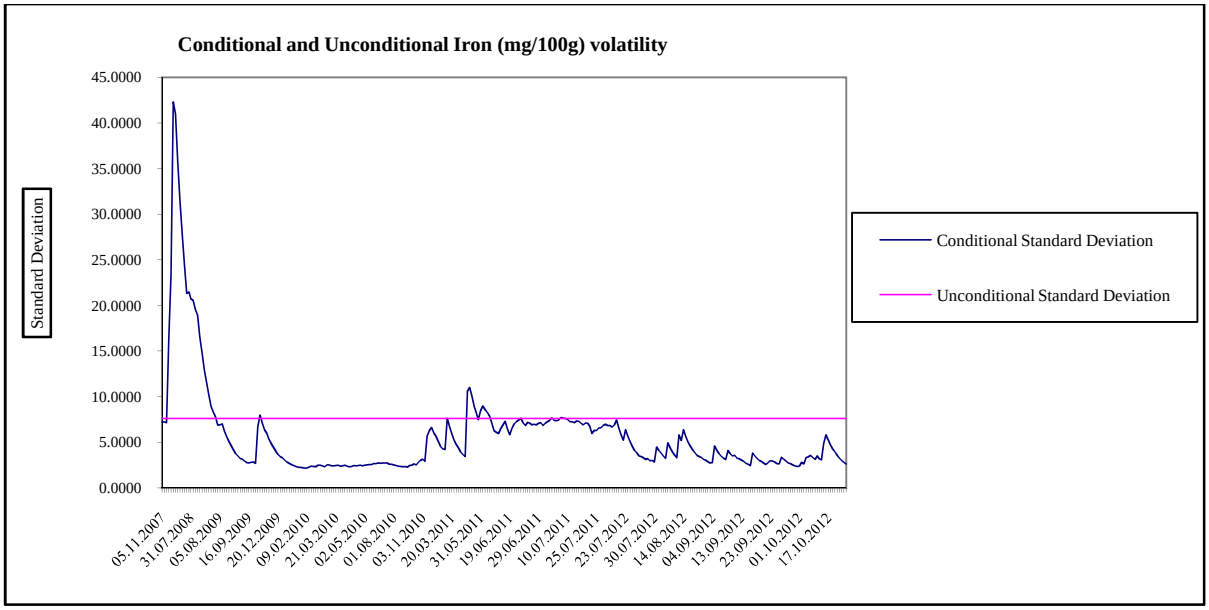


Figure 4. 25: Iron (mg/100g) content of biscuit products for the Period November 2007 to October 2012.

Figure 4.25 shows the conditional and unconditional standard deviation of Iron (mg/100g) content over the period November 2007 to October 2012. Conditional deviations are over 2.00 during the sample period. The results indicate that the deviations are highly spike behaviour at first of the period 2007. As can be seen in Fig. 4.25, the deviation has a decreasing trend between 2009 -12. The deviation is highly volatile during the period 2007–2012.

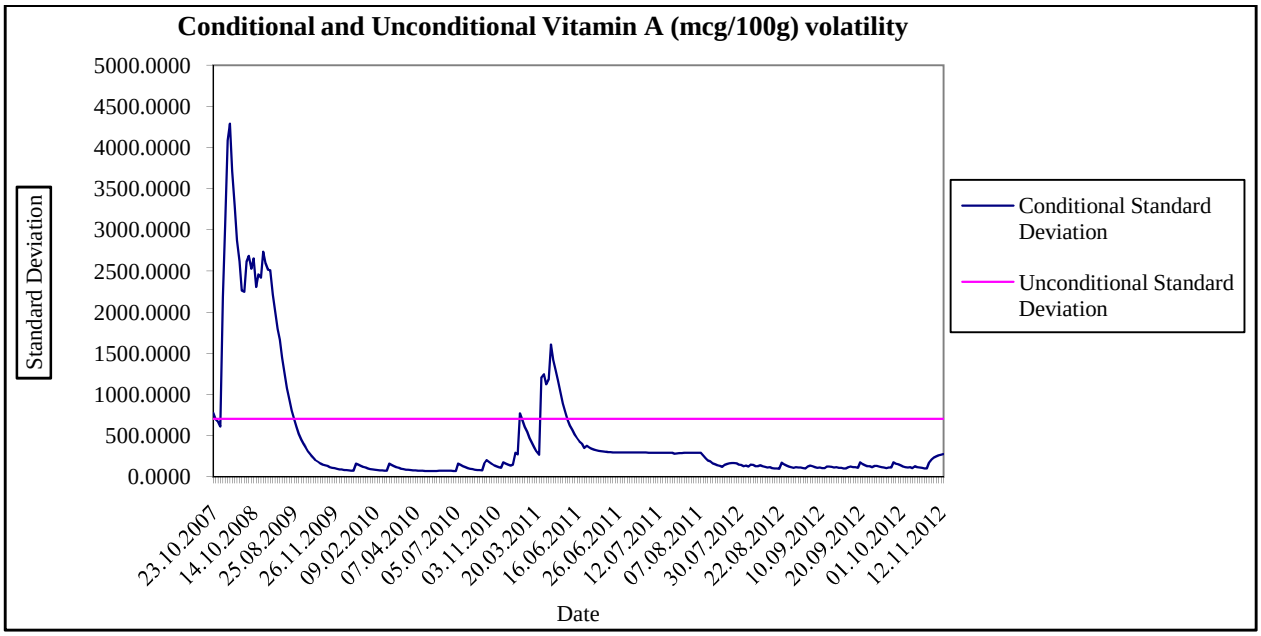


Figure 4. 26: Vitamin A (mcg/100g) content of biscuit products for the Period November 2007 to October 2012.

Figure 4.26 shows the conditional and unconditional standard deviation of Vitamin A (mcg/100g) content over the period November 2007 to October 2012. Conditional deviations are over 80.00 during the sample period. The results indicate that the deviations are highly spike behaviour at first of the period 2007 and 2011 and relatively stable during the period 2012. As can be seen in Fig. 4.26, the deviation has a decreasing trend between 2009 -2012. The deviation is highly volatile during the period 2007–2012.

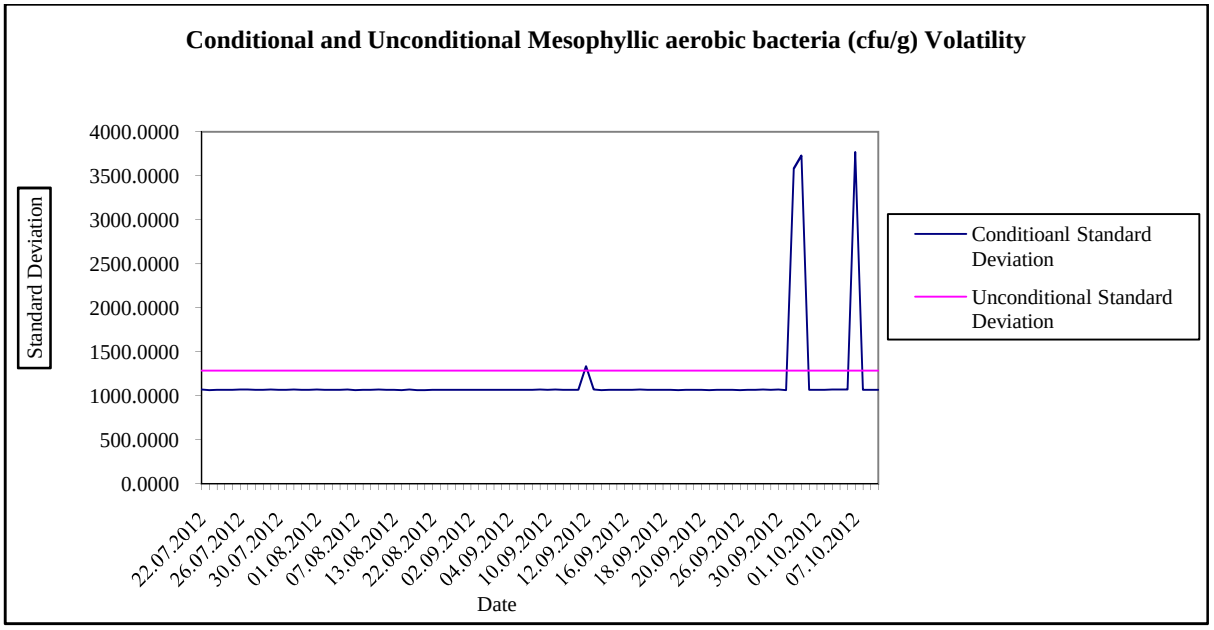


Figure 4. 27: Mesophyllic aerobic bacteria (cfu/g) content of biscuit products for the Period July 2012 to October 2012.

Figure 4.27 shows the conditional and unconditional standard deviation of Mesophyllic aerobic bacteria (cfu/g) content over the period July 2012 to October 2012. Conditional deviations are over 1000.00 during the sample period. The results indicate that the deviations are two peak spike behaviour at the end of the period 2012 and relatively stable during the others period of 2012. The deviation is volatile during the period 2012.

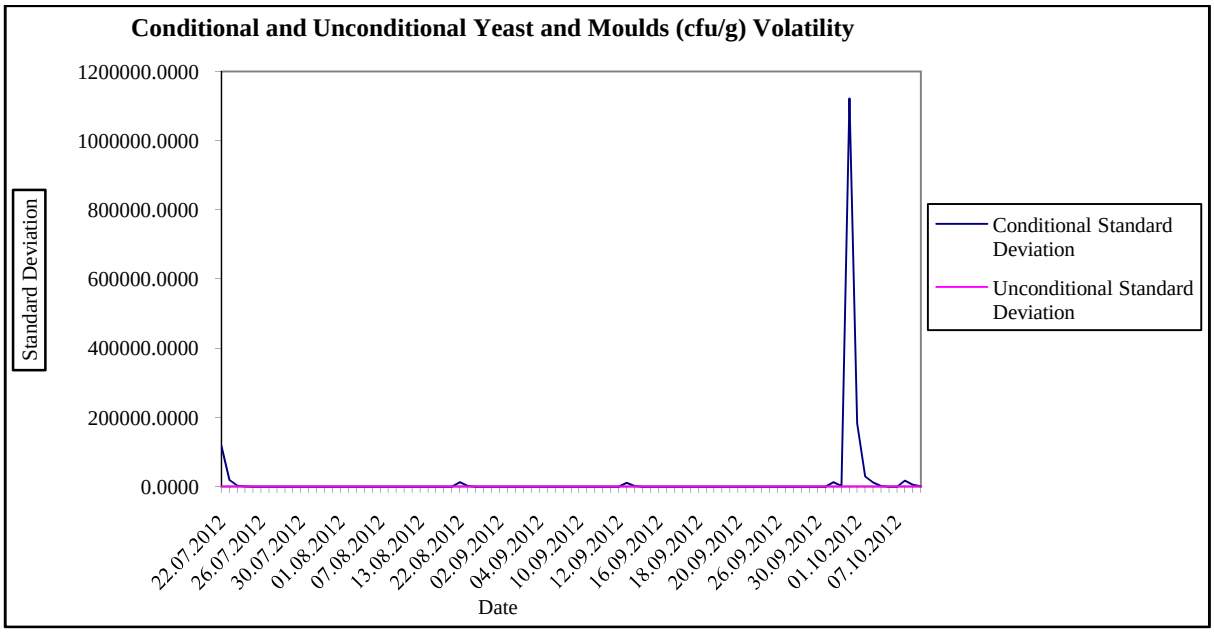


Figure 4. 28: Yeast and Moulds (cfu/g) content of biscuit products for the Period July 2012 to October 2012.

Figure 4.28 shows the conditional and unconditional standard deviation of Yeast and Moulds (cfu/g) content over the period July 2012 to October 2012. Conditional deviations are over 0.00 during the sample period. The results indicate that the deviations are a high spike behaviour at the end of the period 2012 and relatively stable during the others period of 2012. However, volatility in deviation is low in this time period.

4.13 Comparison among three statistical technique

Comparison among Logistic & Probit Regression and Discriminant Analysis in classification groups for fortified high energy biscuits.

Table 4. 1: Summary of statistics of Logit, Probit model and Discriminant function analysis.

		Logistic Regression		**Probit Regression**		**Discriminant analysis**	
Dependent Variable	**Independent Variable**	p-value	GOF	p-value	GOF	p-value	GOF
Protein (%)	Moisture (%)	0.101	0.112	0.103	0.112	0.102	0.751
Fat (%)		0.133	0.522	0.131	0.522	0.132	0.687
Sugar (%)		0.057	0.164	0.063	0.083	0.054	0.618
Total Carbohydrate (%)		0.932	0.115	0.933	0.115	0.932	0.000
Iron (mg/100g)		0.189	0.273	0.186	0.273	0.187	0.670
Vitamin A (mcg/100g)		0.123	0.460	0.122	0.460	0.121	0.027
Enterobacter sakazakii (cfu/g)		0.992	0.999	0.991	0.999	0.992	0.596
Yeast and moulds (cfu/g)		0.152	0.988	0.154	0.996	0.125	0.021

Note: GOF= Goodness-of-fit statistics.

From the above demonstrations of three different technique, Logit & Probit model and Discriminant function analysis, all of them provide are not equal predicted probability of the same variable which is given with the level of accepted range as prescribed by WFP, Dhaka. The level of significance of Goodness-of-fit statistics are >0.05 under Logit and Probit, respectively but under Discriminant analysis are >0.05 except Total Carbohydrate (%) and Yeast and Moulds count (cfu/g) according to accepted range as prescribed by WFP, Dhaka. Obviously, from these results, the Logit and Probit Model perform the better results in terms of the fulfill the assumptions. If in the case of normality assumptions fullfill, Discriminant analysis yields also better results.

CHAPTER 5: DRINKS
COMPLAN NUTRITIONAL DRINK

5.1 Introduction

This chapter describes the Complan Nutritional Drink for product description and analysis for the study. A description of prducts includes the following sub sections: What is Complan?, Ingredients, Analysis of Exports of complan. Then we inclued in this chapter description of soft drinks products. After that we describe about milk product, consumption and price etc.The resulting data were employed in different levels of analysis. The chapter concludes by giving the empirical specification and estimation procedures for the fitted models.

5.2What is Complan?

Complan is a tasty range of nutritional supplement drinks with protein, carbohydrate and 26 vitamins and minerals, including B vitamins. B vitamins are great because they encourage your body to release energy, helping to give you some extra get-up-and-go.

Complan drinks can help to give you extra nourishment when you need it most, such as times when you are not eating as much as normal. It can also benefit those looking to maintain their health or top up their diet with extra nutrition due to the range of vitamins and minerals Complan offers, including vitamin C and Iron to help support the immune system and calcium and vitamin D for the maintenance of bones.

Did you know, Complan easy-to-mix drinks can be used to add extra nutrients to your favourite drinks and foods like tea, coffee and yummy puddings? Our new ready-to-drink milkshakes are also a perfect way to make sure you get those all-important vitamins and minerals whenever and wherever you need them (*What is Complan | Complan*, n.d.).

5.2.1 Ingredients

skimmed cow's milk, maltodextrin, lactose (from cow's milk), vegetable oils (palmolein, sunflower oil), magnesium hydrogen phosphate, sodium L-ascorbate, flavouring (contains cow's milk), calcium carbonate, ferrous sulphate, DL-α-tocopherol, nicotinamide, choline chloride, zinc sulphate, L-ascorbic acid, calcium D-pantothenate, pteroylmonoglutamic acid, D-biotin, phytomenadione, manganese sulphate, cupric sulphate, pyridoxine hydrochloride, thiamin

hydrochloride, DL-α-tocopheryl acetate, retinyl palmitate, riboflavin, cholecalciferol, cyanocobalamin, potassium iodide, chromium chloride, sodium molybdate, sodium selenite (Complan, 2015).

5.2.2 Analysis of Exports of complan

India exported complan worth USD 5,190,004 with total quantity of 1,037,706. Bangladesh is the largest buyer of complan accounting for exports worth USD 2,932,236 followed by Nepal and United States which imported complan worth USD 727,793 and USD 463,532 respectively. Petrapole Road accounted for 56.5% of exports followed by Raxaul and Nhava Sheva Sea which account for 14% and 11.7% of exports respectively (*Export Analysis and trends of of complan | Zauba*, n.d.).

Complan comes in 500g boxes in four flavours: Chocolate, Vanilla, Strawberry and Double Chocolate (*Complan: Meal Replacement & Supplement | For Baby NZ*, n.d.).

5.3 Descriptive Statistics of Complan Nutritional Drink

The mean, standard deviation and other descriptive statistics of Complan Nutritional Drink are displayed as follows.

Table 5. 1: Descriptive Statistics results for proximate analysis of Complan Nutritional Drink.

Proximate Variables	Minimum	Maximum	Mean	Std. Deviation
Energy (kcal/100g)	419.79	469.72	434.97	17.08
Moisture (%)	1.82	4.06	3.0032	0.55
Protein (%)	15.26	19.55	18.05	1.35
Fat (%)	11.03	12.42	11.53	0.43
Total Carbohydrate (%)	61.35	67.15	62.77	1.53

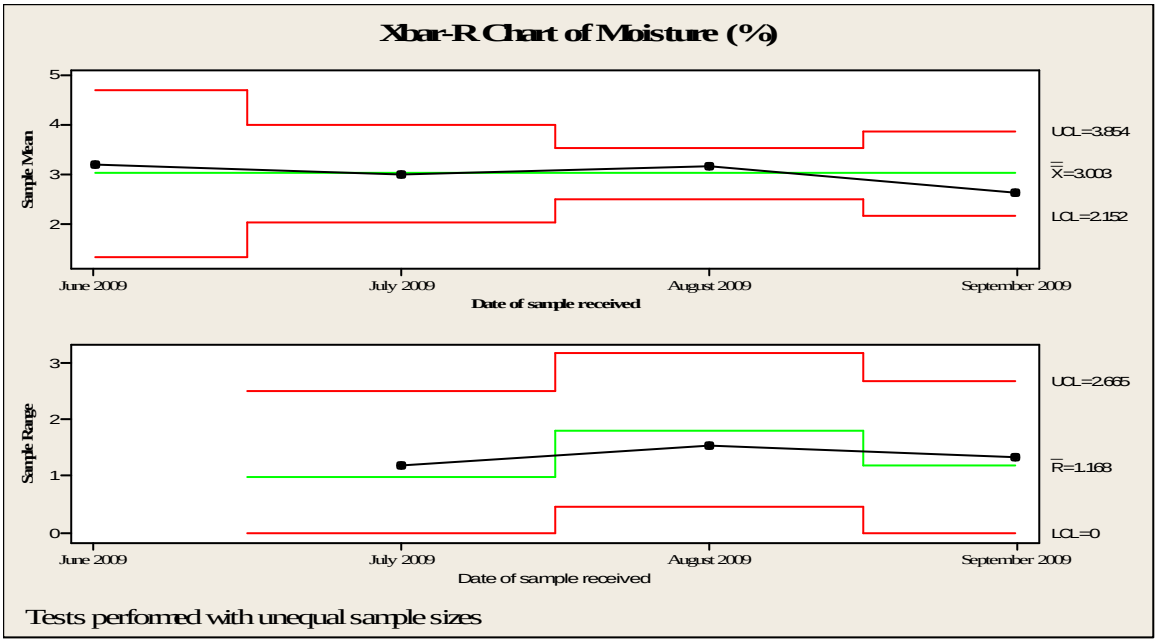
The mean, standard deviation and other descriptive statistics for chemical analysis are displayed in Table 5.1. Here only Energy (kcal/100g) are highly standard deviation (SD>2).

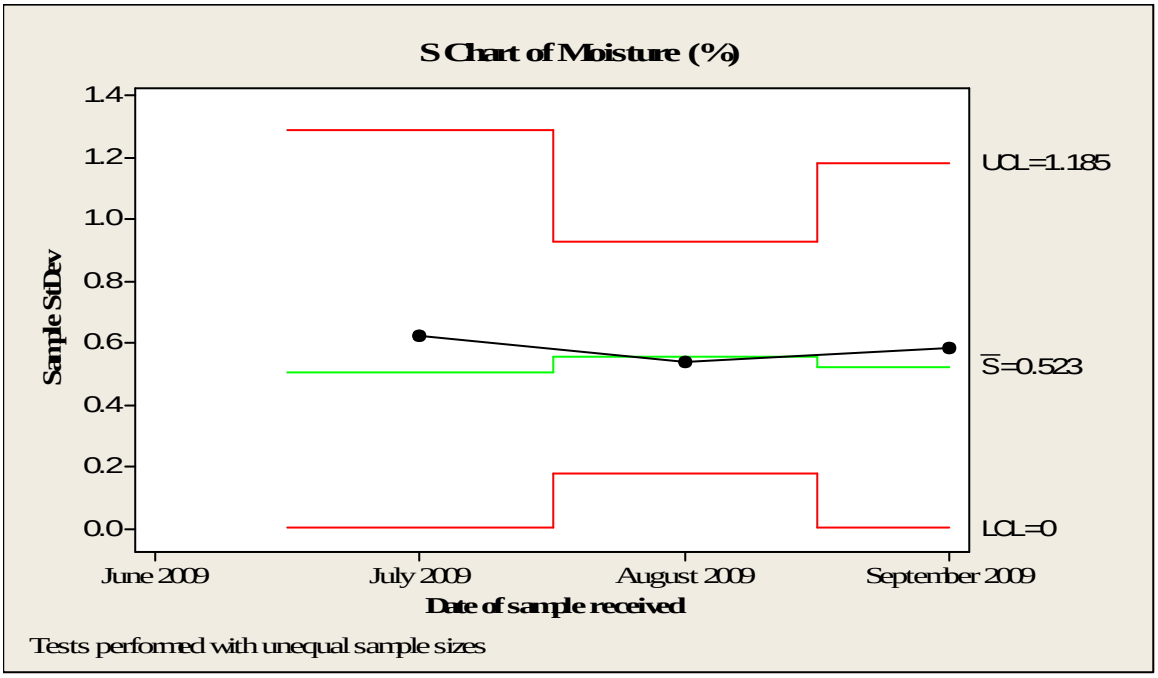
5.4 Application of control charts on Complan Nutritional Drink

In order to verify whether quality of food products were under control condition or not we have adopted following control chart of Complan Nutritional Drinkfor such purposes we have used several Shewhart Control Charts.

In this subsection we present results and analysis that is application of control charts. We show the results and analysis by type of products and types of control chart.

Quality characteristic: Moisture





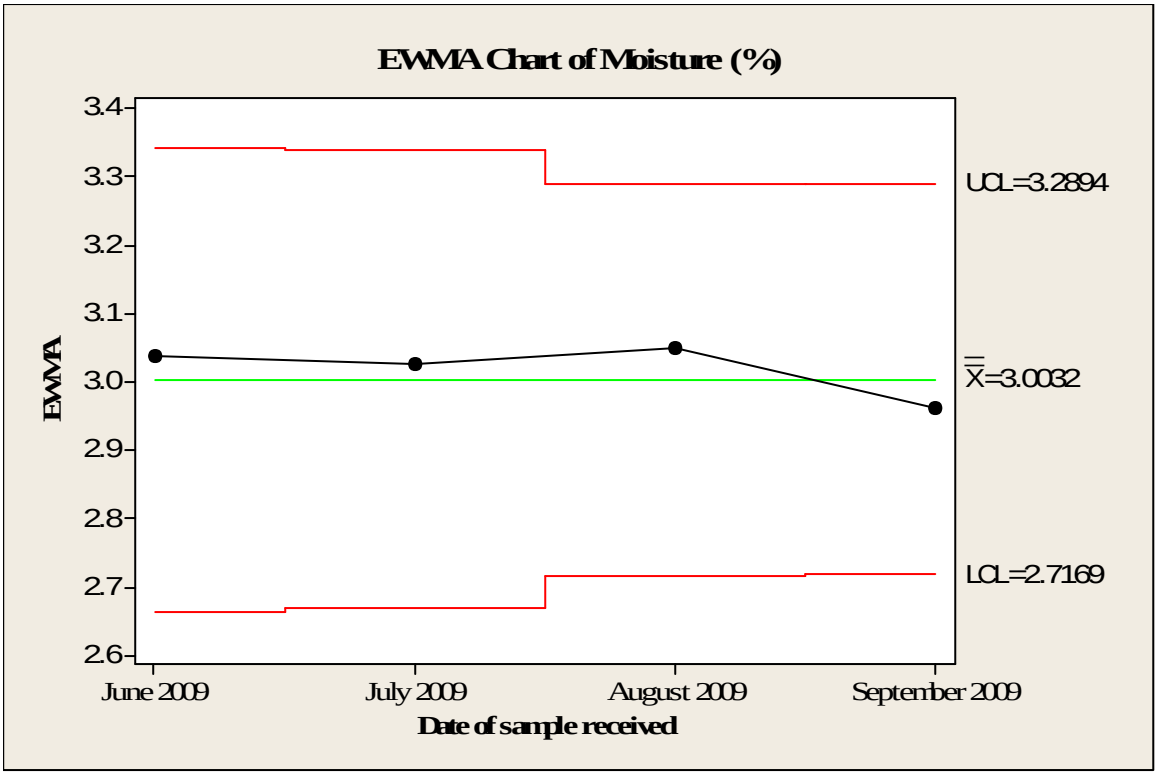
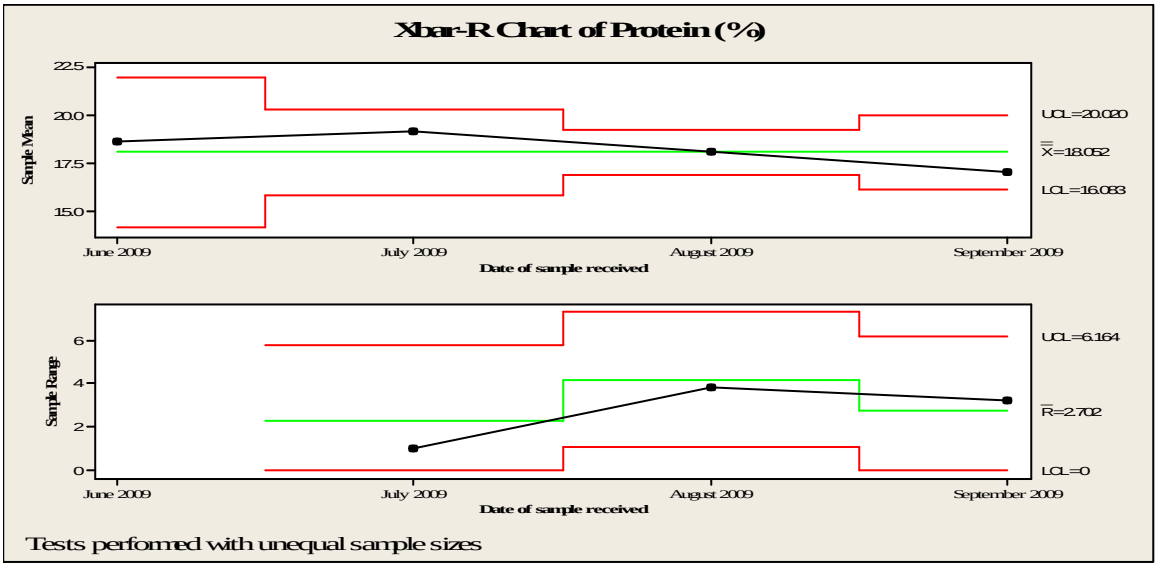


Figure 5. 1: X-bar, R, S and EWMA Charts for Moisture (%) of Complan Nutritional Drink.

The first, second, third and fourth control chart given as output is the chart for the mean, range, standard deviation and exponentially weighted moving average. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control.

Quality Characteristic: Protein



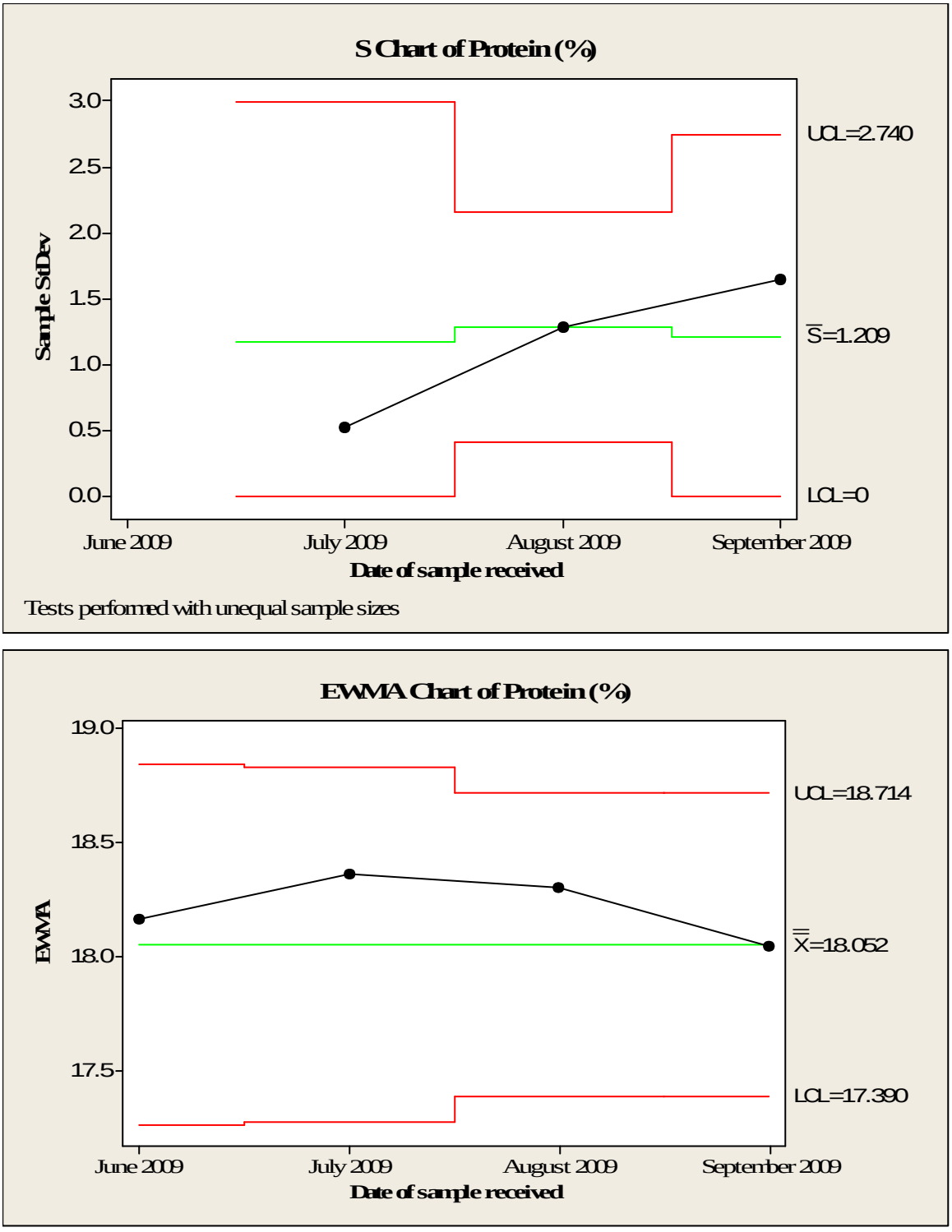
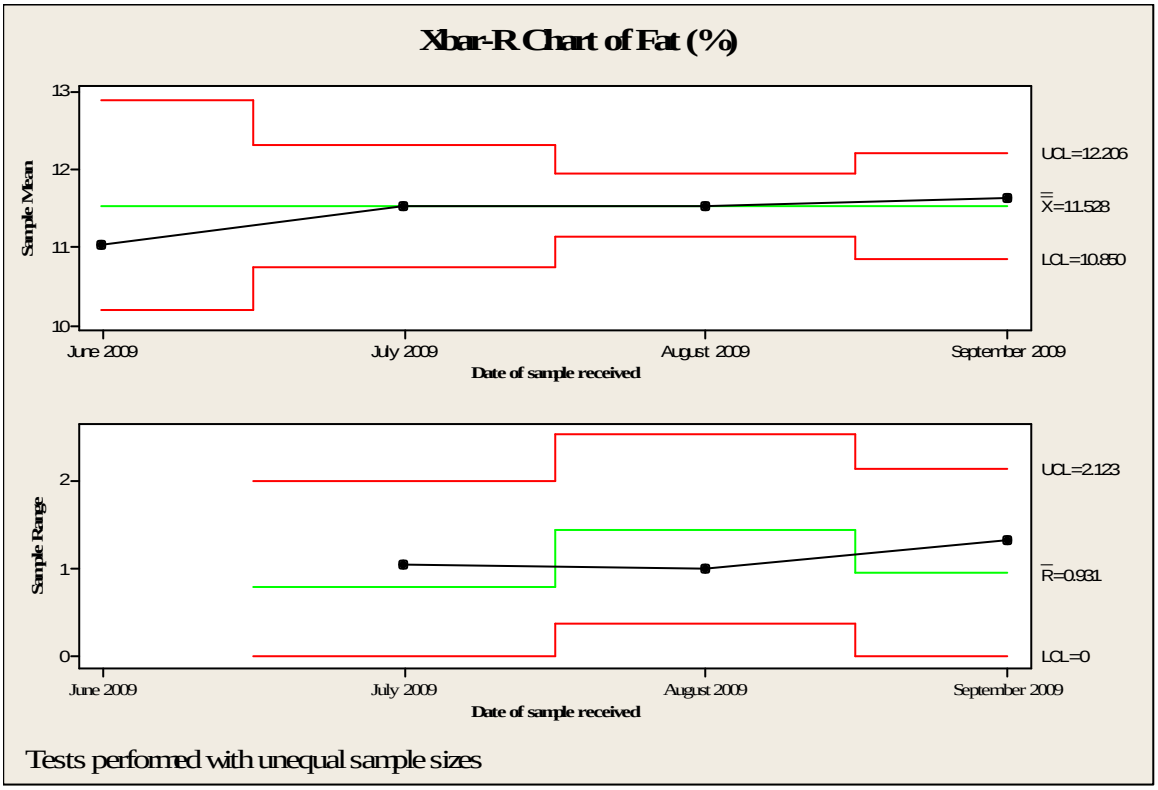
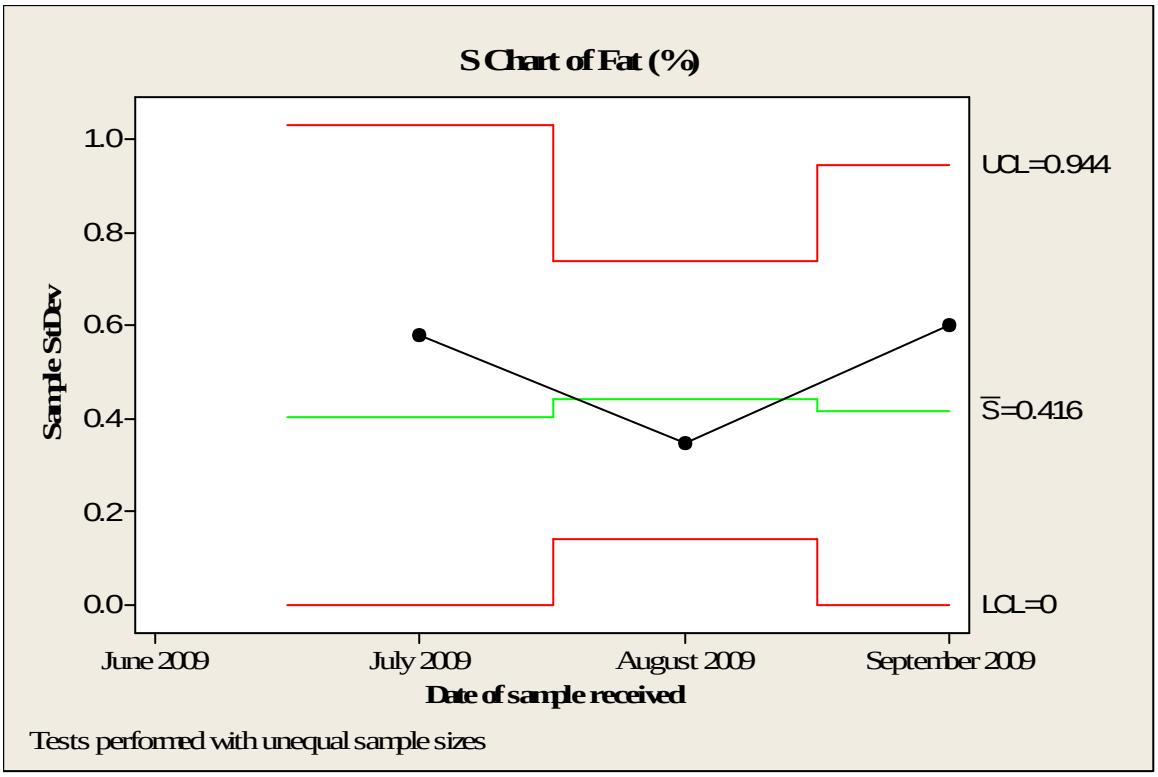


Figure 5. 2: X-bar, R, S and EWMA Charts for Protein (%) of Complan Nutritional Drink.

The first, second, third and fourth control chart given as output is the chart for the mean, range, standard deviation and exponentially weighted moving average of Protein (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in also control.

Quality Characteristic: Fat





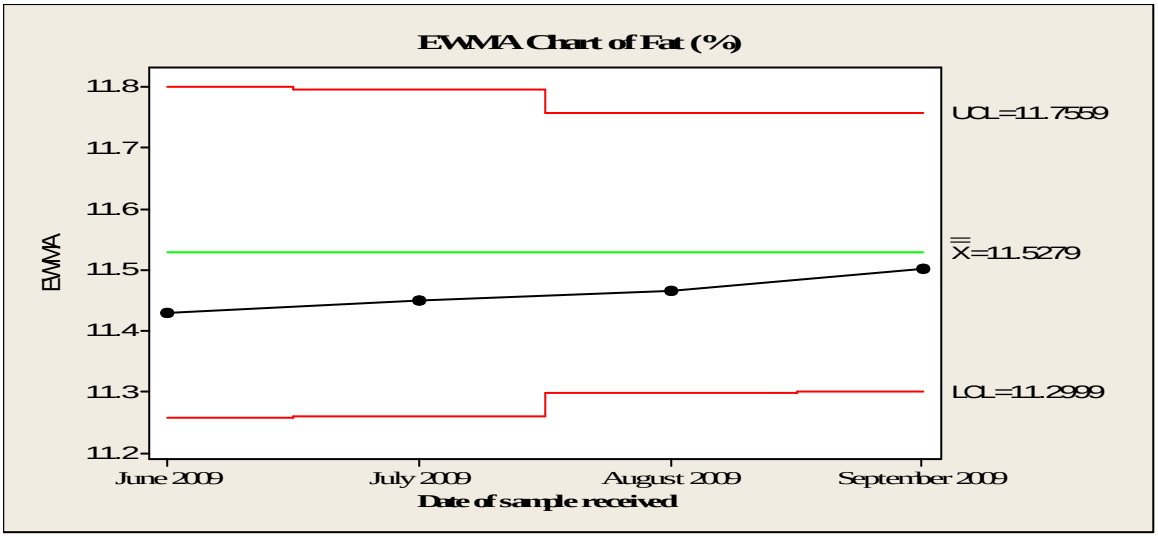
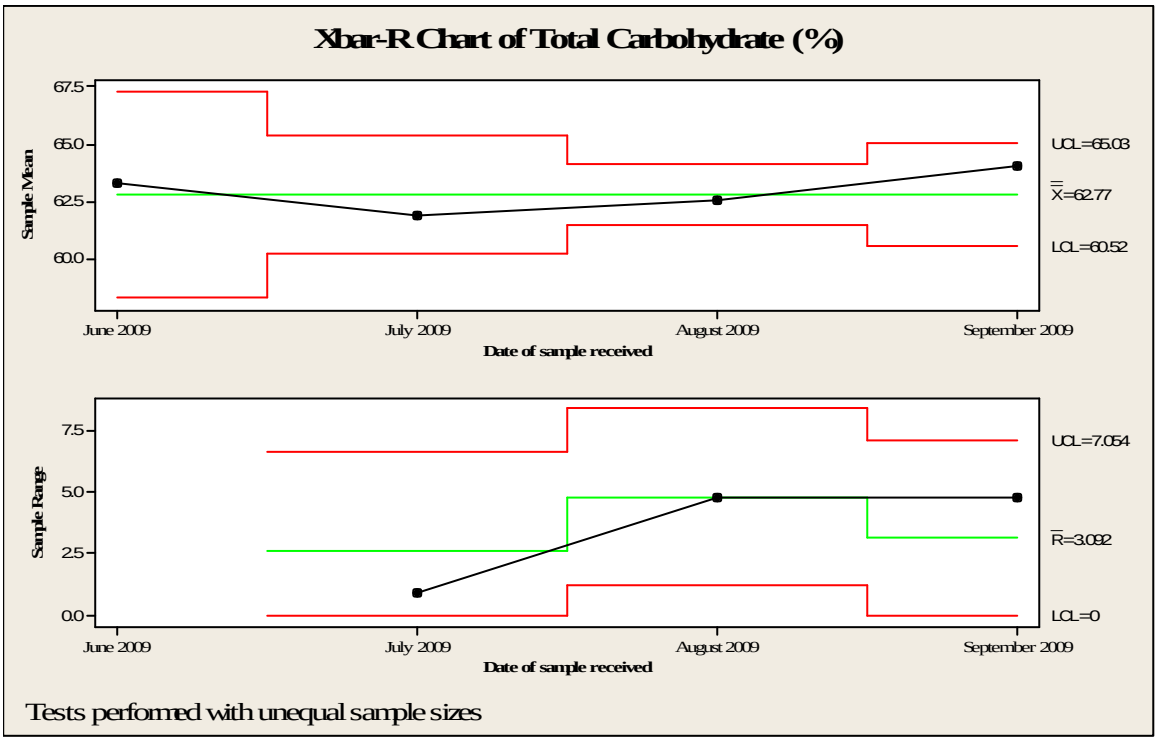


Figure 5. 3: X-bar, R, S and EWMA Charts for Fat (%) of Complan Nutritional Drink.

The first, second, third and fourth control chart given as output is the chart for the mean, range, standard deviation and exponentially weighted moving average of Fat (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in also control.

Quality Characteristic: Total Carbohydrate



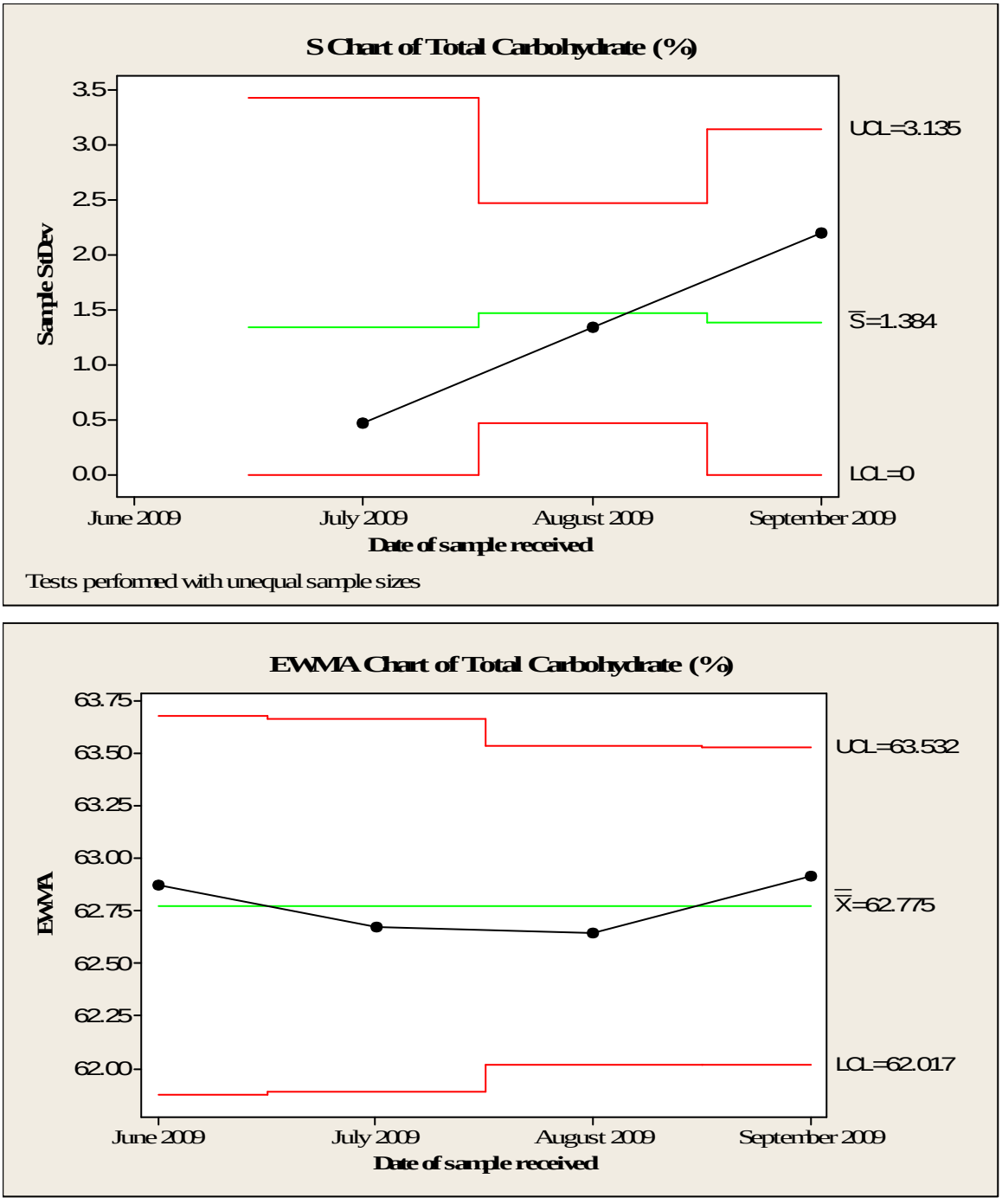


Figure 5. 4: X-bar, R, S and EWMA Charts for Total Carbohydrate (%) of Complan Nutritional Drink.

The first, second, third and fourth control chart given as output is the chart for the mean, range, standard deviation and exponentially weighted moving average of Total Carbohydrate (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in also control.

Quality Characteristic: Energy

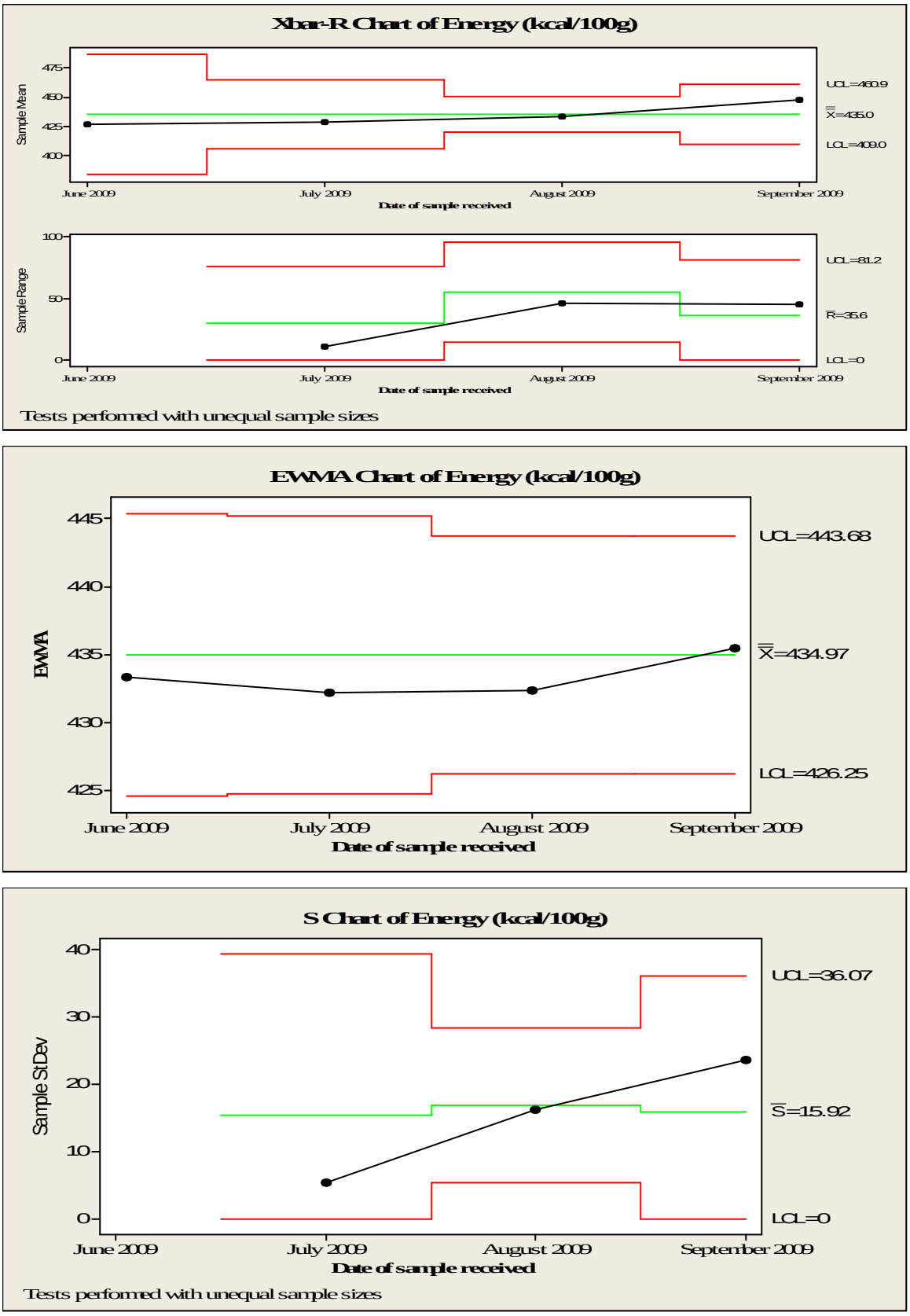


Figure 5. 5: X-bar, R, S and EWMA Charts for Energy (kcal/100g) of Complan Nutritional Drink.

The first, second, third and fourth control chart given as output is the chart for the mean, range, standard deviation and exponentially weighted moving average of Energy (kcal/100g). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in also control.

Summary of discussion:

In this small scale research we have adopted statistical tools on past drinks physiochemical analysis process operations. Quality control chart can monitor and reduce analysis variability, determine when a analysis needs adjusting and when it does not, establish analysis stability and detect analysis changes. Evidence from the results shows that most of the parameters of the complan nutritional drinks as periodically are in control. More and more emphasis should be put on sustaining the quality standard through application of statistical quality control techniques.

SOFT DRINKS

5.5 Description of soft drinks

Soda. Pop. Soft drinks. Anyway you say it, sparkling beverages are non-alcoholic, carbonated drinks containing flavorings, sweeteners and other ingredients. No matter what your taste, sparkling beverages come in many forms, including regular, low-calorie, no-calorie, caffeinated and caffeine-free drinks (*Soft Drinks: The Coca-Cola Company*, n.d.).

Consumers are always looking for new tastes and formats for soft drinks therefore, innovation is the key to success. For this reason, the soft drinks sector is one of the most fast-moving and dynamic industries in the food and drink manufacturing.The main categories of soft drink products are carbonates, fruit juices, dilutables, still and juice drinks and bottled waters (*About Soft drinks - labelling, packaging and ingredients*, n.d.).

Name of soft drinks are as follows:

Sl. No.	Name of soft drinks	Sl. No.	Name of soft drinks
1.	Horse fellness Mixed fruit Energy Drinks	15.	Pina Colada Cocktail Mix
2.	Sprite	16.	Margarita Cocktail Mix

3.	Coca Cola	17.	Carabao Energy Drink
4.	Schweppes Soda Water	18.	Beckers Non-Alcoholic Malt Beverage
5.	Schweppes Tonic Water	19.	Holsten Non-Alcoholic Malt Beverage
6.	Horses Non-Alcoholic Beverage	20.	Hollander Malt Beverage
7.	Holsten Non-Alcoholic Beverage	21.	Horses Beverages
8.	Horses Malt Beverage	22.	Classe Royale Malt Beverage
9.	Red Bull Energy Drink	23.	Festival Malt Drink
10.	Horses Non- Alcoholic Malt Beverage	24.	EFES Malt Beverage
11.	Seven-up	25.	Lemon Soft Drink
12.	Power Plus Energy Drink	26.	Pure Drink
13.	Bacchus Energy Drink	27.	Shark Energy Drink
14.	Bloody Mary Cocktail Mix		

5.6 Preliminary analysis of the data

After collecting data, the first task for a researcher is to organize and simplify the data so that it is possible to get a general overview of the results. One method for simplifying and organizing data is to construct a frequency distribution (*MTH 161 Syllabus.pdf*, n.d.).

Table 5. 2: Frequency distribution for chemical analysis of Soft Drinks.

Proximate Variable		Frequency	Percentage
Total Sugar (%)			
	Acceptable Range	29	52.7
	Not Acceptable Range	26	47.3
Standard Plate Count (cfu/ml)			
	Acceptable Range	26	78.8
	Not Acceptable Range	7	21.2
Coliform (MPN/ml)			
	Acceptable Range	33	100.0
	Not Acceptable Range	0	0.0
Mold Count (cfu/ml)			
	Acceptable Range	27	87.1
	Not Acceptable Range	4	12.9
Alcohol (%)			
	Acceptable Range	11	50.0

	Not Acceptable Range	11	50.0

Frequency distribution presented in Table 5.2 indicates that only Coliform (MPN/ml) contains are acceptable and in case of other variables remarkable number of cases are unacceptable range were compared to the Requirements BDS 1727:2003 ("Bangladesh Standards and Testing Institution (BSTI)- |

-," n.d.).

5.7 Descriptive Statistics of Soft Drinks

An initial step when describing categorical data is to count the number of observations in each category and express them as percentages of the total sample size.

Table 5. 3: Descriptive Statistics results for proximate analysis of Soft Drink.

Proximate Variables	Minimum	Maximum	Mean	Std. Deviation
pH	2.00	6.60	3.59	0.98
Total Soluble Solid (%)	0.00	19.40	7.58	5.40
Reducing Sugar (%)	0.00	13.33	4.64	3.57
Total Sugar (%)	0.00	17.19	6.33	4.96
Acidity (%)	0.00	3.20	0.28	0.48
Standard Plate Count (cfu/ml)	0.00	400.00	42.12	75.24
Coliform (MPN/ml)	0.00	0.00	0.00	0.00
Mold (cfu/ml)	0.00	180.00	7.68	32.39
Yeast (cfu/ml)	0.00	2.00	0.12	0.49
Alcohol (%)	0.00	0.10	0.02	0.03
Vitamin C (mg/100ml)	0.00	12.70	3.71	3.91
Gas Pressure (lb/in^2)	0.00	38.00	28.63	11.06

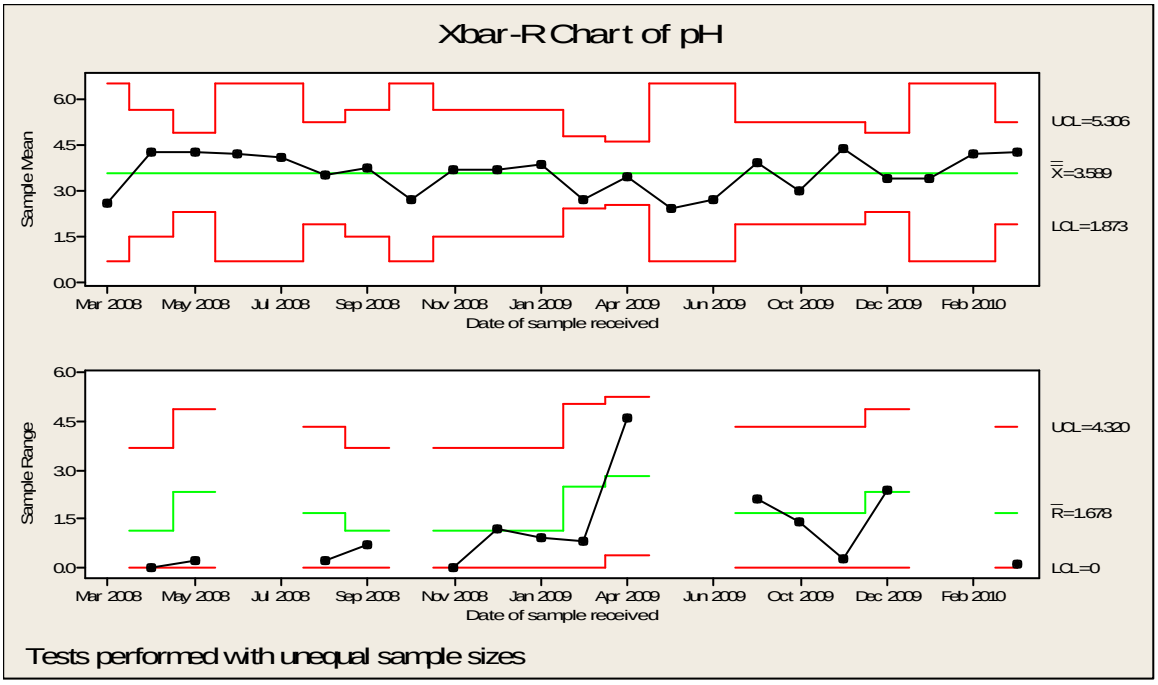
The mean, standard deviation and other descriptive statistics for chemical analysis are displayed in Table 5.3. Here Total Soluble Solid (%), Reducing Sugar (%), Total Sugar (%),Standard Plate Count (cfu/ml), Mold (cfu/ml), Vitamin C (mg/100ml) and Gas Pressure (lb/in^2) are highly standard deviation (SD>2).

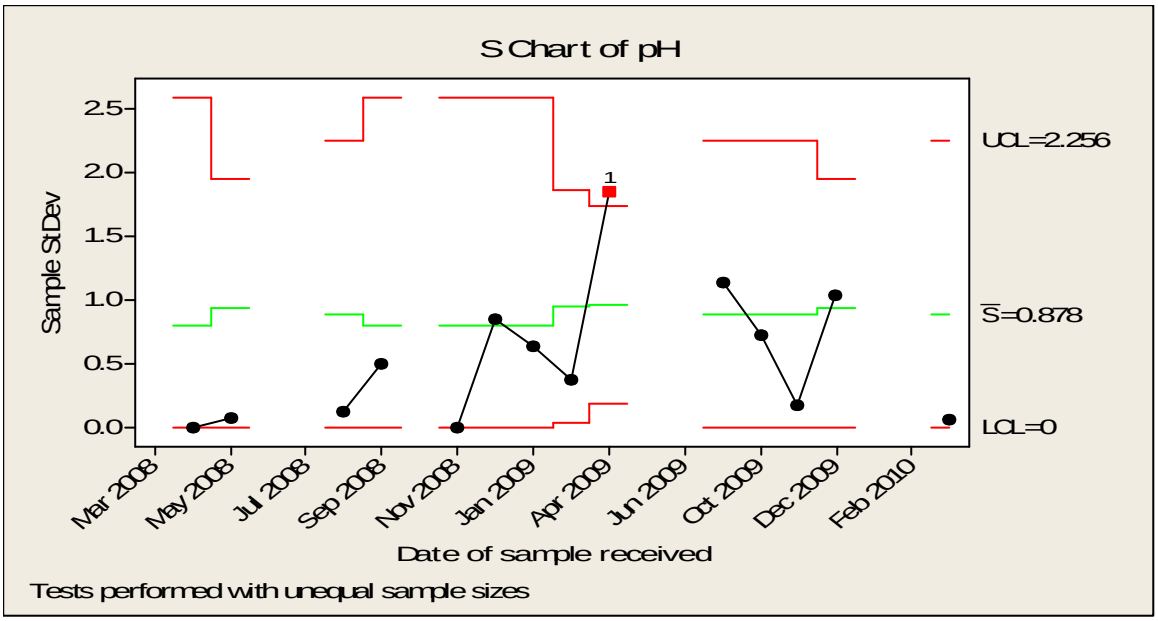
5.8 Application of control charts on Soft Drink

In order to verify whether quality of food products were under control condition or not we have adopted following control chart of Soft Drink for such purposes we have used several Shewhart Control Charts.

In this subsection we present results and analysis that is application of control charts. We show the results and analysis by type of products and types of control chart.

Quality characteristic: pH





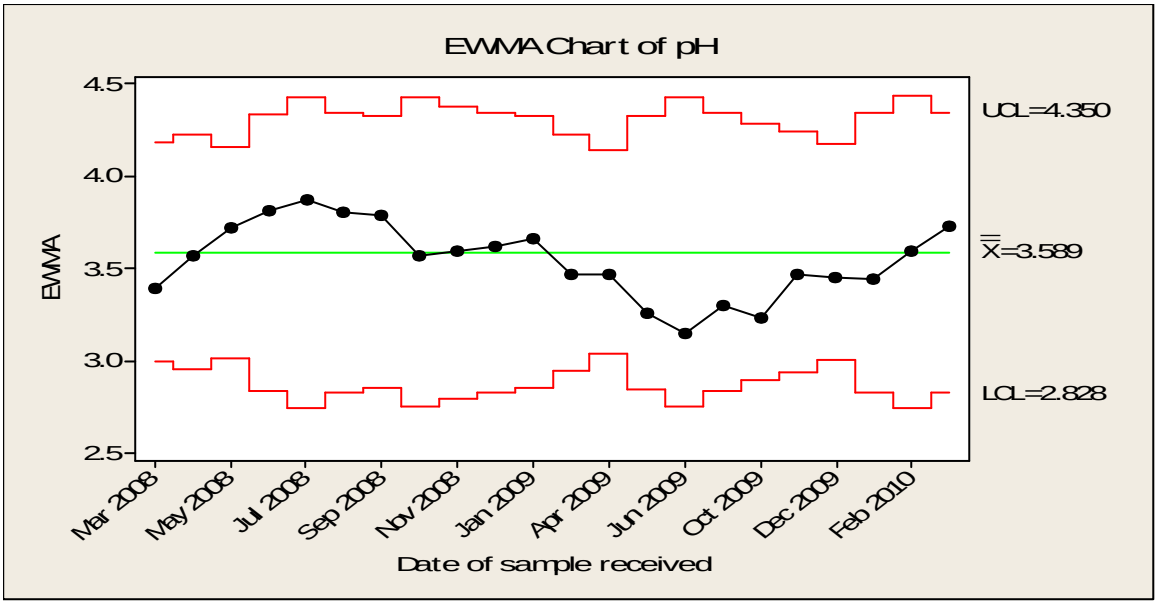
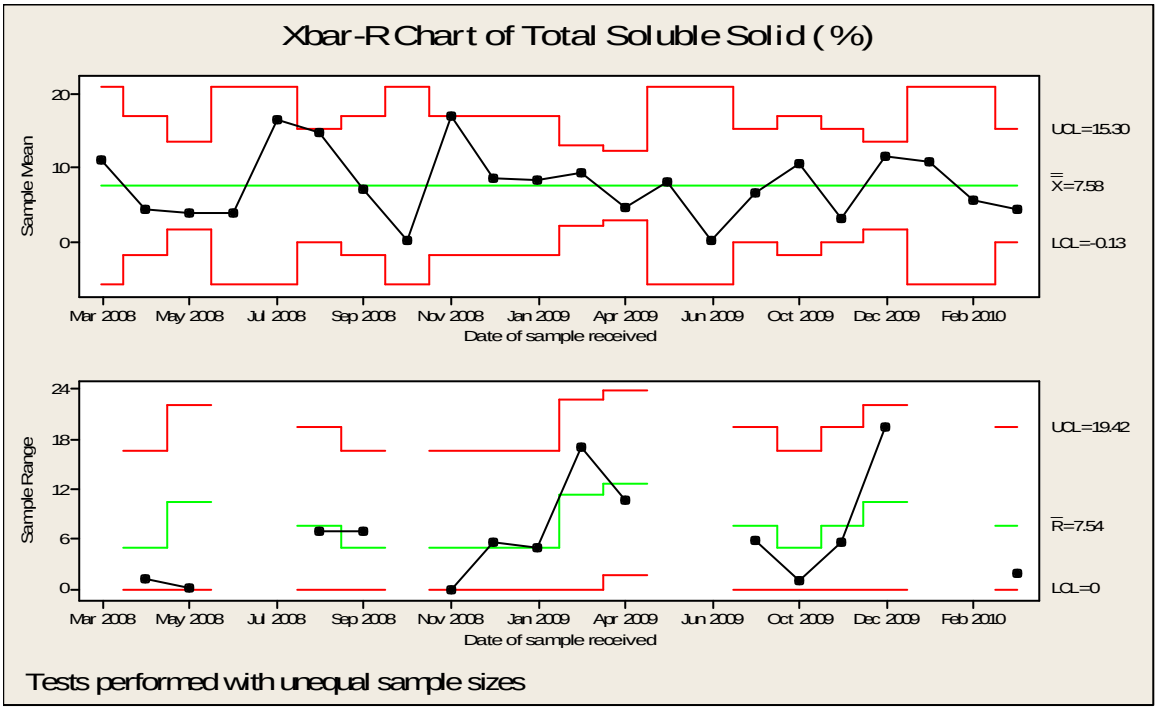


Figure 5. 6: X-bar, R, S and EWMA Charts for pH of Soft Drink.

The first, second, third and fourth control chart given as output is the chart for the mean, range, standard deviation and exponentially weighted moving average. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control except only a point outside in the control limit in standard deviation chart.

Quality Characteristic: Total Soluble Solid



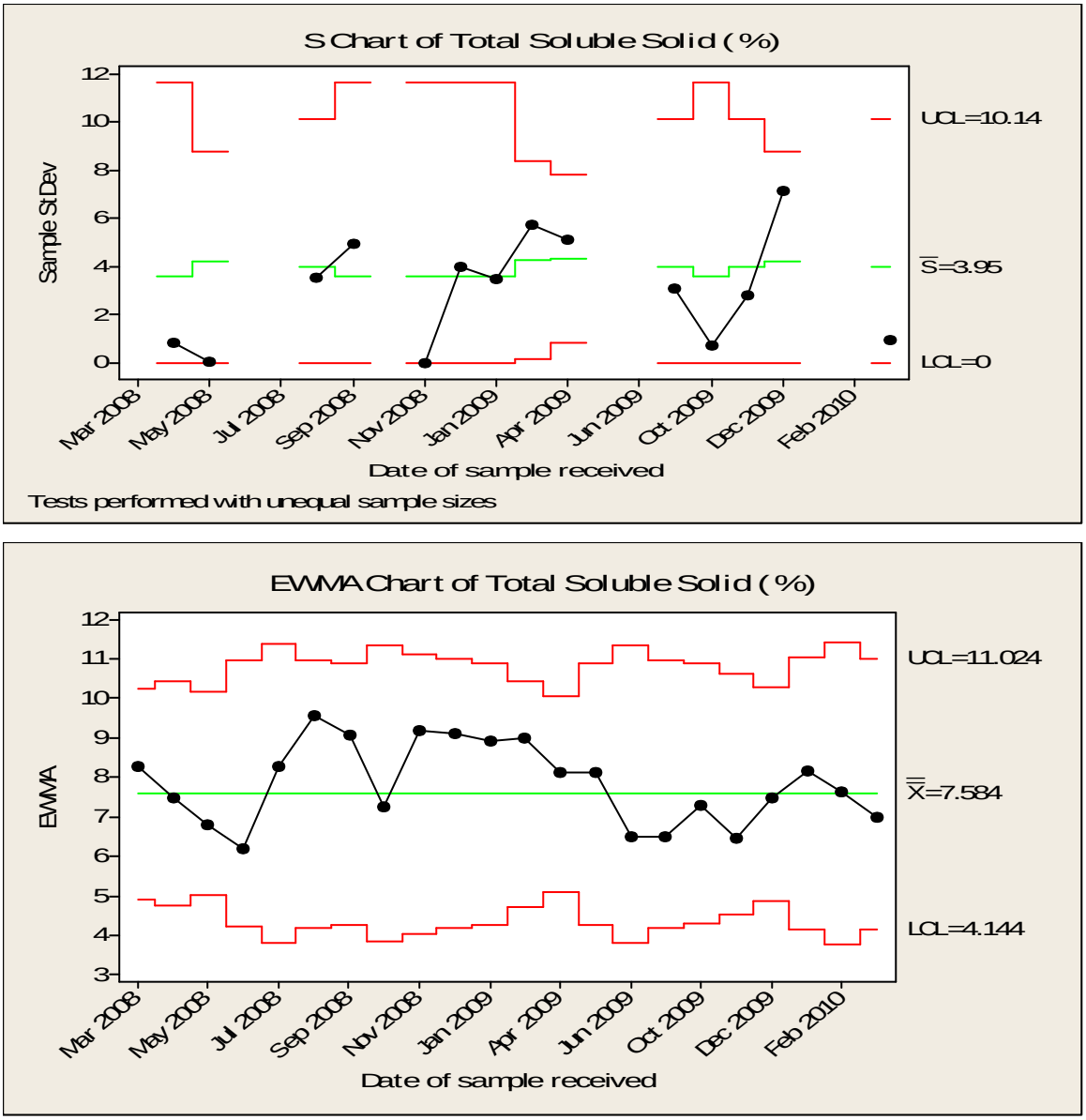


Figure 5. 7: X-bar, R, S and EWMA Charts for Total Soluble Solid (%) of Soft Drink.

The first, second, third and fourth control chart given as output is the chart for the mean, range, standard deviation and exponentially weighted moving average of Total Soluble Solid (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control.

Quality Characteristic: Reducing Sugar

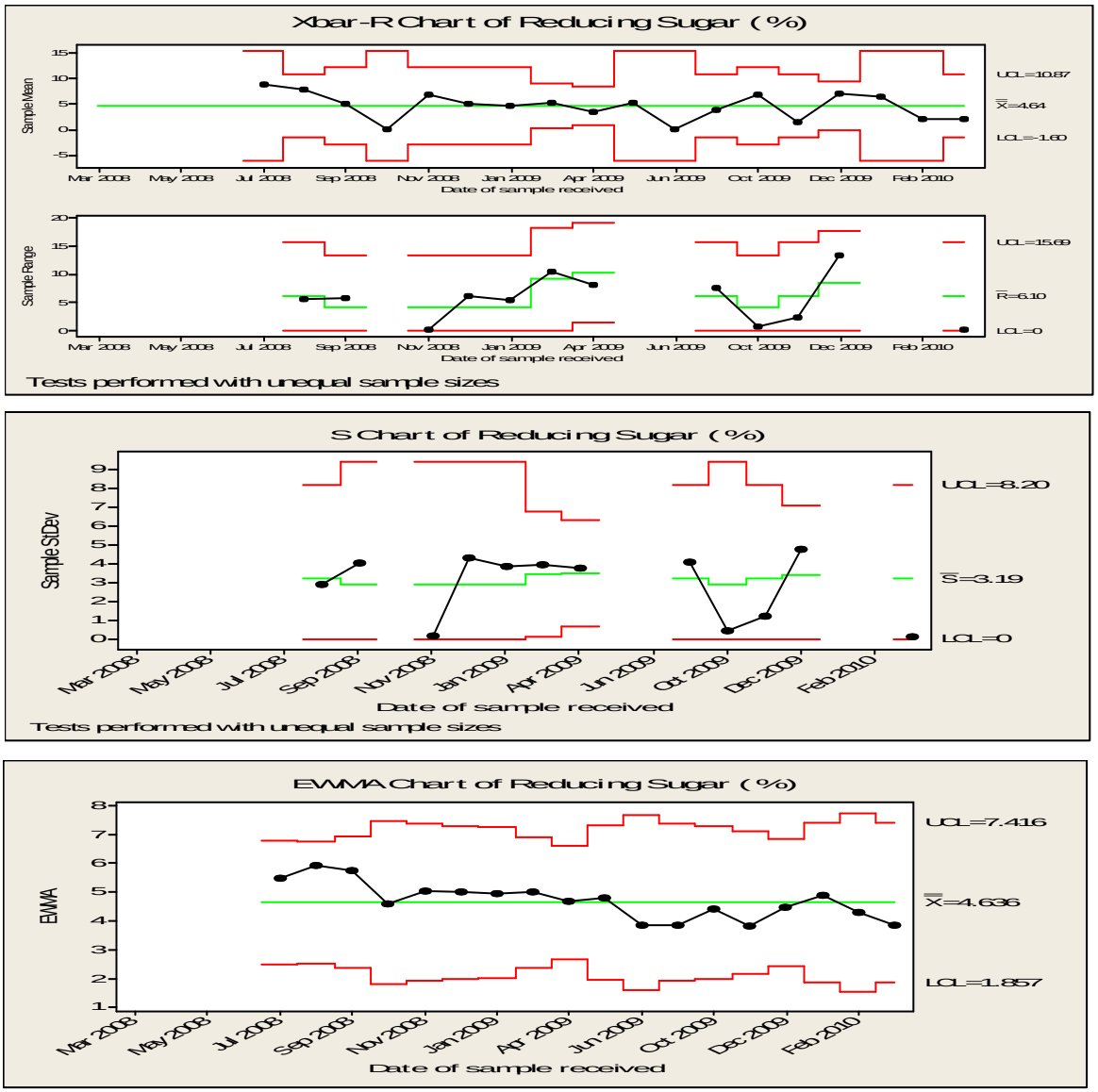
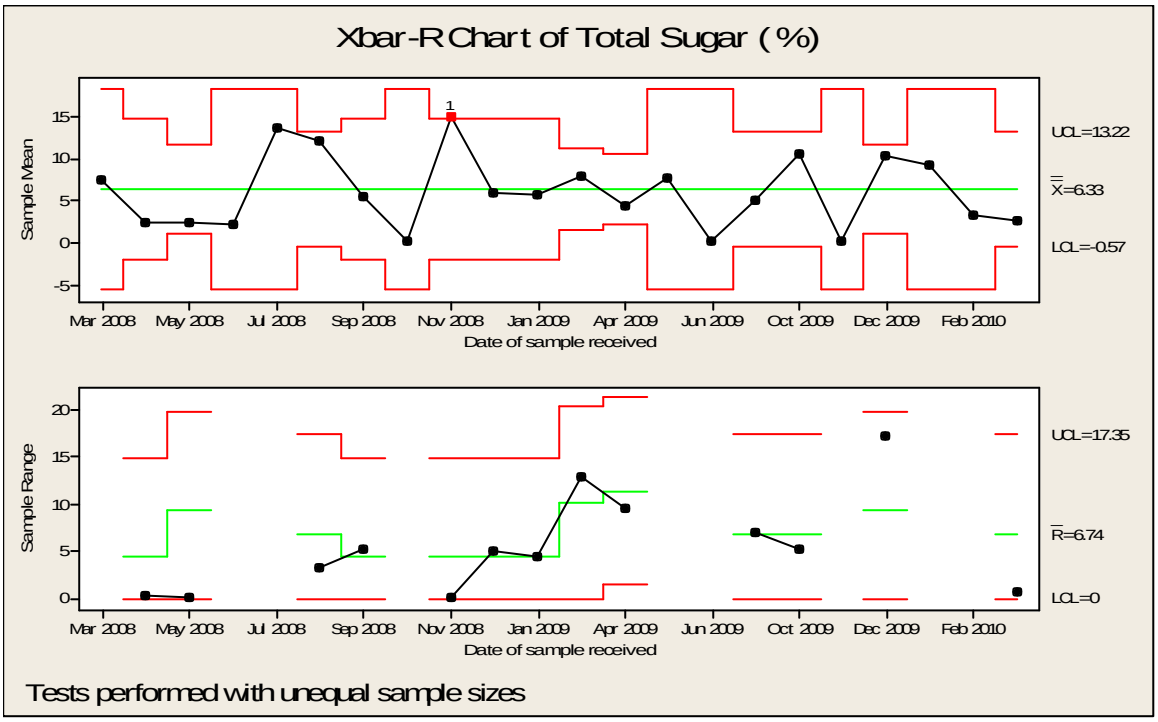
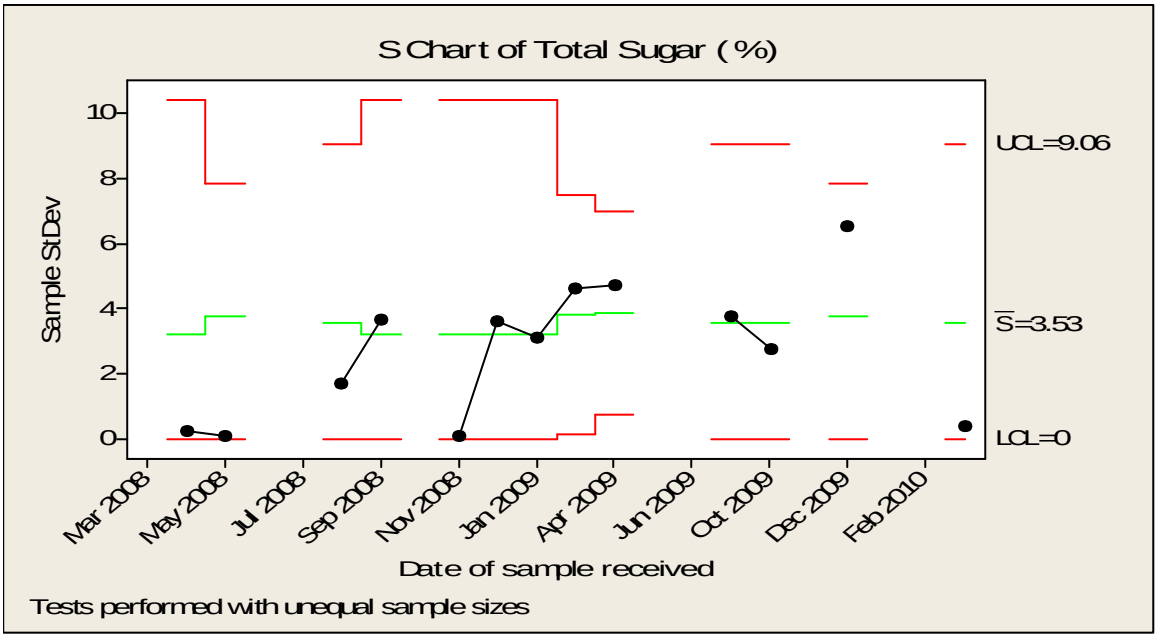


Figure 5. 8: X-bar, R, S and EWMA Charts for Reducing Sugar (%) of Soft Drink.

The first, second, third and fourth control chart given as output is the chart for the mean, range, standard deviation and exponentially weighted moving average of Reducing Sugar (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in also control.

Quality Characteristic: Total Sugar





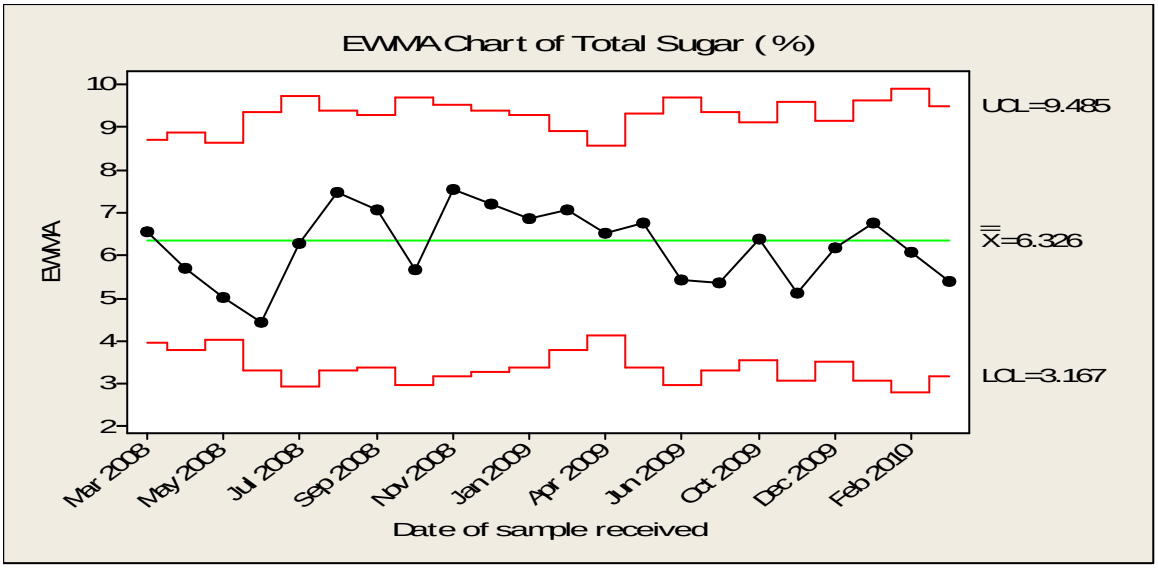
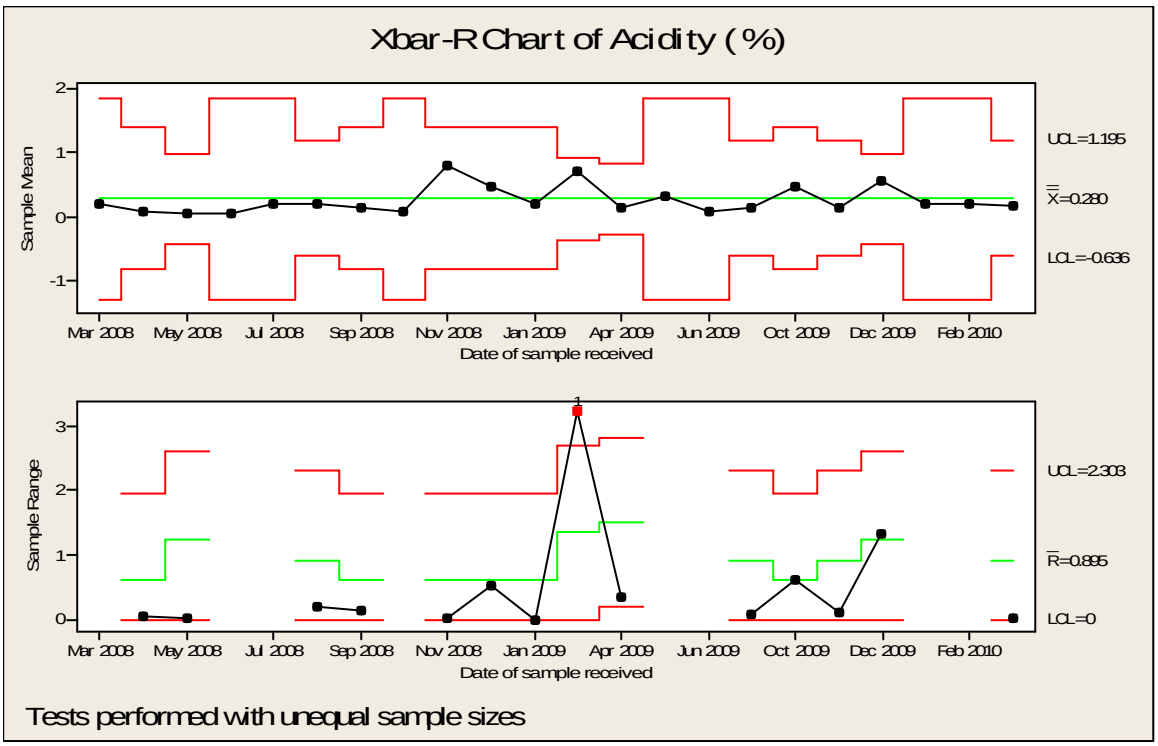


Figure 5. 9: X-bar, R, S and EWMA Charts for Total Sugar (%) of Soft Drink.

The first, second, third and fourth control chart given as output is the chart for the mean, range, standard deviation and exponentially weighted moving average of Total Sugar (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control except only a point outside in the control limit in mean chart.

Quality Characteristic: Acidity



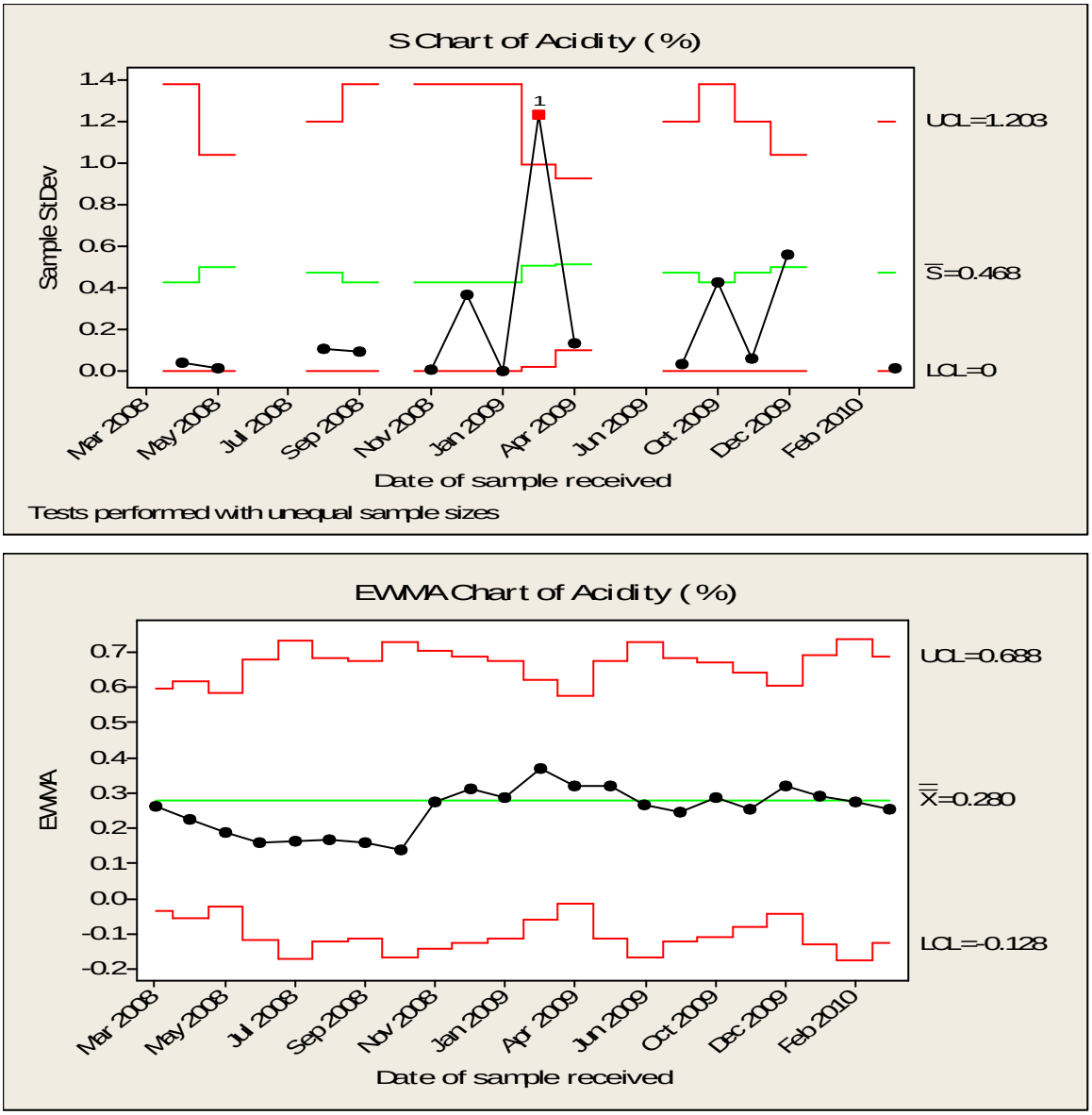


Figure 5. 10: X-bar, R, S and EWMA Charts for Acidity (%) of Soft Drink.

The first, second, third and fourth control chart given as output is the chart for the mean, range, standard deviation and exponentially weighted moving average of Acidity (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control except only a point outside in the control limit in Range and Standard Deviation chart.

Quality Characteristic: Standard Plate Count.

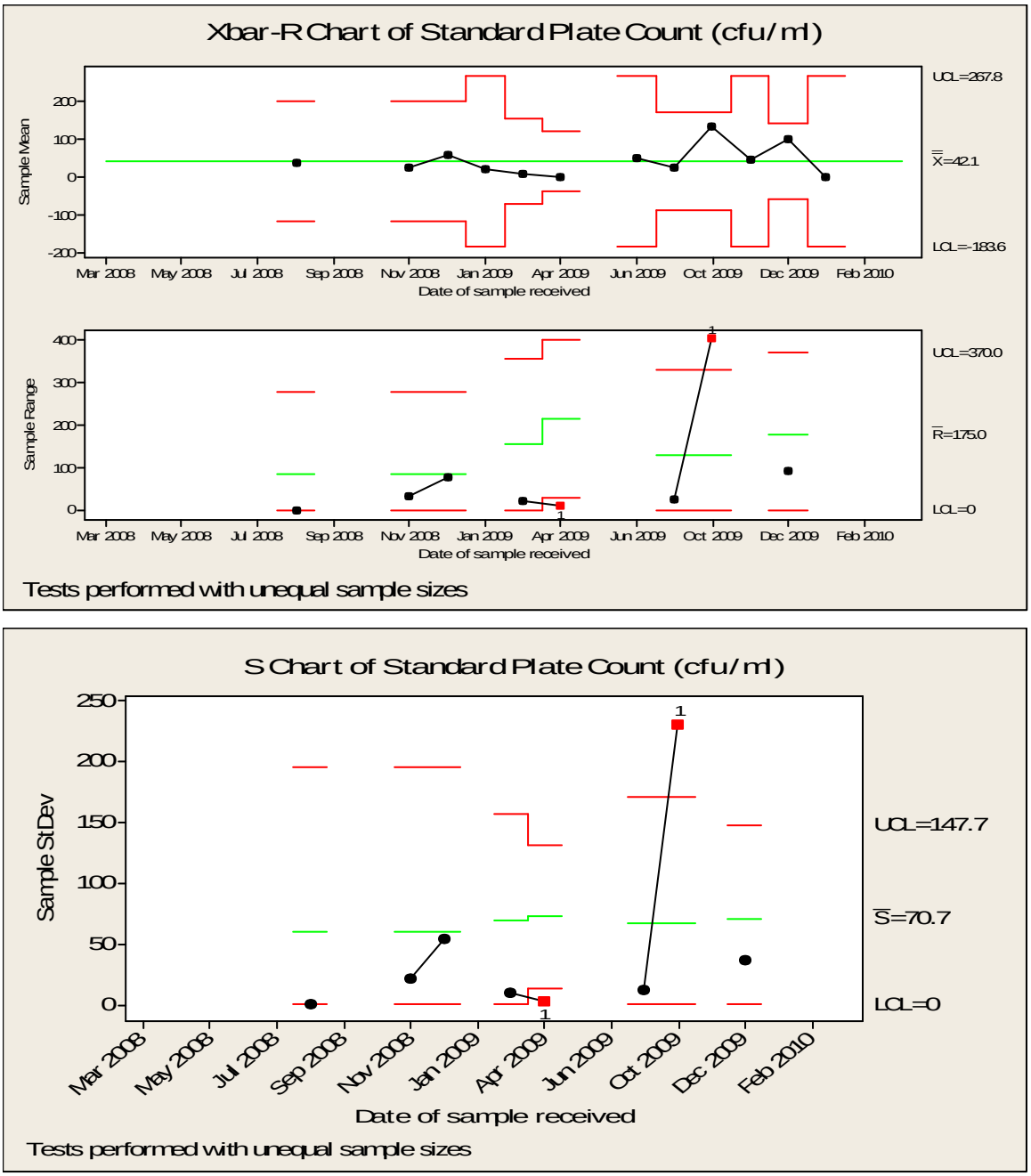


Figure 5. 11: X-bar, R, and S Charts for Standard Plate Count (cfu/ml) of Soft Drink.

The first, second and third control chart given as output is the chart for the mean, range and standard deviation of Standard Plate Count (cfu/ml). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control except only two point outside in the control limit in Range and Standard Deviation chart.

Quality Characteristic: Mold Count

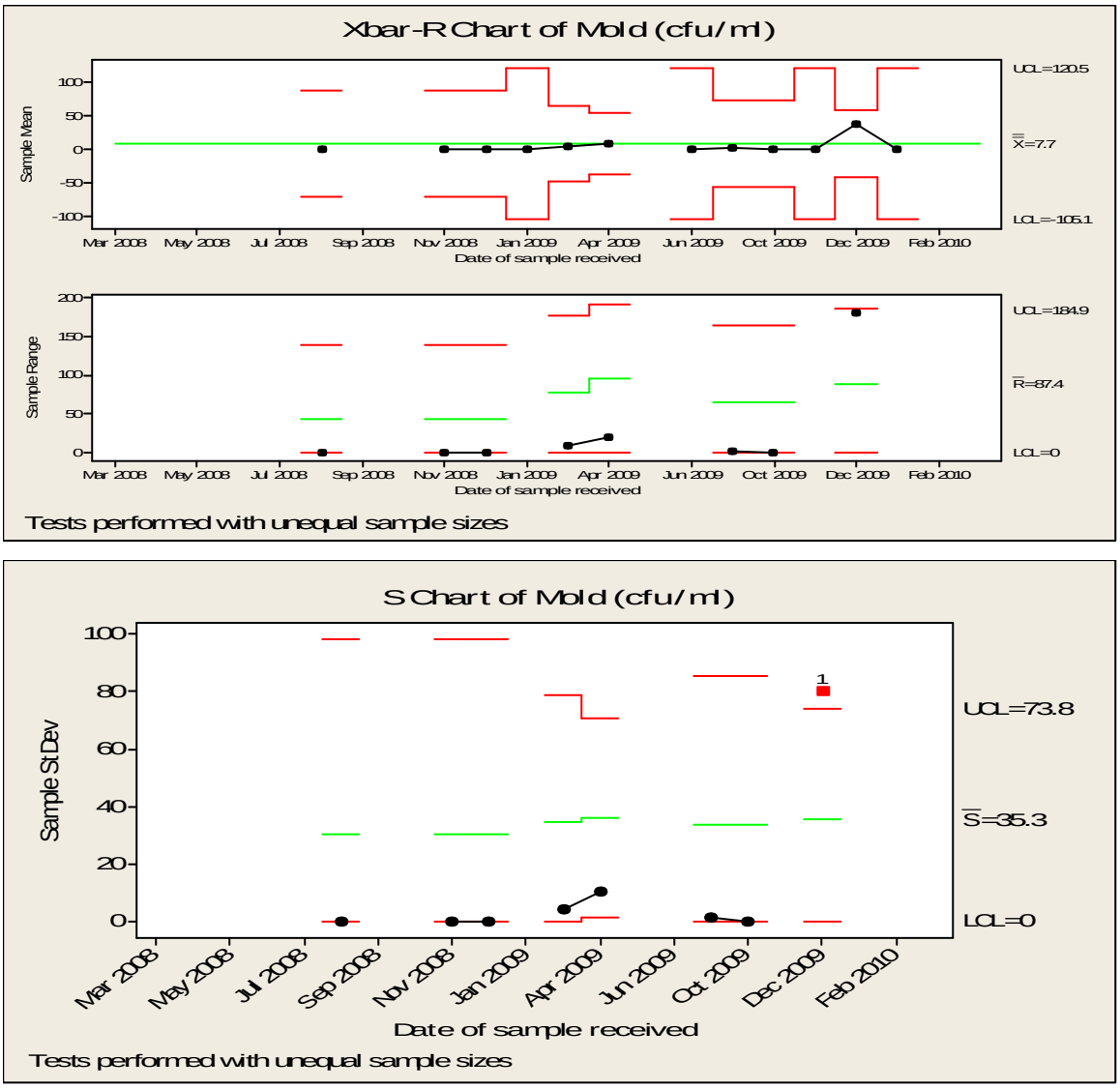


Figure 5. 12: X-bar, R, and S Charts for Mold Count (cfu/ml) of Soft Drink.

The first, second and third control chart given as output is the chart for the mean, range and standard deviation of Mold Count (cfu/ml). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control except only a point outside in the upper control limit in Standard Deviation chart.

Quality Characteristic: Yeast Count

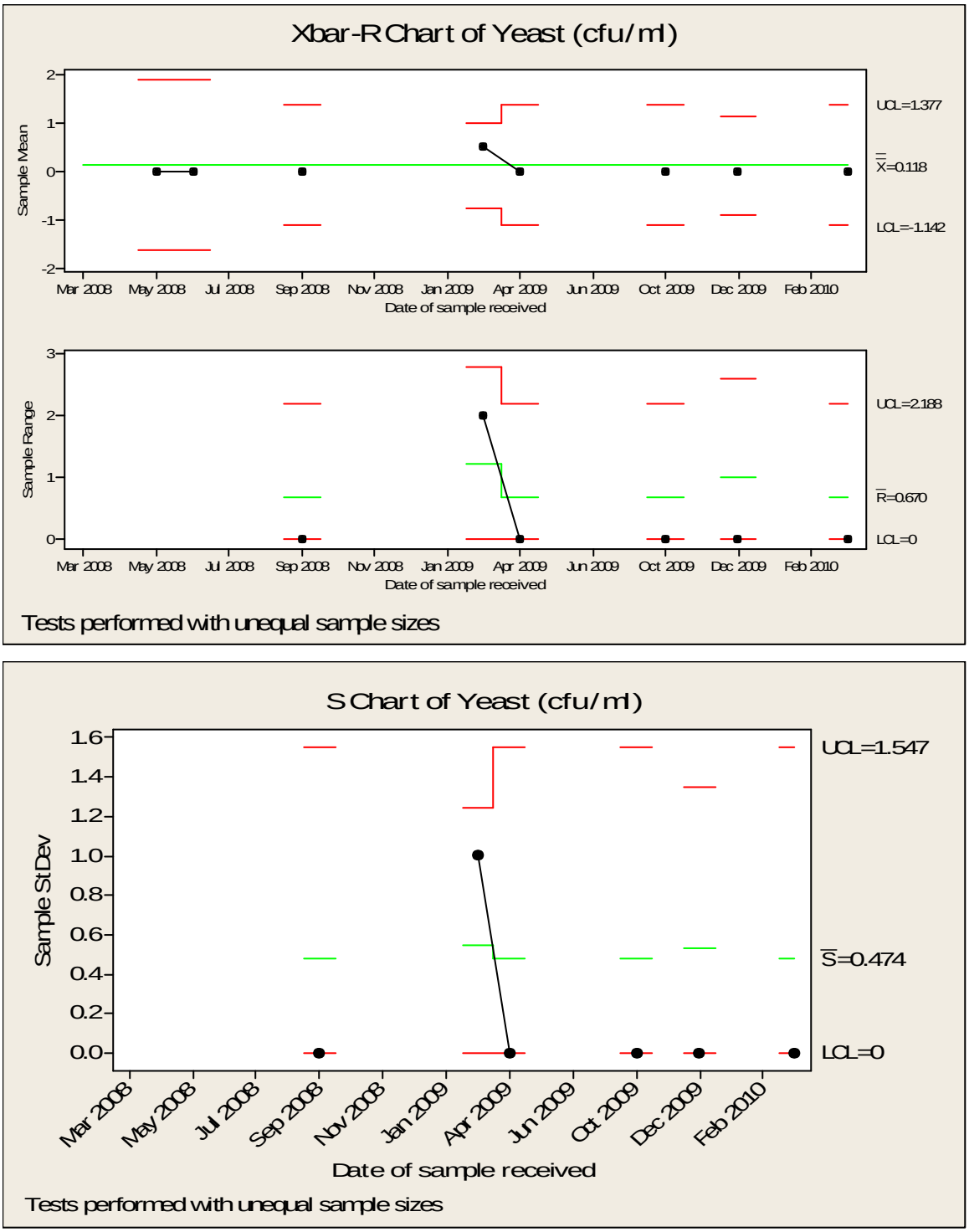


Figure 5. 13: X-bar, R, and S Charts for Yeast Count (cfu/ml) of Soft Drink.

The first, second and third control chart given as output is the chart for the mean, range and standard deviation of Yeast Count (cfu/ml). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clearly shows that the process is in control.

Quality Characteristic: Alcohol

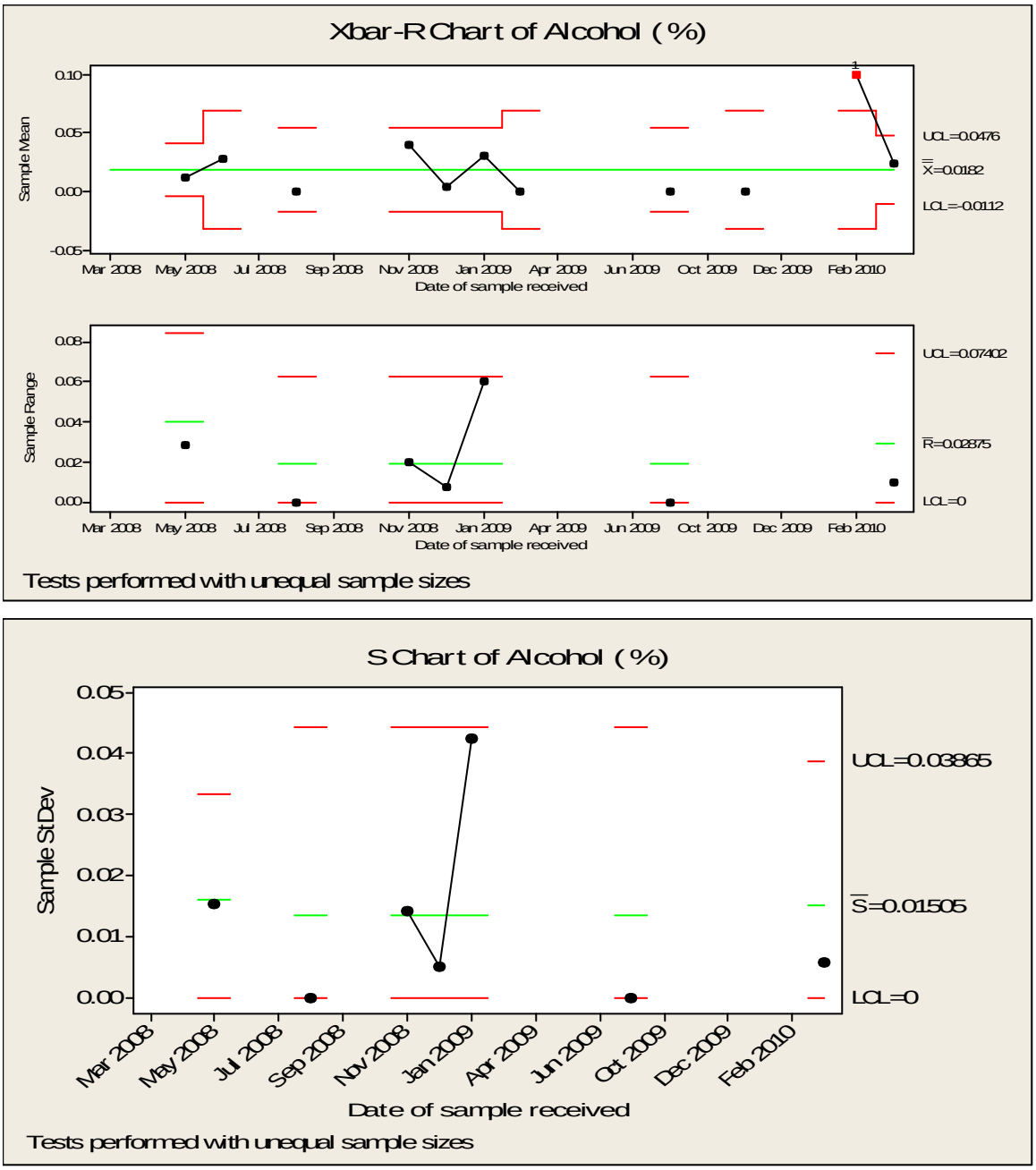


Figure 5. 14: X-bar, R, and S Charts for Alcohol (%) of Soft Drink.

The first, second and third control chart given as output is the chart for the mean, range and standard deviation of Yeast Count (cfu/ml). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clearly shows that the process is in control except only a point outside the upper control limit in average chart.

Quality Characteristic: Vitamin C

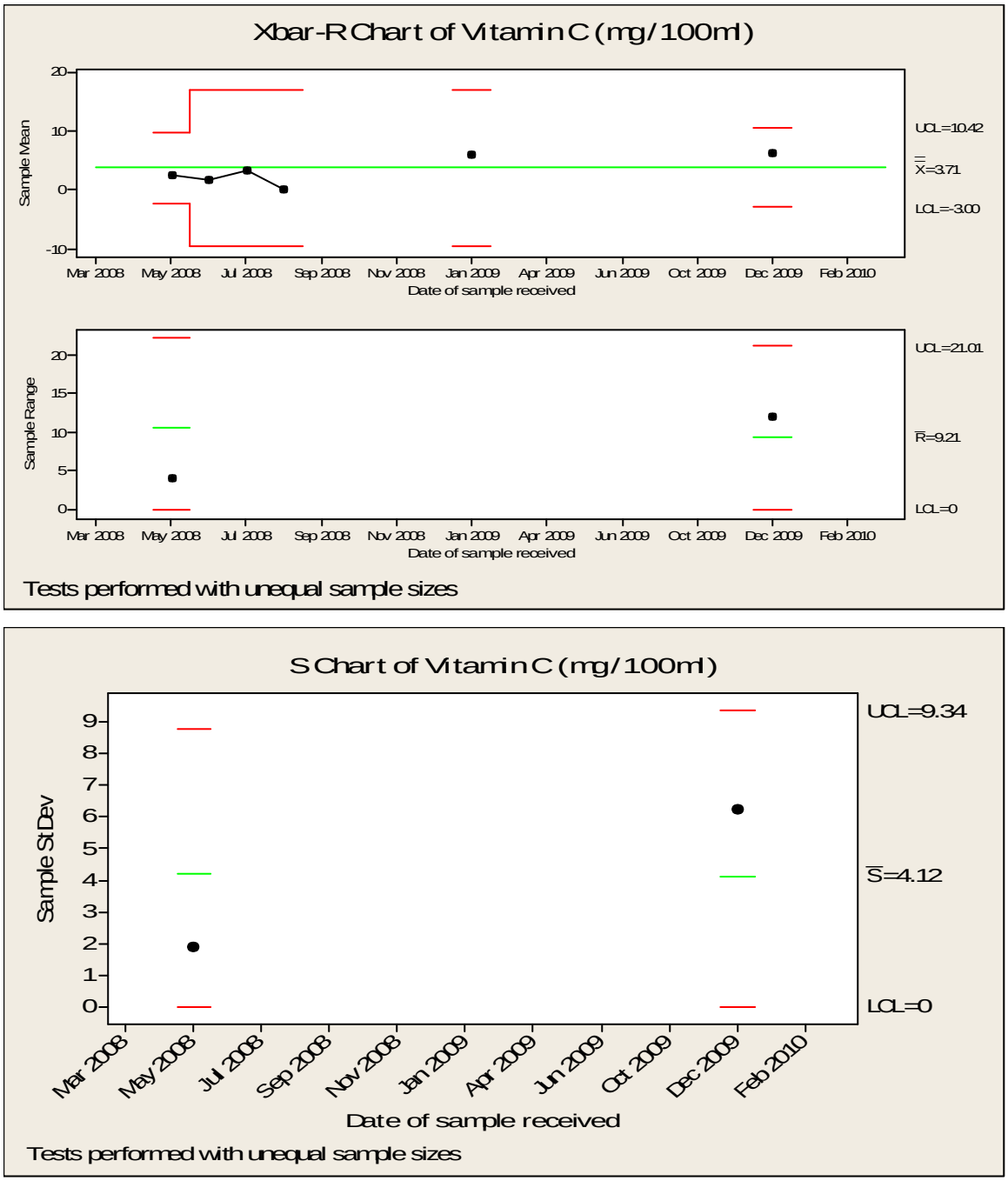


Figure 5. 15: X-bar, R, and S Charts for Vitamin C (mg/100ml) of Soft Drink.

The first, second and third control chart given as output is the chart for the mean, range and standard deviation of Vitamin C (mg/100ml). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clearly shows that the process is in control except only a point outside the upper control limit in average chart.

Quality Characteristic: Gas Pressure

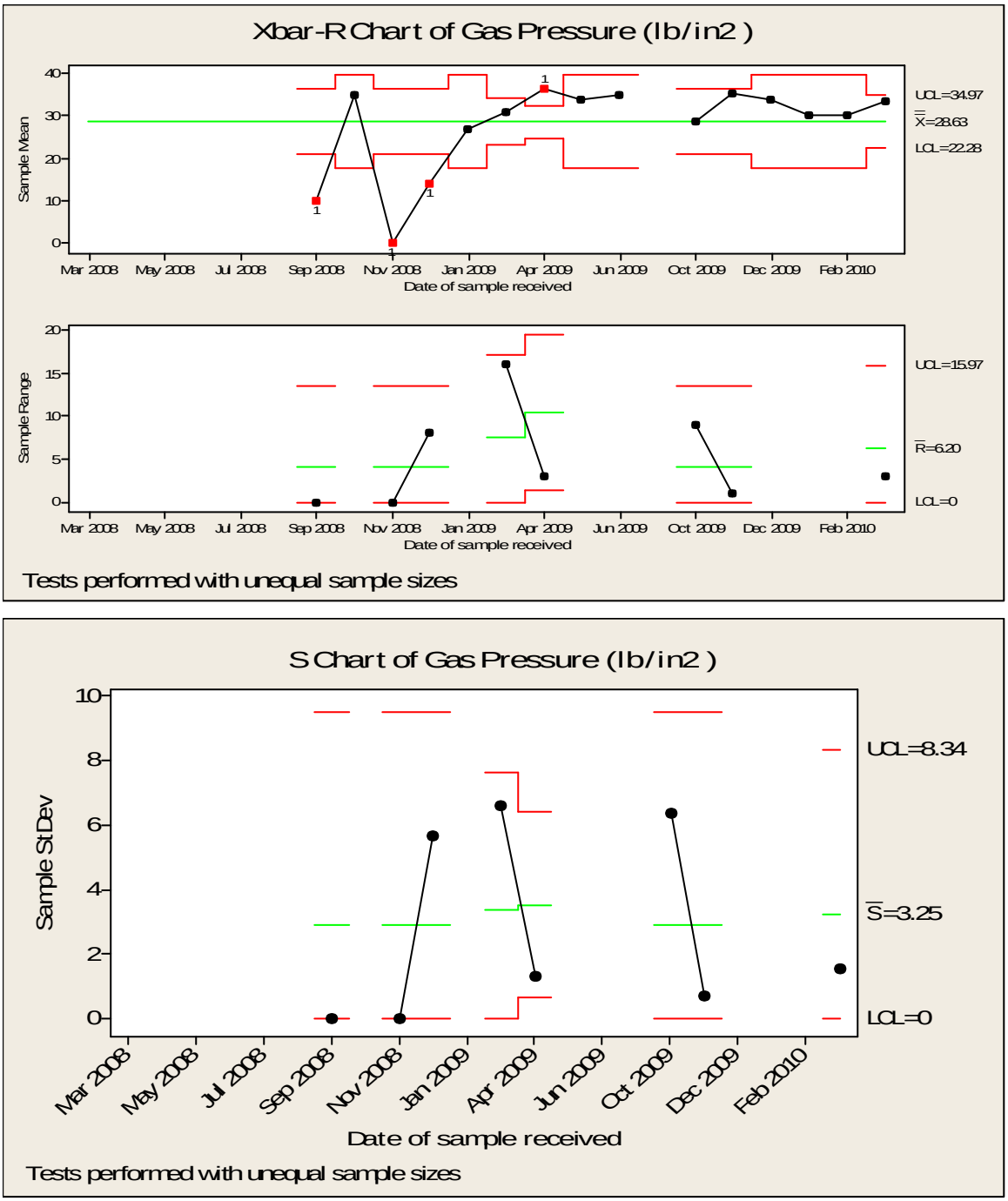


Figure 5. 16: X-bar, R and S Charts for Gas Pressure (lb/in^2) of Soft Drink.

The first, second and third control chart given as output is the chart for the mean, range and standard deviation of Gas Pressure (lb/in^2). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clearly shows that the process is in control except only a few points outside in the control limit in average chart.

5.9 Process Capability Analysis (Using Normal Distribution Curve)

In this case, we want to measure the procedure capability for different industries producing certain soft drinks. The proximate analysis of the soft drinks is of concern. The specification limits on the soft drinks are in given appendix 7. There has been a consistent problem with meeting the specification limits and the some procedure produces a high percentage of rejects.

The histogram of the data shows that proximate analysis of soft drinks follow a normal distribution or approximately normal distribution. The variation from soft drinkstosoft drinks can be estimated using the within group standard deviation. Since the procedure is stable and the measurements are normally or approximately normality distributed, the normal distribution option of process capability analysis can be used.

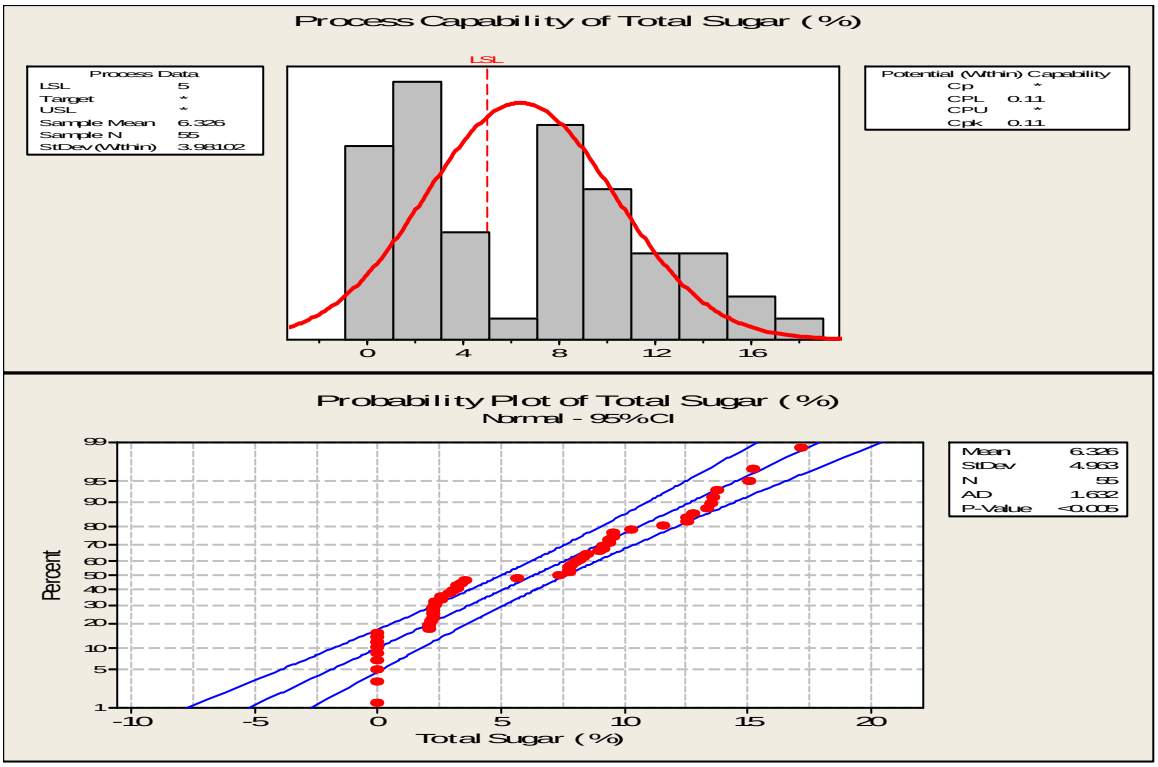


Figure 5. 17: Process Capability Report of Total Sugar (%).

The upper left box reports the process data including the lower specification limit. These values were provided by the Minitab statistical package program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 5.17 shows the histogram of the data along with normal curves overlaid on the histogram. A normal curve with a solid line. The soft drinks products of Total Sugar analysis report by this process exceed the lower specification limit (LSL). Here also notice that significant percentage of the Total Sugar of soft drinks is outside of Lower Specification Limit.

From the Normal probability plot graph in Fig. 5.17, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level (B. K. M. Bower, 2000). This is due to the fact that the p-value is 0.005, which is less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. Cpk =0.11 is less than 1 means that the process is off-centered and is not capable.

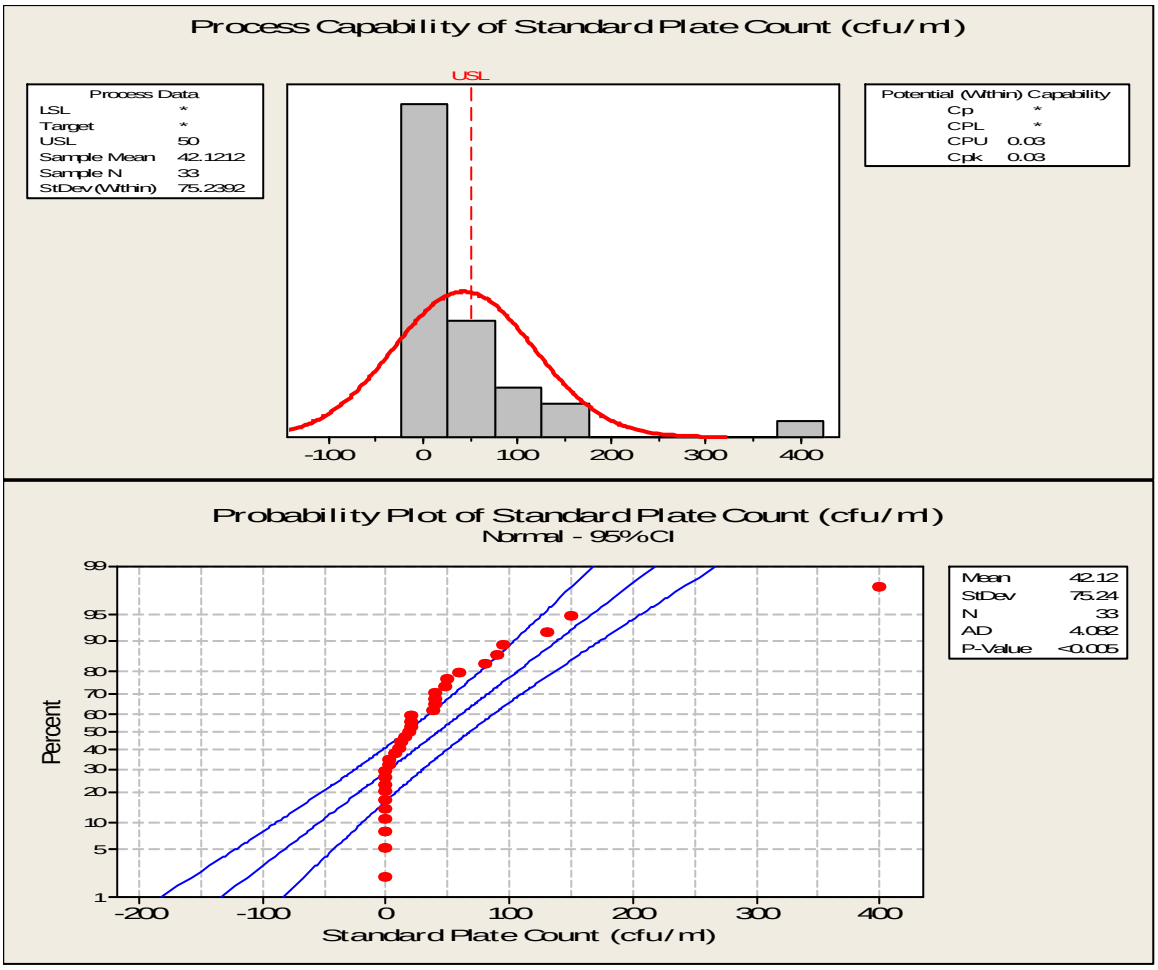


Figure 5. 18: Process Capability Analysis of Standard Plate Count (cfu/ml).

The upper left box reports the process data including the upper specification limit. These values were provided by the program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in figure 5.18shows the histogram of the data along with normal curves overlaid on the histogram. The products of Soft Drinks of Standard Plate Count analysis report by this process exceed the Upper specification limit (USL). A significant percentage of the Standard Plate Count of Soft Drinks is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 5.18, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value is 0.005, which is less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.03 is less than 1 means that the process is off centered and is not capable.

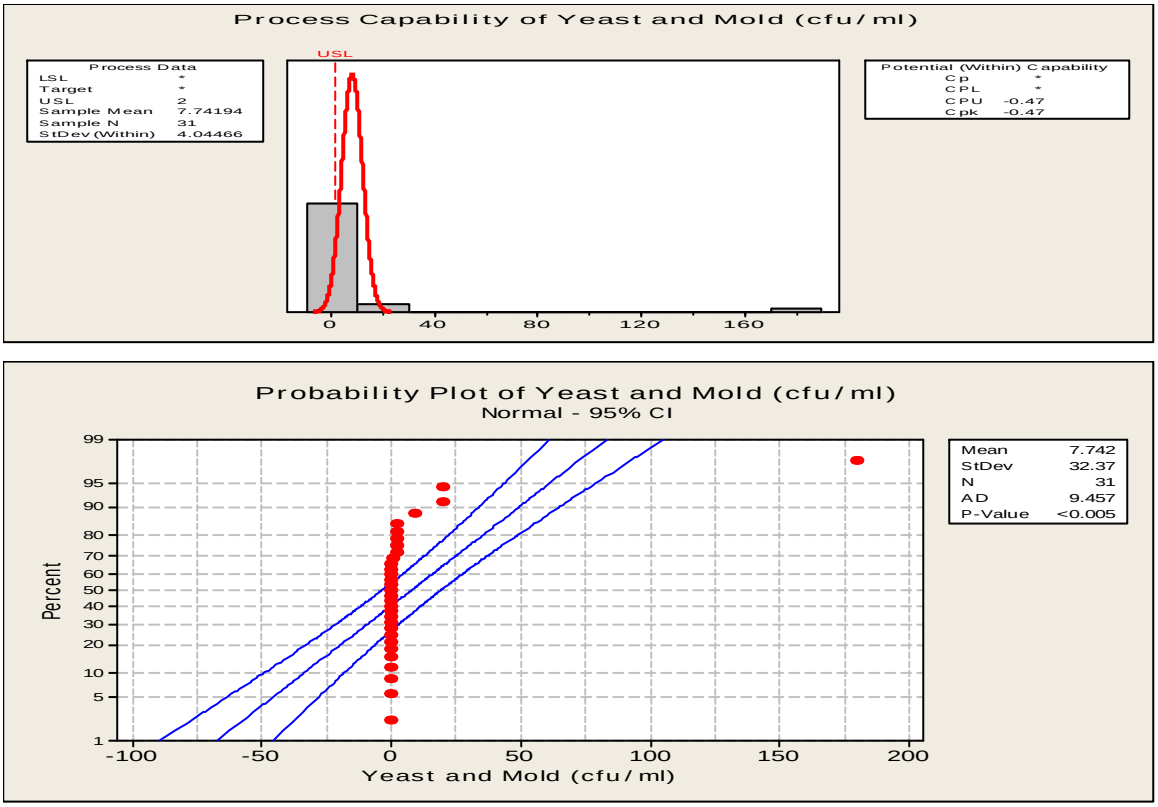


Figure 5. 19: Process Capability Analysis of Yeast and Mold Count (cfu/ml).

The upper left box reports the process data including the upper specification limit. These values were provided by the program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 5.19 shows the histogram of the data along with normal curves overlaid on the histogram. A normal curve with a solid line. The soft drinks products of Yeast and Mold count analysis report by this process exceed the upper specification limit (USL). A significant percentage of the Yeast and Mold counts of soft drinks are outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 5.19, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the test p-value is 0.005, which is less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-0.05 is less than 1 means that the process is off centered is not capable.

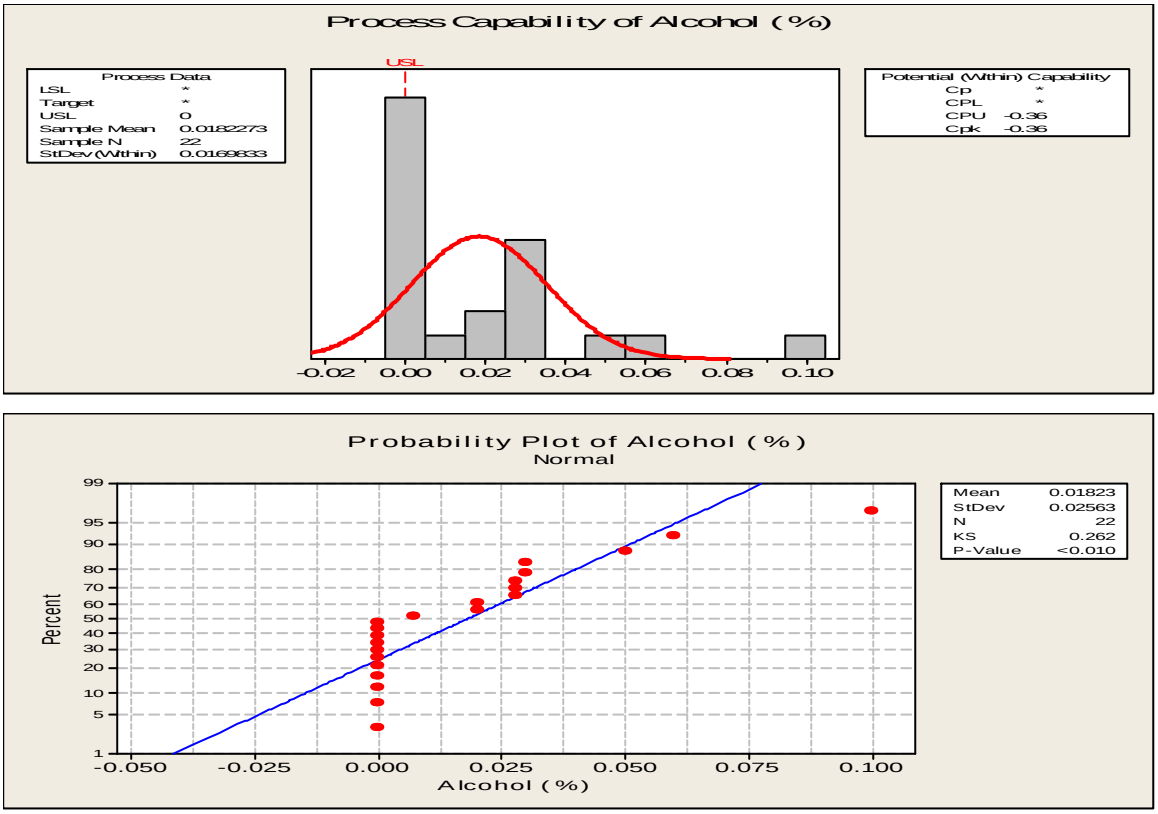


Figure 5. 20: Process Capability Analysis of Alcohol (%).

The upper left box reports the process data including the the upper specification limit. These values were provided by the Minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The Figure 5.20 shows the histogram of the data along with normal curves overlaid on the histogram. A normal curve with a solid line. The histogram and the normal curves can be used to check visually if the process data are normally distributed. To interpret the process capability, the normality assumption must hold. The soft drinks products of Alcohol analysis report by this process exceed the upper specification limit (USL). A significant percentage of the Alcohol of soft drinks are outside of upper Specification Limit.

From the Normal probability plot graph in Fig. 5.20, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the test p-value is 0.005, which is less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-0.36 is less than 1 means that the process is off centered and is not capable.

5.10 Comparison of prametric and non-parametric test

In analytical chemistry it is essential to validate a given analytical method to determine its applicability, reproducibility, repeatability and the accuracy of the data obtained. The analyst should establish some basis to prove that the method is working for its intent use. Normally, the amount of data is rather small and the so-called *Student t distribution* should be used (IAEA, 2003).

(Doane & Seward, 2007) indicated that the Wilcoxon signed-rank test is robust to non-normal, and somewhat asymmetrical, population shapes. In fact, the assumptions underlying the *t*-test are violated in every situation because there is neither an underlying normal distribution nor an interval level of measurement (Meek et al., 2007).

Table 5. 4: Comparison of parametric and non-parametric test for chemical analysis of soft drinks according to their acceptable range as prescribed by BSTI, Dhaka.

Variables	Wilcoxon/sign test	P-value	*t*-test	P-value	Kolmogorov-Smirnov test	P-value
Total Sugar (%)	986.5	0.965	1.98	0.974	0.185	<0.010
Standard Plate Count (cfu/ml)	Sign	>0.99	-0.60	0.724	0.288	<0.010
Yeast and Mold count (cfu/ml)	Sign	1.000	0.99	0.166	0.441	<0.010
Alcohol (%)	1431.0	0.000	3.34	0.003	0.262	<0.010

This study also investigated the behavior of the one sample *t*-test for soft drinks samples. Table 5.4 shows the result of the *t*-test that was insignificant compared with acceptable range as Prescribed by BSTI, Dhaka except alcohol (%).

To test the assumption of normality, we can use the Kolmogorov-Smirnov test. From this test, the Sig. (p) value is compared to the a priori alpha level (level of significance for the statistic) and a determination is made as to reject ($p \leq \alpha$) or retain ($p > \alpha$) the null hypothesis (The & The, n.d.).

For the above example, where $\alpha = 0.05$, given that $p \leq \alpha$ for all variables, we would conclude that Variables were not normally distributed. Therefore, the assumption of normality has not met for this variables. Therefore, the result of p-value as calculated by using *t*-test may be doughtful.

When the null hypothesis was true in wilcoxon signed-rank test as well as sign test performed as efficient or more power than the *t*-test. There were a total of 2 cases in which the Sign test predicted probability (p-value) results more efficent than the *t*-test when H_o was true. But when the null hypothesis was false *t*-test and wilcoxon signed-rank/Sign test given the same results.

5.11 Binary logistic regression analysis of Soft Drinks

A stata software was performed to identify soft drinks quality parameters appropriate for inclusion in a logistic regression model to predict the accepted/ unaccepted as prescribed acceptable range by Bangladesh Standard and Testing Institute (BSTI) in a soft drinks sample.

Logistic regression was used to assess the impact of a physiochemical analysis parameter to identify the quality of soft drinks which was supplied by some soft drinks produced industries.

The model contained three dependent variables as Total Sugar (%), Standard Plate Count (cfu/ml) and yeast & moulds count (cfu/ml) and at best four independent variables as pH, Total Soluble Solid(%), Acidity(%) & Gas Pressure (lb/in2)as presented in table 5.5.

Table 5. 5: Logistic Regression Analysis for physiochemical Analysis of Soft drinks.

Dependent Variable	**Independent Variable**	**Coeff.**	**Std. Error**	**z-value**	**P-value**	**AIC**	**BIC**	**GOF**
Yeast and Mold	pH	-1.162	1.37	-0.85	0.395	23.96	28.68	0.70
Count (cfu/ml)	Total Soluble Solid(%)	0.09	1.20	0.46	0.647			
	Acidity(%)	-10.80	14.47	-0.75	0.455			
	Gas Pressure (lb/in^2)	0.23	0.25	0.94	0.349			
Standard Plate	pH	-0.56	0.83	-0.68	0.498	24.36	29.58	0.52
Count (cfu/ml)	Total Soluble Solid(%)	-0.07	0.17	-0.38	0.701			
	Acidity(%)	-7.85	6.45	-1.22	0.224			
	Gas Pressure (lb/in^2)	-0.17	0.14	-1.23	0.217			
Total Sugar (%)	pH	-44.404	16.908	-2.63	0.009	25.81	33.76	0.90
	Acidity(%)	4.151	1.466	2.83	0.005			
	Gas Pressure (lb/in^2)	0.131	0.134	0.98	0.329			

Note: Coeff.= Coefficient of the model, Std. Err.= Standard Error, AIC= Akaike InformationCriterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

The full model containing pH and Acidity (%) against acceptability of Total Sugar (%) was statistically significant with $P<0.05$, indicating that the model was able to distinguish between soft drinks samples which reported having and not having accepted range as prescribed by BSTI. While other parameters were within acceptable range. The p-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in Table 5.5 with insignificant ($P>0.05$).

5.12 Binary probit regression analysis

To determine the factors influencing the decision to acceptable in food products a probit model were used. The decision to use probit is based on the fact that the decision variable is discrete and dichotomous (one either acceptable or not of soft drinks as prescribed by Bangladesh Standard and Testing Institute), discrete decisions are analyzed using qualitative response models one of which is probit.

Collecting soft drinks analysis data findings revealed that analysis data can be classified into two classes; acceptable and non acceptable according to Requirements BDS 1727:2003. A probit regression was used to determine the factors that influence the decision to analysis value among food producer or analyzer operators.

Table 5. 6: Binary Probit/Normit regression results of physiochemical analysis of Soft drinks.

Dependent Variable	**Independent Variable**	**Coeff.**	**Std. Error**	**z-value**	**P-value**	**AIC**	**BIC**	**GOF**
Yeast and Mold	pH	-0.698	0.763	-0.91	0.360	23.82	28.55	0.71
Count (cfu/ml)	Total Soluble Solid(%)	0.058	0.120	0.48	0.628			
	Acidity(%)	-6.812	8.872	-0.77	0.443			
	Gas Pressure (lb/in^2)	0.141	0.144	0.98	0.328			
Standard Plate	pH	-0.360	0.475	0.76	0.449	24.12	29.34	0.58
Count (cfu/ml)	Total Soluble Solid(%)	-0.030	0.095	-0.32	0.751			
	Acidity(%)	-4.789	3.808	-1.26	0.209			
	Gas Pressure (lb/in^2)	-0.102	0.079	-1.29	0.196			
Total Sugar (%)	pH	2.324	0.760	3.06	0.002	26.00	33.96	0.98
	Acidity(%)	-23.649	7.703	-3.07	0.002			
	Gas Pressure (lb/in^2)	0.087	0.071	1.22	0.222			

Note: Coeff.= Coefficient of the model, Std. Err.= Standard Error, AIC= Akaike Information Criterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

Table 5.6 shows estimates of the probit model for the factors influencing analyzed value among the soft drinks producers or respective analyzer of the study. The model contained three dependent variables as acceptability of Total Sugar (%), Standard Plate Count (cfu/ml) and yeast &moulds count (cfu/ml).

The full model containing pH and Acidity (%) against acceptability of Total Sugar (%) was statistically significant with $P<0.05$, indicating that the model was able to distinguish between soft drinks samples which reported having and not having accepted range as prescribed by BSTI. While other parameters were within acceptable range. The p-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in Table 5.6 with insignificant ($P>0.05$).

To find correct estimates of standard errors and p-values it is necessary to choose better model. To select the model, here, we consider two information criteria used to compare models. In general, "smaller is better" given two models, the one with the smaller AIC fits the data better than the one with the larger AIC. As with the AIC, a smaller BIC indicates a better-fitting model (Samples, n.d.).

We fit a model explaining of soft drinks products has on the basis of acceptability of Total Sugar (%), Standard Plate Count (cfu/ml) and yeast &moulds count (cfu/ml). The goodness-of-fit criteria for comparing these two model results are found in table 5.5and 5.6. AIC and BIC were determined by logit and probit regression of the predicted values obtained in the fit to the true model equation. For the acceptability of Total Sugar (%), Standard Plate Count (cfu/ml) and Yeast &Moulds count (cfu/ml) studied in table 5.5 and 5.6; based on the AIC and BIC criterion were approximated same by using a logit and probit model.

5.13 Discriminant function analysis.

The discriminant analysis to soft drinks under Acceptable Range as BSTI, Dhaka, with the test to determine classify groups of acceptability between the groups using Wilks' Lambda revealed that the diverse parameters yielded a statistical significance at a level of 0.05.

Table 5. 7: Discriminant Function Analysis results of chemical analysis of Soft drinks.

Dependent Variable	**Independent Variable**	**Wilks' Lambda**	**P-value**	**goodness-of-fit test**	
				Box's M	**P-value**
Yeast and Mold Count (cfu/ml)	pH	0.913	0.221	-	-
	Total Soluble Solid(%)	0.956	0.391		
	Acidity(%)	0.915	0.225		
	Gas Pressure (lb/in^2)	0.889	0.162		
Standard Plate Count (cfu/ml)	pH	0.952	0.340	-	-
	Total Soluble Solid(%)	0.977	0.515		
	Acidity(%)	0.960	0.384		
	Gas Pressure (lb/in^2)	0.997	0.811		
Total Sugar (%)	pH	0.736	0.000	91.928	0.000
	Acidity(%)	0.843	0.003		
	Gas Pressure (lb/in^2)	0.961	0.151		

Box's M test the assumption of homogeneity of covariance matrices. This test is very sensitive to meeting the assumption of multivariate normality. Discriminant function analysis is **robust** even when the homogeneity of variances assumption is not met, provided the data do not contain important outliers (Bian, n.d.). For our data, the dependent variable Acceptability of Total Sugar (%) we conclude the groups differ in their covariance matrices, violate assumption of DA. While we can't perform Acceptability of Yeast and Mold Count (cfu/ml) and Standard Plate Count (cfu/ml) as the test of Box's M as fewer than two nonsingular group covariance matrices.

The Wilk's lambda is a measure of the overall statistical significance of the Discriminant Analysis and Wilks's lambda is significant at the 5 percent level of probability for pH and Acidity (%) against acceptability of Total Sugar (%) (Refer to Table 5.7). This implies that the group means for the independent variables are different on the discriminating function and that the differences in the mean discriminant score are greater than can be attributed to non-sampling error. While other parameters are within acceptable range as prescribe by BSTI, Dhaka.

In the table, the smaller the Wilks's lambda, the more important the independent variable to the discriminant function. Wilks's lambda is significant by the F test for all independent variables.

5.14 ARCH-LM test

To detect the presence of ARCH effect in the mean equation of soft drinks we use the ARCH-LM (Lagrange multiplier) test.

Table 5. 8: ARCH-LM and DF test analysis results of chemical parameters of Soft drinks.

Variable	LM test for autoregressive conditional heteroskedasticity (ARCH)		Dickey-Fuller test for unit root	
	Chi-square Statistic	P-value	Test Statistic, Z(t)	P-value
pH	1.259	0.2619	-6.240	0.0000
Total Soluble Solid (%)	4.915	0.0266	-5.296	0.0000
Reducing Sugar (%)	0.085	0.7701	-5.351	0.0000
Total Sugar (%)	2.968	0.0849	-5.033	0.0000
Acidity (%)	0.050	0.8228	-7.254	0.0000

Standard Plate Count (cfu/ml)	0.042	0.8379	-3.927	0.0018
Mold Count (cfu/ml)	0.006	0.9389	-29.235	0.0000
Alcohol (%)	0.072	0.7878	-3.922	0.0019
Vitamin C (mg/100ml)	5.895	0.0152	-2.398	0.1423
Gas Pressure (lb/in^2)	9.218	0.0024	-3.199	0.0201

In our analysis the different value for different variables of above parameters of the ARCH-LM test; the lags included in the test are only 1. The corresponding P-Value is <0.05, which is very low for Total Soluble Solid (%), Vitamin C (mg/100ml) and Gas Pressure (lb/in^2). So we have no difficulty to reject the null hypothesis of no ARCH error and conclude that there is an ARCH error in the analysis series. This confirms that the order of the ARCH error is 3 (three) variables for analysis of soft drinks food products. Other parameters are insignificant that means no ARCH effects of the models. The estimation results are given in the table 5.8.

Table 5.8 shows that the values of DF test for all variables p-value <0.05 at 5%, level of significance except Vitamin Cwhich implies that the variables series is stationary. An outcome of DF test confirms that the physiochemical analysis variables series is stationary.

5.15 Spike Behaviour of ARCH(1) and GARCH(1,1) model estimations

The presence of extreme spikesin our analysis of soft drink products that is a bad characteristic of food products.

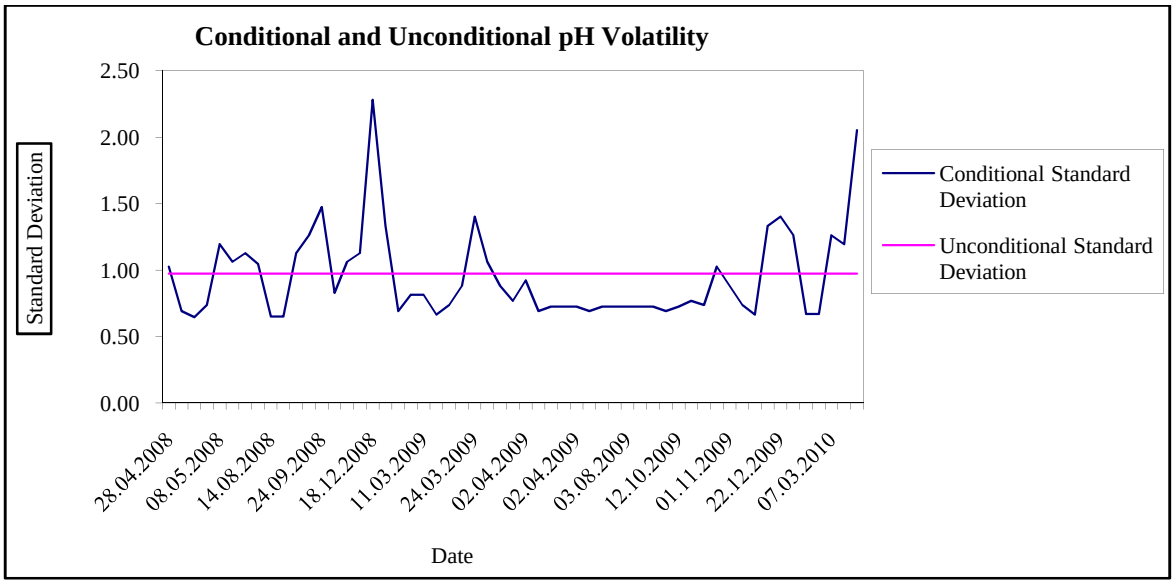


Figure 5. 21: pH content of Soft Drinks products for the Period April 2008 to March 2010.

Figure 5.21 shows the conditional and unconditional standard deviation of pH content over the period April 2008 to March 2010. Conditional standard deviations are over 0.60 during the sample period. The results indicate that the standard deviation almost stable among 2008 to 2010 and in spike behaviour in December 2008 and March 2010. However, volatility in deviations is very low in this time period.

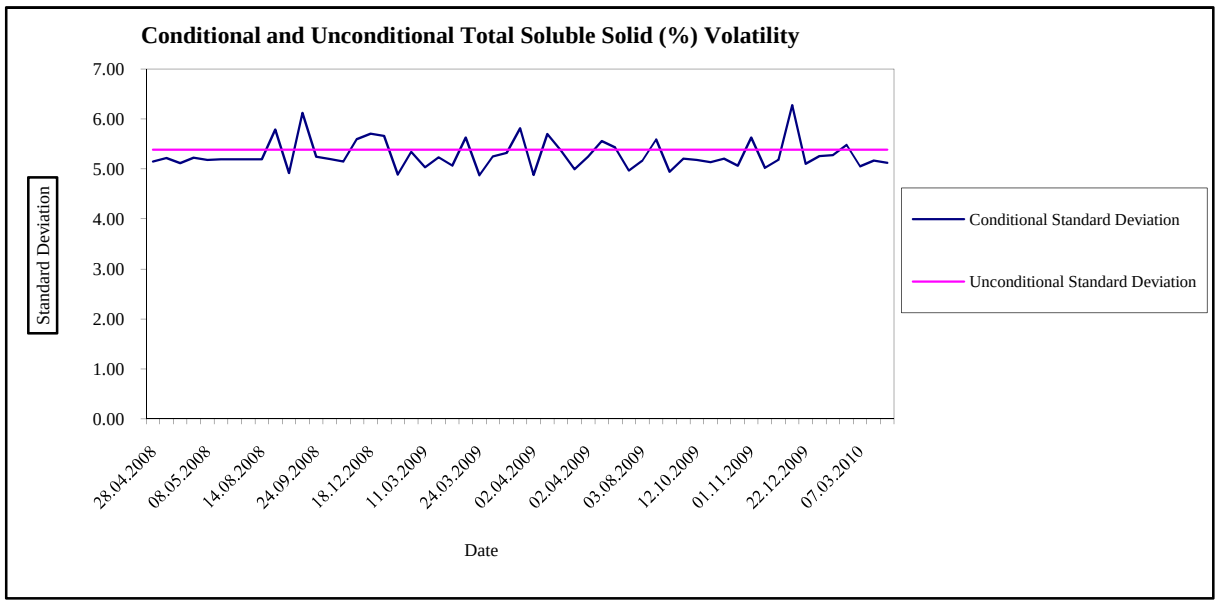


Figure 5. 22: Total Soluble Solid (%) content of Soft Drinks products for the Period April 2008 to March 2010.

Figure 5.22 shows the conditional and unconditional standard deviation of Total Soluble Solid (%) content over the period April 2008 to March 2010. Conditional standard deviations are over 4.80 during the sample period. The results indicate that the deviations relatively stable all over the period. However, volatility in deviation is low in this time period.

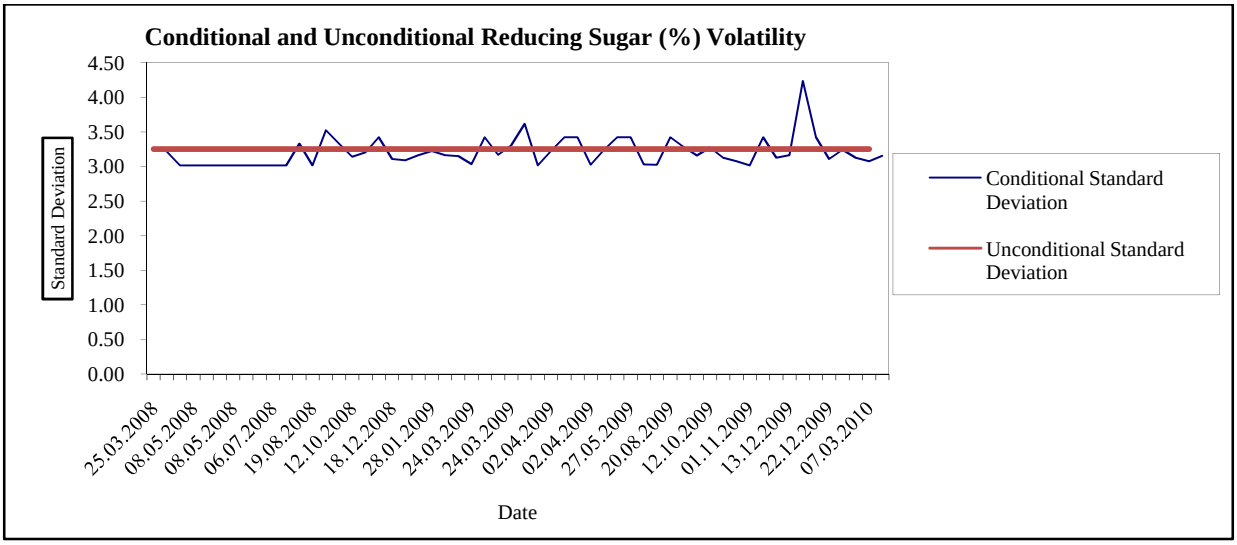


Figure 5. 23: Reducing Sugar (%) content of Soft Drinks products for the Period March 2008 to January 2010.

Figure 5.23 shows the conditional and unconditional standard deviation of Reducing Sugar (%) content over the period March 2008 to January 2010. Conditional standard deviations are over 3.0 during the sample period. As can be seen in Fig. 5.23, the deviation relatively stable all over the period and slight spike behaviour in December 2009. However, volatility in deviation is low in this time period.

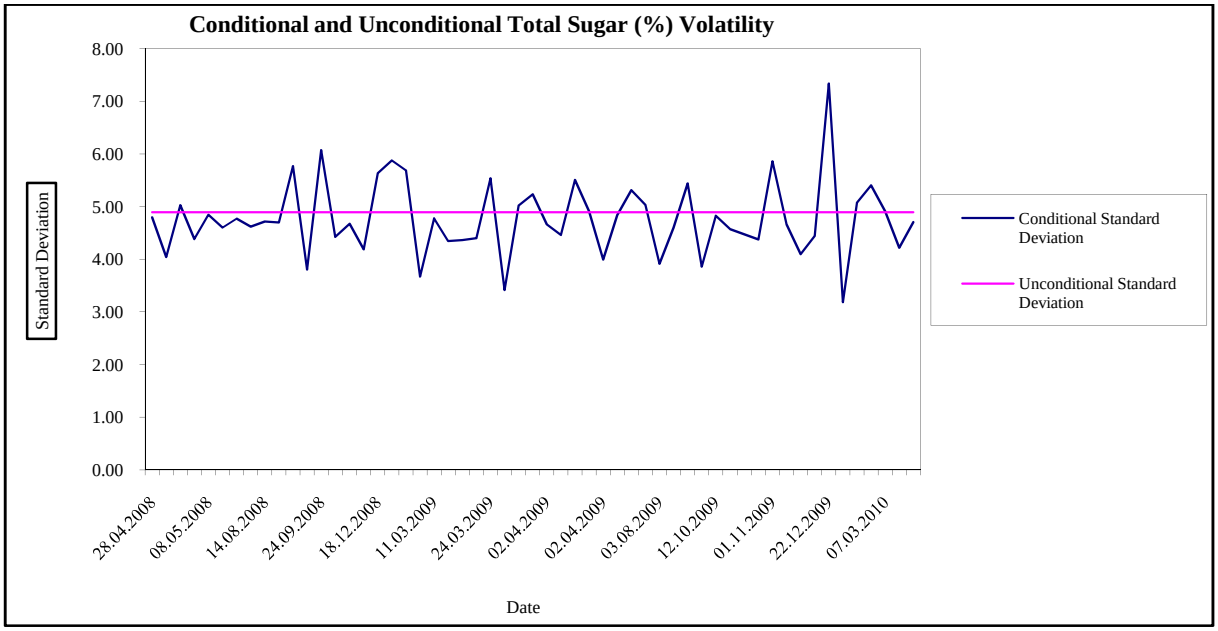


Figure 5. 24: Total Sugar (%) content of Soft Drinks products for the Period April 2008 to March 2010.

Figure 5.24 shows the conditional and unconditional standard deviation of Total Sugar (%) content over the period April 2008 to March 2010. Conditional deviations are over 3.00 during the sample period. The results indicate that the deviation relatively stable all over the period and slight spike behaviour in December 2009. However, volatility in deviations is low in this time period.

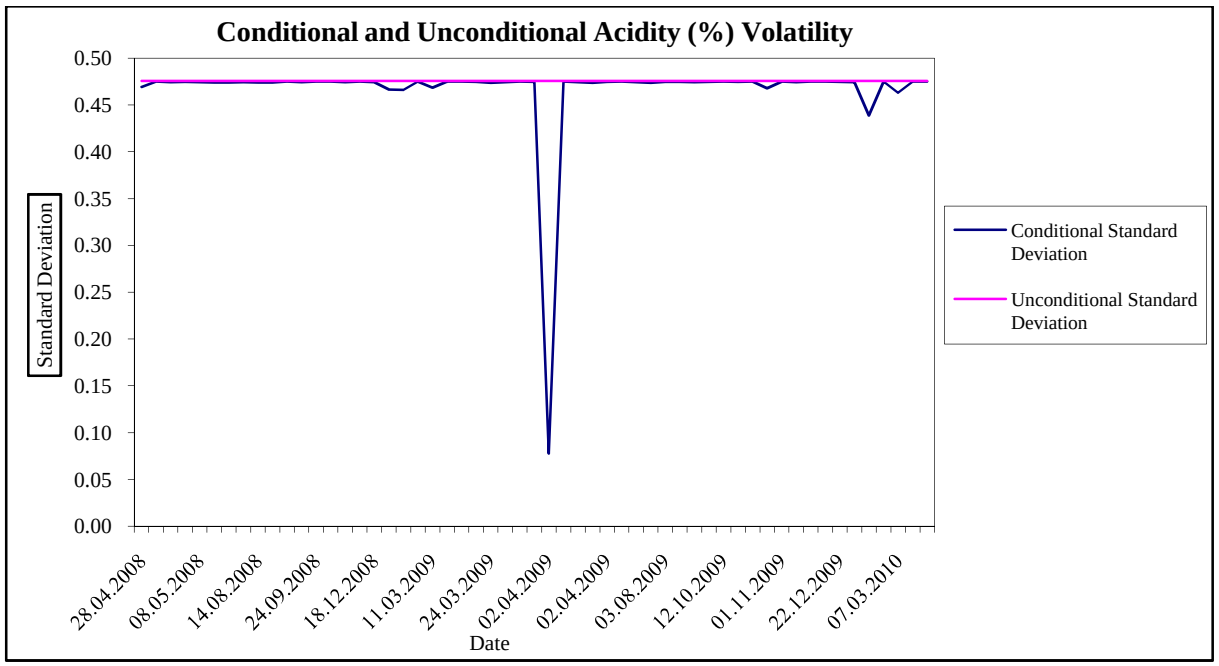


Figure 5. 25: Acidity (%) content of Soft Drinks products for the Period April 2008 to March 2010.

Figure 5.25shows conditional and unconditional standard deviation of Acidity (%) content over the period April 2008 to March 2010. Conditional deviations are over 0.08 during the sample period. As can be seen in Fig. 5.25, the deviation has relatively stable during sample period and spike behaviour in April 2009. However, volatility in deviation is low in this time period.

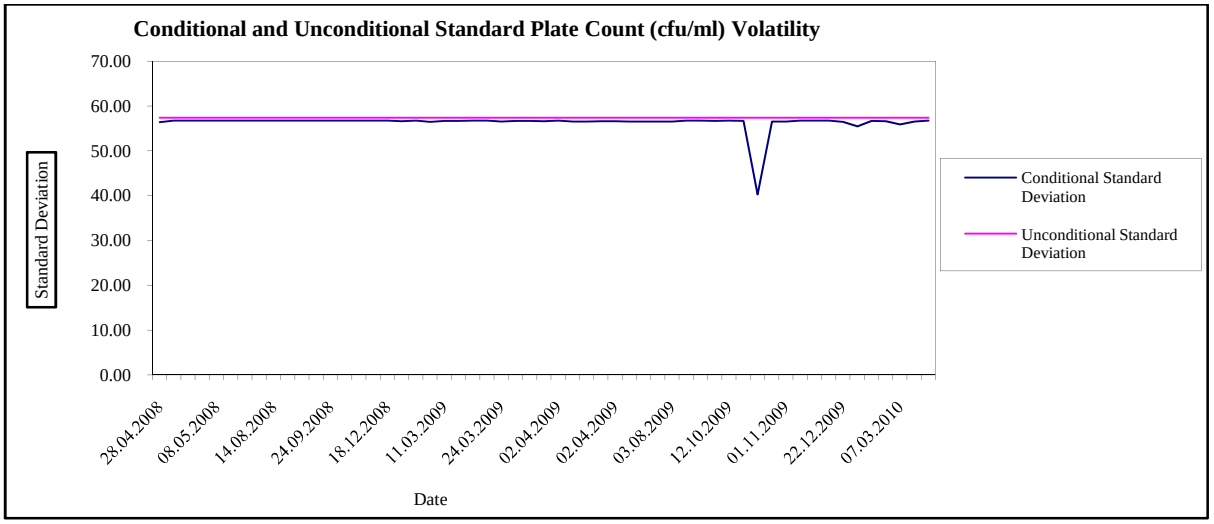


Figure 5. 26: Standard Plate Count (cfu/ml) content of Soft Drinks products for the Period April 2008 to March 2010.

Figure 5.26 shows the conditional and unconditional standard deviation of Standard Plate Count (cfu/ml) content over the period April 2008 to March 2010. Conditional deviations are over 40.26 during the sample period. The results indicate that the deviation relatively stable all over the period and spike behaviour in November 2009.

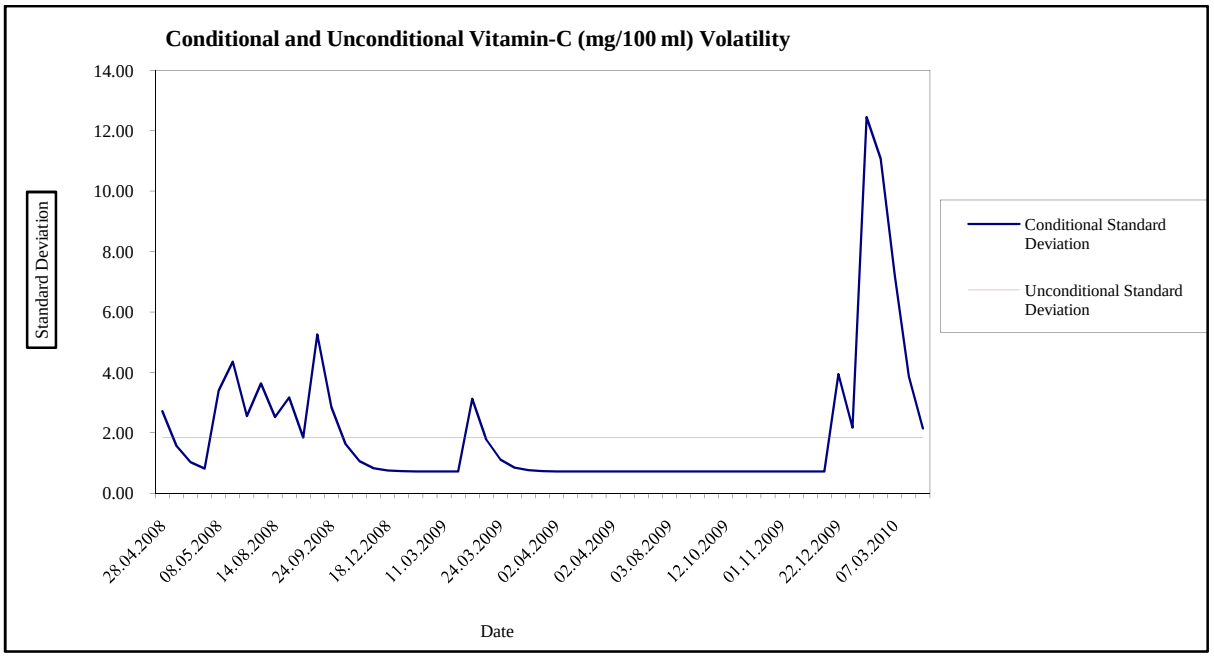


Figure 5. 27: Vitamin A (mcg/100g) content of soft drinks products for the Period April 2008 to March 2010.

Figure 5.27 shows the conditional and unconditional standard deviation of Vitamin A (mcg/100g) content over the period April 2008 to March 2010. Conditional deviations are over

0.70 during the sample period. The results indicate that the deviations are highly spike behaviour at first and last of the period 2008 and 2010 and relatively stable during the period 2009. The deviation is highly volatile during the period 2008–2010.

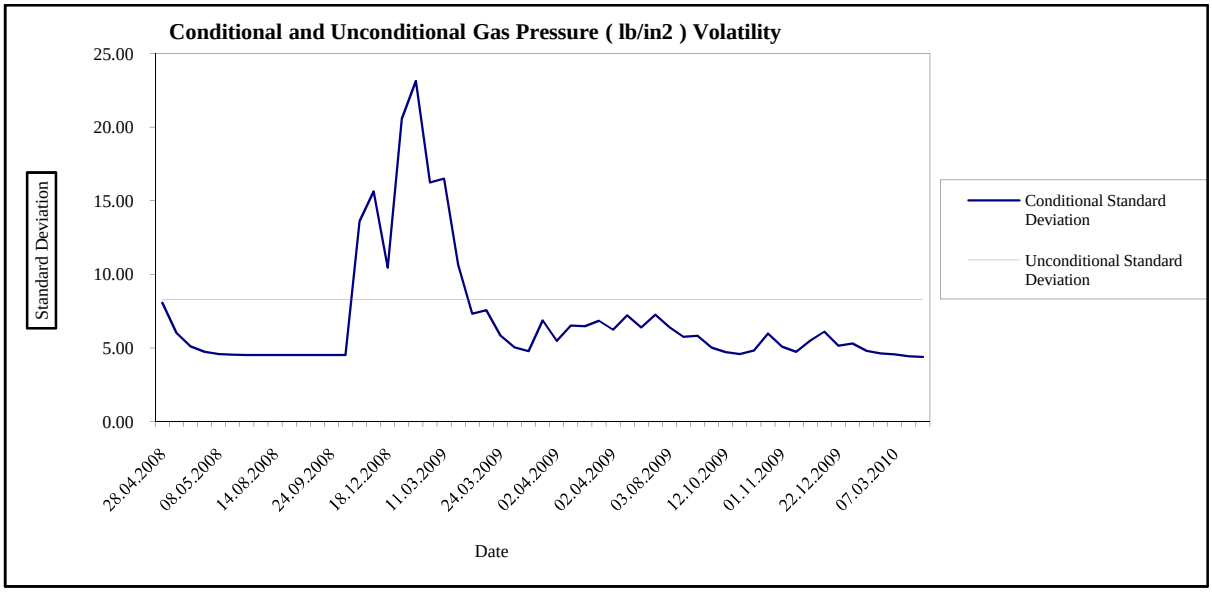


Figure 5. 28: Gas Pressure (lb/in^2) content of biscuit products for the Period April 2008 to March 20010.

Figure 5.28 shows the conditional and unconditional standard deviation of Gas Pressure (lb/in^2) content over the period April 2008 to March 20010. Conditional deviations are over 4.50 during the sample period. The results indicate that the deviation relatively stable all over the period and spike behaviour in December 2008 to March 2009.

5.16: Comparison among three statistical technique

Comparison among Logistic & Probit Regression and Discriminant Analysis in classification groups for soft drinks.

Table 5. 9: Summary of statistics of Logit, Probit model and Discriminant analysis.

		Logistic Regression		**Probit Regression**		**Discriminant analysis**	
Responding variable	**Independent Variable**	p-value	GOF	p-value	GOF	p-value	GOF
Yeast and	pH	0.395	0.70	0.360	0.71	0.221	-
Mold Count	Total Soluble	0.647		0.628		0.391	

(cfu/ml)	Solid(%)						
	Acidity(%)	0.455		0.443		0.225	
	Gas Pressure (lb/in^2)	0.349		0.328		0.162	
Standard Plate	pH	0.498	0.52	0.449	0.58	0.340	-
Count (cfu/ml)	Total Soluble Solid(%)	0.701		0.751		0.515	
	Acidity(%)	0.224		0.209		0.384	
	Gas Pressure (lb/in^2)	0.217		0.196		0.811	
Total Sugar	pH	0.009	0.90	0.002	0.98	0.000	0.000
(%)	Acidity(%)	0.005		0.002		0.003	
	Gas Pressure (lb/in^2)	0.329		0.222		0.151	

Note: GOF= Goodness-of-fit statistics.

From the above demonstrations of three different technique, Logit & Probit model and Discriminant function analysis, all of them provide are not equal predicted probability of the same variable which is given with the level of accepted range as prescribed by BSTI, Dhaka. The level of significance of Goodness-of-fit statistics are >0.05 under Logit and Probit, respectively but under Discriminant analysis are <0.05 according to accepted range of Total Sugar (%). Obviously, from these results, the Logit and Probit Model perform the best results in terms of the fulfill assumptions. If in the case of rejected predicted probility (p-value) Discriminant analysis yields same results of logit and probit model.

MILK

5.17 Description of milk

Milk is the normal mammary secretion of milking animals obtained from one or more milkings without either addition to it or extraction from it, intended for consumption as liquid milk or for further processing (Stan, 1999).

5.17.1 FAO Report on Bangladesh: Milk consumption lowest, prices highest in region

Average milk consumption in Bangladesh is the lowest in the region. Its cost is the highest in the region due to low yield and high production cost, making it almost impossible for the majority people to have the nutritious food item.

In Bangladesh, per capita daily calorie intake through milk is only 24 kilocalories, while in Sri Lanka it is 57, 82 in Nepal, 104 in India and 265 in Pakistan, according to statistical yearbook of Food and Agriculture Organisation (FAO).

Nutritionists say milk is an ideal food that easily provides large amounts of calcium and protein to the body but inadequate intake of milk is causing calcium deficiency and bone-related diseases like rickets.They said nutrients of milk can be had from other food items but people are usually not conscious enough to get the nutrients from other sources.

In the wake of the recent controversy over toxic melamine in milk, health and dairy experts said the best way to meet the milk demand is to expand dairy production at farm and household levels.According to FAO, average annual milk production in Bangladesh is 2,264,000 tonnes and only 13kg of milk is available for every person annually.

Low production results in the import of bulk amount of powdered milk. Bangladesh spent about Tk 1,500 crore to import 42,583.46 tonnes of powdered milk during the last fiscal year, said Tureen Afroze of United Nations Industrial Development Organisation (UNIDO).

"On an average, a Bangladeshi cow reportedly produces around 200kg of milk a year, which is 30 percent lower than an Indian cow's production figures. This low milk yield is mainly caused by poor livestock feed and low milk production of the common breeds of cattle in Bangladesh," says a study of International Farm Comparison Network (IFCN) on milk production in Bangladesh.According to dairy industry insiders, each kilogramme of milk on an average sells between Tk 40 and Tk 45 but in India it is around Tk 22. A litre of pasteurized milk is sold for around Tk 47 in Bangladesh.

Milk prices at farms of Bangladesh are about 40 to 50 percent higher than those of Indian and New Zealand farms, the IFCN study said."First of all, we have low productivity of milk and then the prices are too high. Therefore, milk consumption by majority people of the country is almost impossible," said Prof M Nazmul Hasan of Institute of Food and Nutrition Science at Dhaka University.

Citing a survey at Chokoria in Cox's Bazar, he said the survey found that nine percent of the children in that area suffered from rickets."Calcium deficiency is being seen a lot in recent times. More and more people are suffering from bone-related diseases," Nazmul told The Daily Star.

He suggested that the government should take strong steps to encourage dairy production at farm and household levels to meet the local demand because milk is an ideal food. Mohammad Ali, general manager of Brac Dairy and Food Project, told The Daily Star that shortage of fodder and low productivity of cattle are the two major factors that hold the dairy sector back.

"The dairy farms are mainly located in northern Bangladesh," he said, adding that the government could provide incentives like loan arrangements for farmers to rear cows at household level.Besides, cooperatives could be formed at village level to develop milk marketing system and ensure that the dairy farmers get due price of milk, he said, adding, "Dairy farms could reduce our unemployment problem."

The government should come forward and help set up infrastructure for milk preservation, Mohammad Ali added (The Daily Star, 2008).

Milk prouducts list:

Sl. No.	Name of milk powder
1.	Sagar Skimmed Milk.
2.	Rajat Skimmed Milk.
3.	Madhusudon Skimmed Milk.
4.	Amul Spray Infant Milk.
5.	Skim Milk Powder.
6.	Dried Skimmed Milk (DSM).
7.	Milk Powder.
8.	UHT milk.
9.	Cow head Full Cream Milk.
10.	Milk Chocolate.
11.	UHT Milk Low Fat.
12.	Aarong Pasteurized Milk.
13.	Therapeutic Milk.

14.	Fressh sweetened condensed filled milk.

5.18 Preliminary analysis of the data

After collecting data, the first task for a researcher is to organize and simplify the data so that it is possible to get a general overview of the results. One method for simplifying and organizing data is to construct a frequency distribution.

Table 5. 10: Frequency distribution results for Dried Milk.

Proximate Variable		Frequency	Percentage
Moisture (%)			
	Acceptable Range	4	17.4
	Not Acceptable Range	19	82.6
Protein (%)			
	Acceptable Range	8	28.6
	Not Acceptable Range	20	71.4
Fat (%)			
	Acceptable Range	22	68.8
	Not Acceptable Range	10	31.3
Total Ash (on dry basis), %			
	Acceptable Range	18	66.7
	Not Acceptable Range	9	33.3
Tritratable Acidity (as lactic acid), %			
	Acceptable Range	25	92.6
	Not Acceptable Range	2	7.4
Solubility, %			
	Acceptable Range	6	27.3
	Not Acceptable Range	16	72.7
Total Milk Solid, %			
	Acceptable Range	22	100
	Not Acceptable Range	0	0.0
Standard Plate Count, cfu/g			
	Acceptable Range	27	100
	Not Acceptable Range	0	0.0

Total Coliform, MPN/g			
	Acceptable Range	26	96.3
	Not Acceptable Range	1	3.7
Melamine (ppm/100g)			
	Acceptable Range	11	100
	Not Acceptable Range	0	0.0

Frequency distribution presented in Table 5.10 indicates that only Total Milk Solid (%), Melamine (ppm/100g) and Standard Plate Count (cfu/g) contains are reasonably acceptable for all samples and contains of Lactose (%) are unacceptable range were compared to the standard value prescribed by WFP, Dhaka.

5.19 Descriptive Statistics of Milk

Statistics are a set of tools for obtaining insight into a psychological phenomenon. Descriptive statistics summarise the data, making clear any trends, patterns etc. which may be lurking within them; they consist of visual displays such as graphs and summary statistics such as means (Hole, 2000).

Table 5. 11: Descriptive Statistics results for proximate analysis of Milk.

Proximate Variables	Minimum	Maximum	Mean	Std. Deviation
Moisture, %	2.03	6.36	4.63	1.08
Protein, %	2.55	41.93	25.10	13.73
Milk Fat, %	0.11	29.30	5.92	8.67
Total Ash (on dry basis), %	0.63	8.81	5.98	3.05
Tritratable Acidity (as lactic acid), %	0.12	1.96	1.14	0.61
Solubility , %	96.50	99.83	99.03	0.81
Total Milk Solid, %	20.47	97.64	91.86	15.97
Melamine (ppm/100g)	0.00	0.00	0.00	0.00
Lactose, %	1.99	40.84	14.48	16.14
Standard Plate Count, cfu/g	0.00	$1.24e^{+04}$	$1.95e^{+03}$	$3.04e^{+03}$
Total Coliform, MPN/g	0.00	1.70	0.06	0.33

The mean, standard deviation and other descriptive statistics for physiochemical analysis are displayed in Table 5.11. Here Moisture, %, Tritratable Acidity (as lactic acid), %, Solubility, %, Melamine (ppm/100g) and Total Coliform, MPN/g are comparatively low standard deviation (SD<2).

5.20 Application of control charts on milk

In order to verify whether quality of food products were under control condition or not we have adopted following control chart of milk for such purposes we have used several Shewhart Control Charts.

In this subsection we present results and analysis that is application of control charts. We show the results and analysis by type of products and types of control chart.

5.21 Process Capability Analysis (Using Normal Distribution Curve)

In this case, we want to assess the process capability for different industries producing certain milk. The proximate analysis of the milk is of concern. The specification limits on the milk are in given Appendix2. There has been a consistent problem with meeting the specification limits and the some process produces a high percentage of rejects.

The histogram of the data shows that proximate analysis of milk follow a normal distribution or approximately normal distribution. The variation from milktomilk can be estimated using the within group standard deviation. Since the process is stable and the measurements are normally or approximately normality distributed, the normal distribution option of process capability analysis can be used.

Quality characteristic: Moisture

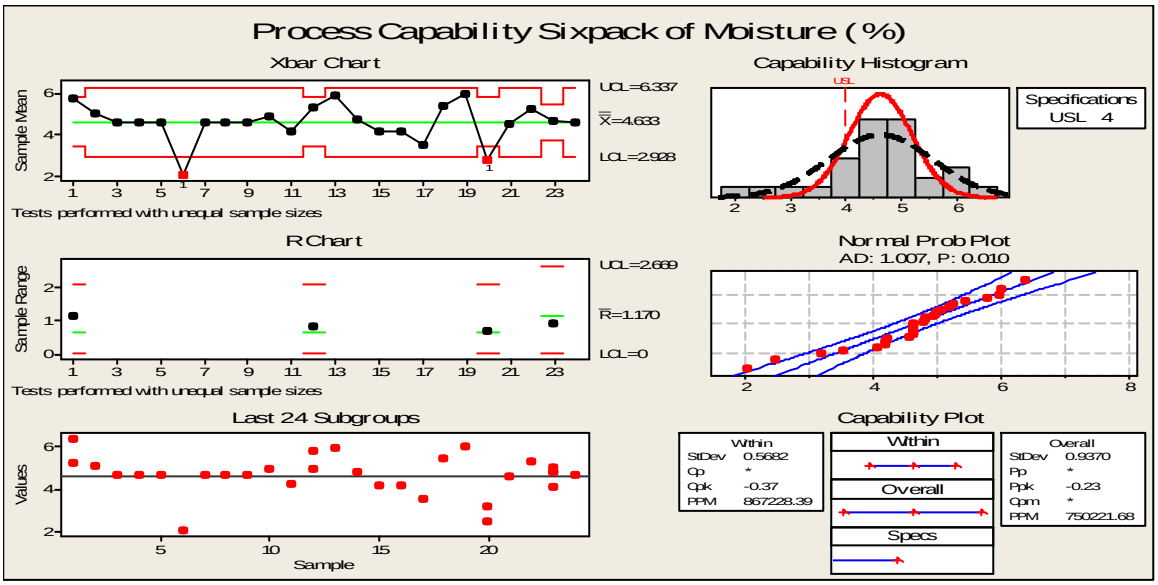


Figure 5. 29: Quality Control Charts and Process Capability Analysis for Moisture (%) of milk.

The quality control and process capability analysis chart given as output is the chart of Moisture (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control in the control limit in mean chart.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

From the Normal probability plot graph in Fig. 5.29, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test.

The report in Figure 5.29 shows the histogram of the data along with normal curves overlaid on the histogram. The products of milk of Moisture analysis report by this process exceed the Upper specification limit (USL). A significant percentage of the Moisture (%) of milk is outside of Upper Specification Limit.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-0.37 is less than 1 means that the process is off centered and is not capable.

Quality characteristic: Protein

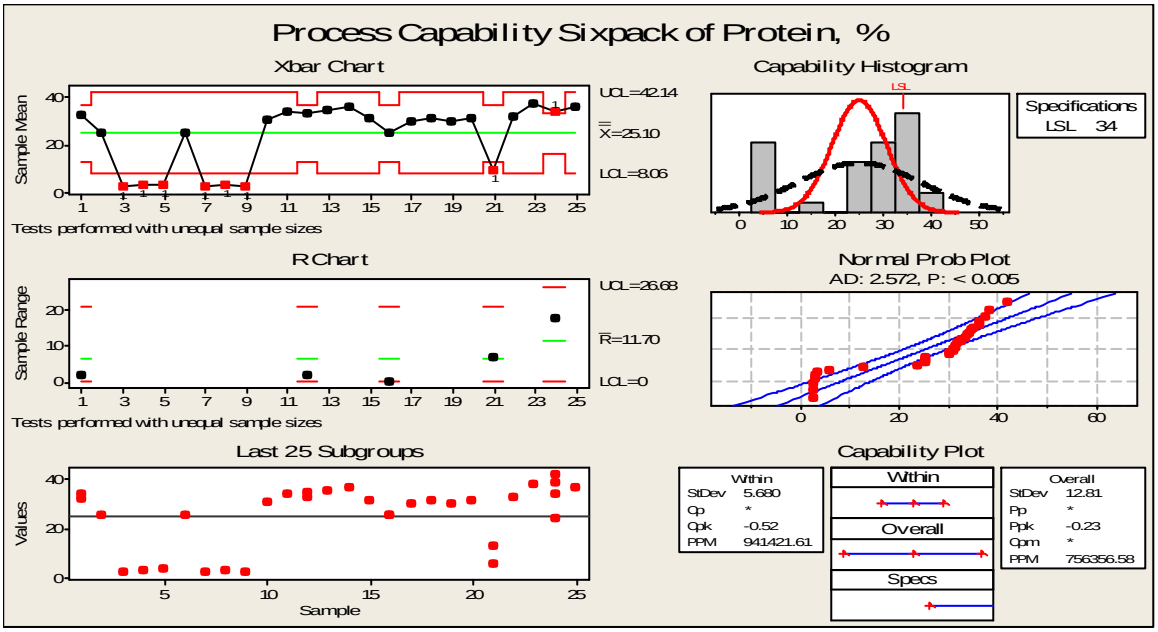


Figure 5. 30: Quality Control Charts and Process Capability Analysis for Protein, % of milk.

The quality control and process capability chart given as output is the chart of Protein, %. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control.

The upper right box reports the process data including the lower specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

From the Normal probability plot graph in Fig. 5.30, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test.

The report in Figure 5.30 shows the histogram of the data along with normal curves overlaid on the histogram. The products of milk of Protein, % analysis report by this process are exceeding the lower specification limit (USL). A significant percentage of the Protein, % of milk is outside of Lower Specification Limit.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-0.52 is less than 1 means that the process is off centered and not capable.

Quality Characteristic: Total Ash (on dry basis), %

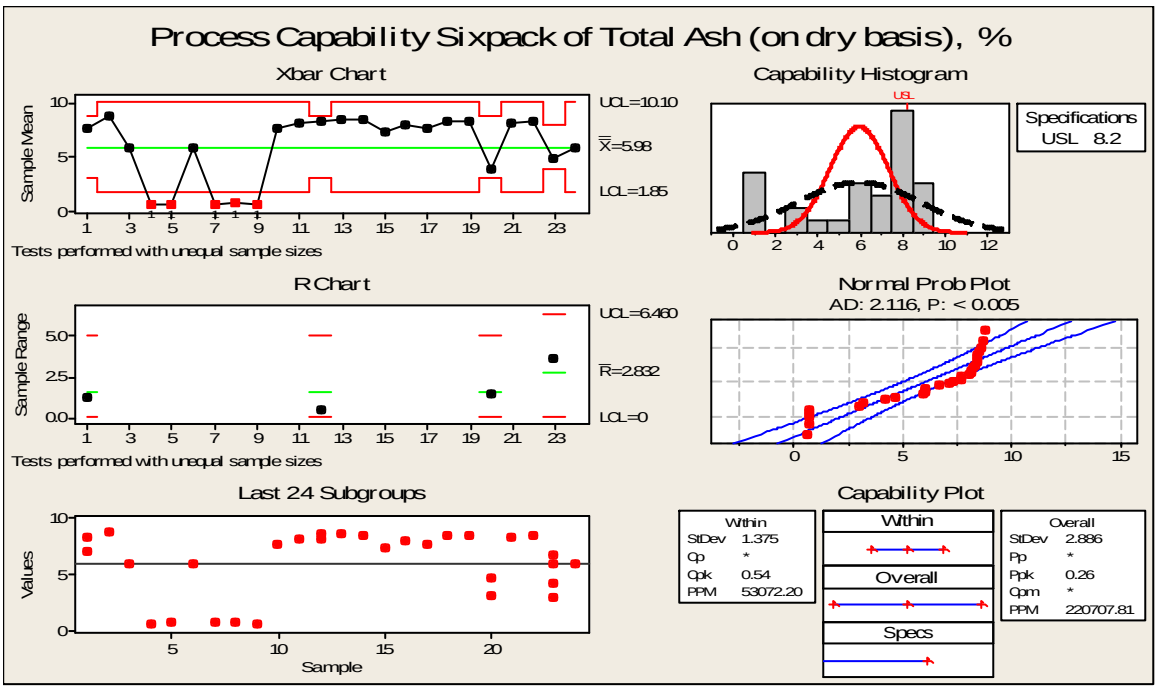


Figure 5. 31: Quality Control Charts and Process Capability Analysis for Total Ash (on dry basis), % of milk.

The quality control and process capability chart given as output is the chart of Total Ash (on dry basis), %. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

From the Normal probability plot graph in Fig. 5.31, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test.

The report in Figure 5.31 shows the histogram of the data along with normal curves overlaid on the histogram. The products of milk of Total Ash (on dry basis), % analysis report by this process are exceeding the Upper specification limit (USL). A significant percentage of the Total Ash (on dry basis), % of milk is outside of Upper Specification Limit.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.54 is less than 1 means that the process is off centered and not capable.

Quality Characteristic: Tritratable Acidity (as lactic acid), %

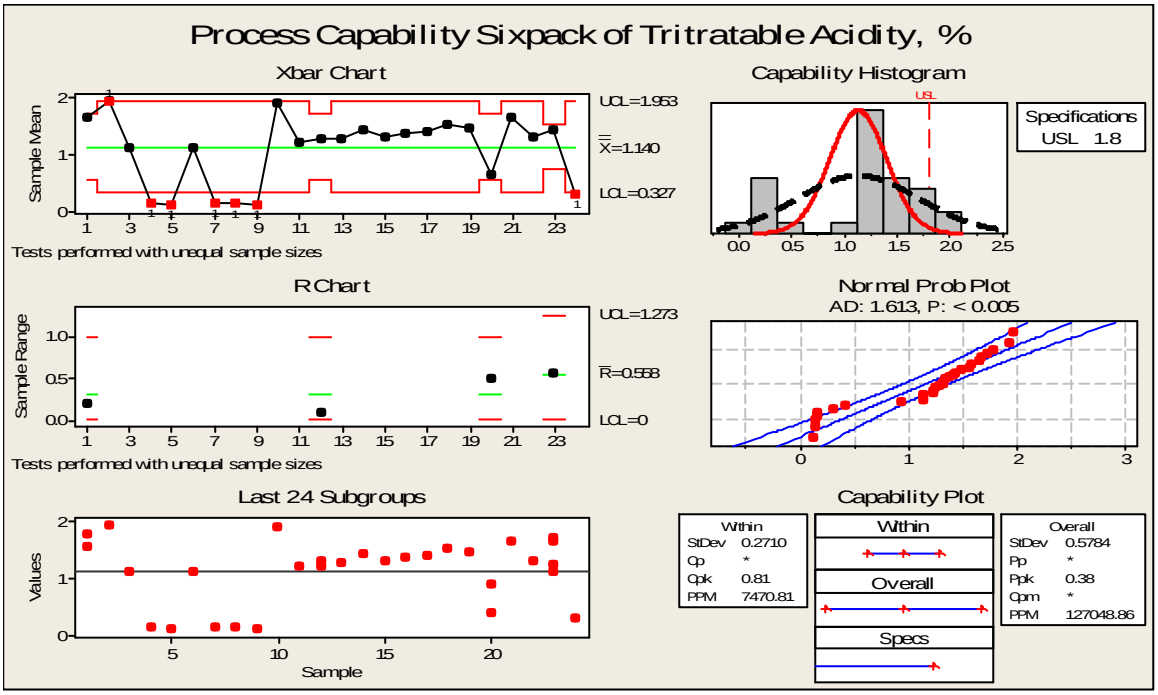


Figure 5. 32: Quality Control Charts and Process Capability Analysis for Tritratable Acidity (as lactic acid), % of milk.

The quality control chart given as output is the chart of Tritratable Acidity (as lactic acid), %. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point

along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

From the Normal probability plot graph in Fig. 5.32, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test.

The report in Figure 5.32 shows the histogram of the data along with normal curves overlaid on the histogram. The products of milk of Tritratable Acidity (as lactic acid) analysis report by this process exceed the Upper specification limit (USL). A significant percentage of the Tritratable Acidity (as lactic acid) (%) of milk is outside of Upper Specification Limit.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.81 is less than 1 means that the process is off centered and is not capable.

Quality Characteristic: Solubility, %

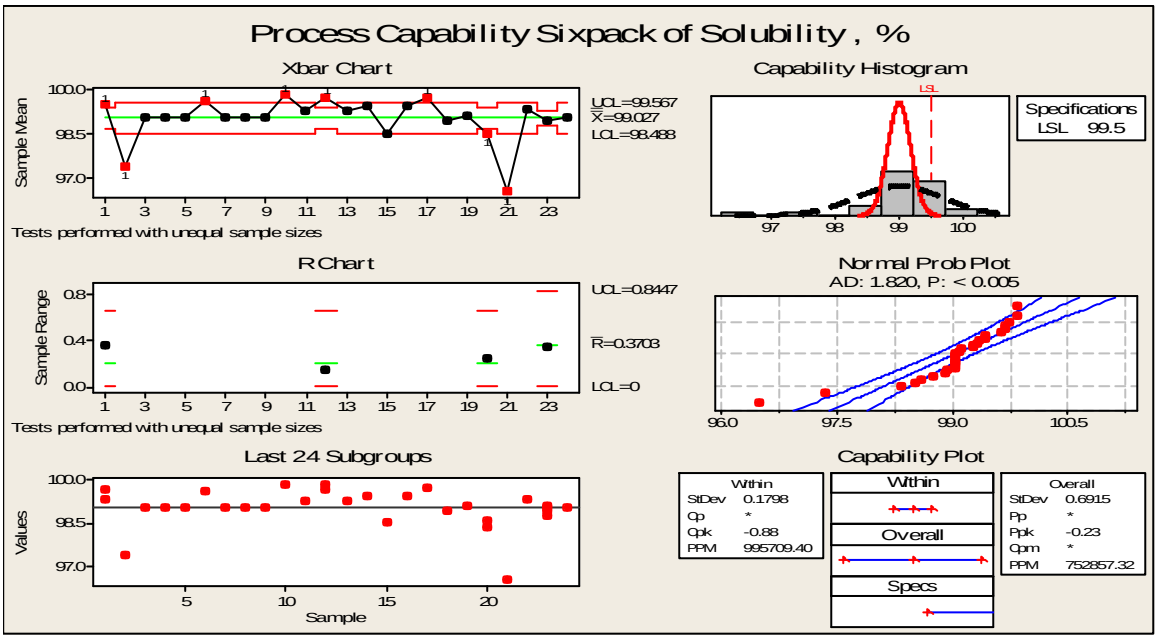


Figure 5. 33: Quality Control Charts and Process Capability Analysis for Solubility, % of milk.

The quality control chart given as output is the chart of Solubility (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

From the Normal probability plot graph in Fig. 5.33, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test.

The report in Figure 5.33 shows the histogram of the data along with normal curves overlaid on the histogram. The products of milk of Solubility analysis report by this process exceed the Lower specification limit (LSL). A significant percentage of the Solubility (%) of milk is outside of Lower Specification Limit.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-0.88 is less than 1 means that the process is off centered and is not capable.

Quality Characteristic: Total Milk Solid, %

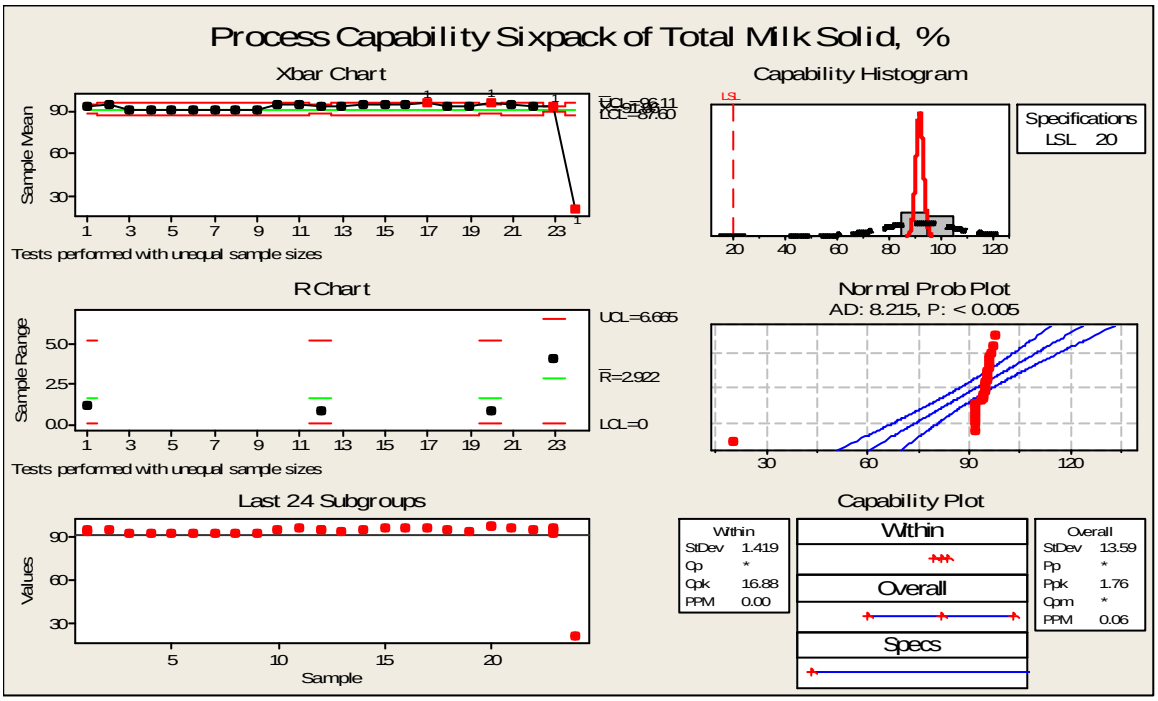


Figure 5. 34: Quality Control Charts and Process Capability Analysis for Total Milk Solid, % of Milk.

The quality control chart given as output is the chart of Total Milk Solid, %. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control.

The upper right box reports the process data including the lower specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

From the Normal probability plot graph in Fig. 5.34, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test.

The report in Figure 5.34 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Milk of Total Milk Solid analysis report by this process is not

exceed the Lower specification limit (LSL). An insignificant percentage of the Total Milk Solid (%) of Milk is outside of Lower Specification Limit.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =16.88 is greater than 1 means that the process is centered and capable.

Quality Characteristic: Standard Plate Count, cfu/g

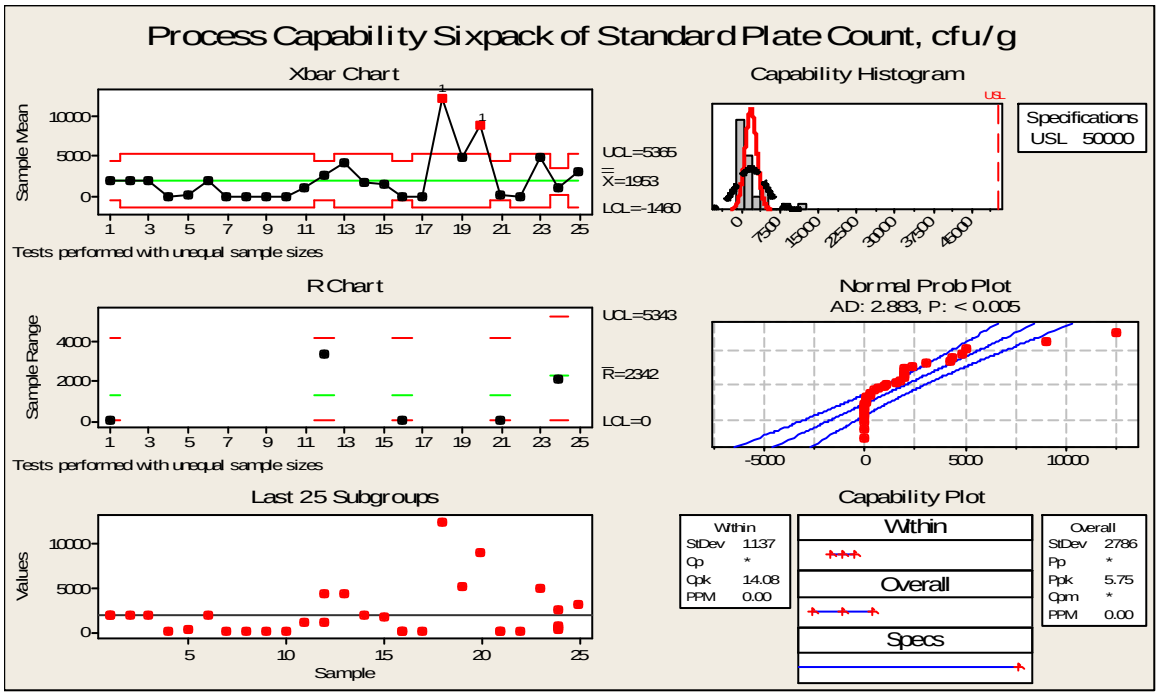


Figure 5. 35: Quality Control Charts and Process Capability Analysis for Standard Plate Count, cfu/g of Milk.

The quality control chart given as output is the chart of Standard Plate Count, cfu/g. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

From the Normal probability plot graph in Fig. 5.35, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is

0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test.

The report in Figure 5.35 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Milk of Standard Plate Count analysis report by this process is not exceed the Upper specification limit (USL). An insignificant percentage of the Standard Plate Count, cfu/g of Milk is outside of Upper Specification Limit.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =14.08 is greater than 1 means that the process is centered and capable.

5.22 Comparison of *t* test and Wilcoxon signed-rank test

In analytical chemistry it is essential to validate a given analytical method to determine its applicability, reproducibility, repeatability and the accuracy of the data obtained. The analyst should establish some basis to prove that the method is working for its intent use. Normally, the amount of data is rather small and the so-called *Student t distribution* should be used (IAEA, 2003).

(Doane & Seward, 2007) indicated that the Wilcoxon signed-rank test is robust to non-normal and somewhat asymmetrical, population shapes. In fact, the assumptions underlying the *t*-test are violated in every situation because there is neither an underlying normal distribution nor an interval level of measurement (Meek et al., 2007).

Table 5. 12: Comparison of *t* test and Wilcoxon signed-rank test for physiochemical analysis of milk according to their acceptable range as prescribed by WFP, Dhaka.

Variables	Wilcoxon test	P-value	*t*-test	P-value	Kolmogorov-Smirnov test	P-value
Moisture, %	269.5	0.000	7.28	0.000	0.156	>0.150
Protein, %	79.0	0.002	-3.43	0.001	0.317	<0.010
Milk Fat, %	5.0	0.000	-13.10	0.000	0.378	<0.010
Total Ash (on dry basis), %	147.5	0.844	-2.25	0.984	0.235	<0.010
Tritratable Acidity (as lactic acid), %	9.0	1.000	-5.61	1.000	0.262	<0.010

Solubility, %	48.0	0.006	-2.73	0.006	0.172	0.087
Total Milk Solid, %	252.0	1.000	19.34	1.000	0.499	<0.010
Standard Plate Count, cfu/g	0.0	1.000	-82.06	1.000	0.261	<0.010
Total Coliform, MPN/g	1.0	1.000	1.00	0.327	0.539	<0.010

This study also investigated the behavior of the one sample *t*-test for milk samples. Table 5.12 shows the result of the *t*-test that was significant in Moisture (%), Protein (%), Milk Fat (%) and Solubility (%) compared with acceptable range as Prescribed by WFP, Dhaka where as others were insignificant.

To test the assumption of normality use the Kolmogorov-Smirnov test. From this test, the Sig. (p) value is compared to the a priori alpha level (level of significance for the statistic) and a determination is made as to reject ($p \leq \alpha$) or retain ($p > \alpha$) the null hypothesis (The & The, n.d.).

For the above example, where $\alpha = 0.05$, given that $p \leq \alpha$ for most of the variables except Moisture (%) and Solubility (%), we found that most of Variables were not normally distributed. Therefore, the assumption of normality has met for this few variables.

When the null hypothesis was true, wilcoxon signed-rank test performed as efficent or more power than the *t*-test. There were a total of 2 cases in which the Wilcoxon signed-rank test predicted probability (p-value) results more power than the *t*-test when H_0 was true as fuffill the assumptions. But when null hypothesis was false, the *t*-test and wilcoxon signed-rank test has given same results though normality assumptions has violated.

5.23 Binary logistic regression analysis of Milk

A stata software was performed to identify Milk quality parameters appropriate for inclusion in a logistic regression model to predict the accepted/ unaccepted as prescribed acceptable range by WFP, Dhaka in a milk sample.

Logistic regression was used to assess the impact of a chemical analysis of milk analysis parameter to identify the quality of Milk which was supplied by some milk sample produced industries. The model contained a independent variables Moisture (%) and 4 (four) dependent variables as acceptability of Protein (%), Total Ash (on dry basis) (%), Tritratable Acidity (as lactic acid) (%) and Solubility (%) as presented in table 5.13.

Table 5. 13: Binary logistic regression results of Proximate Analysis parameters of Milk.

Responding variable	Independent Variable	Coeff. (OR)	Std. Error	z-value	P-value	AIC	BIC	GOF
Protein (%)	Moisture (%)	-0.688 (0.502)	0.535	-1.29	0.198	30.05	32.14	0.273
Total Ash (on dry basis) (%)		3.497 (33.00)	1.653	2.11	0.034	20.39	22.57	0.734
Tritratable Acidity (as lactic acid) (%)		0.320(1.899)	0.858	0.37	0.709	17.06	19.15	0.318
Solubility (%)		0.263 (1.301)	0.437	0.60	0.547	29.420	31.602	0.281

Note: Coeff.= Coefficient of the model, OR=Odds Ratio, Std. Err.= Standard Error, AIC= Akaike Information Criterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

The full model containing a variable Moisture (%) was statistically insignificant with P>0.05 according to accepted range of test parameter as prescribed by WFP, Dhaka except Total Ash (on dry basis) (%). Indicating that the model was able to distinguish between milk samples which reported having and not having accepted range as prescribed by WFP, Dhaka. The *p*-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in Table 5.13 with insignificant (P>0.05).

5.24 Binary probit regression analysis of Milk

To determine the factors influencing the decision to acceptable in food products a probit model were used. The decision to use probit is based on the fact that the decision variable is discrete and dichotomous (one either acceptable of Milk as prescribed by WFP, Dhaka or not), discrete decisions are analyzed using qualitative response models one of which is probit.

Collecting Milk analysis data findings revealed that Milk analysis data can be classified into two classes; acceptable and non acceptable according to WFP and other standard prescribed range. A probit regression was used to determine the factors that influence the decision to analysis value among food producer or analyzer operators.

Table 5. 14: Binary Probit/Normit regression results of proximate parameters of Milk.

Responding variable	Independent	Coeff.	Std.	z-	P-	AIC	BIC	GOF

	Variable	**(M.E.)**	**Err.**	**value**	**value**			
Protein (%)	Moisture (%)	-0.422 (-0.160)	0.322	-1.31	0.190	30.06	32.15	0.274
Total Ash (on dry basis) (%)		2.064 (0.704)	0.904	2.28	0.022	20.21	22.39	0.763
Tritratable Acidity (as lactic acid) (%)		0.190 (0.031)	0.472	0.40	0.687	17.04	19.13	0.325
Solubility (%)		0.156 (0.0515)	0.263	0.59	0.554	29.427	31.609	0.282

Note: Coeff.= Coefficient of the model, M.E.= Marginal Effects, Std. Err.= Standard Error, AIC= Akaike Information Criterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

The full model containing a variable Moisture (%) was statistically insignificant with P>0.05 according to accepted range of test parameter as prescribed by standard Institution except Total Ash (on dry basis) (%). Indicating that the model was able to distinguish between milk samples which reported having and not having accepted range as prescribed by standard Institution. The p-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in Table 5.14 with insignificant (P>0.05).

To find correct estimates of standard errors and p-values it is necessary to choose better model. To select the model, here, we consider two information criteria used to compare models. In general, “smaller is better”: given two models, the one with the smaller AIC fits the data better than the one with the larger AIC. As with the AIC, a smaller BIC indicates a better-fitting model (Samples, n.d.).

We fit a model explaining the quality of milk products has on the basis of Moisture (%) against the acceptability of Protein (%), Total Ash (on dry basis) (%), Tritratable Acidity (as lactic acid) (%) and Solubility (%). The goodness-of-fit criteria for comparing these two model results are found in table 5.13 and 5.14. AIC and BIC were determined by logit and probit regression of the predicted values obtained in the fit to the true model equation. For the test parameter studied in Table 5.13 and 5.14; based on the AIC and BIC criterion were approximated same using a Logistic and probit model.

5.25 Discriminant function analysis

The discriminant analysis to milk under Acceptable Range as WFP, Dhaka, with the test to determine classify groups of acceptability between the groups using Wilks' Lambda revealed that the diverse parameters yielded a statistical significance at a level of 0.05.

Table 5. 15: Discriminant Function Analysis results of physiochemical analysis of Milk.

Responding variable	Independent Variable	Wilks' Lambda	P-value	goodness-of-fit test	
				Box's M	P-value
Protein (%)	Moisture (%)	0.913	0.195	1.370	0.255
Total Ash (on dry basis) (%)		0.590	0.001	0.785	0.388
Tritratable Acidity (as lactic acid) (%)		0.993	0.725	3.769	0.089
Solubility (%)		0.983	0.565	0.738	0.407

Box's M test tests the assumption of homogeneity of covariance matrices. This test is very sensitive to meeting the assumption of multivariate normality. Discriminant function analysis is **robust** even when the homogeneity of variances assumption is not met, provided the data do not contain important outliers (Bian, n.d.). For our data, we found the groups don't differ in their covariance matrices and fulfill the assumption of DA. When n is large, small deviations from homogeneity will be found significant, which is why Box's M must be interpreted in conjunction with inspection of the log determinants.

The Wilk's lambdais a measure of the overall statistical significance of the Linear Discriminant Functions and is statistically insignificant results at the 5 percent level of probability for the LDF 1 of Moisture (%) against the acceptability range of test parameter (refer to Table 5.15). This implies that the group means for the independent variables are not different on the discriminating function. While other parametersTotal Ash (on dry basis) (%) are not.

5.26 ARCH-LM test

To detect the presence of ARCH effect in the mean equation of milk, we use the ARCH-LM (Lagrange multiplier) test.

Table 5. 16: ARCH-LM and DF test analysis results of chemical analysis of Milk.

Variable	LM test for autoregressive conditional heteroskedasticity (ARCH)		Dickey-Fuller test for unit root	
	Chi-square Statistic	P-value	Test Statistic, Z(t)	P-value
Moisture (%)	0.042	0.838	-3.439	0.0097
Protein (%)	10.623	0.001	-2.368	0.1509
Total Ash (on dry basis) (%)	12.467	0.000	-2.422	0.1355
Tritratable Acidity (as lactic acid) (%)	13.100	0.000	-2.905	0.0448
Solubility (%)	0.069	0.793	-3.174	0.0215
Total Milk Solid (%)	1.219	0.270	-3.322	0.0139
Standard Plate Count (cfu/g)	0.029	0.864	-4.889	0.0000

In our analysis the different value for different variables of above parameters of the ARCH-LM test; the lags included in the test are only 1. The corresponding P-Value is <0.05, which is very low for Protein (%), Total Ash (on dry basis) (%) and Tritratable Acidity (as lactic acid) (%). So we have no difficulty to reject the null hypothesis of no ARCH error and conclude that there is an ARCH error in the analysis series. This confirms that the order of the ARCH error is three variables for analysis of milk food products. Whereas other parameters are insignificant that means no ARCH effects of the models. The estimation results are given in the table 5.16.

Table 5.16 shows that the values of DF test for all variables p-value <0.05 at 5%, level of significance for all variable except Protein (%) and Total Ash (%) which implies that the variables series is stationary. An outcome of DF test confirms that the physiochemical analysis variables series is stationary.

5.27 Spike Behaviour of ARCH(1) and GARCH(1,1) model estimations

The presence of extreme spikesin our analysis of milk products that is a bad characteristic of food products.

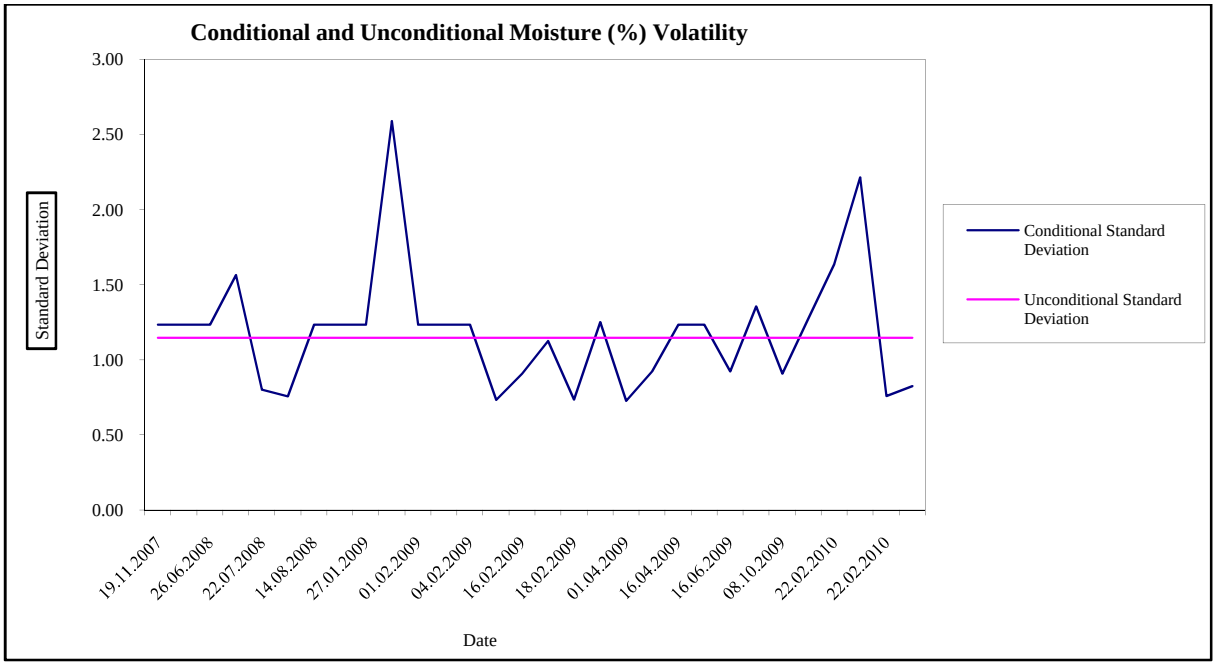


Figure 5. 36: Moisture (%) content of milk products for the Period November 2007 to February 2010.

Figure 5.36 shows the conditional and unconditional standard deviation of Moisture (%) content over the period November 2007 to February 2010. Conditional standard deviations are over 0.50 during the sample period. The results indicate that the standard deviation almost stable among 2007 to 2010 and in spike behaviour in January 2009 and February 2010. However, volatility in deviations is very low in this time period.

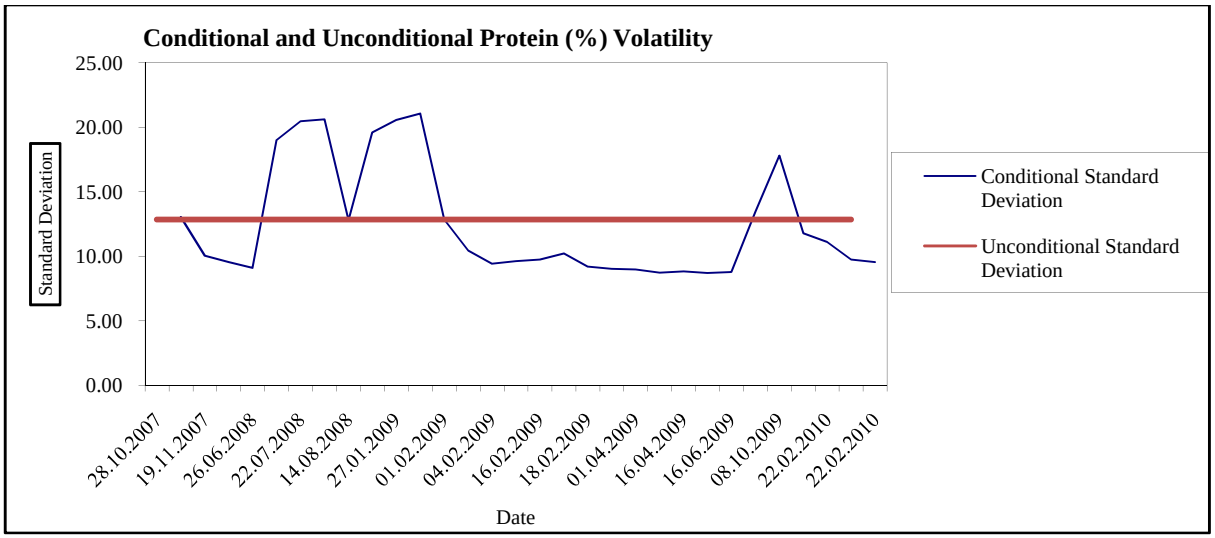


Figure 5. 37: Protein (%) content of Milk products for the Period October 2007 to February 2010.

Figure 5.37 shows the conditional and unconditional standard deviation of Protein (%) content over the period October 2007 to February 2010. Conditional standard deviations are over 8.00 during the sample period. The results indicate that the deviations increased significantly at 2008 and 2009 and decreased between February 2009 to 2010 and also in spike behaviour at October 2009. However, volatility in deviation is low in this time period.

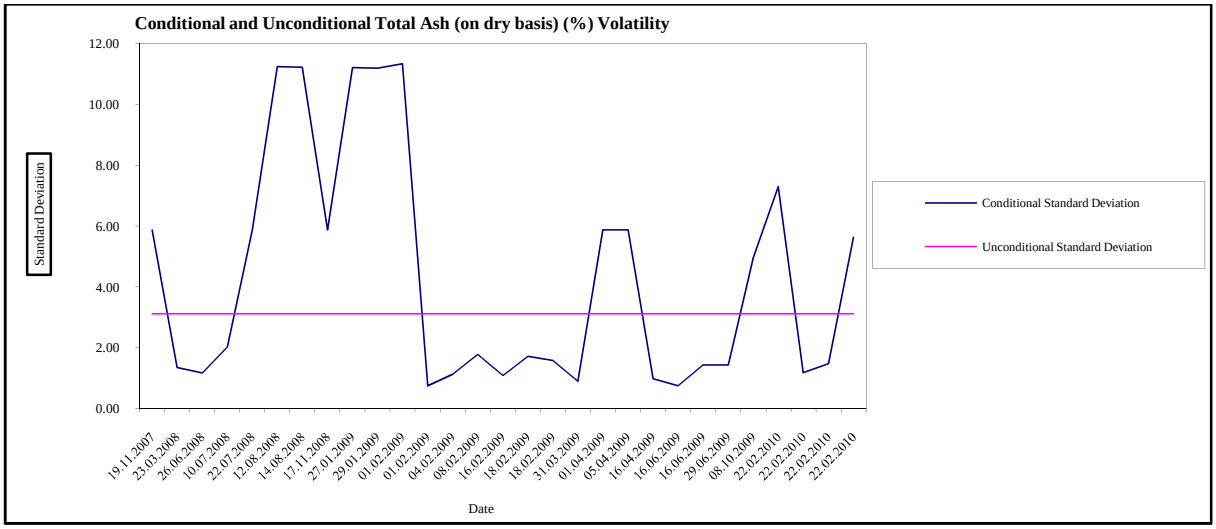


Figure 5. 38: Total Ash (on dry basis) (%) content of milk products for the Period November 2007 to February 2010.

Figure 5.38 shows the conditional and unconditional standard deviation of Total Ash (on dry basis) (%) content over the period November 2007 to February 2010. Conditional standard deviations are over 0.5 during the sample period. As can be seen in Fig. 5.38, the deviation has an increasing trend June 2008 to February 2009 and relatively stable then also ups and down in the period 2009 and 2010. However, volatility in deviation is high in this time period.

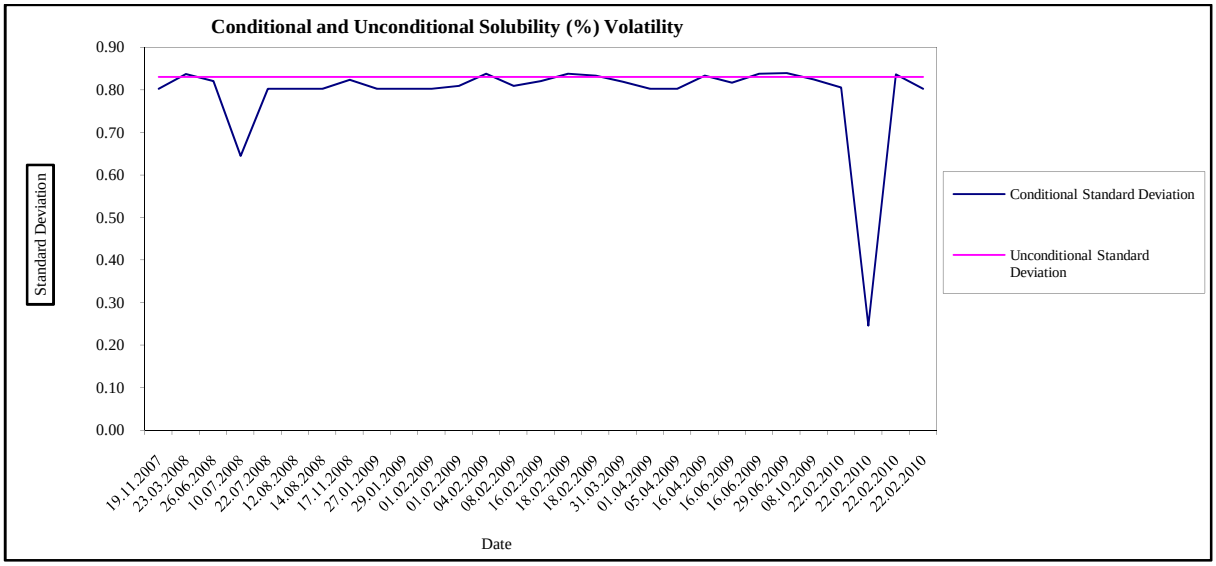


Figure 5. 39: Solubility (%) content of milk products for the Period November 2007 to February 2010.

Figure 5.39 shows the conditional and unconditional standard deviation of Solubility (%) content over the period November 2007 to February 2010. Conditional deviations are over 0.20 during the sample period. The results indicate that the deviations decreasing trend between 2007 -2010 and also spike behaviour at February 2010. However, volatility in deviations is low in this time period.

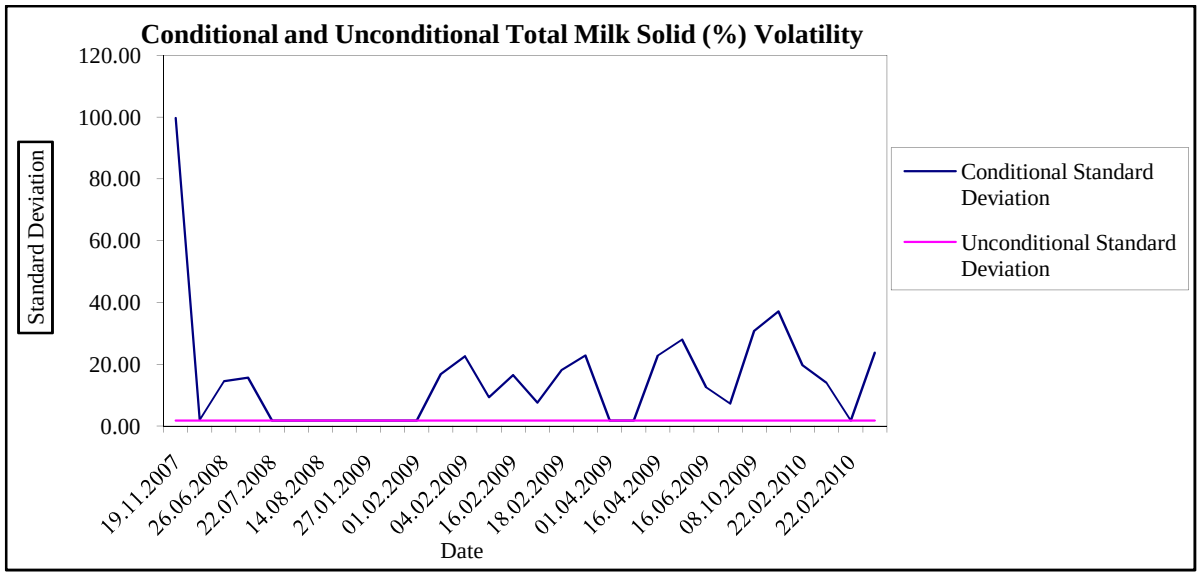


Figure 5. 40: Total Milk Solid (%) content of milk products for the Period November 2007 to February 2010.

Figure 5.40 shows conditional and unconditional standard deviation of Total Milk Solid (%) content over the period November 2007 to February 2010. Conditional deviations are over 1.5 during the sample period. As can be seen in Fig. 5.40, the deviation has relatively stable during sample period. However, volatility in deviation is low in this time period. The deviation is spike behaviour during the period 2007–2010.

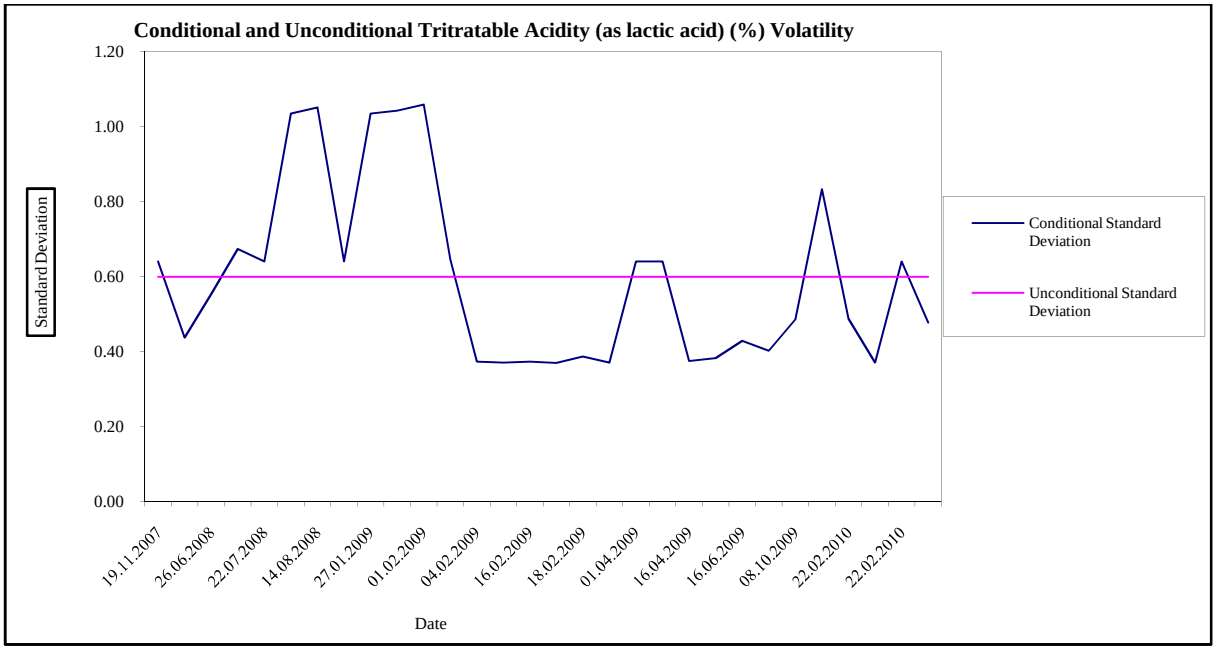


Figure 5. 41: Tritratable Acidity (as lactic acid) (%) content of milk products for the Period November 2007 to February 2010.

Figure 5.41 shows the conditional and unconditional standard deviation of Tritratable Acidity (as lactic acid) (%) content over the period November 2007 to February 2010. Conditional deviations are over 0.35 during the sample period. The results indicate that the deviations are highly spike behaviour at first of the period 2008 and 2009. As can be seen in Fig.5.41, the deviation has a decreasing trend between 2009 -2010. The deviation is highly volatile during the period 2007–2010.

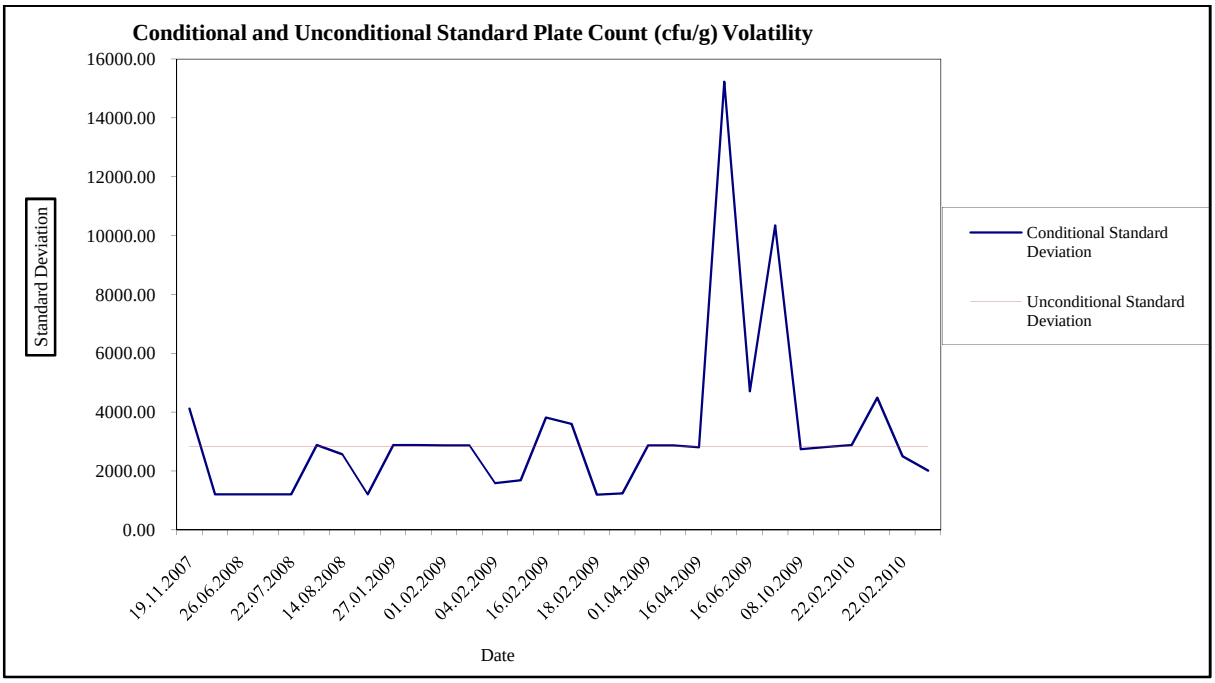


Figure 5. 42: Standard Plate Count (cfu/g) content of milk products for the Period November 2007 to February 2010.

Figure 5.42 shows the conditional and unconditional standard deviation of Vitamin A (mcg/100g) content over the period November 2007 to February 2010. Conditional deviations are over 1200.00 during the sample period. The results indicate that the deviations are low spike behaviour at the period 2007 and 2009 and relatively high spike behaviour during the period March 2009 to October 2009. The deviation is low volatile during the period 2007–2010.

5.28: Comparison of statistical technique:

Comparison among Logistic & Probit Regression and Discriminant Analysis in classification groups for Milk.

Table 5. 17: Summary of statistics of Logit, Probit model and Discriminant function analysis.

		Logistic Regression		**Probit Regression**		**Discriminant analysis**	
Responding variable	Independent Variable	p-value	GOF	p-value	GOF	p-value	GOF
Protein (%)	Moisture (%)	0.198	0.273	0.190	0.274	0.195	0.255
Total Ash (on dry basis) (%)		0.034	0.734	0.022	0.763	0.001	0.388
Tritratable Acidity (as lactic acid) (%)		0.709	0.318	0.687	0.325	0.725	0.089
Solubility (%)		0.547	0.281	0.554	0.282	0.565	0.407

Note: GOF= Goodness-of-fit statistics.

From the above demonstrations of three different technique, Logit & Probit model and Discriminant function analysis, all of them provide are not exact equal predicted probability of the same variable which is given with the level of accepted range as prescribed by standard institution. The level of significance of Goodness-of-fit statistics are >0.05 under Logit &Probit and Discriminant analysis. Obviously, from these results, Discriminant analysis perform the best results in terms of the fulfill the assumptions. If in the case of assumptions fullfill in Discriminant analysis yields better results than logit and probit model.

CHAPTER 6: PARBOILED RICE

6.1 Introduction

This chapter describes the Parboiled rice for product description and analysis for the study. A description of prducts includes the following sub sections: benefits of products, rice production in Bangladesh. The resulting data were employed in different levels of analysis. The chapter concludes by giving the empirical specification and estimation procedures for the fitted models.

6.2 Description of rice

Parboiled Rice is rough rice soaked, steamed and dried before milling. This procedure gelatinizes the starch in the grain and ensures a separateness of grain. Parboiled rice is favored among chefs who desire a fluffy, separate cooked rice ("Parboiled Rice-Cube Suggestions:," n.d., *Rice Parboiled Cube Grains 50 Pound at FoodServiceDirect.com!*, n.d.).

About 90% of the rice is parboiled in Bangladesh (Dasgupta, 2001). People in Bangladesh are habituated to the taste of parboiled rice, which is claimed to have a better shelf-life than raw rice (un-parboiled) due to the gelatinization of starch (Juliano, 1993). Parboiled rice also gives higher milling output than raw rice. The head rice recovery was reported as 51% and 60-80% from raw rice and parboiled rice, respectively (Ahiduzzaman, 2008; Sareepuang, Siriamornpun, Wiset, & Meeso, 2008).

6.2.1 Benefits of using this products

- Favored among chefs who desire a fluffy, separate, cooked rice.
- Longer shelf life.
- Can hold on steam table 4 hours.
- Unlike regular milled white rice which is sticky.
- Can be refregerated and frozen for later use.
- Low cost per serving.
- High in fiber and rich in complex carbohydrates.
- High nutritional value-no cholesterol, fat or sodium ("Parboiled Rice-Cube Suggestions:," n.d.).

6.2.2 Rice Production in Bangladesh

Rice production systems make a vital contribution to the reduction of hunger and poverty in Bangladesh. Total rice production in Bangladesh was 10.32 million tons in the year 1975-76 when the country's population was only 79.90 millions and cultivated rice area was 10.32 million ha. However, the country is now producing 27.32 million tons in 10.71 million ha rice area to feed more than 140 million people ha (DAE, 2007; statistics, 2007). This indicates that the growth of rice production was much faster than the growth of population and the cultivable rice area change is not very significant between the years 1975 and 2007. This increase in rice production has been possible owing largely to the adoption of modern rice varieties on around 73% of the cultivated rice land which contributes to about 85% of the country's total rice production, modern rice cultivation technology, improvement irrigation facilities and applications of fertilizer and pesticides (BBS, 2006) ("Effects of Increasing Temperature and Population Growth on Rice Production in Bangladesh : Implications for Food Security," n.d.).

6.3 Preliminary analysis of the data

After collecting data, the first task for a researcher is to organize and simplify the data so that it is possible to get a general overview of the results. One method for simplifying and organizing data is to construct a frequency distribution (*MTH 161 Handouts*, n.d.).

Table 6. 1: Frequency distribution for physiochemical parameter of Parboiled Rice.

Variable		Frequency	Percentage
Broken (%)			
	Acceptable Range	17	100.0
	Not Acceptable Range	0	0.0
Moisture (%)			
	Acceptable Range	14	82.4
	Not Acceptable Range	3	17.6
Damaged/discoloured (%)			
	Acceptable Range	17	100.0
	Not Acceptable Range	0	0.0
Yellow Kernels (%)			
	Acceptable Range	16	94.1
	Not Acceptable Range	1	5.9
Red and Streaked (%)			
	Acceptable Range	17	100.0
	Not Acceptable Range	0	0.0

Chalky grain (%)			
	Acceptable Range	17	100.0
	Not Acceptable Range	0	0.0
Paddy per Kg			
	Acceptable Range	17	100.0
	Not Acceptable Range	0	0.0
Other Varieties (%) Category			
	Acceptable Range	17	100.0
	Not Acceptable Range	0	0.0
Milling Degree			
	Acceptable Range	17	100.0
	Not Acceptable Range	0	0.0
SPC(cfu/g)			
	Acceptable Range	8	53.3
	Not Acceptable Range	7	46.7
Total Coli Form (MPN/g)			
	Acceptable Range	12	80.0
	Not Acceptable Range	3	20.0
Total Fungi (cfu/g)			
	Acceptable Range	15	100.0
	Not Acceptable Range	0	0.0
Aspergillus flavus (cfu/g)			
	Acceptable Range	13	100.0
	Not Acceptable Range	0	0.0
Aflatoxin (B1, B2, G1, G2)			
	Acceptable Range	15	100.0
	Not Acceptable Range	0	0.0

Frequency distribution presented in Table 6.1 indicates that only Standard Plate Count (cfu/g) contains remarkable number of cases are unacceptable range were compared to the Requirements (Riviana Foods Pty Ltd—Product Specification – Tastic Parboiled Rice). On the other hand rest of the analysis contains are reasonably acceptable range were compared to the standard value prescribed by WFP, Dhaka, UGANDA, FDUS EAS, Riviana Foods Pty Ltd—Product Specification, The African Organization for Standardization, Regional Organisation for Standards and Quality, CROSQ and Role of the CDPHE Laboratory in Retail Marijuana.

6.4 Descriptive Statistics of Parboiled Rice

Statistics are a set of tools for obtaining insight into a psychological phenomenon. Descriptive statistics summarise the data, making clear any trends, patterns etc. which may be

lurking within them; they consist of visual displays such as graphs, and summary statistics such as means (Hole, 2000).

Table 6. 2: Descriptive Statistics results for proximate analysis of Parboiled Rice.

Variables	Minimum	Maximum	Mean	Std. Deviation
Broken (%)	1.85	25.00	11.95	6.74
Moisture (%)	11.86	17.19	13.31	1.35
Damaged/Discoloured (%)	0.05	3.06	1.13	0.73
Yellow Kernels (%)	0.11	2.37	1.14	0.72
Red and Streaked (%)	0.00	1.00	0.48	0.34
Chalky grain (%)	0.05	6.00	1.46	1.92
Paddy per Kg	0.00	30.00	12.35	12.52
Other Varieties (%)	0.00	4.44	1.32	1.38
Milling Degree	1	1	1.00	0.00
SPC(cfu/g)	$9.00e^{+02}$	$8.80e^{+05}$	$1.05e^{+05}$	$2.31e^{+05}$
Total Coli Form (MPN/g)	0.00	460.00	76.82	135.38
Total Fungi (cfu/g)	0.00	4200.00	399.53	1064.48
Aspergillus flavus (cfu/g)	0.00	0.00	0.00	0.00
Aflatoxin (B1, B2, G1, G2)	0	1	0.13	0.35

The mean, standard deviation and other descriptive statistics for physiochemical and microbial analysis are displayed in Table 6.2. Here Broken (%), Paddy per Kg, Standard Plate Count (cfu/g), Total Coli Form (MPN/g) and Total Fungi (cfu/g) are highly standard deviation (SD>2).

6.5 Application of control charts on Parboiled Rice

In order to verify whether quality of food products were under control condition or not we have adopted following control chart of Parboiled Rice for such purposes we have used several Shewhart Control Charts.

In this subsection we present results and analysis that is application of control charts. We show the results and analysis by type of products and types of control chart.

6.6 Process Capability Analysis (Using Normal Distribution Curve)

In this case, we want to assess the process capability for different industries producing certain Parboiled Rice. The proximate analysis of the Parboiled Rice is of concern. The specification limits on the Parboiled Rice are in given appendix 3. There has been a consistent problem with meeting the specification limits and the some process produces a high percentage of rejects.

The histogram of the data shows that proximate analysis of Parboiled Rice follow a normal distribution or approximately normal distribution. The variation from Parboiled RicetoParboiled Rice can be estimated using the within group standard deviation. Since the process is stable and the measurements are normally or approximately normality distributed, the normal distribution option of process capability analysis can be used.

Quality characteristic: Broken (%)

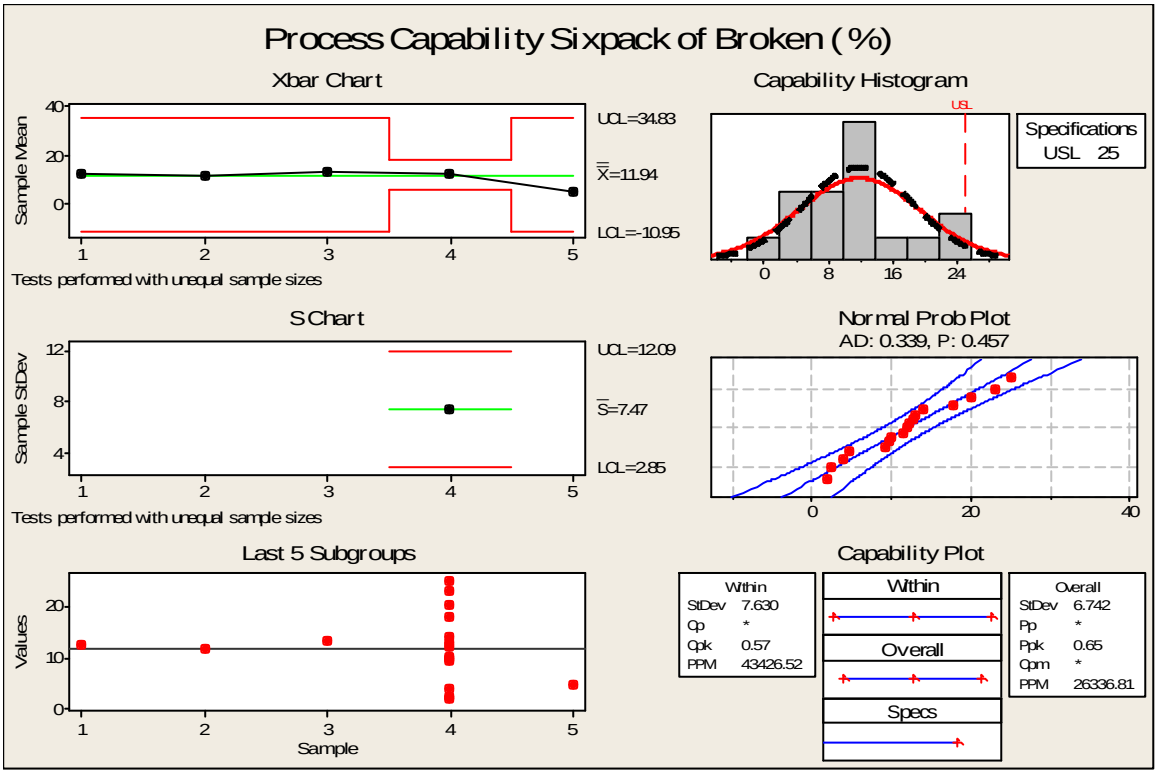


Figure 6. 1: Quality Control Charts and Process Capability Analysis for Broken (%) of Parboiled Rice.

The output is the quality control chart and process capability analysis. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control.

The right box reports the process data including the upper specification limit. These values were provided by the Minitab statistical package program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 6.1 shows the histogram of the data along with normal curves overlaid on the histogram. A normal curve with a solid line. The Parboiled Rice products of broken analysis report by this process slight exceed the upper specification limit (USL). Here also notice that insignificant percentage of the broken of parboiled rice is outside of Upper Specification Limit.

From the Normal probability plot graph in Figure 6.1, the Anderson-Darling (AD) Normality test shows that we are unable to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the $\alpha = 0.05$ significance level (K. M. Bower, n.d.). This is due to the fact that the p-value for the A-D test is 0.457, which is greater than 0.05 - a frequently used level of significance for such a hypothesis test.The necessary assumptions appear to have been fulfilled and we may investigate the capability of this process, as shown in Figure 6.1.

The potential or within process capability of the process is reported on the right hand side. Cpk =0.57 is less than 1 means that the process is off-centered and is not capable.

Quality Characteristic: Moisture (%)

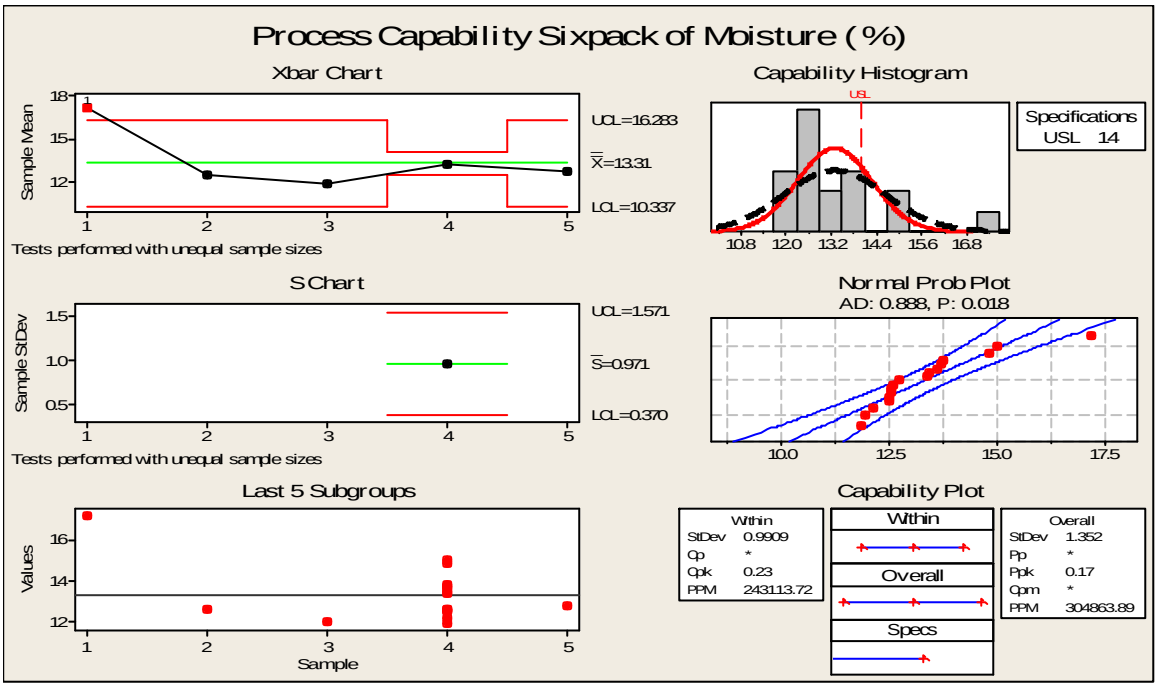


Figure 6. 2: Quality Control Charts and Process Capability Analysis for Moisture (%) of Parboiled Rice.

The quality control and process capability analysis chart given as output is the chart of Moisture (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control except only a point outside in the control limit in mean chart.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 6.2 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Parboiled Rice of Moisture analysis report by this process exceed the Upper specification limit (USL). A significant percentage of the Moisture (%) of Parboiled Rice is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 6.2, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level (K. M. Bower, n.d.). This is due to the

fact that the p-value test is 0.018, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.23 is less than 1 means that the process is off centered and is not capable.

Quality Characteristic: Damaged/discoloured (%)

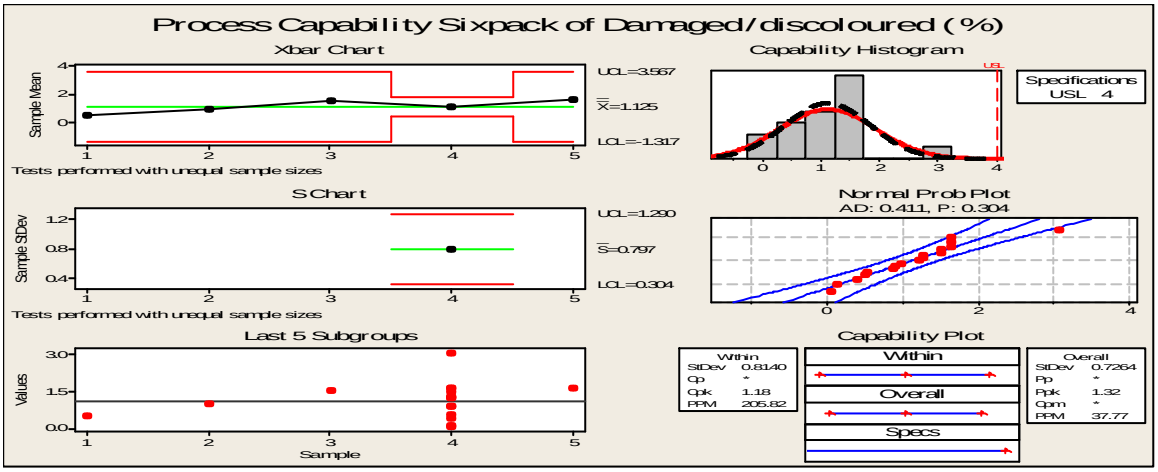


Figure 6. 3: Quality Control Charts and Process Capability Analysis for Damaged/ discoloured (%) of Parboiled Rice.

The quality control and process capability chart given as output is the chart of Damaged/discoloured (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 6.3 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Parboiled Rice of Damaged/discoloured analysis report by this process are not exceeding the Upper specification limit (USL). An insignificant

percentage of the Damaged/discoloured (%) of Parboiled Rice is outside of Upper Specification Limit.

From the Normal probability plot graph in Figure 6.3, the Anderson-Darling (AD) Normality test shows that the A-D test exhibits a p-value greater than 0.05 (in this case, the p-value = 0.304) and there are no serious deviations from linearity in the Normal probability plot. We may therefore reasonably conclude that (i) the process is in statistical control and (ii) the data can be assumed to approximately follow a Normal distribution. The necessary assumptions appear to have been fulfilled and we may investigate the capability of this process, as shown in Figure 6.3.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =1.18 is greater than 1 means that the process is centered and capable.

Quality Characteristic: Yellow Kernels (%)

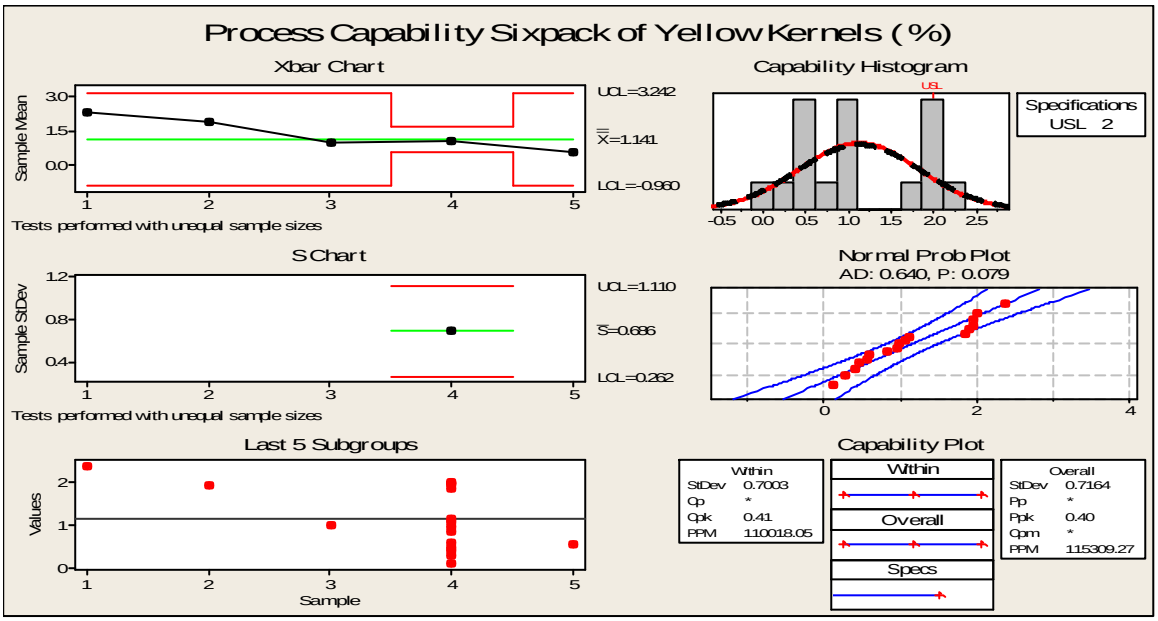


Figure 6. 4: Quality Control Charts and Process Capability Analysis for Yellow Kernels (%) of Parboiled Rice.

The quality control chart given as output is the chart of Yellow Kernels (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 6.4 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Parboiled Rice of Yellow Kernels analysis report by this process exceed the Upper specification limit (USL). A significant percentage of the Yellow Kernels (%) of Parboiled Rice is outside of Upper Specification Limit.

From the Normal probability plot graph in Figure 6.4, the Anderson-Darling (AD) Normality test shows that the A-D test exhibits a p-value greater than 0.05 (in this case, the p-value = 0.079) and there are no serious deviations from linearity in the Normal probability plot. We may therefore reasonably conclude that (i) the process is in statistical control and (ii) the data can be assumed to approximately follow a Normal distribution. The necessary assumptions appear to have been fulfilled and we may investigate the capability of this process, as shown in Figure 6.4.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.41 is less than 1 means that the process is off centered and is not capable.

Quality Characteristic: Red and Streaked (%)

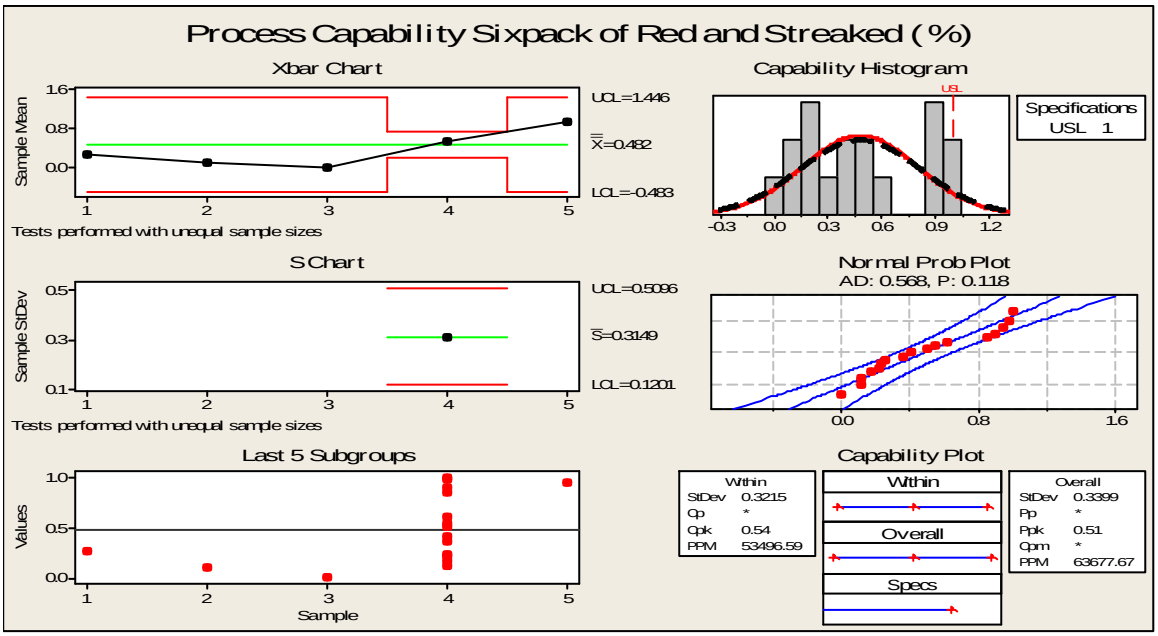


Figure 6. 5: Quality Control Charts and Process Capability Analysis for Red and Streaked (%) of Parboiled Rice.

The quality control chart given as output is the chart of Red and Streaked (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 6.5 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Parboiled Rice of Red and Streaked analysis report by this process exceed the Upper specification limit (USL). A significant percentage of the Red and Streaked (%) of Parboiled Rice is outside of Upper Specification Limit.

From the Normal probability plot graph in Figure 6.5, the Anderson-Darling (AD) Normality test shows that the A-D test exhibits a p-value greater than 0.05 (in this case, the p-value = 0.118) and there are no serious deviations from linearity in the Normal probability plot. We may therefore reasonably conclude that (i) the process is in statistical control and (ii) the data can be assumed to approximately follow a Normal distribution. The necessary assumptions appear to have been fulfilled and we may investigate the capability of this process, as shown in Figure 6.5.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.54 is less than 1 means that the process is off centered and is not capable.

Quality Characteristic: Chalky grain (%)

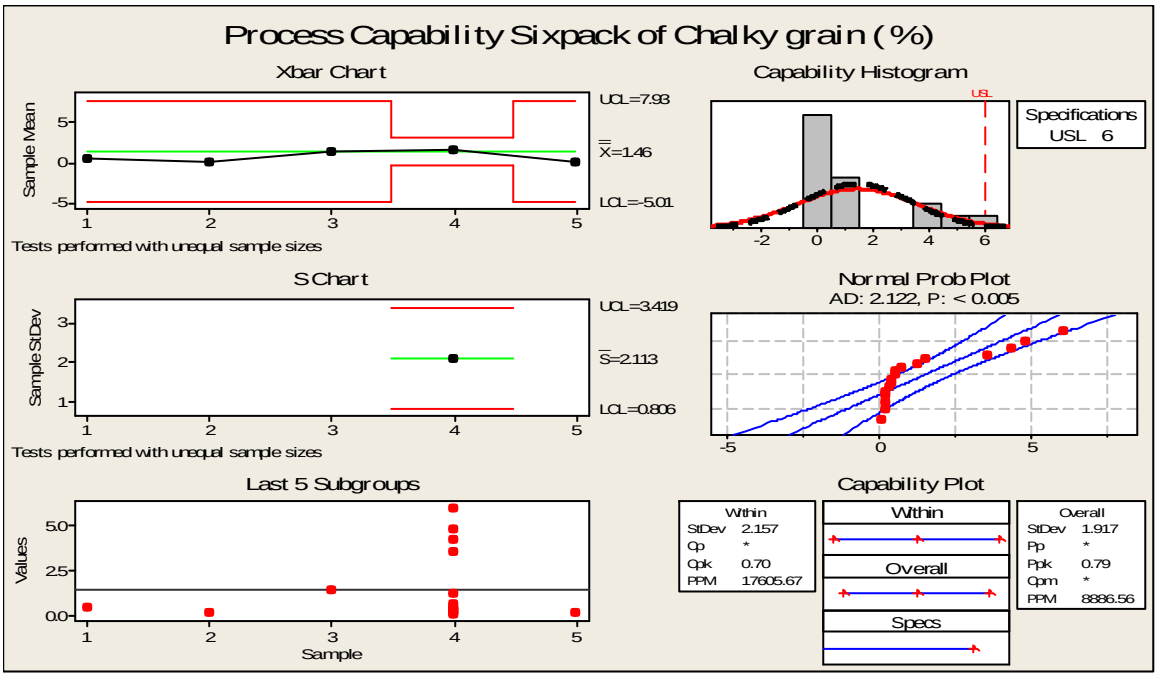


Figure 6. 6: Quality Control Charts and Process Capability Analysis for Chalky grain (%) of Parboiled Rice.

The quality control chart given as output is the chart of Chalky grain (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 6.6 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Parboiled Rice of Chalky grain analysis report by this process exceed the Upper specification limit (USL). A significant percentage of the Chalky grain (%) of Parboiled Rice is slight outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 6.6, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value

test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.70 is less than 1 means that the process is off centered, platykurtic and is not capable.

Quality Characteristic: Paddy per Kg

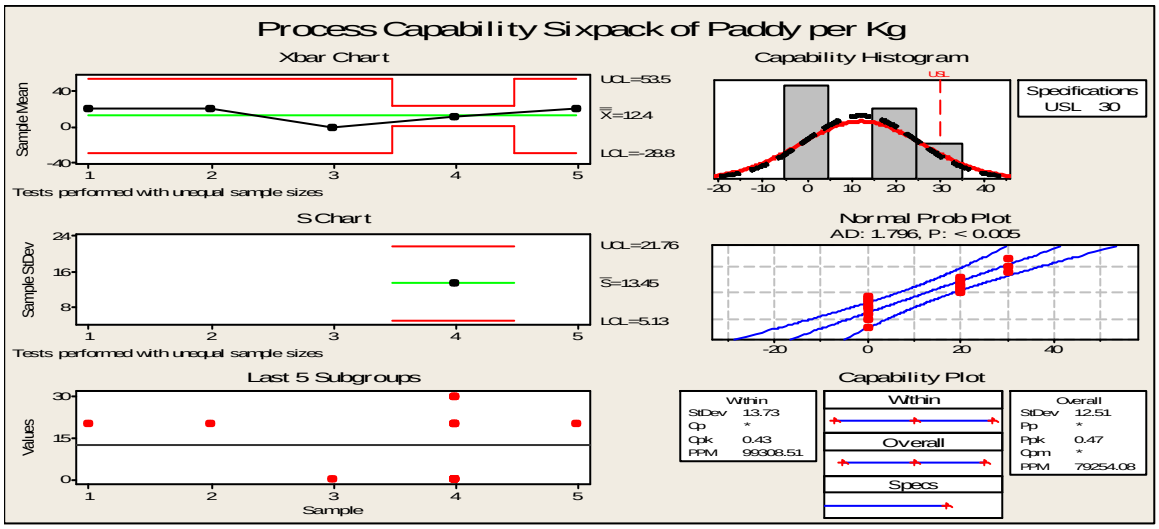


Figure 6. 7: Quality Control Charts and Process Capability Analysis for Paddy per Kg of Parboiled Rice.

The quality control chart given as output is the chart of Paddy per Kg. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 6.7 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Parboiled Rice of Paddy analysis report by this process exceed the Upper specification limit (USL). A significant percentage of the Paddy per Kg of Parboiled Rice is slight outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 6.7, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.43 is less than 1 means that the process is off centered and is not capable.

Quality Characteristic: Other Varieties (%)

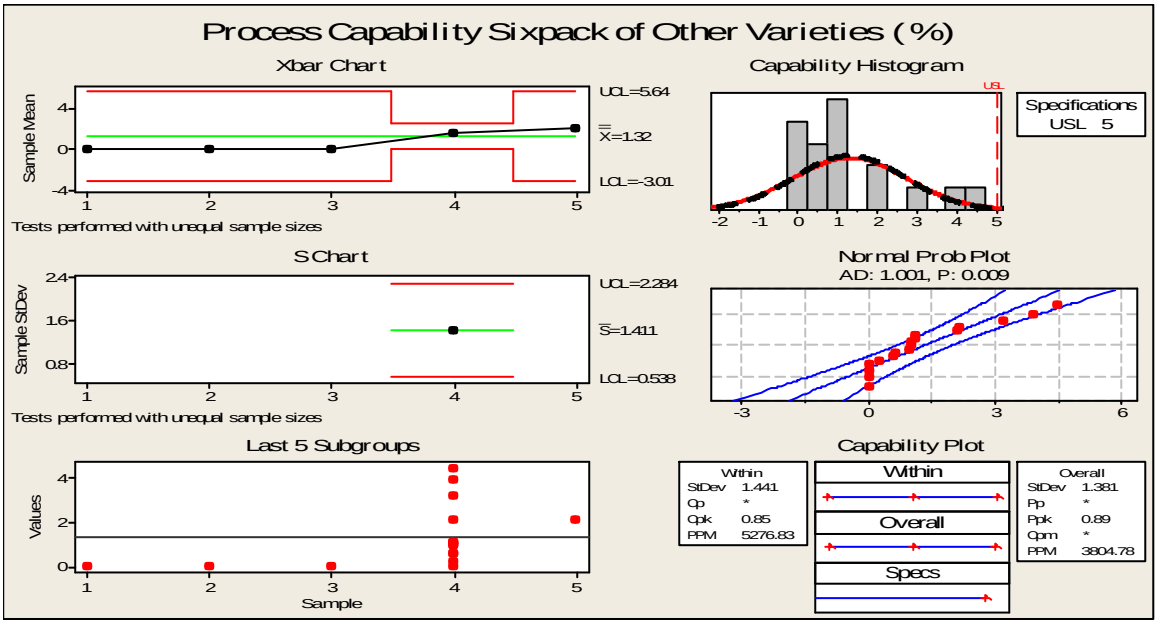


Figure 6. 8: Quality Control Charts and Process Capability Analysis for Other Varieties (%) of Parboiled Rice.

The quality control chart given as output is the chart for the mean and standard deviation of Other Varieties (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clearly shows that the process is in control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 6.8 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Parboiled Rice of Other Varieties analysis report by this process are not exceeding the Upper specification limit (USL). An insignificant percentage of the Other Varieties (%) of Parboiled Rice is inside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 6.8, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.009, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.85 is less than 1 means that the process is off centered, platykurtic and is not capable.

Quality Characteristic: Standard Plate Count (cfu/g)

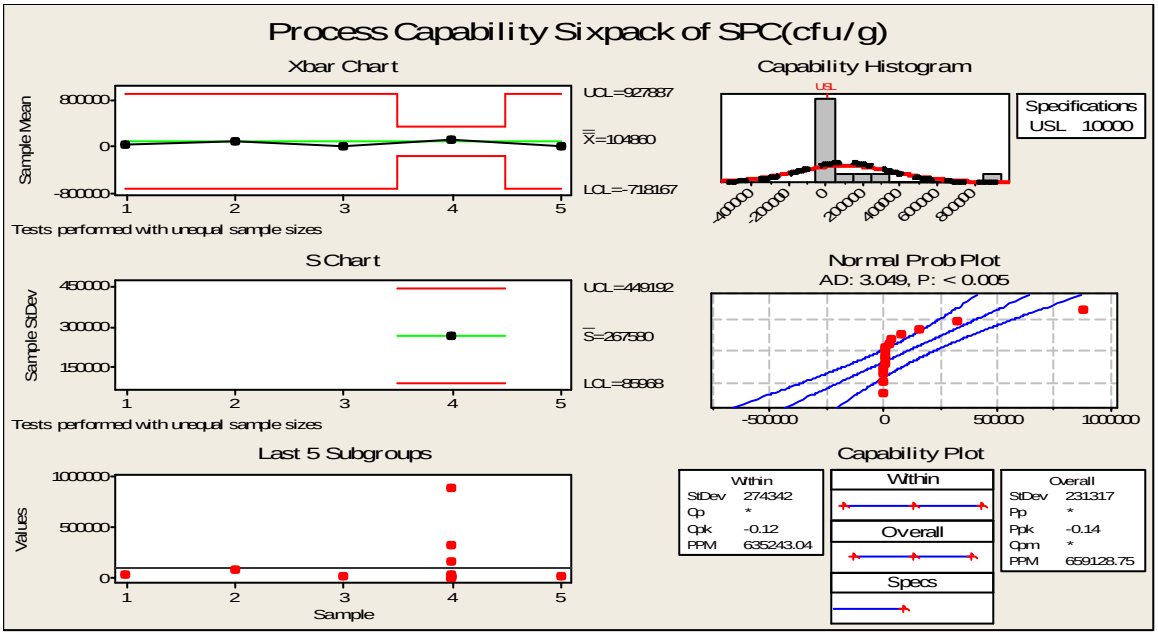


Figure 6. 9: Quality Control Charts and Process Capability Analysis for Standard Plate Count (cfu/g) of Parboiled Rice.

The quality control chart given as output is the chart for the mean and standard deviation of Standard Plate Count (cfu/g). These charts, which are pretty much self-explanatory, clearly

shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clearly shows that the process is in control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 6.9 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Parboiled Rice of Standard Plate Count analysis report by this process are not exceeding the Upper specification limit (USL). A significant percentage of the Standard Plate Count (cfu/g) of Parboiled Rice is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 6.9, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk = -0.12 is less than 1 means that the process is off centered, platykurtic and is not capable.

Quality Characteristic: Total Coli Form (MPN/g)

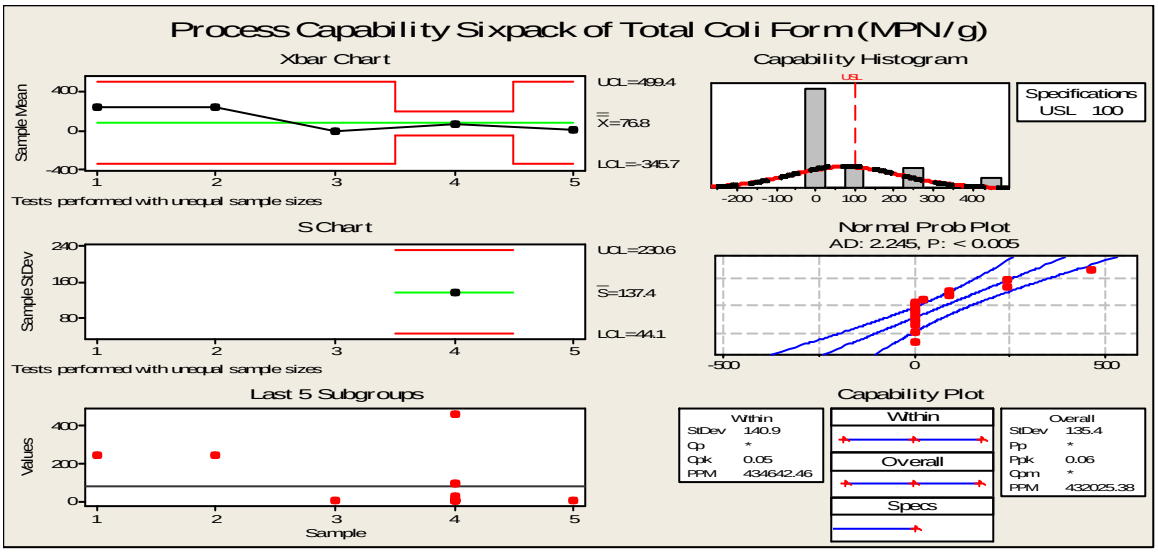


Figure 6. 10: Quality Control Charts and Process Capability Analysis for Standard Plate Count (cfu/g) of Parboiled Rice.

The quality control chart given as output is the chart for the mean and standard deviation of Total Coli Form (MPN/g). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clearly shows that the process is in control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 6.10 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Parboiled Rice of Total Coli Form analysis report by this process are not exceeding the Upper specification limit (USL). A significant percentage of the Total Coli Form (MPN/g) of Parboiled Rice is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 6.10, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk = 0.05 is less than 1 means that the process is off centered, platykurtic and is not capable.

Quality Characteristic: Total Fungi (cfu/g)

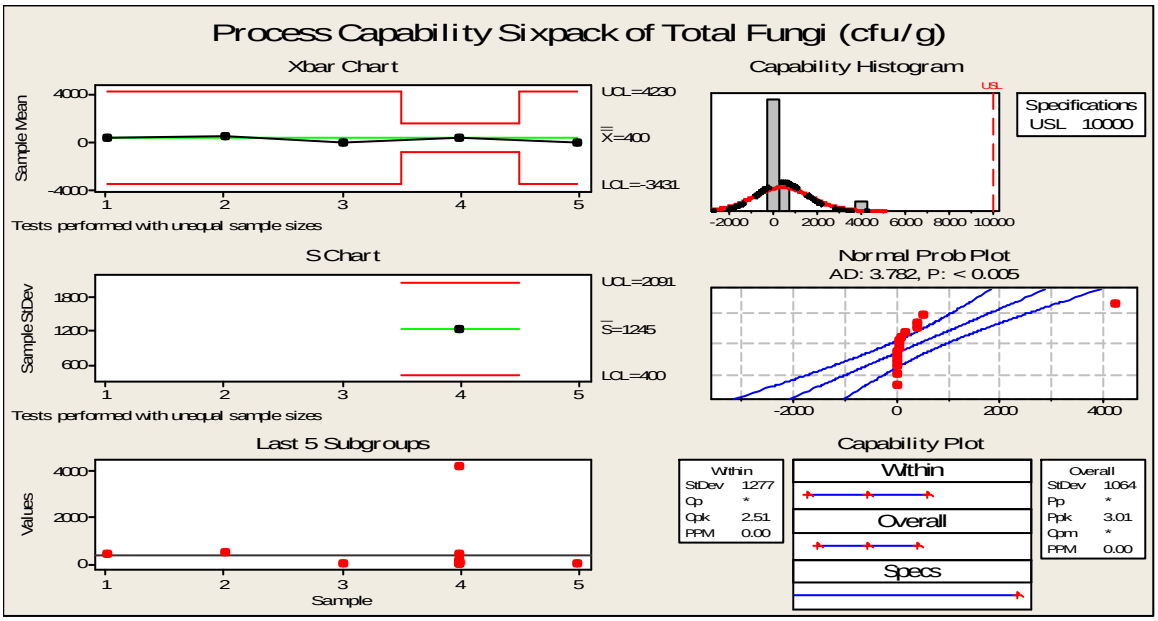


Figure 6. 11: Quality Control Charts and Process Capability Analysis for Total Fungi (cfu/g) of Parboiled Rice.

The quality control chart given as output is the chart for the mean and standard deviation of Total Fungi (cfu/g). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clearly shows that the process is in control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 6.11 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Parboiled Rice of Total Fungi analysis report by this process are not exceeding the Upper specification limit (USL). An insignificant percentage of the Total Fungi (cfu/g) of Parboiled Rice is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 6.11, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the

p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk = 2.51 is greater than 1 means that the process is centered, platykurtic and is capable.

6.7 Comparison of *t* test and Wilcoxon signed-rank test

In analytical chemistry it is essential to validate a given analytical method to determine its applicability, reproducibility, repeatability and the accuracy of the data obtained. The analyst should establish some basis to prove that the method is working for its intent use. Normally, the amount of data is rather small and the so-called *Student t distribution* should be used (IAEA, 2003).

(Doane & Seward, 2007) indicated that the Wilcoxon signed-rank test is robust to non-normal and somewhat asymmetrical, population shapes. In fact, the assumptions underlying the *t*-test are violated in every situation because there is neither an underlying normal distribution nor an interval level of measurement (Meek et al., 2007).

Table 6. 3: Comparison of *t* test and Wilcoxon signed-rank test for characteristics of physiochemical parameters of Parboiled Rice according to their acceptable range as prescribed by WFP, Dhaka.

Variables	Wilcoxon test	P-value	*t*-test	P-value	Kolmogorov-Smirnov test	P-value
Broken (%)	1.00	1.000	-6.77	1.000	0.145	>0.150
Moisture (%)	30.0	0.987	-2.10	0.974	0.196	0.082
Damaged/discoloured (%)	26.0	0.986	-2.13	0.975	0.176	>0.150
Yellow Kernels (%)	0.0	1.000	-7.82	1.000	0.192	0.094
Red and Streaked (%)	0.0	1.000	-66.94	1.000	0.155	>0.150
Chalky grain (%)	0.0	1.000	-11.92	1.000	0.306	<0.010
Paddy per Kg	93.0	0.224	0.78	0.225	0.309	<0.010
Other Varieties (%)	92.0	0.239	1.39	0.092	0.265	<0.010
Standard Plate Count (cfu/g)	80.0	0.134	1.59	0.067	0.349	<0.010
Total Coli Form (MPN/g)	42.0	0.853	-0.66	0.741	0.321	<0.010

Total Fungi (cfu/g)	0.0	1.000	-34.93	1.000	0.396	<0.010

This study also investigated the behavior of the one sample *t-test* for Parboiled Rice samples. Table 6.3 shows the result of the *t-test*. Here all variables were insignificant (p>0.05) compared with acceptable range as Prescribed by WFP, Dhaka.

For the above test, where α = 0.05, given that p >α for the Broken (%), Moisture (%), Damaged/discoloured (%), Yellow Kernels (%) and Red and Streaked (%), we would conclude that only five Variable (test parameter) are normally distributed. Therefore, the assumption of normality has been met for this few variables.

Even so, the results indicate that, in almost every case when the null hypothesis was true, wilcoxon signed-rank test performed as efficient or more power than the *t*-test. There were a total of 3 cases in which the Wilcoxon signed-rank test predicted probability (p-value) results more power than the *t*-test when H_0 was true as fufill assumptions.

6.8 Binary logistic regression analysis of Parboiled Rice

A stata software was performed to identify Parboiled Rice quality parameters appropriate for inclusion in a logistic regression model to predict the accepted/ unaccepted as prescribed acceptable range by WFP, Dhaka and different food standard institution in a parboiled rice sample.

Logistic regression was used to assess the impact of a physiochemical analysis parameter to identify the quality of Parboiled Rice which was supplied by some Parboiled Rice produced industries. The model contained a independent variables Moisture (%) and 4 (four) dependent variables as acceptability of Broken (%), Damaged/discoloured (%), Standard Plate Count (cfu/g) and Total Coli Form (MPN/g) as presented in table 6.4.

Table 6. 4: Binary logistic regression results of Parboiled Rice.

Responding variable	Independent Variable	Coeff. (OR)	Std. Err.	z-value	P-value	AIC	BIC	GOF
Broken (%)	Moisture (%)	-1.031 (0.357)	1.669	-0.62	0.537	10.99	12.66	0.636
Damaged/discoloured (%)		-0.012 (0.988)	0.408	-0.03	0.977	24.60	26.26	0.319

Standard Plate Count (cfu/g)		0.904 (2.468)	0.673	1.34	0.180	21.79	23.21	0.389
Total Coli Form (MPN/g)		1.370 (3.936)	0.907	1.51	0.131	13.82	15.24	0.152

Note: Coeff.= Coefficient of the model, OR=Odds Ratio, Std. Err.= Standard Error, AIC= Akaike Information Criterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

The full model containing a variable Moisture (%)was statistically insignificant with P>0.05 according to accepted range of test parameter as prescribed by WFP, Dhaka.Indicating that the model was able to distinguish between rice samples which reported having and not having accepted range as prescribed by standard specified institution. The *p*-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in Table 6.4 with insignificant (P>0.05).

6.9 Binary probit regression analysis

To determine the factors influencing the decision to acceptable in food products a probit model were used. The decision to use probit is based on the fact that the decision variable is discrete and dichotomous (one either acceptable or not of Parboiled Rice as prescribed by WFP, Dhaka and different food standard institution in a parboiled rice sample), discrete decisions are analyzed using qualitative response models one of which is probit.

Collecting Parboiled Rice analysis data findings revealed that analysis data can be classified into two classes; acceptable and non acceptable according to Requirements WFP, Dhaka and different food standard institution in a parboiled rice sample. A probit regression was used to determine the factors that influence the decision to analysis value among food producer or analyzer operators.

Table 6. 5: Binary Probit/Normit regression results of Parboiled Rice.

Responding variable	**Independent Variable**	**Coeff. (M.E.)**	**Std. Err.**	**z-value**	**P-value**	**AIC**	**BIC**	**GOF**
Broken (%)	Moisture (%)	-0.550 (-0.041)	0.879	-0.63	0.531	10.93	12.60	0.665
Damaged/discoloured (%)		-0.007 (-0.003)	0.253	-0.03	0.977	24.60	26.26	0.319
Standard Plate Count (cfu/g)		0.568	0.414	1.37	0.170	21.72	23.14	0.390

Total Coli Form (MPN/g)		(0.227) 0.724 (3.936)	0.433	1.67	0.094	14.01	15.43	0.214

Note: Coeff.= Coefficient of the model, M.E.= Marginal Effects, Std. Err.= Standard Error, AIC= Akaike Information Criterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

The full model containing a variable Moisture (%) was statistically insignificant with P>0.05 according to accepted range of test parameter as prescribed by standard Institution. Indicating that the model was able to distinguish between Parboiled Rice samples which reported having and not having accepted range as prescribed by standard Institution. The p-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in Table 6.5 with insignificant (P>0.05).

To find correct estimates of standard errors and p-values it is necessary to choose better model. To select the model, here, we consider two information criteria used to compare models. In general, "smaller is better": given two models, the one with the smaller AIC fits the data better than the one with the larger AIC. As with the AIC, a smaller BIC indicates a better-fitting model (Samples, n.d.).

We fit a model explaining the quality of Parboiled Rice products has on the basis of Moisture (%) against the acceptability of Broken (%), Damaged/discoloured (%), Standard Plate Count (cfu/g) and Total Coli Form (MPN/g). The goodness-of-fit criteria for comparing these two model results are found in table 6.4 and 6.5. AIC and BIC were determined by logit and probit regression of the predicted values obtained in the fit to the true model equation. For the test parameter studied in Table 6.4 and 6.5; based on the AIC and BIC criterion were approximated same using a Logistic and probit model.

6.10 Discriminant function analysis

The discriminant analysis to Parboiled Rice under Acceptable Range as WFP, Dhaka and others with the test to determine classify groups of acceptability between the groups using Wilks' Lambda revealed that the diverse parameters yielded a statistical significance at a level of 0.05.

Table 6. 6: Discriminant Function Analysis results of analyzed parameters of Parboiled Rice.

Responding variable	Independent Variable	Wilks' Lambda	P-value	goodness-of-fit test	
				Box's M	P-value
Broken (%)	Moisture (%)	0.977	0.559	-	-
Damaged/discoloured (%)		1.000	0.979	0.623	0.451
Standard Plate Count (cfu/g)		0.834	0.132	3.925	0.056
Total Coli Form (MPN/g)		.628	0.016	7.338	0.011

Box's M test tests the assumption of homogeneity of covariance matrices. This test is very sensitive to meeting the assumption of multivariate normality. Discriminant function analysis is **robust** even when the homogeneity of variances assumption is not met, provided the data do not contain important outliers (Bian, n.d.). For our data only one of the variables are insignificant which is Yellow Kernels (%), we conclude the groups do not differ in their covariance matrices, whereas other parameters do differ in their covariance matrices violating assumption of Discriminant Analysis (DA). When n is large, small deviations from homogeneity will be found significant, which is why Box's M must be interpreted in conjunction with inspection of the log determinants.

The Wilk‘s lambdais a measure of the overall statistical significance of the Linear Discriminant Functions and is statistically insignificant results at the 5 percent level of probability for the Discriminant Analysis Tests of Equality of Group Means of Moisture (%) against the acceptability range of test parameter (refer to Table 6.6). This implies that the group means for the independent variables are not different on the discriminating function except Total Coli Form (MPN/g).

6.11 ARCH-LM test

To detect the presence of ARCH effect in the mean equation of Parboiled Rice, we use the ARCH-LM (Lagrange multiplier) test.

Table 6. 7: ARCH-LM and DF test analysis results of physiochemical analysis parameters of Parboiled Rice.

Variable	LM test for autoregressive	Dickey-Fuller test for unit

	conditional heteroskedasticity (ARCH)		root	
	Chi-square Statistic	P-value	Test Statistic, Z(t)	P-value
Broken (%)	0.410	0.5218	-3.654	0.0048
Moisture (%)	0.003	0.9531	-6.225	0.0000
Damaged/discoloured (%)	0.561	0.4537	-3.930	0.0018
Yellow Kernels (%)	2.157	0.1419	-2.698	0.0745
Red and Streaked (%)	0.187	0.6650	-2.192	0.2092
Chalky grain (%)	0.717	0.3971	-5.116	0.0000
Paddy per Kg	0.019	0.8890	-1.881	0.0115
Other Varieties (%)	1.296	0.2549	-3.109	0.0259
Standard Plate Count (cfu/g)	0.089	0.7654	-3.954	0.0017
Total Coli Form (MPN/g)	0.118	0.7311	-5.915	0.0000
Total Fungi (cfu/g)	0.040	0.8421	-22.928	0.0000

In our analysis the different value for different variables of above parameters of the ARCH-LM test; the lags included in the test are only 1. The corresponding P-Value is >0.05, which is for all variables. So we have accepted the null hypothesis of no ARCH error and conclude that there is a no ARCH error in the analysis series. This confirms all variables are insignificant that means no ARCH effects of the models. The estimation results are given in the table 6.7.

Table 6.7 shows that the values of DF test for variables p-value <0.05 at 5%, level of significance exceptYellow Kernels (%) and Red and Streaked (%) which implies that the variables series is stationary. An outcome of DF test confirms that the physiochemical analysis variables series is stationary.

6.12: Comparison statistical technique

Comparison among Logistic & Probit Regression and Discriminant Analysis in classification groups for Parboiled Rice.

Table 6. 8: Summary of statistics of Logit, Probit model and Discriminant function analysis.

		Logistic Regression		**Probit Regression**		**Discriminant analysis**	
Responding variable	Independent Variable	p-value	GOF	p-value	GOF	p-value	GOF
Broken (%)	Moisture (%)	0.537	0.636	0.531	0.665	0.559	-
Damaged/discoloured (%)		0.977	0.319	0.977	0.319	0.979	0.451
Standard Plate Count (cfu/g)		0.180	0.389	0.170	0.390	0.132	0.056
Total Coli Form (MPN/g)		0.131	0.152	0.094	0.214	0.016	0.011

Note: GOF= Goodness-of-fit statistics.

From the above demonstrations of three different technique, Logit & Probit model and Discriminant function analysis, all of them provide are not exact equal predicted probability of the same variable which is given with the level of accepted range as prescribed by standard institution. The level of significance of Goodness-of-fit statistics are >0.05 under Logit & Probit and Discriminant analysis. Obviously, from these results, Logit &Probit model perform the best results in terms of the fulfill the assumptions. If in the case of assumptions fullfill in Discriminant analysis yields better results than logit and probit model.

CHAPTER 7: WHEAT SOYA BLEND (WSB)

7.1 Introduction

This chapter describes the Wheat Soya Blend (WSB) for product description and analysis for the study. A description of prducts includes the following sub sections: Fortified Blended Foods (FBFs) anddescription of Wheat Soya Blend (WSB). The resulting data were employed in different levels of analysis. The chapter concludes by giving the empirical specification and estimation procedures for the fitted models.

7.2 Fortified Blended Foods (FBFs)

What are they?

FBFs are blends of partially precooked and milled cereals, soya, beans, pulses fortified with micronutrients (vitamins and minerals). Special formulations may contain vegetable oil or milk powder. Corn Soya Blend (CSB) is the main blended food distributed by WFP but Wheat Soya Blend (WSB) is also sometimes used.

When and where used?

FBFs are designed to provide protein supplements. In food assistance programs to prevent and address nutritional deficiencies. They are generally used in WFP Supplementary Feeding and Mother and Child Health programs. Also, to provide extra micronutrients to complement the general ration.

How are they used?

Usually mixed with water and cooked as a porridge (WFP, n.d.).

7.3 Description of Wheat Soya Blend (WSB)

Wheat Soya Blend is a product preferred for young children aged 6 months – 2 years. The product is to be used as a complement to breastfeeding. The product is not a breast-milk replacer.

7.3.1 Product type

Super Cereal *plus* is prepared from heat treated wheat and **de-hulled** soya beans, sugar, dried skim milk, refined soya bean oil, vitamins and minerals. If **Super Cereal *plus*- Wheat**

Soya Blend is consumed as a porridge or gruel, it should be prepared by mixing an appropriate proportion of flour and clean water (i.e. 50g of **Super Cereal *plus*- Wheat Soya Blend** with 250 g of water) followed by a boiling time at simmering point from five to ten minutes.

7.3.2 Main ingredients

Super Cereal *plus*- Wheat Soya Blend shall be manufactured from fresh wheat grain and soy beans of good quality, free from foreign materials, substances hazardous to health, excessive moisture, insect damage and fungal contamination and shall comply with all relevant national food laws and standards. Sugar, dried milk powder and soya bean oil shall be of optimal food quality and meet the Codex standards for these commodities (Alimentarius & Control, 2015).

7.4 Preliminary analysis of the data

After collecting data, the first task for a researcher is to organize and simplify the data so that it is possible to get a general overview of the results. One method for simplifying and organizing data is to construct a frequency distribution (*MTH 161 Handouts*, n.d.).

Table 7. 1: Frequency distribution results for Wheat Soya Blend (WSB).

Proximate Variable		Frequency	Percentage
Moisture (%)			
	Acceptable Range	34	100.0
	Not Acceptable Range	0	0.0
Protein (%)			
	Acceptable Range	30	93.8
	Not Acceptable Range	2	6.3
Fat (%)			
	Acceptable Range	16	47.1
	Not Acceptable Range	18	52.9
Total Carbohydrate (%)	Acceptable Range	31	100.0
	Not Acceptable Range	0	0.0
Sugar (as sucrose) (%)			

	Acceptable Range	29	96.7
	Not Acceptable Range	1	3.3
Vitamin A (IU/100g)			
	Acceptable Range	0	0.0
	Not Acceptable Range	27	100.0
Iron (mg/100g)			
	Acceptable Range	10	37.0
	Not Acceptable Range	17	63.0
Standard Plate Count (cfu/g)			
	Acceptable Range	25	89.3
	Not Acceptable Range	3	10.7
Total Coliform (MPN/g)			
	Acceptable Range	23	17.9
	Not Acceptable Range	5	82.1
Escherichia Coli (MPN/g)			
	Acceptable Range	22	84.6
	Not Acceptable Range	4	15.4

Frequency distribution presented in Table 7.1 indicates that only Fat (%), Vitamin A (IU/100g) and Iron (mg/100g) contains are reasonably unacceptable were compared to the standard value prescribed by WFP, Dhaka.

7.5 Descriptive Statistics of Wheat Soya Blend (WSB)

Statistics are a set of tools for obtaining insight into a psychological phenomenon. Descriptive statistics summarise the data, making clear any trends, patterns etc. which may be lurking within them; they consist of visual displays such as graphs, and summary statistics such as means (Hole, 2000).

Table 7. 2: Descriptive Statistics results for proximate analysis of Wheat Soya Blend (WSB).

Proximate Variables	Minimum	Maximum	Mean	Std. Deviation
Moisture (%)	0.69	8.82	3.857	1.771
Protein (%)	8.35	20.30	16.970	2.362

Fat (%)	3.54	20.66	6.457	2.995
Sugar (as sucrose) (%)	9.87	18.88	13.321	2.161
Total Carbohydrate (%)	65.48	73.70	69.061	2.170
Vitamin A (IU/100g)	293.00	4281.00	1229.852	716.271
Iron (mg/100g)	6.17	22.61	12.203	3.984
Standard Plate Count (cfu/g)	0.00	$5.60e^{+06}$	$2.20e^{+05}$	$1.06e^{+06}$
Total Coliform (MPN/g)	0.00	240.01	41.750	81.379
E. Coli (MPN/g)	0.00	240.00	11.192	47.017

The mean, standard deviation and other descriptive statistics for physiochemical analysis are displayed in Table 7.2. Here only Moisture, % are comparatively low standard deviation (SD<2).

7.6 Application of control charts on Wheat Soya Blend (WSB)

In order to verify whether quality of food products were under control condition or not we have adopted following control chart of Wheat Soya Blend (WSB) for such purposes we have used several Shewhart Control Charts.

In this subsection we present results and analysis that is application of control charts. We show the results and analysis by type of products and types of control chart.

7.7 Process Capability Analysis (Using Normal Distribution Curve)

In this case, we want to assess the process capability for different industries producing certain Wheat Soya Blend (WSB). The proximate analysis of the Wheat Soya Blend (WSB) is of concern. The specification limits on the Wheat Soya Blend (WSB) are in given appendix 4. There has been a consistent problem with meeting the specification limits and the some process produces a high percentage of rejects.

The histogram of the data shows that proximate analysis of Wheat Soya Blend (WSB) follow a normal distribution or approximately normal distribution. The variation from Wheat Soya Blend (WSB) toWheat Soya Blend (WSB) can be estimated using the within group standard deviation. Since the process is stable and the measurements are normally or approximately

normality distributed, the normal distribution option of process capability analysis can be used.

Quality characteristic: Moisture

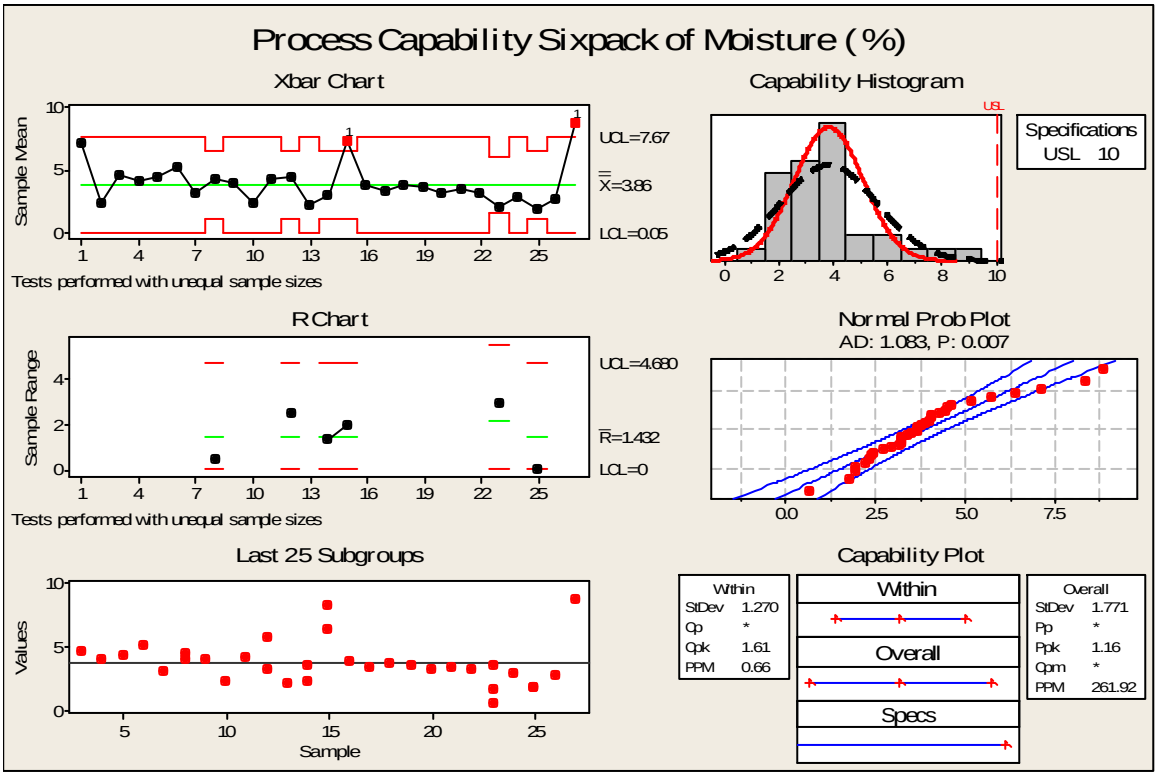


Figure 7. 1: Quality Control Charts and Process Capability Analysis for Moisture (%) of Wheat Soya Blend (WSB).

The quality control and process capability analysis chart given as output is the chart of Moisture (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control in the control limit in mean chart.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 7.1 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Wheat Soya Blend (WSB) of Moisture analysis report by

this process exceed the Upper specification limit (USL). An insignificant percentage of the Moisture (%) of Wheat Soya Blend (WSB) is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 7.1, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.007, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =1.61 is greater than 1 means that the process is centered and capable.

Quality characteristic: Protein

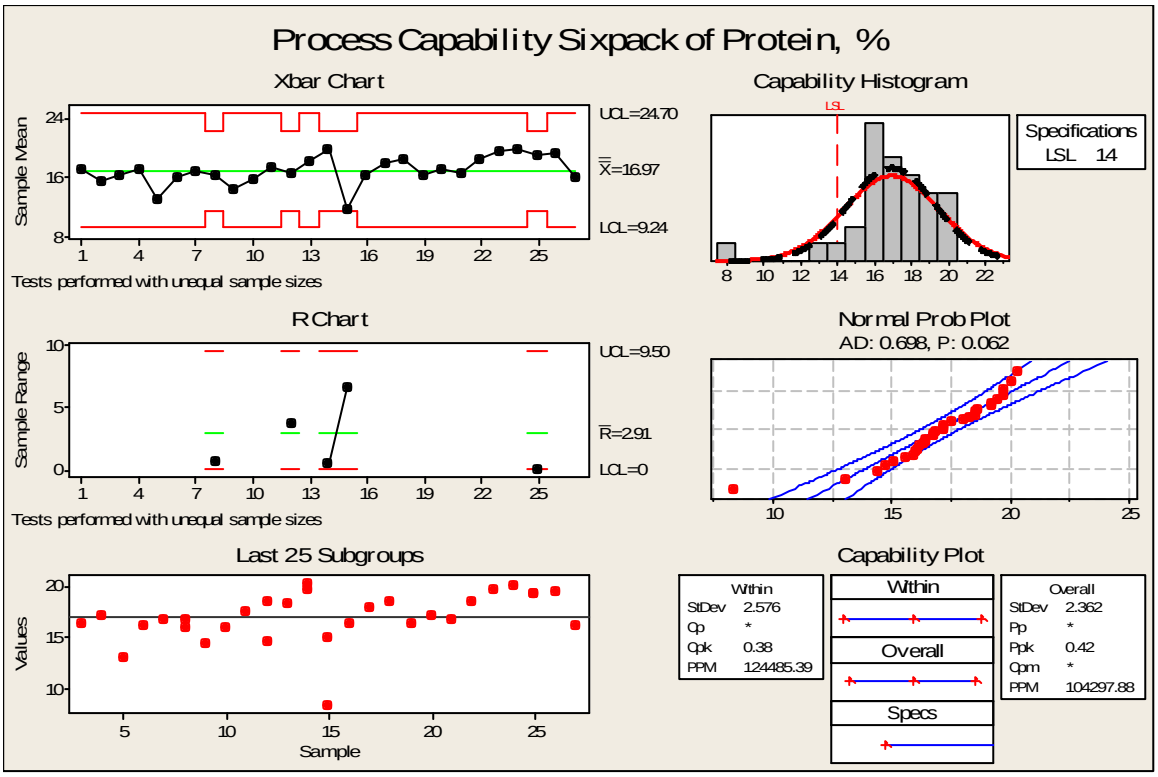


Figure 7. 2: Quality Control Charts and Process Capability Analysis for Protein, % of Wheat Soya Blend (WSB).

The quality control and process capability chart given as output is the chart of Protein, %. These charts, which are pretty much self-explanatory, clearly shows the date wise sample

point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control.

The upper right box reports the process data including the lower specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 7.2 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Wheat Soya Blend (WSB) of Protein, % analysis report by this process are exceeding the lower specification limit (USL). A significant percentage of the Protein, % of Wheat Soya Blend (WSB) is outside of Lower Specification Limit.

From the Normal probability plot graph in Figure 7.2, the Anderson-Darling (AD) Normality test shows that we are unable to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the $\alpha = 0.05$ significance level. This is due to the fact that the p-value for the A-D test is 0.062, which is greater than 0.05 - a frequently used level of significance for such a hypothesis test, The necessary assumptions appear to have been fulfilled and we may investigate the capability of this process, as shown in Figure 7.2.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.38 is less than 1 means that the process is off centered and not capable.

Quality Characteristic: Fat, %

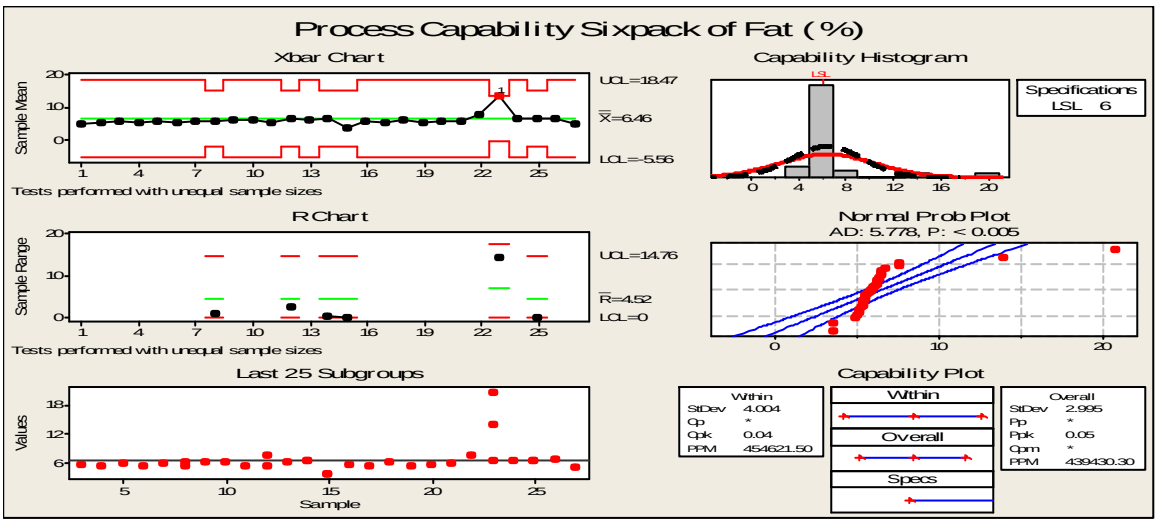


Figure 7. 3: Quality Control Charts and Process Capability Analysis for Fat, % of Wheat Soya Blend (WSB).

The quality control and process capability chart given as output is the chart of Total Ash (on dry basis), %. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in of control except only a point outside of upper control limit.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 7.3 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Wheat Soya Blend (WSB) of Fat, % analysis report by this process are exceeding the Upper specification limit (USL). A significant percentage of the Fat, % of Wheat Soya Blend (WSB) is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 7.3, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.04 is less than 1 means that the process is off centered and not capable.

Quality Characteristic: Vitamin A (IU/100g)

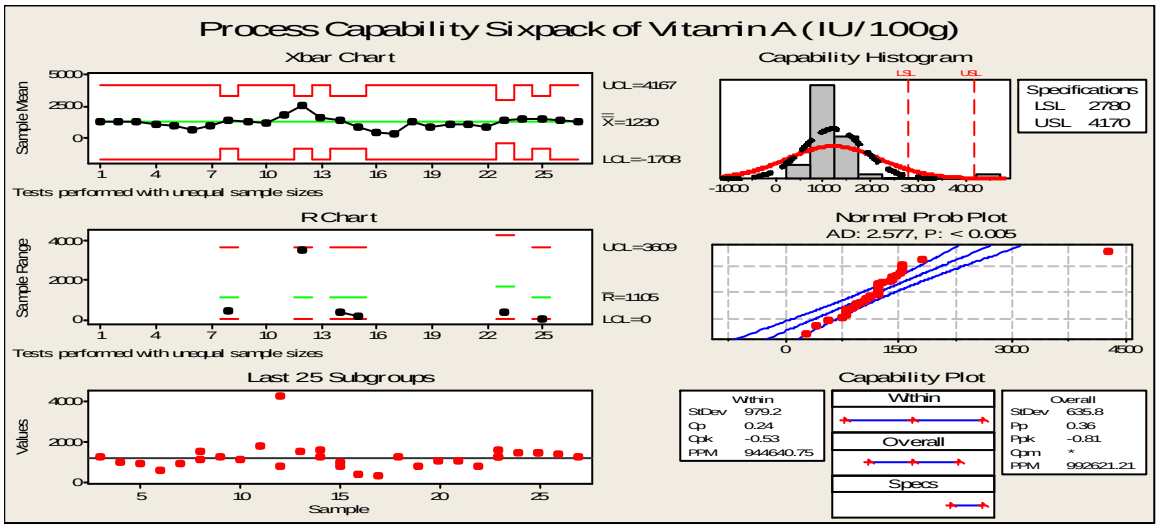


Figure 7. 4: Quality Control Charts and Process Capability Analysis for Vitamin A (IU/100g) of Wheat Soya Blend (WSB).

The quality control chart given as output is the chart of Vitamin A (IU/100g). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 7.4 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Wheat Soya Blend (WSB) of Vitamin A (IU/100g) analysis report by this process exceed the lower specification limit (LSL) and Upper specification limit (USL). A significant percentage of the Vitamin A (IU/100g) of Wheat Soya Blend (WSB) is outside of lower specification limit (LSL) and Upper Specification Limit.

From the Normal probability plot graph in Fig. 7.4, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-0.53 is less than 1 means that the process is off centered and is not capable.

Quality Characteristic: Iron (mg/100g)

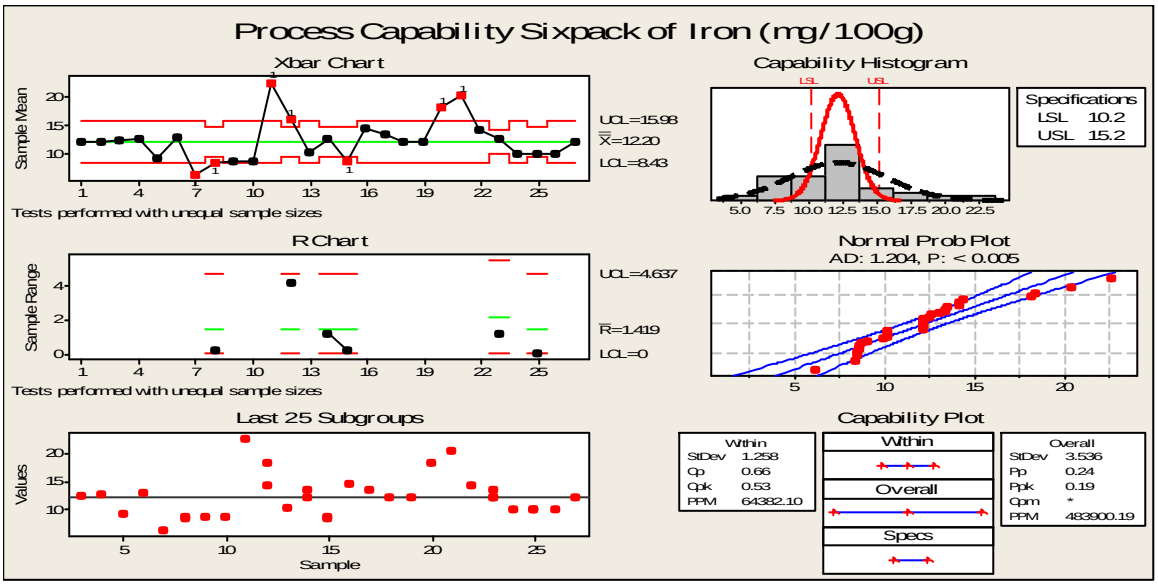


Figure 7. 5: Quality Control Charts and Process Capability Analysis for Iron (mg/100g) of Wheat Soya Blend (WSB).

The quality control chart given as output is the chart of Iron (mg/100g). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 7.5 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Wheat Soya Blend (WSB) of Iron (mg/100g) analysis report by this process exceed the Lower specification limit (LSL) and upper specification limit (USL). A significant percentage of the Iron (mg/100g) (%) of Wheat Soya Blend (WSB) is outside of Lower Specification Limit and upper specification limit (USL).

From the Normal probability plot graph in Fig. 7.5, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-0.53 is less than 1 means that the process is off centered and is not capable.

Quality Characteristic: Standard Plate Count (cfu/g)

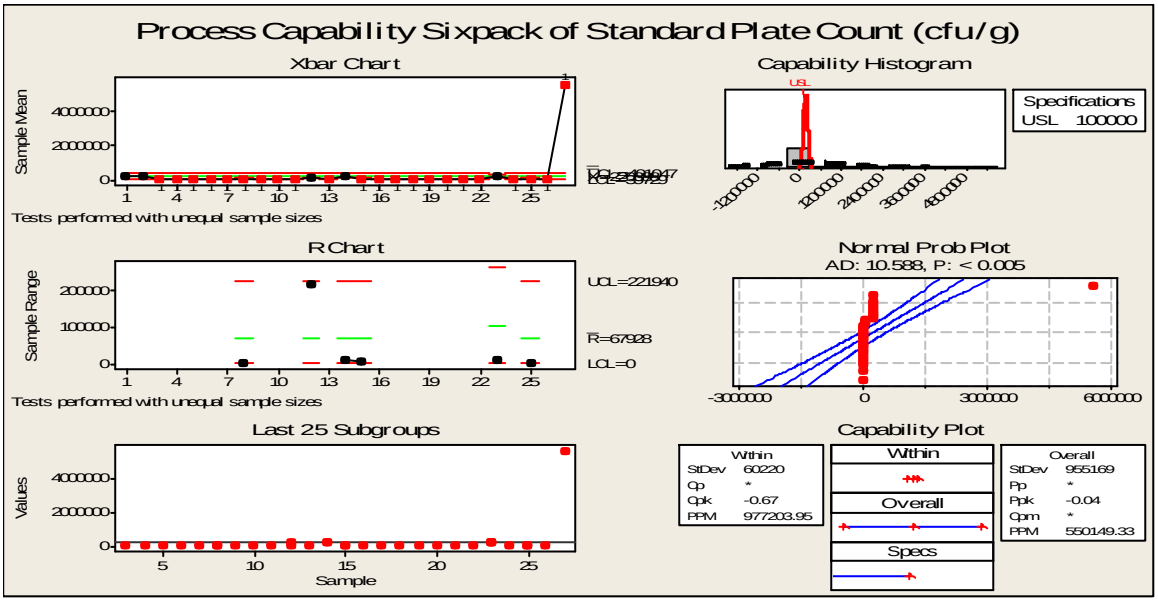


Figure 7. 6: Quality Control Charts and Process Capability Analysis for Standard Plate Cournt (cfu/g) of Wheat Soya Blend (WSB).

The quality control chart given as output is the chart of Standard Plate Cournt (cfu/g). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control.

The upper right box reports the process data including the lower specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 7.6 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Wheat Soya Blend (WSB) of Standard Plate Count Analysis report by this process are exceeding the Upper specification limit (USL). A significant percentage of the Standard Plate Count (cfu/g) of Wheat Soya Blend (WSB) is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 7.6, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-0.67 is less than 1 means that the process is off centered and is not capable.

Quality Characteristic: Total Coliform (MPN/g)

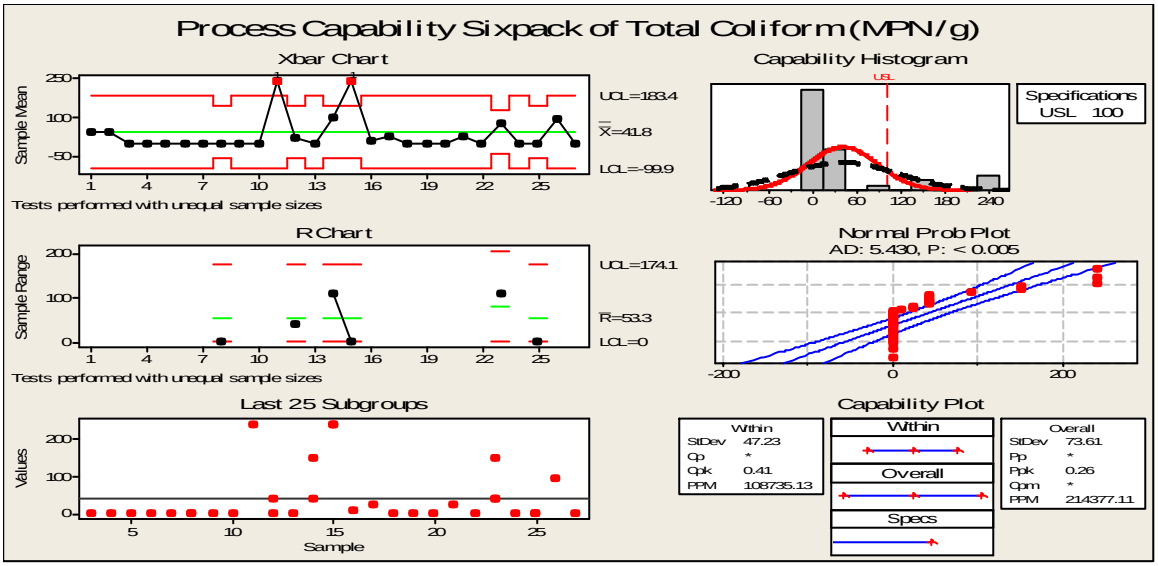


Figure 7. 7: Quality Control Charts and Process Capability Analysis for Total Coliform (MPN/g) of Wheat Soya Blend (WSB).

The quality control chart given as output is the chart of Total Coliform (MPN/g). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point

along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 7.7 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Wheat Soya Blend (WSB) of Total Coliform report by this process exceed the Upper specification limit (USL). A significant percentage of the Total Coliform (MPN/g) of Wheat Soya Blend (WSB) is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 7.7, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.41 is less than 1 means that the process is off centered and is not capable.

Quality Characteristic: Escherichia Coli (MPN/g)

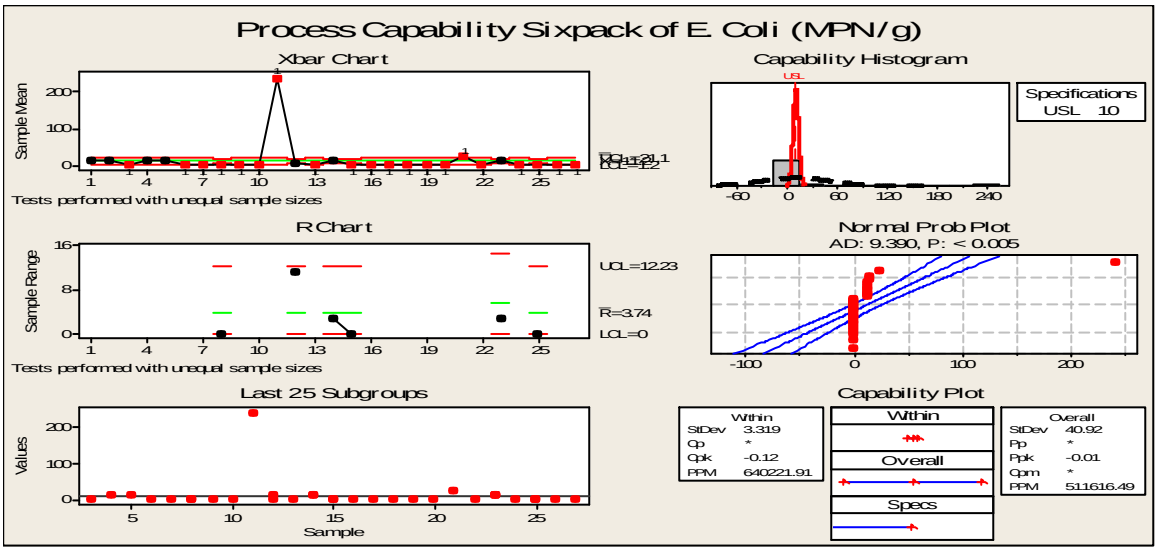


Figure 7. 8: Quality Control Charts and Process Capability Analysis for *E. Coli* (MPN/g) of Wheat Soya Blend (WSB).

The quality control chart given as output is the chart of *E. Coli* (MPN/g). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 7.8 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Wheat Soya Blend (WSB) of E. Coli report by this process exceed the Upper specification limit (USL). A significant percentage of the E. Coli (MPN/g) of Wheat Soya Blend (WSB) is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 7.8, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-0.12 is less than 1 means that the process is off centered and is not capable.

7.8 Comparison of *t* test and Wilcoxon signed-rank/Sign test

In analytical chemistry it is essential to validate a given analytical method to determine its applicability, reproducibility, repeatability and the accuracy of the data obtained. The analyst should establish some basis to prove that the method is working for its intent use. Normally, the amount of data is rather small and the so-called Student t distribution should be used (IAEA, 2003).

(Doane & Seward, 2007) indicated that the Wilcoxon signed-rank test is robust to non-normal and somewhat asymmetrical, population shapes. In fact, the assumptions underlying the *t*-test are violated in every situation because there is neither an underlying normal distribution nor an interval level of measurement (Meek et al., 2007).

Table 7. 3: Comparison of *t* test and Wilcoxon signed-rank/Sign test for characteristics of physiochemical parameters of Wheat Soya Blend (WSB) according to their acceptable range as prescribed by WFP, Dhaka.

Variables	Wilcoxon/ Sign test	P-value	*t*-test	P-value	Kolmogorov-Smirnov test	P-value
Moisture (%)	0.0	1.000	-20.22	1.000	0.158	0.038
Protein (%)	497.0	1.000	7.11	1.000	0.142	0.096
Fat (%)	Sign	0.364	0.89	0.810	0.351	<0.010
Sugar (as sucrose)(%)	464.0	1.000	8.42	1.000	0.147	0.096
Total Carbohydrate (%)	496.0	1.000	23.25	1.000	0.084	>0.150
Vitamin A (IU/100g)	32.0	0.000	-3.15	0.002	0.246	<0.010
Iron (mg/100g)	370.0	1.000	5.48	1.000	0.178	0.035
Standard Plate Count (cfu/g)	Sign	1.000	0.60	0.276	0.467	<0.010
Total Coliform (MPN/g)	Sign	0.999	-3.79	1.000	0.377	<0.010
E. Coli (MPN/g)	Sign	1.000	0.13	0.449	0.440	<0.010

This study also investigated the behavior of the one sample *t-test* for Wheat Soya Blend (WSB) samples. Table 7.3 shows the result of the *t-test*. All variables were insignificant compared with acceptable range as Prescribed by WFP, Dhaka except Vitamin A (IU/100g).

For the above test, where $\alpha = 0.05$, given that $p > \alpha$ for the Protein (%), Sugar (as sucrose) (%) and Total Carbohydrate (%) we would conclude that only three Variable (test parameter) are normally distributed. Therefore, the assumption of normality has been met for this variables.

Here we observe that when the null hypothesis was true, wilcoxon signed-rank test performed as efficient or more power than the *t*-test. There were a total of 3 cases in which the Wilcoxon signed-rank test predicted probability (p-value) results more power than the *t*-test when H_0 was true. But if null hypothesis was false, *t*-test as well as wilcoxon signed-rank/Sign test was same results though normality assumptions violated.

7.9 Binary logistic regression analysis of Wheat Soya Blend (WSB)

Stata software was performed to identify Wheat Soya Blend (WSB) quality parameters appropriate for inclusion in a logistic regression model to predict the accepted/ unaccepted as prescribed acceptable range by WFP, Dhaka in a Wheat Soya Blend (WSB) sample.

Logistic regression was used to assess the impact of a chemical analysis of Wheat Soya Blend (WSB) analysis parameter to identify the quality of Wheat Soya Blend (WSB) which was supplied by some Wheat Soya Blend (WSB) sample produced industries. The model contained three dependent variables as acceptability of protein (%), Fat (%) and Iron (mg/100g) and against three independent variables of each dependent variable as Moisture (%), Sugar (as sucrose) (%) and Total Carbohydrate (%) were presented in table 7.4.

Table 7. 4: Binary logistic regression results of Proximate Analysis parameters of Wheat Soya Blend (WSB).

Responding variable	Independent Variable	Coeff.	Std. Err.	z-value	P-value	AIC	BIC	GOF
Acceptability of protein (%)	Moisture (%)	-0.566	0.723	- 0.78	0.434	19.92	25.10	0.795
	Sugar (as sucrose)(%)	-0.424	0.404	-1.05	0.294			
	Total Carbohydrate (%)	0.290	0.522	0.55	0.579			
Acceptability of Fat (%)	Moisture (%)	-0.214	0.266	-0.80	0.421	42.73	48.20	0.429
	Sugar (as sucrose)(%)	-0.201	0.191	-1.05	0.293			
	Total Carbohydrate (%)	-0.232	0.214	-1.08	0.280			
Acceptability of Iron (mg/100g)	Moisture (%)	0.230	0.326	0.70	0.482	31.78	36.32	0.326
	Sugar (as sucrose)(%)	0.468	0.260	1.80	0.071			
	Total Carbohydrate (%)	-0.396	0.302	-1.31	0.190			

Note: Coeff.= Coefficient of the model, Std. Err.= Standard Error, AIC= Akaike Information Criterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

The full model containing Moisture (%), Sugar (as sucrose) (%) and Total Carbohydrate (%) against acceptability of protein (%),Fat (%) andIron (mg/100g) was statistically insignificant with P>0.05, indicating that the model was able to distinguish between Wheat Soya Blend (WSB) samples which reported having and not having accepted range as prescribed by WFP,

Dhaka. The *p*-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in Table 7.4 with insignificant (P>0.05).

7.10 Binary probit regression analysis of Wheat Soya Blend (WSB)

To determine the factors influencing the decision to acceptable in food products a probit model were used. The decision to use probit is based on the fact that the decision variable is discrete and dichotomous (one either acceptable of Wheat Soya Blend (WSB) as prescribed by WFP, Dhaka or not), discrete decisions are analyzed using qualitative response models one of which is probit.

Collecting Wheat Soya Blend (WSB) analysis data findings revealed that Wheat Soya Blend (WSB) analysis data can be classified into two classes; acceptable and non acceptable according to WFP and other standard prescribed range. A probit regression was used to determine the factors that influence the decision to analysis value among food producer or analyzer operators.

Table 7. 5: Binary Probit/Normit regression results of proximate parameters of Wheat Soya Blend (WSB).

Responding variable	Independent Variable	Coeff.	Std. Err.	z-value	P-value	AIC	BIC	GOF
Acceptability of protein (%)	Moisture (%)	-0.325	0.400	-0.81	0.416	19.69	24.88	0.828
	Sugar (as sucrose)(%)	-0.241	0.221	-1.09	0.275			
	Total Carbohydrate (%)	0.155	0.270	0.57	0.566			
Acceptability of Fat (%)	Moisture (%)	-0.128	0.158	-0.81	0.419	42.79	48.26	0.433
	Sugar (as sucrose)(%)	-0.121	0.114	-1.06	0.289			
	Total Carbohydrate (%)	-0.140	0.125	-1.12	0.264			
Acceptability of Iron (mg/100g)	Moisture (%)	0.118	0.182	0.65	0.518	31.66	36.20	0.361
	Sugar (as sucrose)(%)	0.295	0.156	1.90	0.058			
	Total Carbohydrate (%)	-0.232	0.165	-1.41	0.160			

Note: Coeff.= Coefficient of the model, Std. Err.= Standard Error, AIC= Akaike Information Criterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

Table 7.5 shows estimates of the probit model for the factors influencing analyzed value among the Wheat Soya Blend (WSB) producers or respective analyzer of the study. The

model contained three dependent variables as acceptability of protein (%),Fat (%) andIron (mg/100g) and against three independent variables of each dependent variable as Moisture (%), Sugar (as sucrose) (%) and Total Carbohydrate (%) were presented in table 7.4.

The full model containing Moisture (%), Sugar (as sucrose) (%) and Total Carbohydrate (%) against acceptability of protein (%),Fat (%) andIron (mg/100g) was statistically insignificant with P>0.05, indicating that the model was able to distinguish between Wheat Soya Blend (WSB) samples which reported having and not having accepted range as prescribed by WFP, Dhaka. The *p*-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in Table 7.4 with insignificant (P>0.05).

To find correct estimates of standard errors and p-values it is necessary to choose better model. To select the model, here, we consider two information criteria used to compare models. In general, "smaller is better": given two models, the one with the smaller AIC fits the data better than the one with the larger AIC. As with the AIC, a smaller BIC indicates a better-fitting model (Samples, n.d.).

We fit a model explaining the type of Wheat Soya Blend (WSB) products has on the basis of Moisture (%), Sugar (as sucrose) (%) and Total Carbohydrate (%). The goodness-of-fit criteria for comparing these two model results are found in table 7.4 and 7.5. AIC and BIC were determined by logit and probit regression of the predicted values obtained in the fit to the true model equation. For the test parameter studied in Table 7.4 and 7.5; based on the AIC and BIC criterion were approximated same using a Logistic and probit model.

7.11 Discriminant function analysis.

The discriminant analysis to Wheat Soya Blend (WSB) under Acceptable Range as WFP, Dhaka and others with the test to determine classify groups of acceptability between the groups using Wilks' Lambda revealed that the diverse parameters yielded a statistical significance at a level of 0.05.

Table 7. 6: Discriminant Function Analysis results of physiochemical analysis of Wheat Soya Blend (WSB).

Dependent	Independent Variable	Wilks'	P-value	goodness-of-fit test

Variable		Lambda		Box's M	P-value
Acceptability of protein (%)	Moisture (%)	0.791	0.015	-	-
	Sugar (as sucrose)(%)	0.995	0.729		
	Total Carbohydrate (%)	0.800	0.017		
Acceptability of Fat (%)	Moisture (%)	0.747	0.005	13.945	0.061
	Sugar (as sucrose)(%)	0.994	0.687		
	Total Carbohydrate (%)	0.716	0.003		
Acceptability of Iron (mg/100g)	Moisture (%)	1.000	0.937	9.710	0.229
	Sugar (as sucrose)(%)	0.944	0.243		
	Total Carbohydrate (%)	0.854	0.054		

Box's M test the assumption of homogeneity of covariance matrices. This test is very sensitive to meeting the assumption of multivariate normality. Discriminant function analysis is **robust** even when the homogeneity of variances assumption is not met, provided the data do not contain important outliers (Bian, n.d.). For our data except Acceptability of protein (%) we conclude the groups do not differ in their covariance matrices, fulfill assumption of DA.We didn't perform Acceptability of protein (%) the test of Box's M as fewer than two nonsingular group covariance matrices.

The Wilk's lambdais a measure of the overall statistical significance of the Linear Discriminant Functions and is statistically significant results at the 5 percent level of probability for the Discriminant Analysis Tests of Equality of Group Means of Moisture (%) and Total Carbohydrate (%) against the acceptability range of protein (%) and Fat (%) (refer to Table 7.6). This implies that the group means for the independent variables weredifferent on the discriminating function. Where as other variable were insignificant.

7.12 ARCH-LM test

To detect the presence of ARCH effect in the mean equation of Wheat Soya Blend (WSB), we use the ARCH-LM (Lagrange multiplier) test.

Table 7. 7: ARCH-LM and DF test analysis results of physiochemical analysis parameter of Wheat Soya Blend (WSB).

Variable	LM test for autoregressive conditional heteroskedasticity	Dickey-Fuller test for unit root

	(ARCH)			
	Chi-square Statistic	P-value	Test Statistic, Z(t)	P-value
Moisture (%)	1.289	0.256	-4.715	0.0001
Protein (%)	0.212	0.645	-4.433	0.0003
Fat (%)	1.373	0.241	-3.407	0.0107
Sugar (as sucrose) (%)	0.085	0.771	-2.639	0.0851
Total Carbohydrate (%)	0.574	0.449	-4.493	0.0002
Vitamin A (IU/100g)	0.008	0.927	-3.655	0.0048
Iron (mg/100g)	0.687	0.407	-2.915	0.0436
Standard Plate Count (cfu/g)	2.435	0.119	0.959	0.9938
Total Coliform (MPN/g)	1.948	0.163	-3.856	0.0024
E. Coli (MPN/g)	0.058	0.810	-4.458	0.0002

In our analysis the different value for different variables of above parameters of the ARCH-LM test; the lags included in the test are only 1. The corresponding P-value is >0.05, which is very high. So we have no difficulty to accept the null hypothesis of no ARCH error in the analysis series. The parameters of Wheat Soya Blend (WSB) analysis are insignificant that means no ARCH effects of the models. The estimation results are given in the table 7.7 shows that the values of DF test for all variables p-value <0.05 at 5%, level of significance except Sugar (as sucrose) (%) and Standard Plate Count (cfu/g) which implies that the variables series is stationary. An outcome of DF test confirms that the physiochemical analysis variables series is stationary.

7.13: Comparison among three statistical technique

Comparison among Logistic & Probit Regression and Discriminant Analysis in classification groups for Parboiled Rice.

Table 7. 8: Summary of statistics of Logit, Probit model and Discriminant function analysis.

		Logistic Regression		**Probit Regression**		**Discriminant analysis**	
Responding	Independent Variable	p-value	GOF	p-value	GOF	p-value	GOF

variable							
Acceptability of protein (%)	Moisture (%)	0.434	0.795	0.416	0.828	0.015	-
	Sugar (as sucrose)(%)	0.294		0.275		0.729	
	Total Carbohydrate (%)	0.579		0.566		0.017	
Acceptability of Fat (%)	Moisture (%)	0.421	0.429	0.419	0.433	0.005	0.061
	Sugar (as sucrose)(%)	0.293		0.289		0.687	
	Total Carbohydrate (%)	0.280		0.264		0.003	
Acceptability of Iron (mg/100g)	Moisture (%)	0.482	0.326	0.518	0.361	0.937	0.229
	Sugar (as sucrose)(%)	0.071		0.058		0.243	
	Total Carbohydrate (%)	0.190		0.160		0.054	

Note: GOF= Goodness-of-fit statistics.

From the above demonstrations of three different technique, Logit & Probit model and Discriminant function analysis, all of them provide are notequal predicted probability of the same variable which is given with the level of accepted range as prescribed by WFP, Dhaka. The level of significance of Goodness-of-fit statistics are >0.05 under Logit &Probit and Discriminant analysis. Obviously, from these results, Discriminant analysis perform the better results in terms of the fulfill the assumptions except the dependent variable acceptability of protein (%) as there exist fewer than two nonsingular group covariance matrices. We know that if in the case of assumptions fullfill in Discriminant analysis yields better results than logit and probit model.

CHAPTER 8: YELLOW SPLIT PEAS

8.1 Introduction

This chapter describes the Yellow Split Peas for product description and analysis for the study. A description of prducts includes the following sub sections: description of Yellow Split Peas, production, trade and product description. The resulting data were employed in different levels of analysis. The chapter concludes by giving the empirical specification and estimation procedures for the fitted models.

8.2 Description of Yellow Split Peas

Dry peas, *Pisum sativum*, also referred to as field peas, are a cool-season pulse crop. As a legume, dry peas convert atmospheric nitrogen into soil-borne nitrogen that can be used by subsequent crops. Hence, dry peas may provide benefits in rotations with cereal crops by increasing yields and, to some extent, reducing fertilizer expenditures. Two main varieties of dry peas are produced: green cotyledon and yellow cotyledon(Joseph, Gary, & Vincent, 2014).

Production: Dry peas are grown commercially in almost 100 countries, but production is concentrated in Canada, Russia, and China. Jointly, these three countries produce over one-half of the world's dry peas. Canadian dry pea production increased considerably over the past 30 years, expanding from less than 200,000 metric tons per year in the early 1980s to approximately 3 million metric tons in 2012, or 12 percent per year (Joseph et al., 2014).

Trade: Canada is the world's dominant exporter accounting for slightly more than 60 percent of world exports between 2008 and 2011. The United States was second in dry pea exports over the same period. France, Russia, and Australia are other important exporting countries. French exports have declined since the early 1990s when France was the world's largest dry pea exporter. Russian exports, generally negligible for most of the post-Soviet period, have increased dramatically since 2009 (Joseph et al., 2014).

India and China import the majority of internationally traded dry peas. Both countries are also important pea producers. Other major importers include Bangladesh and Pakistan where consumers have tastes and preferences similar to those of India. Belgium, Italy, Spain, and Germany use peas for animal feed (Joseph et al., 2014).

Product discription: Yellow Split Peas are a great low-fat source of protein and are high in fiber and iron. With a mild, earthy flavor and soft texture, split peas are similar to lentils in terms of their versatility and nourishment.

Often referred to as "pulses", split peas (and lentils) are the edible seeds of legume plants. Split peas have been husked and split along a natural seam so that they will cook faster than a whole dried pea. However, this does not significantly impact their nutritional benefits. Yellow split peas are about ¼ inch wide and range in color from medium to pale yellow in color (*Yellow Split Peas, Organic - Shiloh Farms Online Marketplace*, n.d.).

8.3 Preliminary analysis of the data

After collecting data, the first task for a researcher is to organize and simplify the data so that it is possible to get a general overview of the results. One method for simplifying and organizing data is to construct a frequency distribution (*MTH 161 Syllabus.pdf*, n.d.).

Table 8. 1: Frequency distribution of Yellow Split Peas.

Proximate Variable		Frequency	Percentage
Moisture (%)			
	Acceptable Range	30	100.0
	Not Acceptable Range	0	0.0
Purity (%)			
	Acceptable Range	9	31.0
	Not Acceptable Range	20	69.0
Whole peas (%)			
	Acceptable Range	29	100.0
	Not Acceptable Range	0	0.0
Heat damage (%)			
	Acceptable Range	24	82.8
	Not Acceptable Range	5	17.2
Other damage (%)			
	Acceptable Range	26	89.7
	Not Acceptable Range	3	10.3
Foreign matter (%)			

	Acceptable Range	27	90.0
	Not Acceptable Range	3	10.0
Other colour (%)			
	Acceptable Range	29	100.0
	Not Acceptable Range	0	0.0
Insect damage (%)			
	Acceptable Range	18	62.1
	Not Acceptable Range	11	37.9
Broken (%)			
	Acceptable Range	4	13.8
	Not Acceptable Range	25	86.2

Frequency distribution presented in Table 8.1 indicates that only Purity (%), Insect damage (%) and Broken (%) contains are reasonably unacceptable were compared to the standard value as prescribed by WFP, Dhaka.

8.4 Descriptive Statistics of Yellow Split Peas

Statistics are a set of tools for obtaining insight into a psychological phenomenon. Descriptive statistics summarise the data, making clear any trends, patterns etc. which may be lurking within them; they consist of visual displays such as graphs, and summary statistics such as means (Hole, 2000).

Table 8. 2: Descriptive Statistics results for proximate analysis of Yellow Split Peas.

Variables	Minimum	Maximum	Mean	Std. Deviation
Moisture (%)	11.43	13.78	12.6240	0.61976
Purity (%)	96.98	99.92	98.5121	0.80264
Whole peas (%)	0.00	0.46	0.1028	0.10974
Heat damage (%)	0.00	0.88	0.0672	0.18033
Other damage (%)	0.00	1.08	0.2376	0.25176
Foreign matter (%)	0.00	0.60	0.1680	0.18386
Other colour (%)	0.00	1.49	0.5948	0.42576
Insect damage (%)	0.00	1.57	0.3000	0.38230
Broken (%)	0.24	15.53	8.1014	3.91972

The mean, standard deviation and other descriptive statistics for physiochemical analysis are displayed in Table 8.2. Here only Broken (%) are comparatively high standard deviation (SD>2).

8.5 Application of control charts on Yellow Split Peas

In order to verify whether quality of food products were under control condition or not we have adopted following control chart of Yellow Split Peas for such purposes we have used several Shewhart Control Charts.

In this subsection we present results and analysis that is application of control charts. We show the results and analysis by type of products and types of control chart.

8.6 Process Capability Analysis (Using Normal Distribution Curve)

In this case, we want to assess the process capability for different industries producing certain Yellow Split Peas. The proximate analysis of the Yellow Split Peas is of concern. The specification limits on the Yellow Split Peas are in given appendix 5. There has been a consistent problem with meeting the specification limits and the some process produces a high percentage of rejects.

The histogram of the data shows that proximate analysis of Yellow Split Peas follow a normal distribution or approximately normal distribution. The variation from Yellow Split Peas toYellow Split Peas can be estimated using the within group standard deviation. Since the process is stable and the measurements are normally or approximately normality distributed, the normal distribution option of process capability analysis can be used.

Quality characteristic: Moisture

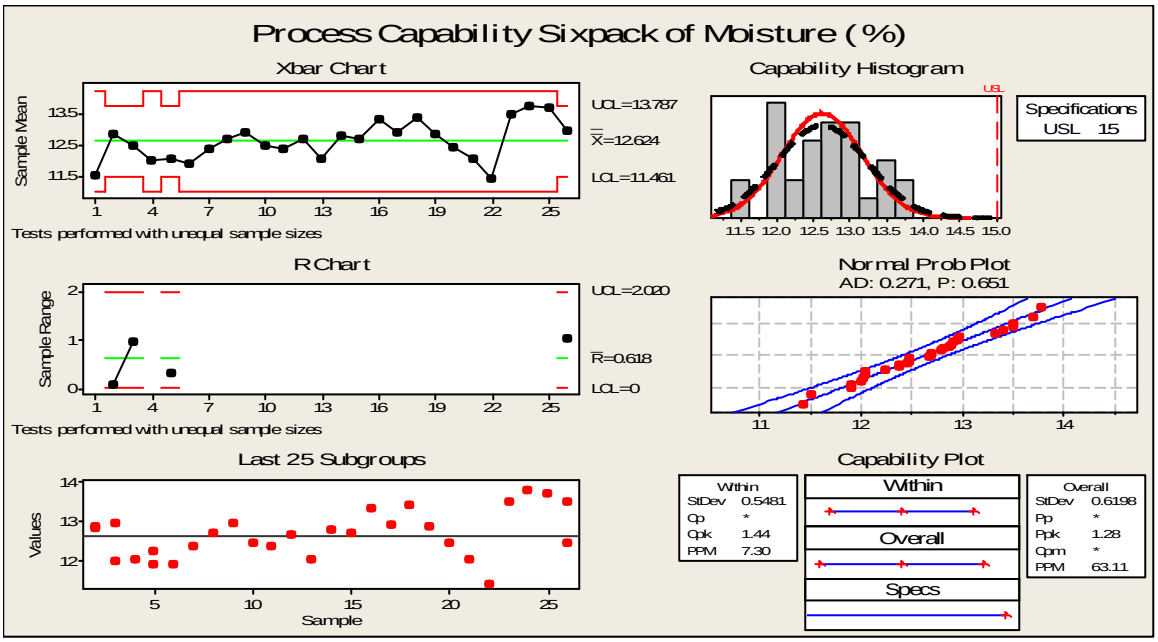


Figure 8. 1: Quality Control Charts and Process Capability Analysis for Moisture (%) of Yellow Split Peas.

The quality control and process capability analysis chart given as output is the chart of Moisture (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control in the control limit in mean and range chart.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 8.1 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Yellow Split Peas of Moisture analysis report by this process is not exceed the Upper specification limit (USL). An insignificant percentage of the Moisture (%) of Yellow Split Peas is outside of Upper Specification Limit.

From the Normal probability plot graph in Figure 8.1, the Anderson-Darling (AD) Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the $\alpha = 0.05$ significance level. This is due to the fact that the p-value for the A-D test is 0.651, which is greater than 0.05 - a frequently

used level of significance for such a hypothesis test, as necessary assumptions appear to have been fulfilled and we may investigate the capability of this process, as shown in Figure 8.1.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =1.44 is greater than 1 means that the process is centered and capable.

Quality Characteristic: Purity, %

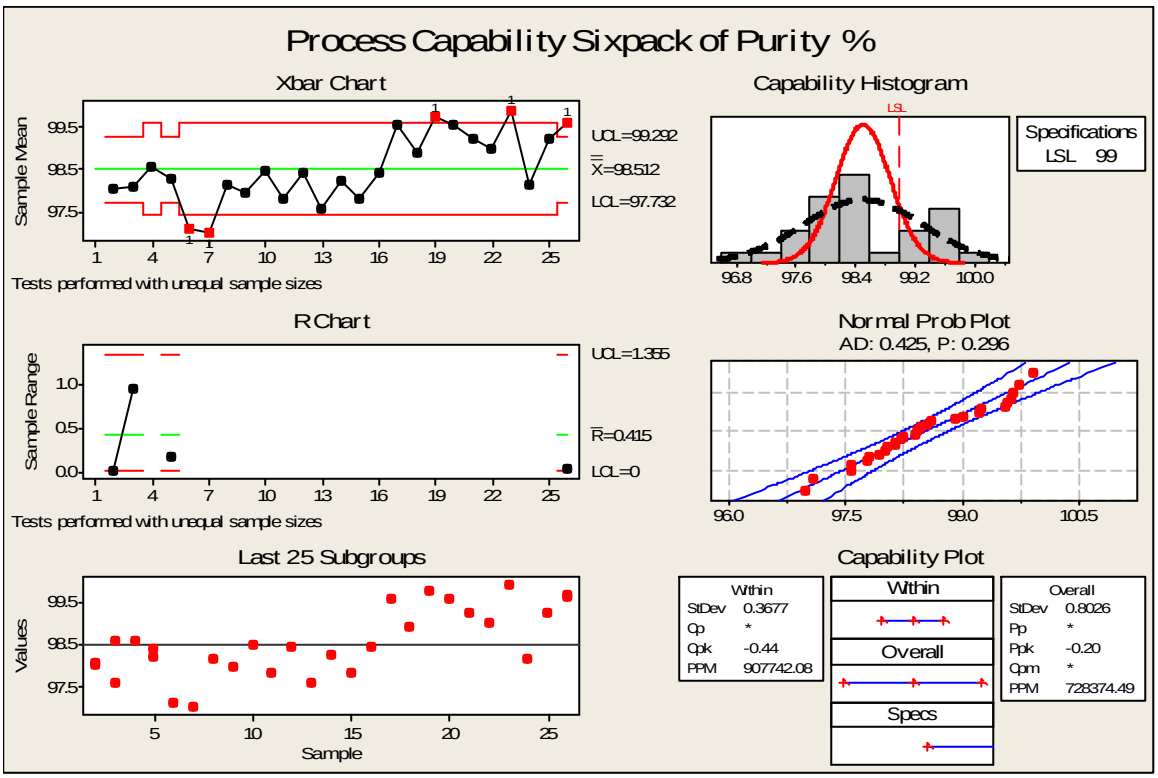


Figure 8. 2: Quality Control Charts and Process Capability Analysis for Purity, % of Yellow Split Peas.

The quality control and process capability chart given as output is the chart of Purity, %. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control in mean chart.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 8.2 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Yellow Split Peas of Purity, % analysis report by this process are exceeding the Lower specification limit (LSL). A significant percentage of the Purity, % of Yellow Split Peas is outside of Lower Specification Limit.

From the Normal probability plot graph in Figure 8.2, the Anderson-Darling (AD) Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the $\alpha = 0.05$ significance level. This is due to the fact that the p-value for the A-D test is 0.296, which is greater than 0.05 - a frequently used level of significance for such a hypothesis test.The necessary assumptions appear to have been fulfilled and we may investigate the capability of this process, as shown in Figure 8.2.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-0.44 is less than 1 means that the process is off centered and not capable.
Quality Characteristic: Whole peas (%)

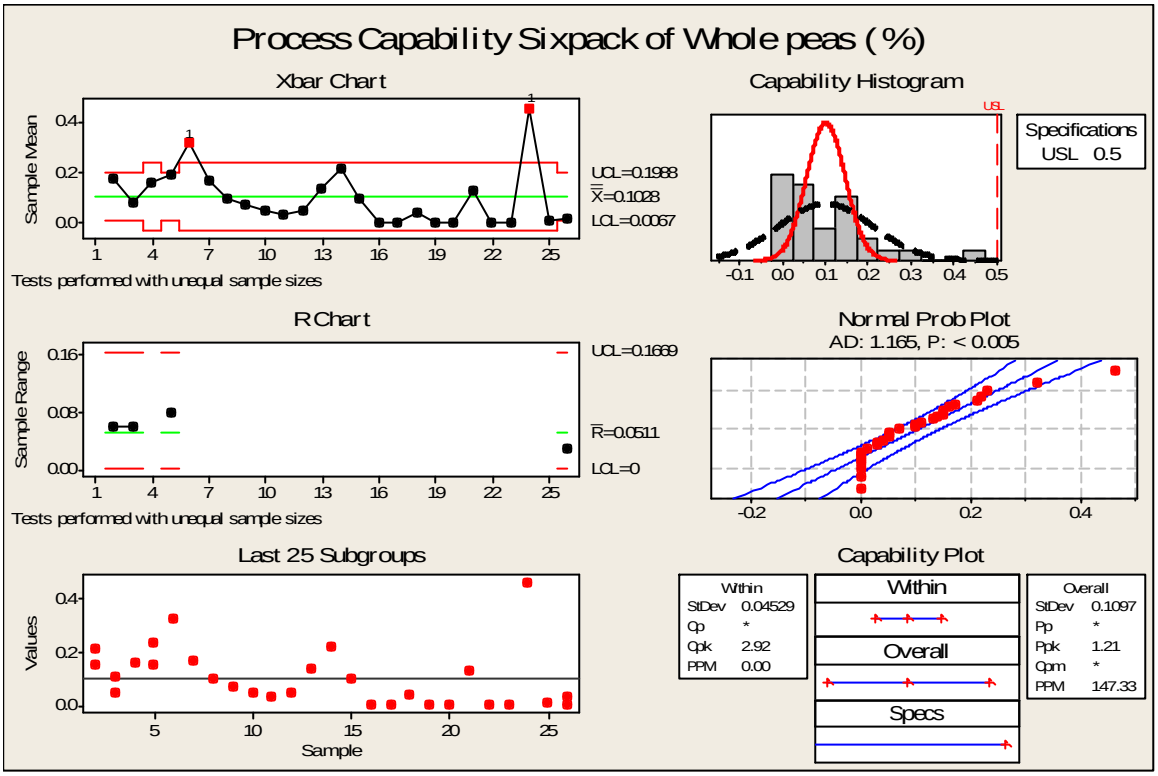


Figure 8. 3: Quality Control Charts and Process Capability Analysis for Whole peas (%) of Yellow Split Peas.

The quality control chart given as output is the chart of Whole peas (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control in mean chart.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 8.3 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Yellow Split Peas of Whole peas (%) analysis report by this process exceed the Upper specification limit (USL). An insignificant percentage of the Whole peas (%) of Yellow Split Peas are outside of Upper specification limit (USL).

From the Normal probability plot graph in Fig. 8.3, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =2.92 is greater than 1 means that the process is centered and capable.

Quality Characteristic: Heat damage (%)

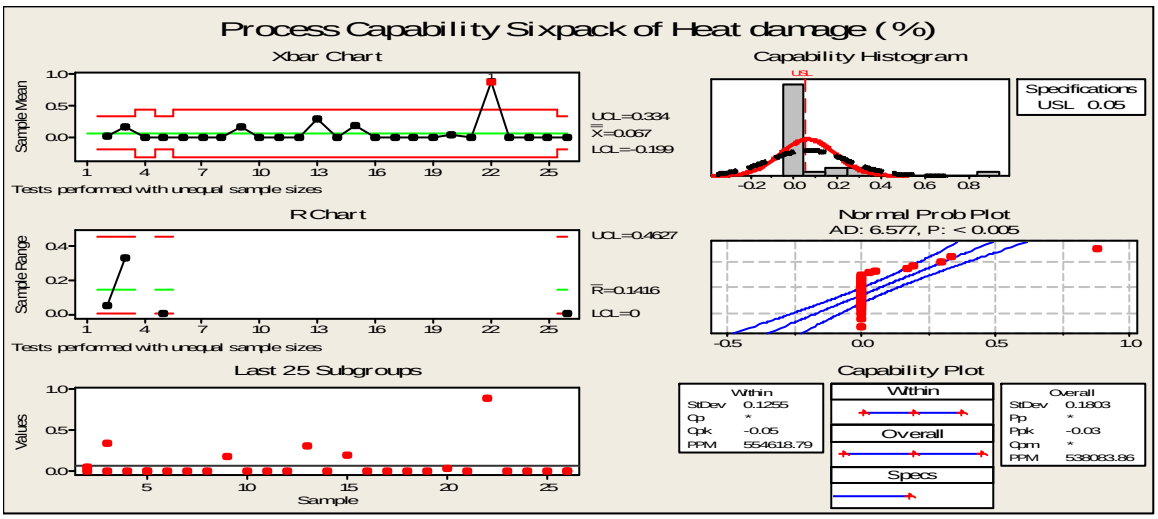


Figure 8. 4: Quality Control Charts and Process Capability Analysis for Heat damage (%) of Yellow Split Peas.

The quality control chart given as output is the chart of Heat damage (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control except only one point in outside in upper control limit.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 8.4 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Yellow Split Peas of Heat damage (%) analysis report by this process exceed the upper specification limit (USL). A significant percentage of the Heat damage (%) of Yellow Split Peas is outside of upper specification limit (USL).

From the Normal probability plot graph in Fig. 8.4, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-0.05 is less than 1 means that the process is off centered and is not capable.

Quality Characteristic: Other damage (%)

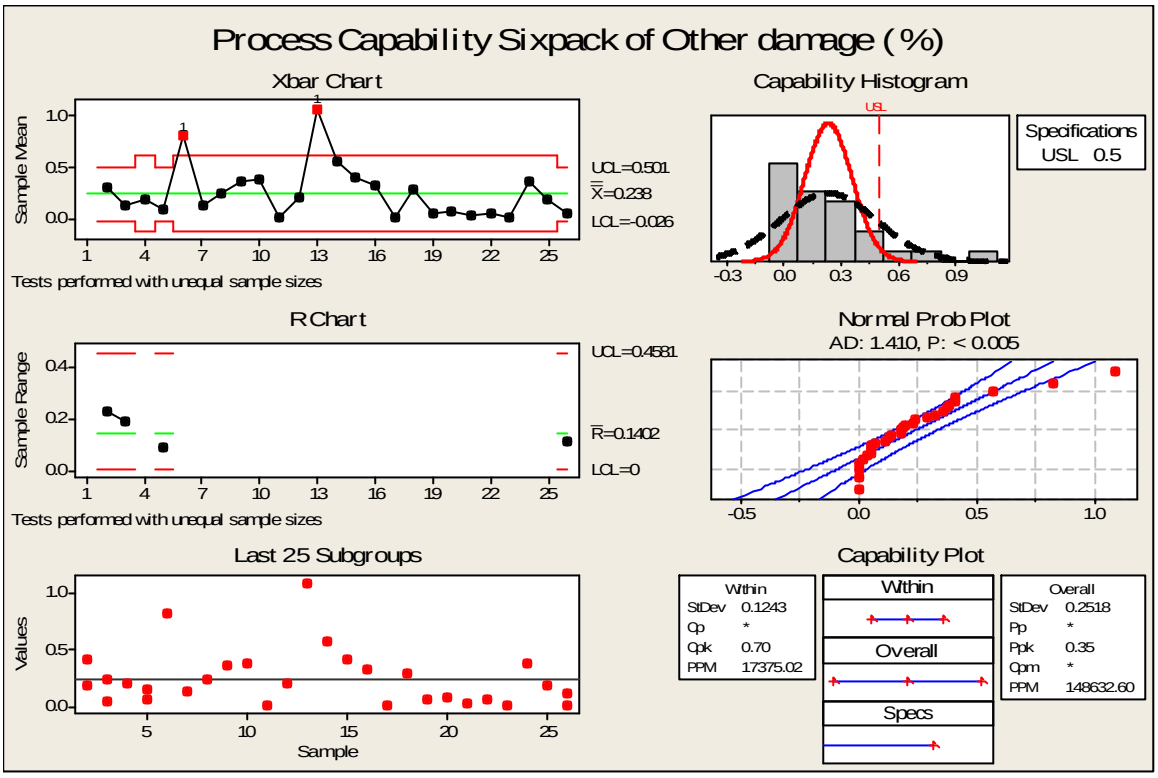


Figure 8. 5: Quality Control Charts and Process Capability Analysis for Other damage (%) of Yellow Split Peas.

The quality control chart given as output is the chart of other damage (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control except only one point in outside in upper control limit.

The upper right box reports the process data including the lower specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 8.5 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Yellow Split Peas of Standard Plate Count analysis report by this process is not exceed the Upper specification limit (USL). An insignificant percentage of the other damage (%) of Yellow Split Peas is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 8.5, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =1.15 is greater than 1 means that the process is centered and capable.

Quality Characteristic: Foreign matter (%)

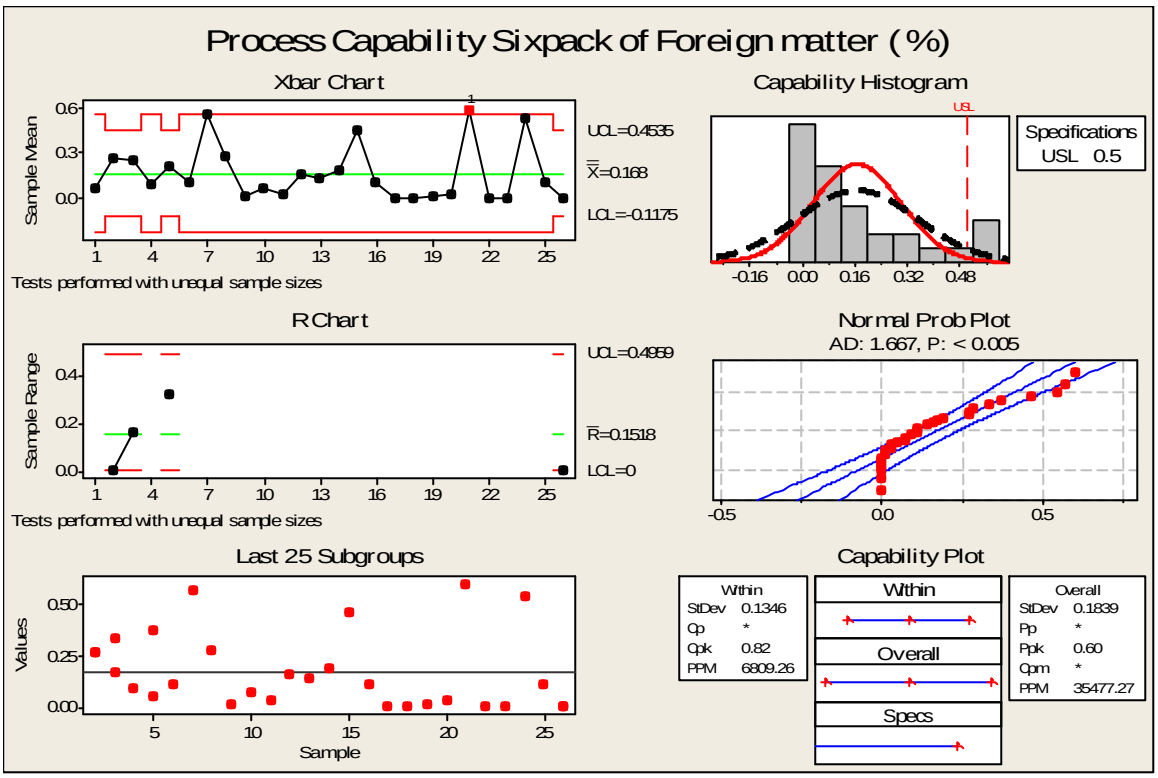


Figure 8. 6: Quality Control Charts and Process Capability Analysis for Foreign matter (%) of Yellow Split Peas.

The quality control chart given as output is the chart of foreign matter (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control except only one point in outside in upper control limit.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 8.6 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Yellow Split Peas of foreign matter report by this process exceed the Upper specification limit (USL). A significant percentage of the foreign matter (%) of Yellow Split Peas is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 8.6, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.82 is less than 1 means that the process is off centered and is not capable.

Quality Characteristic: Other colour (%)

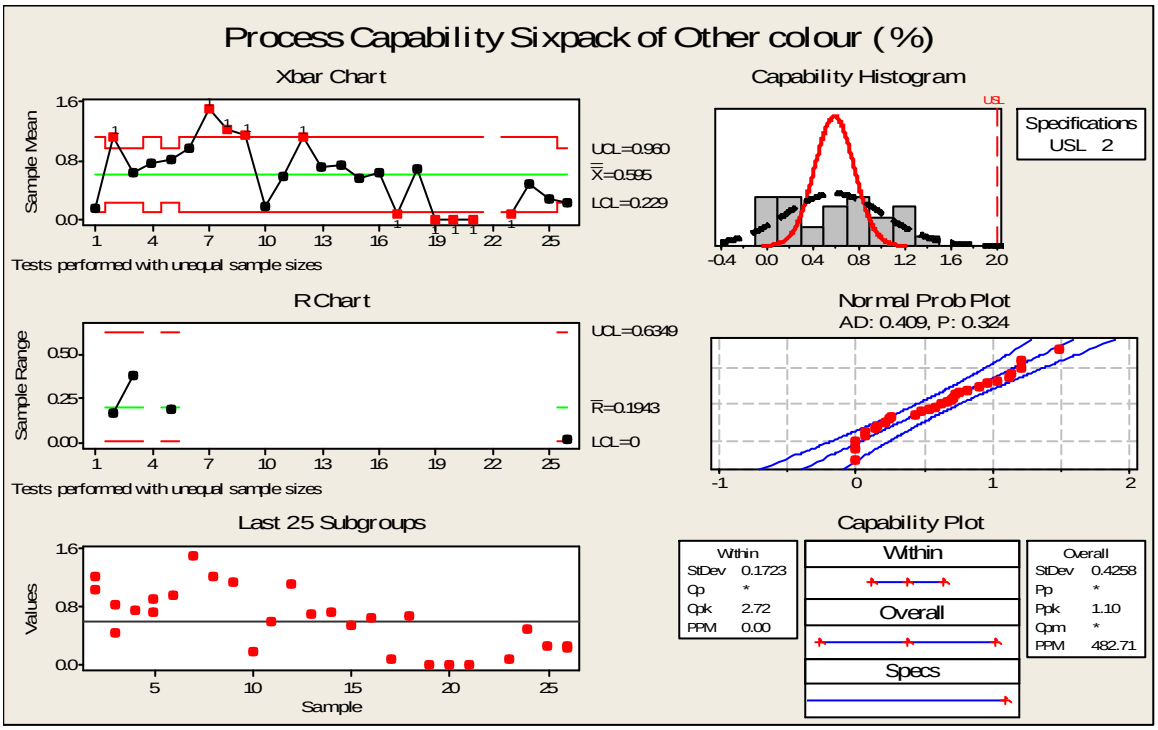


Figure 8. 7: Quality Control Charts and Process Capability Analysis for Other colour (%) of Yellow Split Peas.

The quality control chart given as output is the chart of other colour (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 8.7 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Yellow Split Peas of Other colour report by this process is not exceed the Upper specification limit (USL). An insignificant percentage of the other colour (%) of Yellow Split Peas is outside of Upper Specification Limit.

From the Normal probability plot graph in Figure 8.7, the Anderson-Darling (AD) Normality test shows that we are unable to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the $\alpha = 0.05$ significance level. This is due to the fact that the p-value for the A-D test is 0.324, which is greater than 0.05 - a frequently used level of significance for such a hypothesis test.The necessary assumptions appear to have been fulfilled and we may investigate the capability of this process, as shown in Figure 8.7.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =2.72 is greater than 1 means that the process is centered and capable.

Quality Characteristic: Insect damage (%)

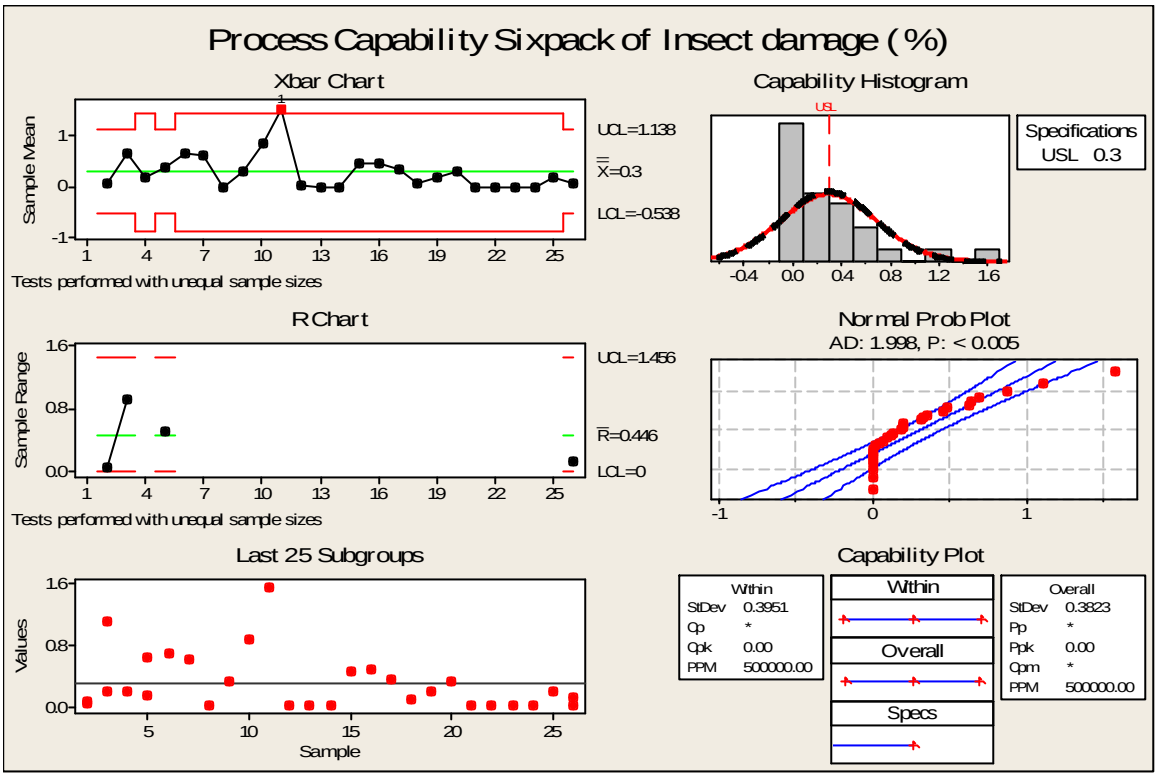


Figure 8. 8: Quality Control Charts and Process Capability Analysis for Insect damage (%) of Yellow Split Peas.

The quality control chart given as output is the chart of Insect damage (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in control except only one point in outside in upper control limit.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 8.8 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Yellow Split Peas of Insect damage (%) report by this process exceed the Upper specification limit (USL). A significant percentage of the Insect damage (%) of Yellow Split Peas is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 8.8, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.00 is less than 1 means that the process is off-centered and not capable.

Quality Characteristic: Broken (%)

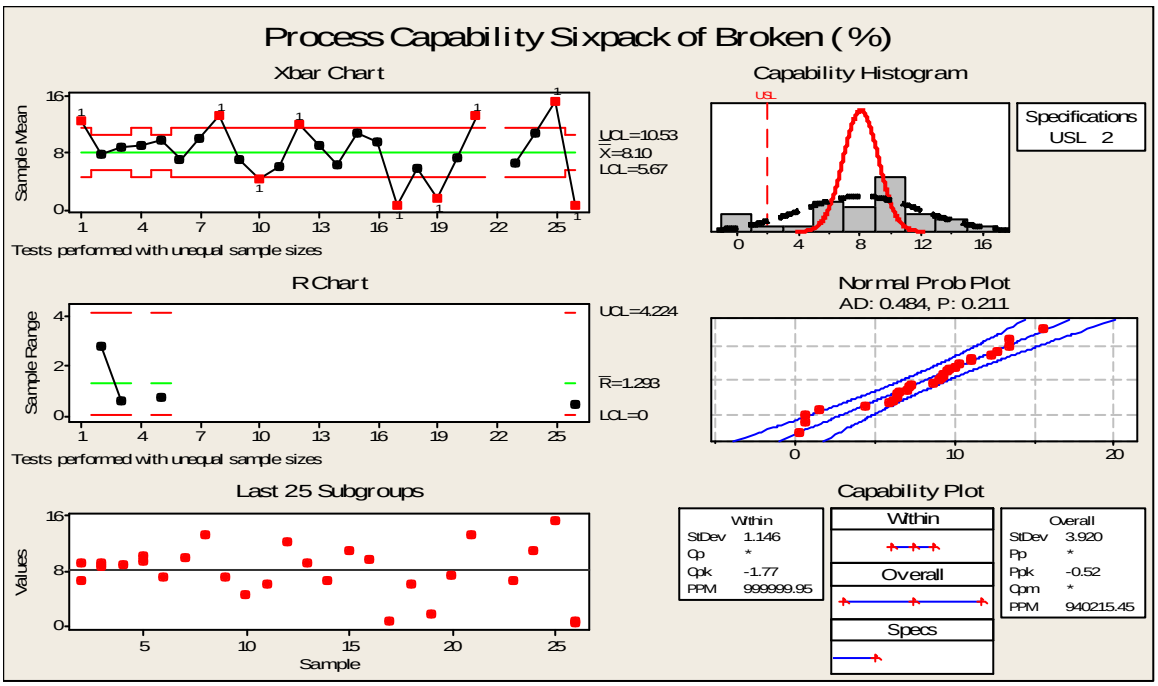


Figure 8. 9: Quality Control Charts and Process Capability Analysis for Broken (%) of Yellow Split Peas.

The quality control chart given as output is the chart of Broken (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control mean chart.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 8.9 shows the histogram of the data along with normal curves overlaid on the histogram. The products of Yellow Split Peas of Broken (%) report by this process exceed the Upper specification limit (USL). A significant percentage of the Broken (%) of Yellow Split Peas is outside of Upper Specification Limit.

From the Normal probability plot graph in Figure 8.9, the Anderson-Darling (AD) Normality test shows that we are unable to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the $\alpha = 0.05$ significance level. This is due to the fact that the p-value for the A-D test is 0.211, which is greater than 0.05 - a frequently used level of significance for such a hypothesis test. The necessary assumptions appear to have been fulfilled and we may investigate the capability of this process, as shown in Figure 8.9.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =-1.77 is less than 1 means that the process is off-centered and not capable.

8.7 Comparison of *t* test and Wilcoxon signed-rank test

In analytical chemistry it is essential to validate a given analytical method to determine its applicability, reproducibility, repeatability and the accuracy of the data obtained. The analyst should establish some basis to prove that the method is working for its intent use. Normally, the amount of data is rather small and the so-called Student *t* distribution should be used (IAEA, 2003).

(Doane & Seward, 2007) indicated that the Wilcoxon signed-rank test is robust to non-normal, and somewhat asymmetrical, population shapes. In fact, the assumptions underlying the *t*-test are violated in every situation because there is neither an underlying normal distribution nor an interval level of measurement (Meek et al., 2007).

Table 8. 3: Comparison of *t* test and Wilcoxon signed-rank test for proximate analysis of Yellow Split Peas according to their acceptable range as prescribed by WFP, Dhaka.

Variables	**Wilcoxon test**	**P-value**	***t*-test**	**P-value**	**Kolmogorov-Smirnov test**	**P-value**

Moisture (%)	0.00	1.000	-21.00	1.000	0.094	>0.150
Purity (%)	88.5	0.003	-3.27	0.001	0.116	>0.150
Whole peas (%)	0.00	1.000	-19.49	1.000	0.175	0.032
Heat damage (%)	130.00	0.953	0.51	0.305	0.404	<0.010
Other damage (%)	44.00	1.000	-5.61	1.000	0.173	0.035
Foreign matter (%)	8.50	1.000	-9.89	1.000	0.190	<0.010
Other colour (%)	0.00	1.000	-17.77	1.000	0.129	>0.150
Insect damage (%)	183.50	0.772	-0.00	0.500	0.224	<0.010
Broken (%)	425.0	0.000	8.38	0.000	0.119	>0.150

This study also investigated the behavior of the one sample *t*-test for Yellow Split Peas samples. Table 8.3 shows the result of the *t-test*. Purity (%) and Broken (%) were significant compared with acceptable range as Prescribed by WFP, Dhaka. While other variables are insignificant.

For the above test, where $\alpha = 0.05$, given that $p > \alpha$ for the Moisture (%), Purity (%), Other colour (%) and Broken (%), we would conclude that only four Variable (test parameter) are normally distributed. Therefore, the assumption of normality has been met for this few variables.

Even so, the results indicate that, in almost every case whenthe null hypothesis was false, the *t*-testperformed as same with the Wilcoxon signed-rank test though normality assumptions were violated. There were a total of 2 cases in which the Wilcoxon signed-rank test perform efficient predicted probability (p-value) than the *t*-test when H_0 was true as fulfill assumptions.

8.8 Binary logistic regression analysis of Yellow Split Peas

Stata software was performed to identify Yellow Split Peas quality parameters appropriate for inclusion in a logistic regression model to predict the accepted/ unaccepted as prescribed acceptable range by WFP, Dhaka in a Yellow Split Peas sample.

Logistic regression was used to assess the impact of a chemical analysis of Yellow Split Peas analysis parameter to identify the quality of Yellow Split Peas which was supplied by some

Yellow Split Peas sample produced industries. The model contained single independent variables against single dependent variable.

Table 8. 4: Logistic Regression Analysis of acceptancey for Proximate Analysis of Yellow Split Peas.

Response variable	Independent Variable	Coef.	Std. Err.	z-value	P-value	AIC	BIC	GOF
Purity (%)	Moisture (%)	-0.444	0.697	-0.64	0.524	39.51	42.25	0.336
Heat damage (%)		-0.946	0.919	-1.03	0.303	29.51	32.25	0.437
Other damage (%)		-1.557	1.256	-1.24	0.215	21.47	24.20	0.624
Foreign matter (%)		0.317	1.002	0.32	0.751	23.40	26.21	0.422
Insect damage (%)		-0.438	0.670	-0.65	0.513	42.06	44.79	0.316
Broken (%)		-0.972	0.971	-1.00	0.317	26.21	28.95	0.655

Note: Coeff.= Coefficient of the model, Std. Err.= Standard Error, AIC= Akaike Information Criterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

The full model containing a variable Moisture (%) was statistically insignificant with P>0.05 according to accepted range of test parameter as prescribed by WFP, Dhaka.Indicating that the model was able to distinguish between Yellow Split Peas samples which reported having and not having accepted range as prescribed by WFP, Dhaka. The *p*-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in Table 8.4 with insignificant (P>0.05).

8.9 Binary probit regression analysis of Yellow Split Peas

To determine the factors influencing the decision to acceptable in food products a probit model were used. The decision to use probit is based on the fact that the decision variable is discrete and dichotomous (one either acceptable of Yellow Split Peas as prescribed by WFP, Dhaka or not), discrete decisions are analyzed using qualitative response models one of which is probit.

Collecting Yellow Split Peas analysis data findings revealed that Yellow Split Peas analysis data can be classified into two classes; acceptable and non acceptable according to WFP and other standard prescribed range. A probit regression was used to determine the factors that influence the decision to analysis value among food producer or analyzer operators.

Table 8. 5: Binary Probit/Normit regression of acceptancey for Proximate Analysis of Yellow Split Peas.

Response variable	Independent Variable	Coef.	Std. Error	z-value	P-value	AIC	BIC	GOF
Purity (%)	Moisture (%)	-0.253	0.406	-0.62	0.534	39.54	42.27	0.339
Heat damage (%)		-0.525	0.511	-1.03	0.304	29.52	32.26	0.446
Other damage (%)		-0.846	0.665	-1.27	0.203	21.38	24.12	0.617
Foreign matter (%)		0.151	0.497	0.30	0.761	23.41	26.21	0.421
Insect damage (%)		-0.281	0.420	-0.67	0.503	42.04	44.78	0.315
Broken (%)		-0.578	0.553	-1.05	0.296	26.12	28.85	0.664

Note: Coeff.= Coefficient of the model, Std. Err.= Standard Error, AIC= Akaike Information Criterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

Table 8.5 shows estimates of the probit model for the factors influencing analyzed value among the Yellow Split Peas producers or respective analyzer of the study. The model contained single independent variables against single dependent variables.

The full model containing a variable Moisture (%) was statistically insignificant with P>0.05 according to accepted range of test parameter as prescribed by WFP, Dhaka. Indicating that the probit model was able to distinguish between Yellow Split Peas samples which reported having and not having accepted range as prescribed by WFP, Dhaka. The *p*-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in Table 8.5 with insignificant (P>0.05).

To find correct estimates of standard errors and p-values it is necessary to choose better model. To select the model, here, we consider two information criteria used to compare models. In general, “smaller is better”: given two models, the one with the smaller AIC fits the data better than the one with the larger AIC. As with the AIC, a smaller BIC indicates a better-fitting model (Samples, n.d.).

We fit a model explaining Yellow Split Peas products has on the basis of accepted range of Purity (%), Heat damage (%), Other damage (%), Foreign matter (%), Insect damage (%) and Broken (%)against Moisture (%). The goodness-of-fit criteria for comparing these two model results are found in table 8.4 and 8.5. AIC and BIC were determined by logit and probit regression of the predicted values obtained in the fit to the true model equation. For using

logit and probit model studied in Table 8.4 and 8.5; based on the AIC and BIC criterions were approximated same using a Logistic and probit model.

8.10 Discriminant function analysis

The discriminant analysis to Yellow Split Peas under Acceptable Range as WFP, Dhaka with the test to determine classify groups of acceptability between the groups using Wilks' Lambda revealed that the diverse parameters yielded a statistical significance at a level of 0.05.

Table 8. 6: Discriminant Function Analysis results of physiochemical analysis of Yellow Split Peas.

Response variable	Independent Variable	Wilks' Lambda	P-value	goodness-of-fit test	
				Box's M	P-value
Purity (%)	Moisture (%)	0.986	0.539	1.568	0.221
Heat damage (%)		0.962	0.309	0.130	0.730
Other damage (%)		0.942	0.206	0.139	0.732
Foreign matter (%)		0.997	0.761	0.882	0.386
Insect damage (%)		0.985	0.528	2.012	0.164
Broken (%)		0.964	0.322	0.528	0.492

Box's M test the assumption of homogeneity of covariance matrices. This test is very sensitive to meeting the assumption of multivariate normality. Discriminant function analysis is **robust** even when the homogeneity of variances assumption is not met, provided the data do not contain important outliers (Bian, n.d.). For our data the variables product Moisuture (%) were not got differ in their covariance matrices.That is fullfill assumptions ofdiscriminant analysis.

The Wilk‘s lambda is a measure of the overall statistical significance of the Linear Discriminant Functions and is statistically insignificant at the 5 percent level of probability for the Tests of Equality of Group Means of product moisture (%) against test parameter according to acceptable range as prescribe by WFP, Dhaka. (Refer to Table 8.6). This implies that the group means for the independent variable product moisture (%) are insignificant relationship on the discriminating analysis.

8.11 ARCH-LM test

To detect the presence of ARCH effect in the mean equation of Yellow Split Peas, we use the ARCH-LM (Lagrange multiplier) test.

Table 8. 7: ARCH-LM test analysis results of physiochemical analysis parameter of Yellow Split Peas.

Variable	LM test for autoregressive conditional heteroskedasticity (ARCH)		Dickey-Fuller test for unit root	
	Chi-square Statistic	P-value	Test Statistic, Z(t)	P-value
Moisture (%)	0.570	0.450	-4.286	0.0005
Purity (%)	6.316	0.012	-4.408	0.0003
Whole peas (%)	0.017	0.895	-5.024	0.0000
Heat damage (%)	0.076	0.782	-5.896	0.0000
Other damage (%)	0.001	0.978	-4.220	0.0006
Foreign matter (%)	0.416	0.519	-7.139	0.0000
Other colour (%)	1.305	0.253	-4.685	0.0001
Insect damage (%)	27.031	0.000	6.987	1.0000
Broken (%)	0.004	0.948	-6.639	0.0000
Husk (%)	0.135	0.7136	-3.532	0.0072
Cotyledon with hush (%)	3.536	0.060	-	-
Standard Plate count (cfu/gm)	1.461	0.227	-	-
Mold (cfu/gm)	0.335	0.5624	-	-

In our analysis the different value of above variables of the ARCH-LM test; the lags included in the test are only 1. The corresponding P-Value is >0.05, which is very high except Purity (%) and Insect damage (%) variables. So we have no difficulty to accept the null hypothesis of no ARCH error in the analysis series. The parameters of Yellow Split Peas analysis are insignificant that means no ARCH effects of the models. The estimation results are given in the table 8.7.

Table 8.7 shows that the values of DF test for all variables p-value <0.05 at 5%, level of significance for all variable except Insect damage (%)which implies that the variables series

is stationary. An outcome of DF test confirms that the physiochemical analysis variables series is stationary except Insect damage (%).

8.12 Spike Behaviour of ARCH(1) and GARCH(1,1) model estimations

The presence of extreme spikesin our analysis of Yellow Split Peas products that is a bad characteristic of food products.

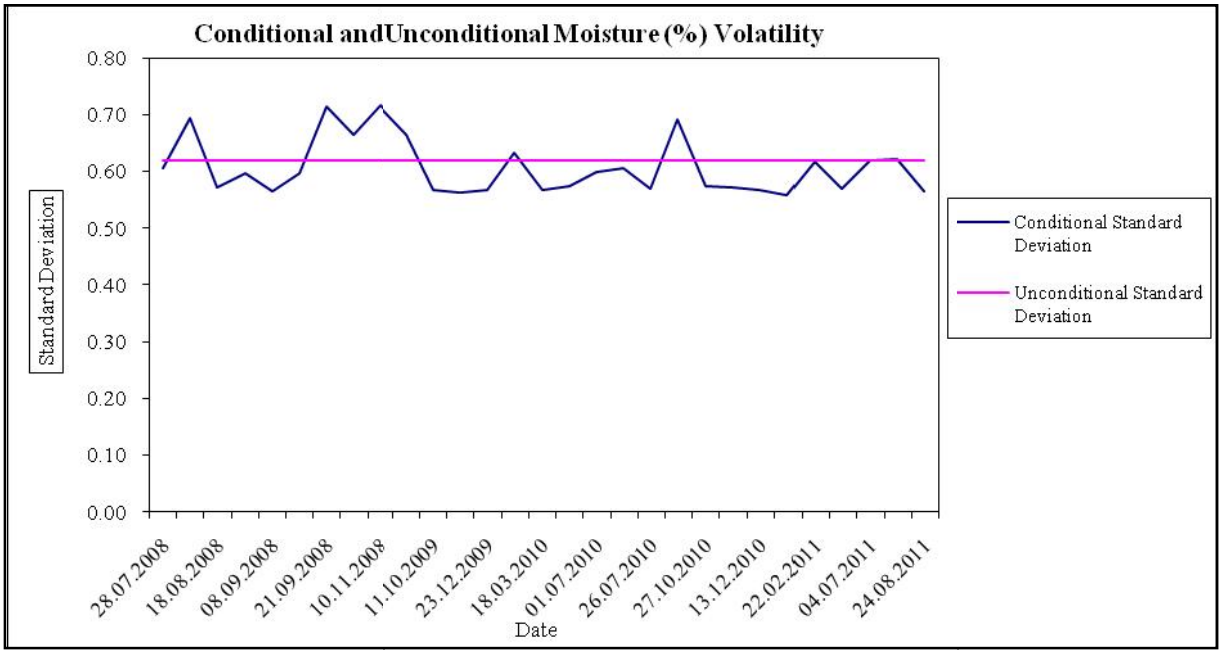


Figure 8. 10: Moisture (%) content of Yellow Split Peas products for the Period November 2007 to February 2010.

Figure 8.10 shows the conditional and unconditional standard deviation of Moisture (%) content over the period July 2008 to August 2011. Conditional standard deviations are over 0.50 during the sample period. The results indicate that the standard deviation almost stable among 2008 to 2011 and volatility in deviations is very low in this time period.

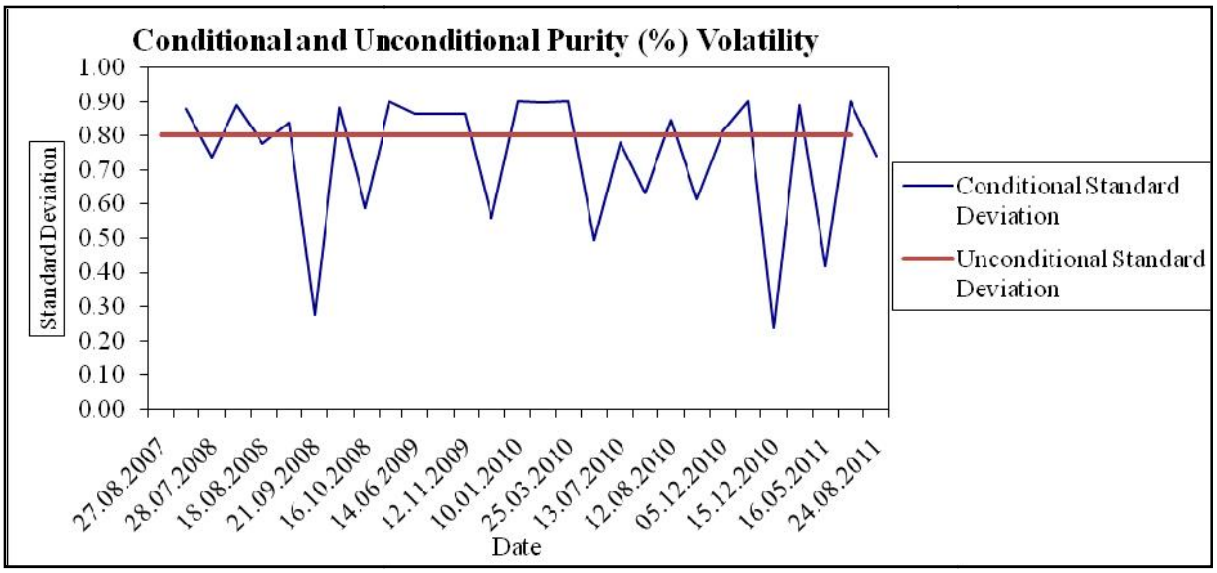


Figure 8. 11: Purity (%) content of Yellow Split Peas products for the Period August 2007 to August 2011.

Figure 8.11 shows the conditional and unconditional standard deviation of Purity (%) content over the period August 2007 to August 2011. Conditional standard deviations are over 0.20 during the sample period. The results indicate that the deviations significantly ups and down at whole period and also in spike behaviour at September 2008 and December 2010. However, volatility in deviation is low in this time period.

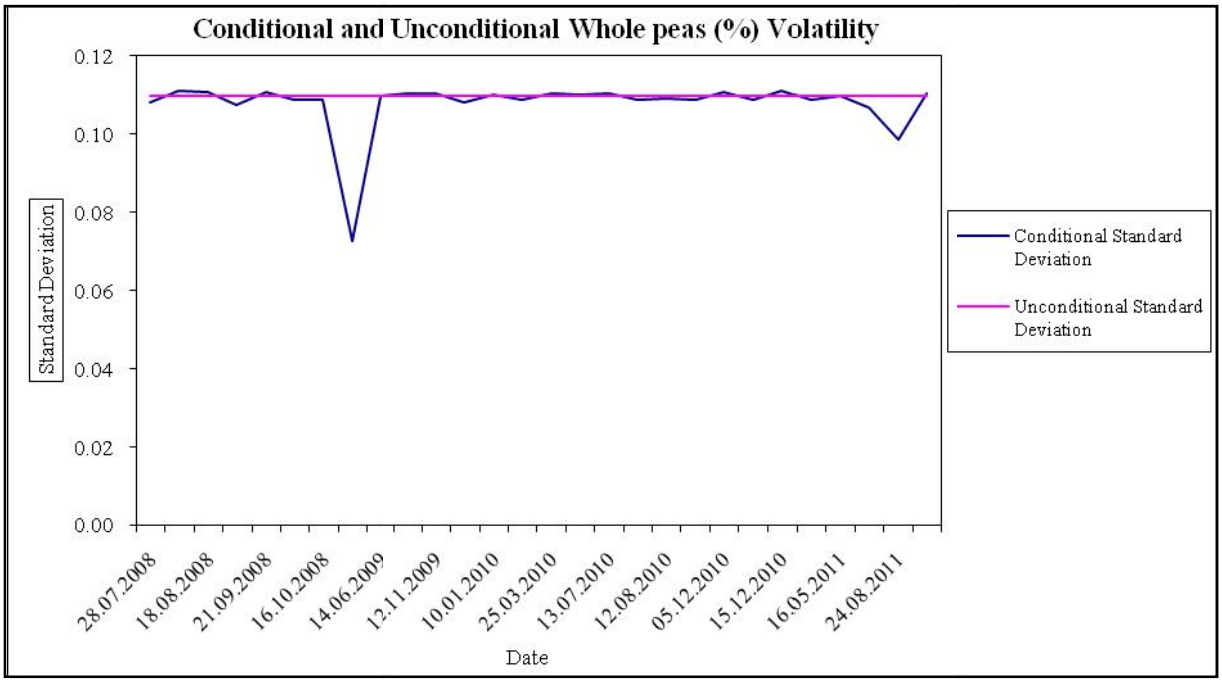


Figure 8. 12: Whole peas (%) content of Yellow split peas products for the Period July 2008 to August 2011.

Figure 8.12 shows the conditional and unconditional standard deviation of Whole peas (%) content over the period July 2008 to August 2011. Conditional standard deviations are over 0.7 during the sample period. As can be seen in Figure 8.12, the deviation has relatively stable then also spike in the period July 2009. However, volatility in deviation is low in this time period.

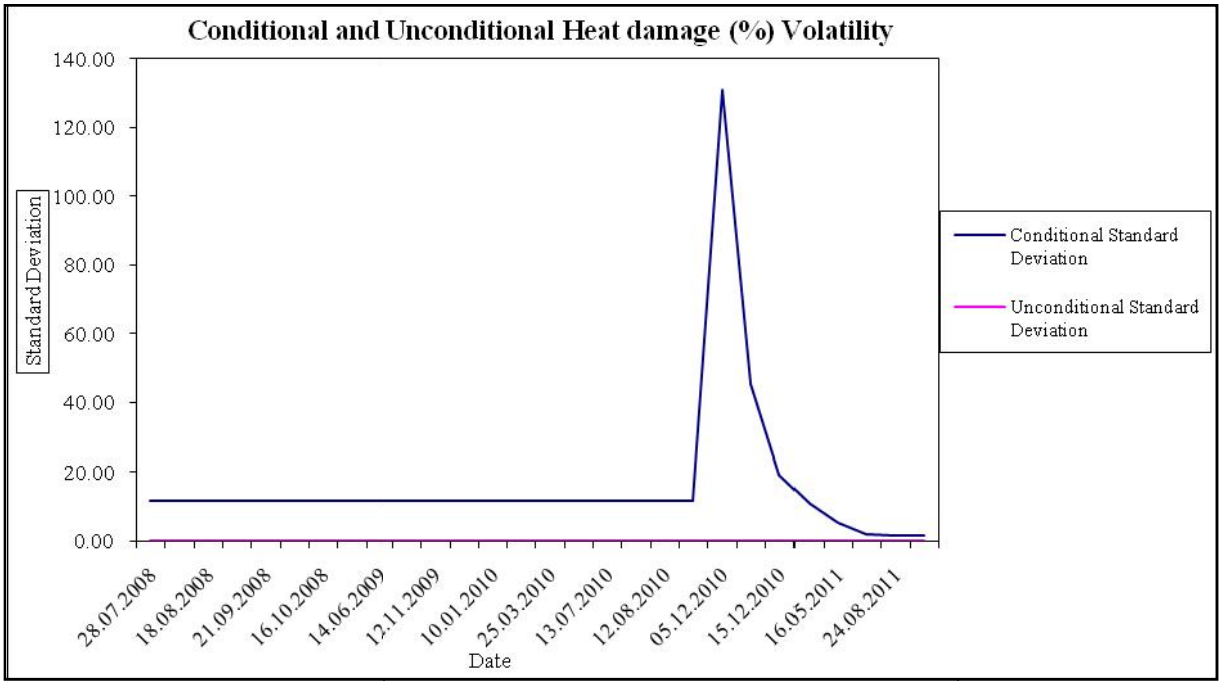


Figure 8. 13: Heat damage (%) content of Yellow split peas products for the Period July 2008 to August 2011.

Figure 8.13 shows the conditional and unconditional standard deviation of Solubility (%) content over the period July 2008 to August 2011. Conditional deviations are over 0.00 during the sample period. The results indicate that the deviations almos stable and also spike behaviour at December 2010. However, volatility in deviations is low in this time period.

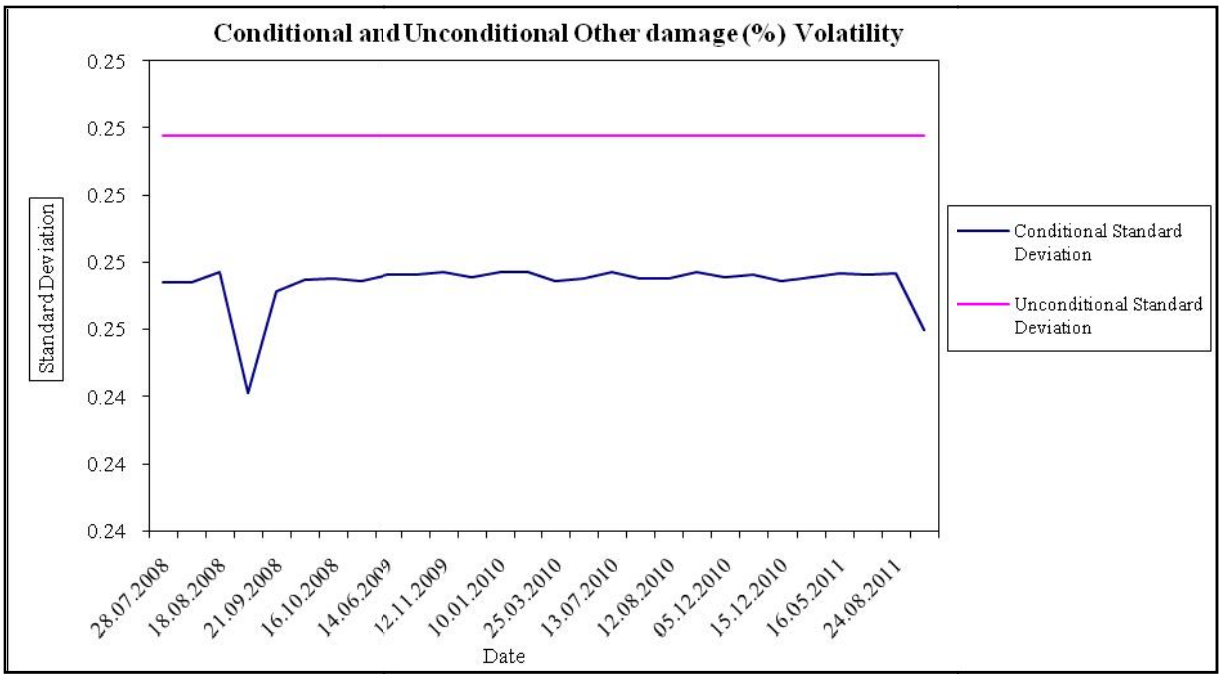


Figure 8. 14: Other damage (%) content of Yellow split peas products for the Period July 2008 to August 2011.

Figure 8.14 shows conditional and unconditional standard deviation of Other damage (%) content over the period July 2008 to August 2011. Conditional deviations are over 0.24 during the sample period. As can be seen in Fig. 8.14, the deviation has relatively stable during sample period. However, volatility in deviation is low in this time period. The deviation is spike behaviour during the period august to september 2008.

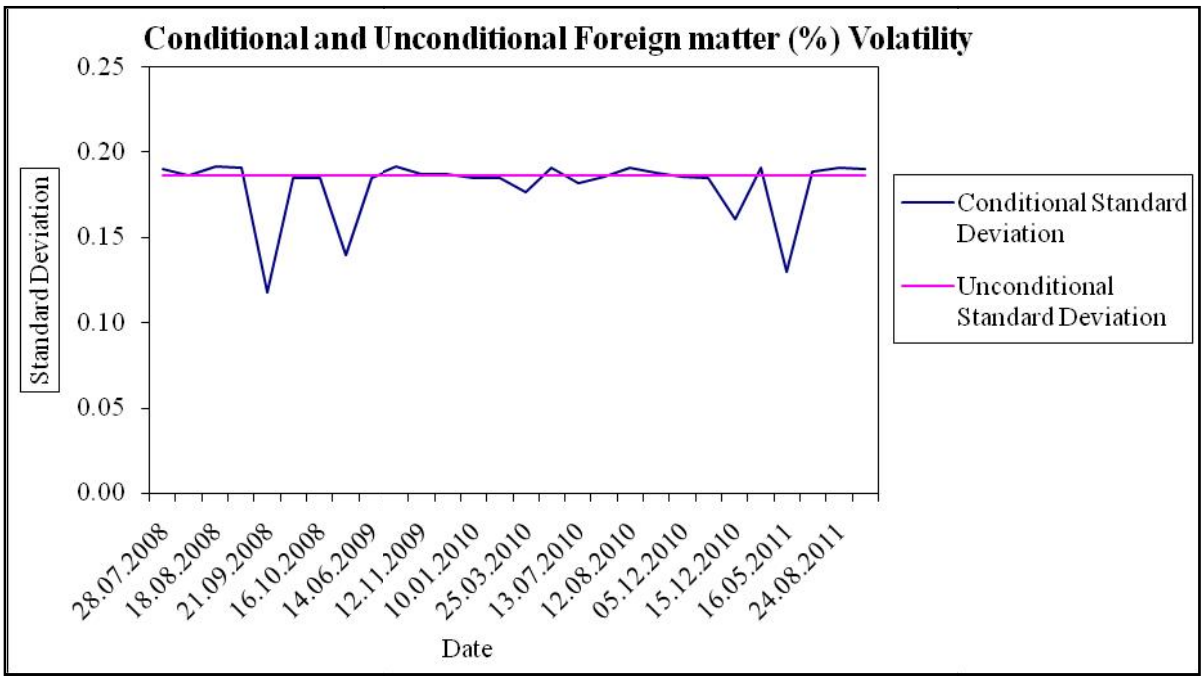


Figure 8. 15: Foreign matter (%) content of Yellow split peas products for the Period July 2008 to August 2011.

Figure 8.15 shows the conditional and unconditional standard deviation of Foreign matter (%) content over the period July 2008 to August 2011. Conditional deviations are over 0.10 during the sample period. The results indicate that the deviations are also stabe behaviour. The deviation is volatile during the period 2008 and 2011.

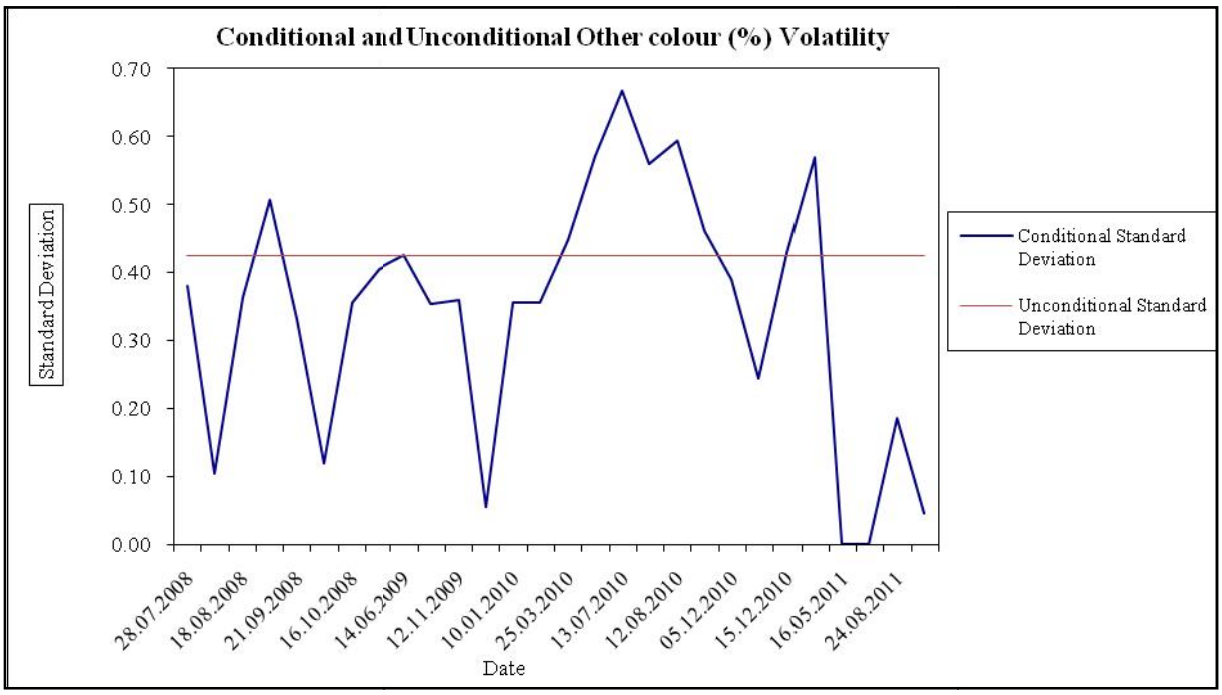


Figure 8. 16: Other colour (%) content of Yellow split peas products for the Period July 2008 to August 2011.

Figure 8.16 shows the conditional and unconditional standard deviation of Other colour (%) content over the period November 2007 to February 2010. Conditional deviations are over 0.00 during the sample period. The results indicate that the deviations are high spike behaviour at the period 2008 and 2011 and relatively high deviation during the whole period. The deviation is high volatile during the period 2008–2011.

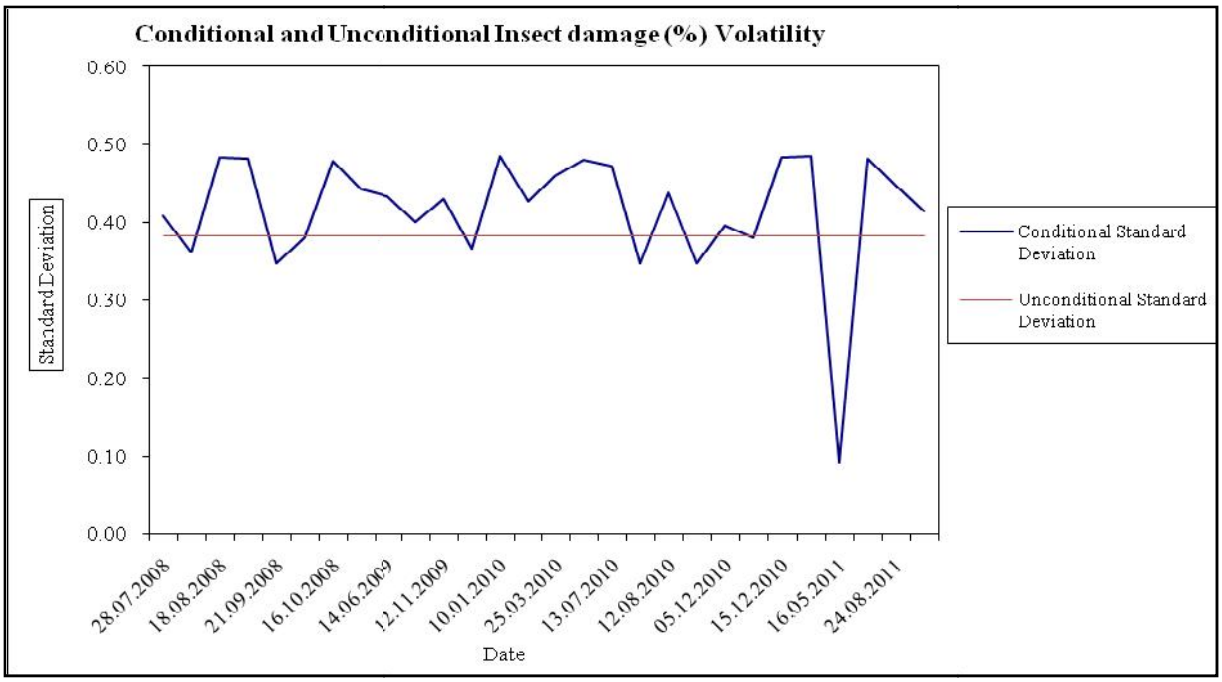


Figure 8. 17: Insect damage (%) content of Yellow split peas products for the Period July 2008 to August 2011.

Figure 8.17 shows the conditional and unconditional standard deviation of Insect damage(%) content over the period July 2008 to August 2011. Conditional deviations are over 0.05 during the sample period. The results indicate that the deviations are low spike behaviour at the period 2008 and 2010 and relatively high spike behaviour during the period May 2011.

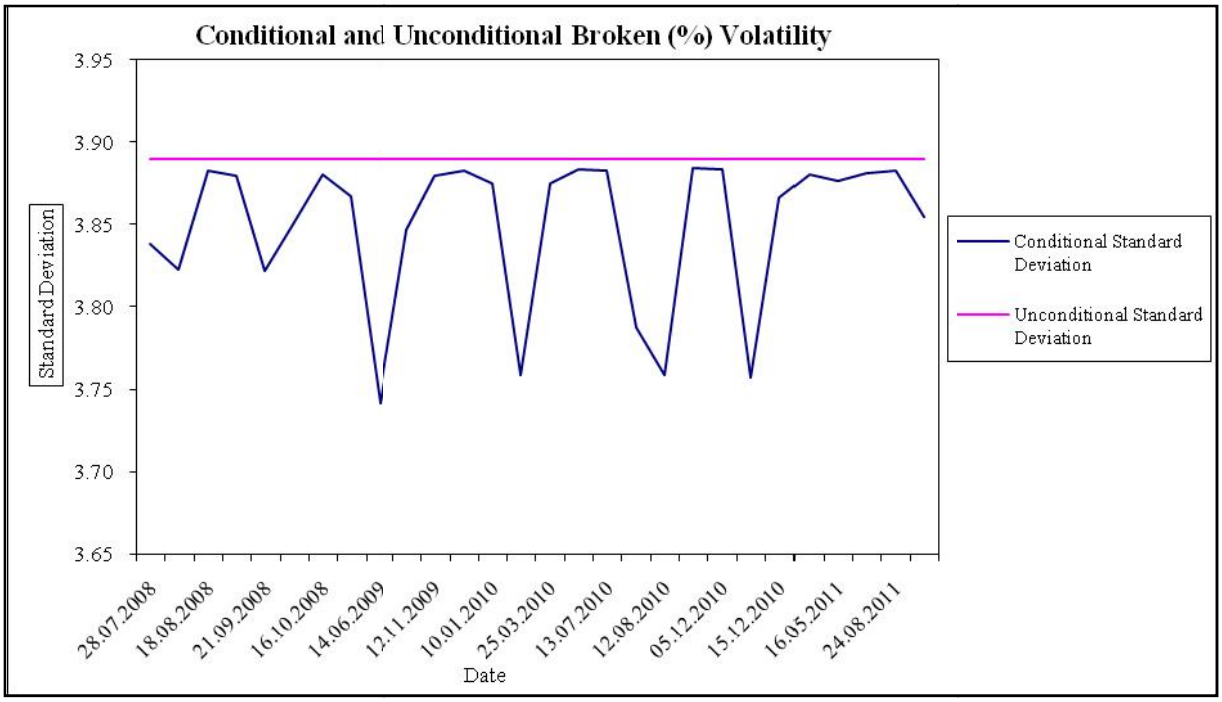


Figure 8. 18: Broken (%) content of Yellow split peas products for the Period July 2008 to August 2011.

Figure 8.18 shows the conditional and unconditional standard deviation of broken (%) content over the period July 2008 to August 2011. Conditional deviations are over 3.70 during the sample period. The results indicate that the deviations are high spike behaviour at the period 2008 and 2011.

8.13 Comparison among three statistical technique

Comparison among Logistic & Probit Regression and Discriminant Analysis in classification groups for Yellow Split Peas.

Table 8. 8: Summary of statistics of Logit, Probit model and Discriminant function analysis.

		Logistic Regression		**Probit Regression**		**Discriminant analysis**	
Response variable	Independent Variable	p-value	GOF	p-value	GOF	p-value	GOF
Purity (%)	Moisture (%)	0.524	0.336	0.534	0.339	0.539	0.221
Heat damage (%)		0.303	0.437	0.304	0.446	0.309	0.730
Other damage (%)		0.215	0.624	0.203	0.617	0.206	0.732
Foreign matter (%)		0.751	0.422	0.761	0.421	0.761	0.386
Insect damage (%)		0.513	0.316	0.503	0.315	0.528	0.164
Broken (%)		0.317	0.655	0.296	0.664	0.322	0.492

Note: GOF= Goodness-of-fit statistics.

From the above demonstrations of three different technique, Logit & Probit model and Discriminant function analysis, all of them provide almost equal predicted probability of the same variable which is given with the level of accepted range as prescribed by WFP, Dhaka. The level of significance of Goodness-of-fitstatistics are >0.05 under Logit, Probit and Discriminant analysis.

CHAPTER 9:WHITE SUGAR

9.1 Introduction

This chapter describes the White Sugar for product description and analysis for the study. A description of prducts includes the following sub sections: product description and production of white sugar, trade. The resulting data were employed in different levels of analysis. The chapter concludes by giving the empirical specification and estimation procedures for the fitted models.

9.2 Prduct Description and production

Around 80 percent of the worlds sugar is derived from sugar cane, grown by millions of small-scale farmers and plantation workers in developing countries. Raw sugar is derived from both cane sugar and sugar beet. Brazil and India are the world's two largest sugar producers. Together, they have accounted for over half the world's sugar cane production for the past 40 years. The EU is the third-largest producer and accounts for around half the world's sugar-beet production (Briefing, 2013a).

Trade: World exports of raw sugar are forecast at 58 million tonnes for 2011-12 – 1 per cent higher than the previous year – led by Brazil (24.6 million tonnes) and Thailand (9 million tonnes) (Briefing, 2013b).

Imports of raw sugar are forecast at 49 million tonnes for 2011-12. The EU, US and Indonesia are the leading importers, at around 3 million tonnes each per year. China is poised to join them, its imports more than doubling from 972,000 tonnes in 2007-08 to 2.4 million tonnes in 2011-12, but future imports are likely to be offset by increased production.

In some countries (including India, Bangladesh and Nepal), cane prices are fixed by the government, while in others the price is negotiated between growers and processors at the start of the season (Briefing, 2013b).

White Sugar is sound, fair and marketable quality, dry, in homogeneous granulated, free-flowing crystals. The white crystal cane sugar is from a crop of the year (FSC, 2010).

9.3 Preliminary analysis of the data

After collecting data, the first task for a researcher is to organize and simplify the data so that it is possible to get a general overview of the results. One method for simplifying and organizing data is to construct a frequency distribution.

Table 9. 1: Frequency distribution results for chemical analysis of White Sugar.

Proximate Variable		Frequency	Percentage
Moisture (%)			
	Acceptable Range	105	77.8
	Not Acceptable Range	30	22.2
Sulphated Ash (%)			
	Acceptable Range	131	98.5
	Not Acceptable Range	2	1.5
Colour of the solution, in ICUMSA units			
	Acceptable Range	136	96.5
	Not Acceptable Range	5	3.5
Sulphur dioxide, ppm			
	Acceptable Range	77	58.8
	Not Acceptable Range	54	41.2

Frequency distribution presented in Table 9.1 indicates that only Sulphated Ash (%) and Colour of the solution, in ICUMSA units contains are reasonably acceptable and for in case of other variables remarkable number of cases are unacceptable range were compared to the standard value prescribed by WFP, Dhaka and African Organisation for Standardisation.

9.4 Descriptive Statistics of White Sugar

Statistics are a set of tools for obtaining insight into a psychological phenomenon. Descriptive statistics summarise the data, making clear any trends, patterns etc. which may be lurking within them; they consist of visual displays such as graphs, and summary statistics such as means (Hole, 2000).

Table 9. 2: Descriptive Statistics results for proximate analysis of White Sugar.

Variables	Minimum	Maximum	Mean	Std. Deviation

Moisture, %	0.00	0.30	0.06	0.06
Sulphated Ash, %	0.00	0.10	0.02	0.02
Colour of the solution, in ICUMSA units	7.29	213.00	60.92	42.17
Sucrose, %	35.64	99.99	99.21	5.45
Sulphur dioxide, ppm	1.60	29.00	12.81	5.40
Hydrogen Peroxide, ppm	0.00	85.00	0.99	7.64
Hydrose, ppm	0.00	609.00	11.48	66.72

The mean, standard deviation and other descriptive statistics for proximate analysis are displayed in Table 9.2. Here Moisture, %, and Sulphated Ash, % are low standard deviation (SD<2).

9.5 Application of control charts on White Sugar

In order to verify whether quality of food products were under control condition or not we have adopted following control chart of White Sugar for such purposes we have used several Shewhart Control Charts.

In this subsection we present results and analysis that is application of control charts. We show the results and analysis by type of products and types of control chart.

9.6 Process Capability Analysis (Using Normal Distribution Curve)

In this case, we want to assess the process capability for different industries producing certain White Sugar. The proximate analysis of the White Sugar is of concern. The specification limits on the White Sugar are in given appendix 6. There has been a consistent problem with meeting the specification limits and the some process produces a high percentage of rejects.

The histogram of the data shows that proximate analysis of White Sugar follow a normal distribution or approximately normal distribution. The variation from White Sugar-to-White Sugar can be estimated using the within group standard deviation. Since the process is stable and the measurements are normally or approximately normality distributed, the normal distribution option of process capability analysis can be used.

Quality characteristic: Moisture

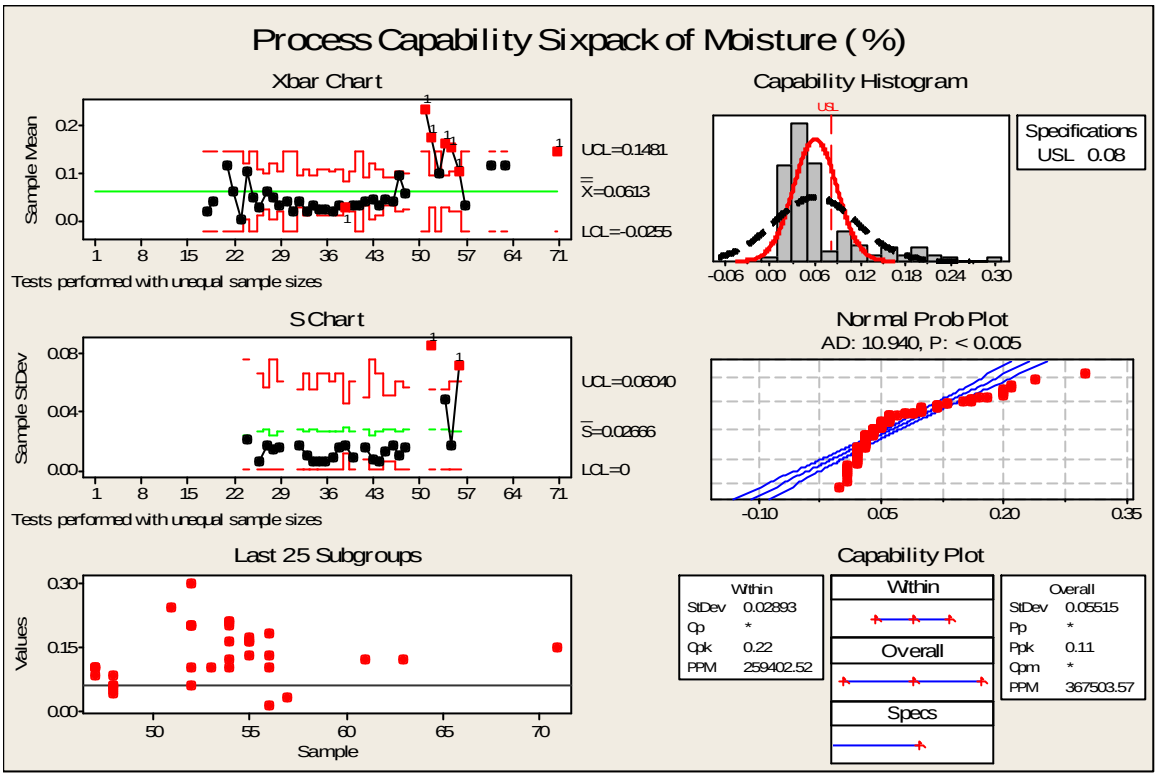


Figure 9. 1: Quality Control Charts and Process Capability Analysis for Moisture (%) of White Sugar.

The quality control and process capability analysis chart given as output is the chart of Moisture (%). These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control in the control limit in mean and range chart.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 9.1 shows the histogram of the data along with normal curves overlaid on the histogram. The products of White Sugar of Moisture analysis report by this process exceed the Upper specification limit (USL). A significant percentage of the Moisture (%) of White Sugar is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 9.1, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.22 is less than 1 means that the process is off centered and not capable.

Quality Characteristic: Sulphated Ash, %

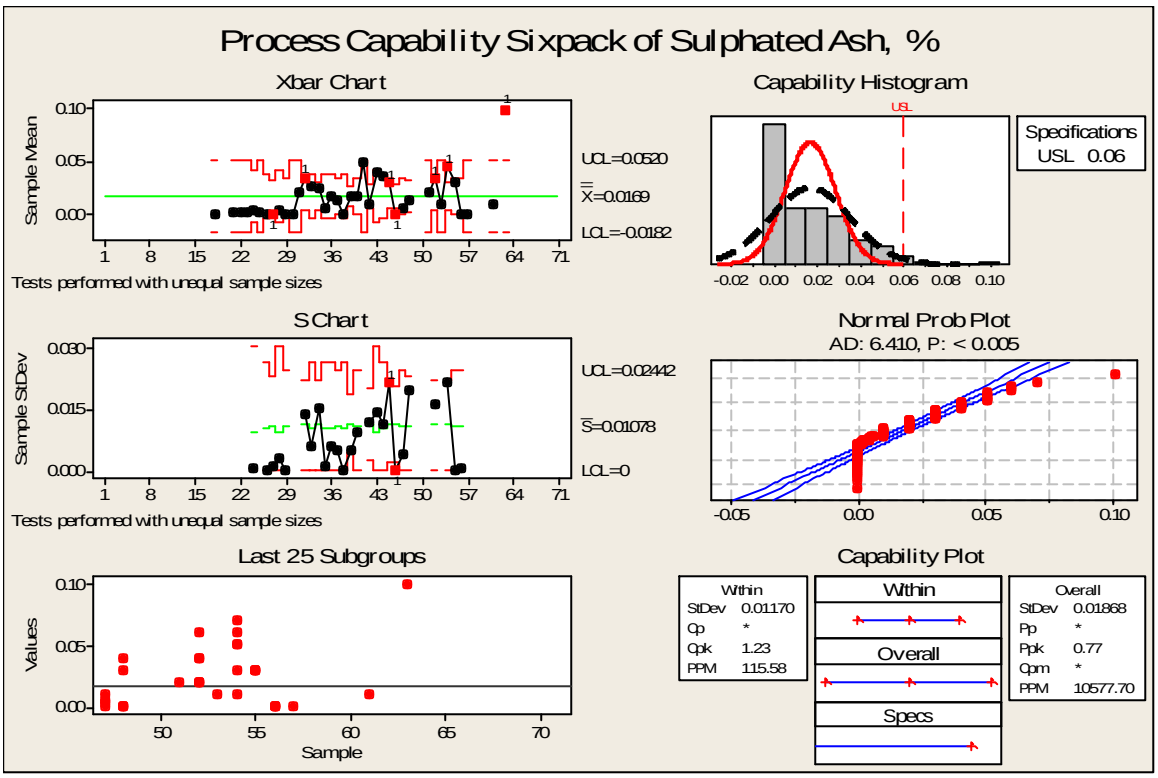


Figure 9. 2: Quality Control Charts and Process Capability Analysis for Sulphated Ash, % of White Sugar.

The quality control and process capability chart given as output is the chart of Sulphated Ash, %. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control in mean and range chart.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 9.2 shows the histogram of the data along with normal curves overlaid on the histogram. The products of White Sugar of Sulphated Ash, % analysis report by this process are not exceeding the Upper specification limit (USL). An insignificant percentage of the Sulphated Ash, % of White Sugar is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 9.2, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =1.23 is greater than 1 means that the process is centered and capable.

Quality Characteristic: Colour of the solution, in ICUMSA units

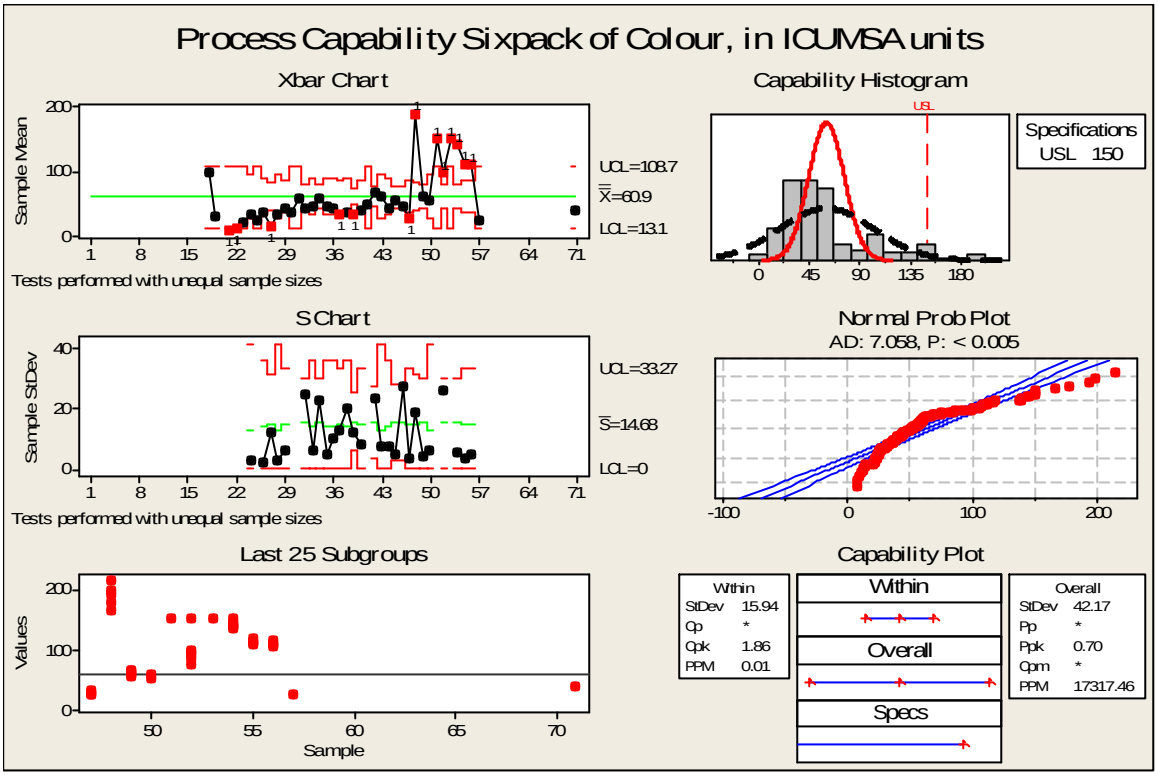


Figure 9. 3: Quality Control Charts and Process Capability Analysis for Colour of the solution, in ICUMSA units of White Sugar.

The quality control chart given as output is the chart of Colour of the solution, in ICUMSA units. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 9.3 shows the histogram of the data along with normal curves overlaid on the histogram. The products of White Sugar of Colour of the solution, in ICUMSA units analysis report by this process is not exceed the Upper specification limit (USL). An insignificant percentage of the Colour of the solution, in ICUMSA units of White Sugar is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 9.3, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =1.86 is greater than 1 means that the process is centered and capable.

Quality Characteristic: Sucrose, %

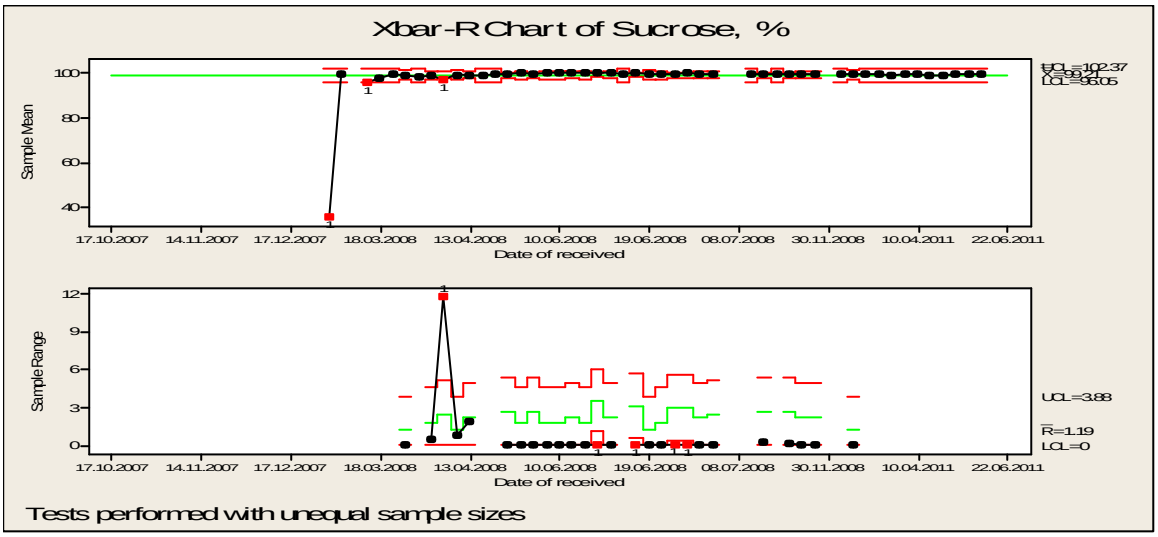


Figure 9. 4: Quality Control Charts for Sucrose, % of White Sugar.

The quality control chart given as output is the chart of Sucrose, %. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control in mean and range chart in Figure 9.4.

Quality Characteristic: Sulpher dioxide, ppm

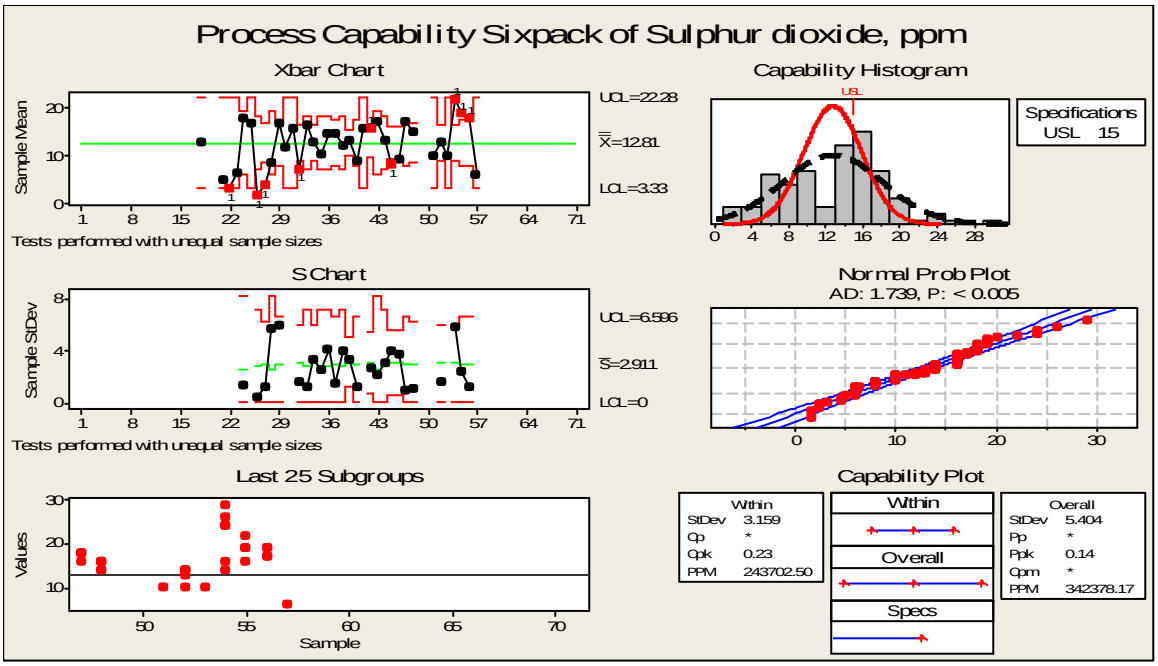


Figure 9. 5: Quality Control Charts and Process Capability Analysis for Sulpher dioxide, ppm of White Sugar.

The quality control chart given as output is the chart of Sulpher dioxide, ppm. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control.

The upper right box reports the process data including the upper specification limit. These values were provided by the minitab program. The calculated values are the process sample mean and the estimates of within standard deviations.

The report in Figure 9.5 shows the histogram of the data along with normal curves overlaid on the histogram. The products of White Sugar of Sulpher dioxide analysis report by this process exceed the Upper specification limit (USL). A significant percentage of the Sulpher dioxide, ppm of White Sugar is outside of Upper Specification Limit.

From the Normal probability plot graph in Fig. 9.5, the Normality test shows that we are able to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is p-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The potential or within process capability of the process is reported on the right hand side. The value of Cpk =0.23 is less than 1 means that the process is off centered and is not capable.

Quality Characteristic: Hydrogen Peroxide, ppm

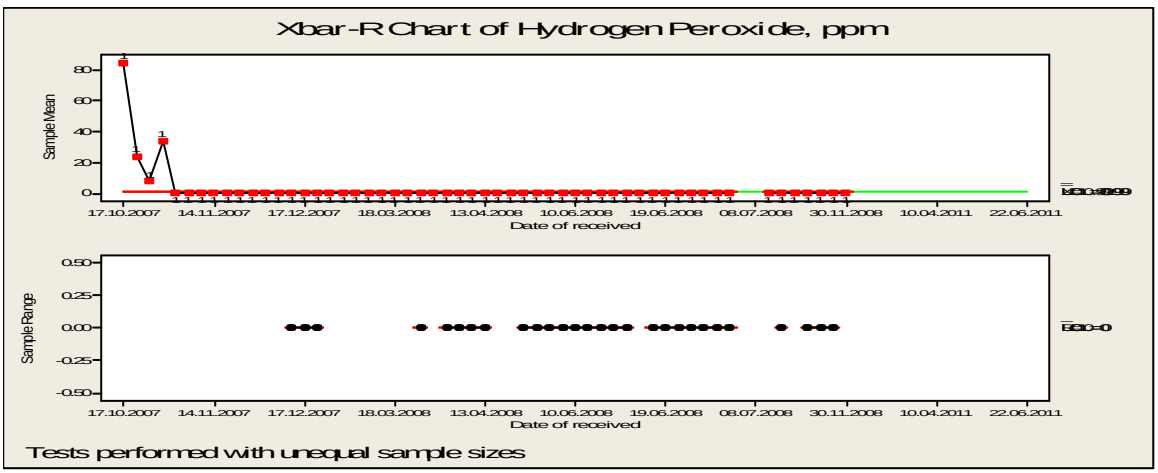


Figure 9. 6: Quality Control Charts and Process Capability Analysis for Hydrogen Peroxide, ppm of White Sugar.

The quality control chart given as output is the chart of Hydrogen Peroxide, ppm. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control in meant chart but range chart is in control in Figure 9.6.

Quality Characteristic: Hydrose, ppm

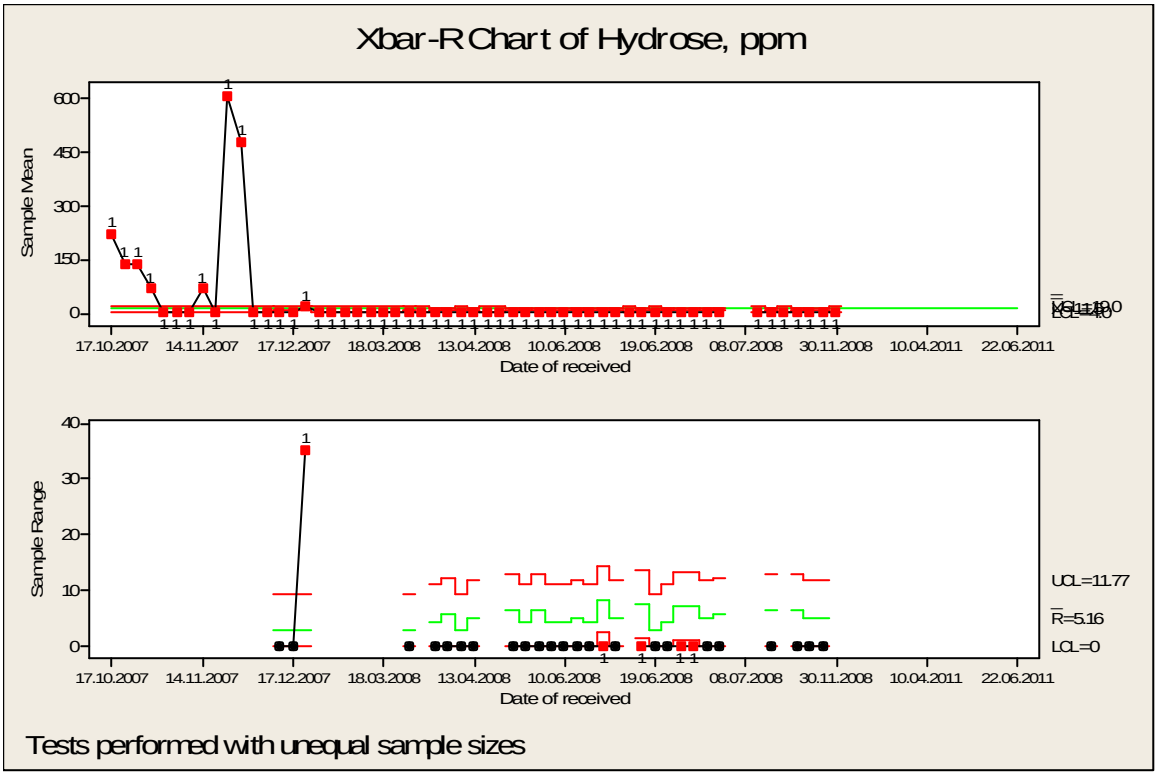


Figure 9. 7: Quality Control Charts and Process Capability Analysis for Hydrose, ppm of White Sugar.

The quality control chart given as output is the chart of Hydrose, ppm. These charts, which are pretty much self-explanatory, clearly shows the date wise sample point along with the unspecified (UCL and LCL) control limits. It is clear that the process is in out of control in mean and range chart in Figure 9.7.

9.7 Comparison of *t* test and Wilcoxon signed-rank test

In analytical chemistry it is essential to validate a given analytical method to determine its applicability, reproducibility, repeatability and the accuracy of the data obtained. The analyst should establish some basis to prove that the method is working for its intent use. Normally, the amount of data is rather small and the so-called Student *t* distribution should be used (IAEA, 2003).

(Doane & Seward, 2007) indicated that the Wilcoxon signed-rank test is robust to non-normal, and somewhat asymmetrical, population shapes. In fact, the assumptions underlying the *t*-test are violated in every situation because there is neither an underlying normal distribution nor an interval level of measurement (Meek et al., 2007).

Table 9. 3: Comparison of *t* test and Wilcoxon signed-rank test for proximate analysis of White Sugar according to their acceptable range as prescribed by WFP, Dhaka.

Variables	Wilcoxon test	P-value	*t*-test	P-value	Kolmogorov-Smirnov test	P-value
Moisture, %	1415.5	1.000	-8.15	1.000	0.265	<0.010
Sulphated Ash, %	51.0	1.000	-26.58	1.000	0.194	<0.010
Colour of the solution, in ICUMSA units	70.5	1.000	-25.09	1.000	0.207	<0.010
Sulphur dioxide, ppm	261.5	1.000	-15.24	1.000	0.135	<0.010
Polarization (^{0}C)	10.0	0.978	4.31	0.989	0.256	>0.150
Sucrose, %	8616.0	1.000	-0.64	0.261	0.443	<0.010

This study also investigated the behavior of the one sample *t-test* for White Sugar samples. Table 9.3 shows the result of the *t-test*. All variables were insignificant compared with acceptable range as Prescribed by WFP, Dhaka. For the above test, where $\alpha = 0.05$, given that $p < \alpha$ for the all varibles in table 9.3 except Polarization (^{0}C). Therefore, the violation of assumption of normality for this variables.

Even so, the results indicate that, in almost every case when the null hypothesis was true, the Wilcoxon signed-rank test perform efficient predited probability (p-value) than the *t*-test.
There were a total of 1 cases in which the Wilcoxon signed-rank test perform efficient predicted probability (p-value) than the *t*-test when H_0 was true as fulfill assumptions.

9.8 Binary logistic regression analysis of White Sugar

A stata software was performed to identify White Sugar quality parameters appropriate for inclusion in a logistic regression model to predict the accepted/ unaccepted as prescribed acceptable range by WFP, Dhaka and African Organisation for Standardisation in a White Sugar sample.

Table 9. 4: Binary logistic regression results of chemical analysis of White Sugar.

Response variable	Independent Variable	Coef.	Std. Error	z-value	P-value	AIC	BIC	GOF
Colour of the solution, in ICUMSA units	Moisture (%)	-1.72	17.39	-0.10	0.921	45.91	54.27	0.995
	Sucrose (%)	8.56	12.72	0.67	0.501			
Sulphated Ash (%)	Moisture (%)	33.66	16.18	2.08	0.038	14.72	23.14	1.000
	Sucrose (%)	-1.44	1.60	-0.90	0.370			

Note: Coeff.= Coefficient of the model, Std. Err.= Standard Error, AIC= Akaike Information Criterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

Logistic regression was used to assess the impact of a chemical analysis of White Sugar parameter to identify the quality of White Sugar which was supplied by some White Sugar sample produced industries. We were analyzed only two dependent variables against two independent variable each according to acceptable range as prescribe by WFP, Dhaka as presented in table 9.4.

The full model containing a variable Moisture (%) was statistically significant with P<0.05 against Sulphated Ash (%) while others were insignificant. Also Sucrose (%) was statistically insignificant with P>0.05 against all dependent variables according to accepted range of test parameter as prescribed by WFP, Dhaka. Indicating that the model was able to distinguish between White Sugar samples which reported having and not having accepted range as prescribed by WFP, Dhaka. The *p*-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in Table 9.4 with insignificant (P>0.05).

9.9 Binary probit regression analysis

To determine the factors influencing the decision to acceptable in food products a probit model were used. The decision to use probit is based on the fact that the decision variable is discrete and dichotomous (one either acceptable of White Sugar as prescribed by WFP,

Dhaka or not), discrete decisions are analyzed using qualitative response models one of which is probit.

Collecting analysis data findings revealed that White Sugar analysis data can be classified into two classes; acceptable and non acceptable according to WFP and ARS prescribed range. A probit regression was used to determine the factors that influence the decision to analysis value among food producer or analyzer operators.

Table 9. 5: Binary Probit/Normit regression results of chemical analysis of White Sugar.

Response variable	Independent Variable	Coef.	Std. Error	z-value	P-value	AIC	BIC	GOF
Colour of the solution, in ICUMSA units	Moisture (%)	-0.93	7.98	-0.12	0.908	45.81	54.18	0.995
	Sucrose (%)	8.56	12.72	0.67	0.501			
Sulphated Ash (%)	Moisture (%)	16.51	8.70	1.90	0.058	14.67	23.09	1.000
	Sucrose (%)	-0.65	0.88	-0.74	0.459			

Note: Coeff.= Coefficient of the model, Std. Err.= Standard Error, AIC= Akaike Information Criterion, BIC=Bayesian information criterion, GOF= Goodness-of-fit statistics.

Table 9.5 shows estimates of the probit model for the factors influencing analyzed value among the White Sugar producers or respective analyzer of the study. We were analyzed only two dependent variables against two independent variable each according to acceptable range as prescribe by WFP, Dhaka as presented in table 9.5.

The full model containing a variable Moisture (%) was statistically insignificant with P>0.05 against all dependent varialble. Also Sucrose (%) was statistically insignificant with P>0.05 against all dependent variables according to accepted range of test parameter as prescribed by WFP, Dhaka. Indicating that the model was able to distinguish between White Sugar samples which reported having and not having accepted range as prescribed by WFP, Dhaka. The *p*-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in Table 9.5 with insignificant (P>0.05).

To find correct estimates of standard errors and p-values it is necessary to choose better model. To select the model, here, we consider two information criteria used to compare models. In general, “smaller is better”: given two models, the one with the smaller AIC fits

the data better than the one with the larger AIC. As with the AIC, a smaller BIC indicates a better-fitting model (Samples, n.d.).

We fit a model explaining the type of White Sugar products has on the basis of Colour of the solution, in ICUMSA units and Sulphated Ash (%). The goodness-of-fit criteria for comparing these two model results are found in table 9.4 and 9.5. AIC and BIC were determined by logit and probit regression of the predicted values obtained in the fit to the true model equation. For the Colour of the solution, in ICUMSA units and Sulphated Ash (%) studied in Table 9.4 and 9.5; based on the AIC and BIC criterions were approximately same by using Logit and probit model.

9.10 Discriminant function analysis.

The discriminant analysis to White Sugar under Acceptable Range as WFP, Dhaka with the test to determine classify groups of acceptability between the groups using Wilks' Lambda revealed that the diverse parameters yielded a statistical significance at a level of 0.05.

Table 9. 6: Discriminant Function Analysis results of chemical analysis of White Sugar.

Response variable	**Independent Variable**	**Wilks' Lambda**	**P-value**	**goodness-of-fit test**	
				Box's M	**P-value**
Colour of the solution, in ICUMSA units	Moisture (%)	1.000	0.934	52.690	0.000
	Sucrose (%)	0.999	0.762		
Sulphated Ash (%)	Moisture (%)	0.950	0.010	-	-
	Sucrose (%)	1.000	0.925		

Box's M test tests the assumption of homogeneity of covariance matrices. This test is very sensitive to meeting the assumption of multivariate normality. Discriminant function analysis is **robust** even when the homogeneity of variances assumption is not met, provided the data do not contain important outliers (Bian, n.d.). For our data we found the groups do differ in their covariance matrices, violating an assumption of DA. When n is large, small deviations from homogeneity will be found significant, which is why Box's M must be interpreted in conjunction with inspection of the log determinants. We can't perform Acceptability of Sulphated Ash (%) the test of Box's M as fewer than two nonsingular group covariance matrices.

The Wilk‘s lambda is a measure of the overall statistical significance of the Linear Discriminant Functions and is statistically significant at the 5 percent level of probability for the Tests of Equality of Group Means of Moisture (%) against against Sulphated Ash (%) (refer to Table 9.6). This implies that the group means for the independent variables Moisture (%) against Sulphated Ash (%) are different on the discriminating function and that the differences in the mean discriminant score are greater than can be attributed to non-sampling error. While other parameters are within acceptable range as prescribe acceptable rang by WFP, Dhaka and African Organisation for Standardisation (ARS).

9.12 ARCH-LM and DF test

To detect the presence of ARCH effect in the mean equation of White Sugar, we use the ARCH-LM (Lagrange multiplier) test.

Table 9. 7: ARCH-LM and DF test analysis results of chemical analysis of White Sugar.

Variable	LM test for autoregressive conditional heteroskedasticity (ARCH)		Dickey-Fuller test for unit root	
	Chi-square Statistic	P-value	Test Statistic, Z(t)	P-value
Moisture, %	52.672	0.000	-5.116	0.000
Sulphated Ash, %	8.132	0.004	-6.159	0.0000
Colour of the solution, in ICUMSA units	69.425	0.000	-4.327	0.0004
Sucrose, %	0.010	0.920	-59.868	0.000
Sulphur dioxide, ppm	50.033	0.000	-5.431	0.000
Hydrogen Peroxide, ppm	28.288	0.000	-25.169	0.000
Hydrose, ppm	28.947	0.000	-7.453	0.000

In our analysis the different value for different variables of above parameters of the ARCH-LM test; the lags included in the test are only 1. The corresponding P-Value is <0.05, which is very low for Moisture, %, Sulphated Ash, %, Colour of the solution, in ICUMSA units,

Sulphur dioxide, ppm, Hydrogen Peroxide, ppm and Hydrose, ppm. So we have no difficulty to reject the null hypothesis of no ARCH error and conclude that there is an ARCH error in the analysis series. This confirms that the order of the ARCH error is six variables for analysis of White Sugar food products. Others parameters Sucrose, % was insignificant that means no ARCH effects of the models. The estimation results are given in the table 9.7.

Table 9.7 shows that the values of DF test for all variables p-value <0.05 at 5%, level of significance which implies that the variables series is stationary. An outcome of DF test confirms that the physiochemical analysis variables series is stationary.

9.13 Spike Behaviour of ARCH(1) and GARCH(1,1) model estimations

The presence of extreme spikesin our analysis of White Sugar products that is a bad characteristic of food products.

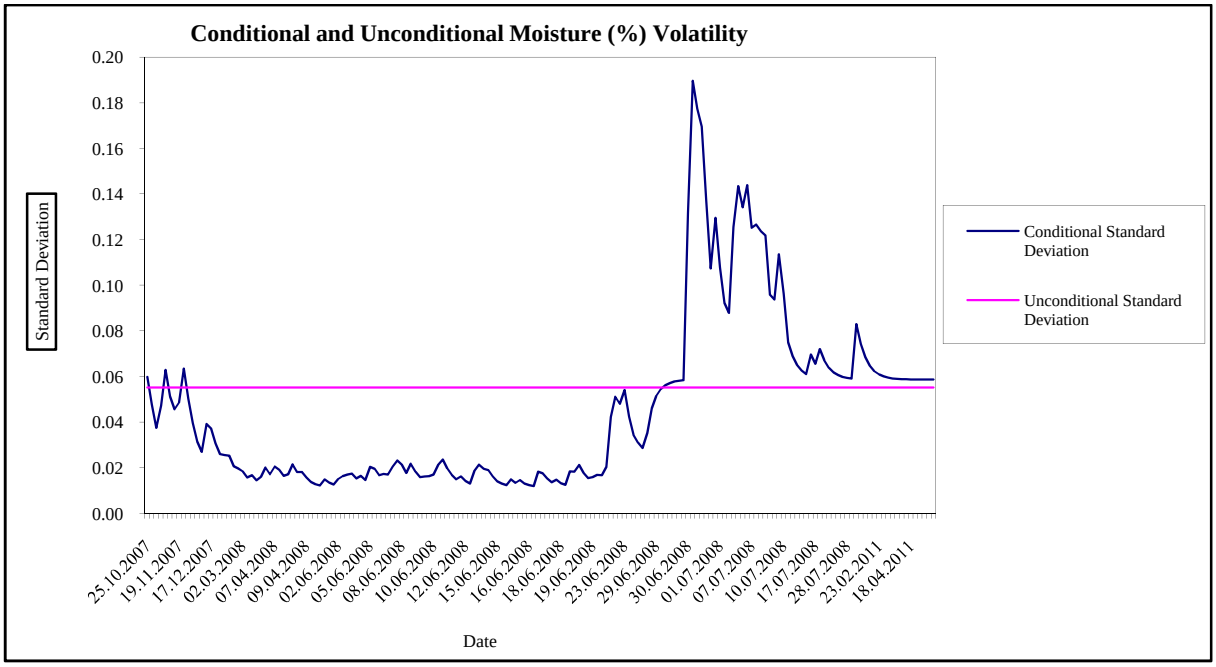


Figure 9. 8: Moisture (%) content of White Sugar products for the Period October 2007 to May 2011.

Figure 9.8 shows the conditional and unconditional standard deviation of Moisture (%) content over the period October 2007 to May 2011. Conditional standard deviations are over 0.013 during the sample period. The results indicate that the standard deviation almost stable among October 2007 to June 2008 and in spike behaviour in July 2008 to February 2011. However, volatility in deviations is very high in this time period.

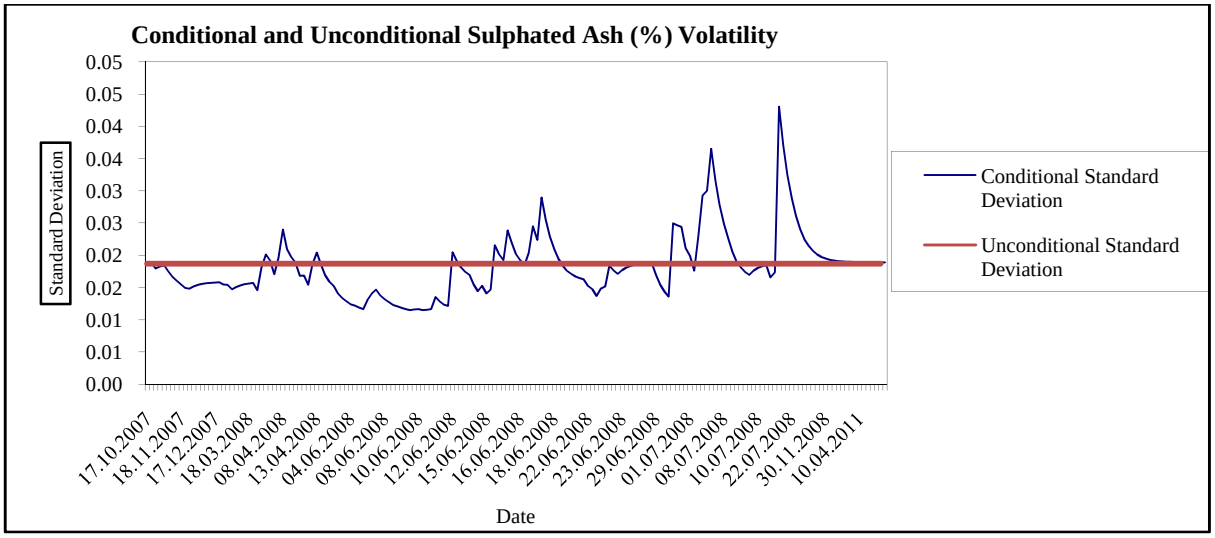


Figure 9. 9: Sulphated Ash (%) content of White Sugar products for the Period October 2007 to March 2011.

Figure 9.9 shows the conditional and unconditional standard deviation of Sulphated Ash (%) content over the period October 2007 to March 2011. Conditional standard deviations are over 0.01 during the sample period. The results indicate that the deviations increased significantly between 2007 and 2011 and also in spike behaviour at the end of 2008. However, volatility in deviation is high in this time period.

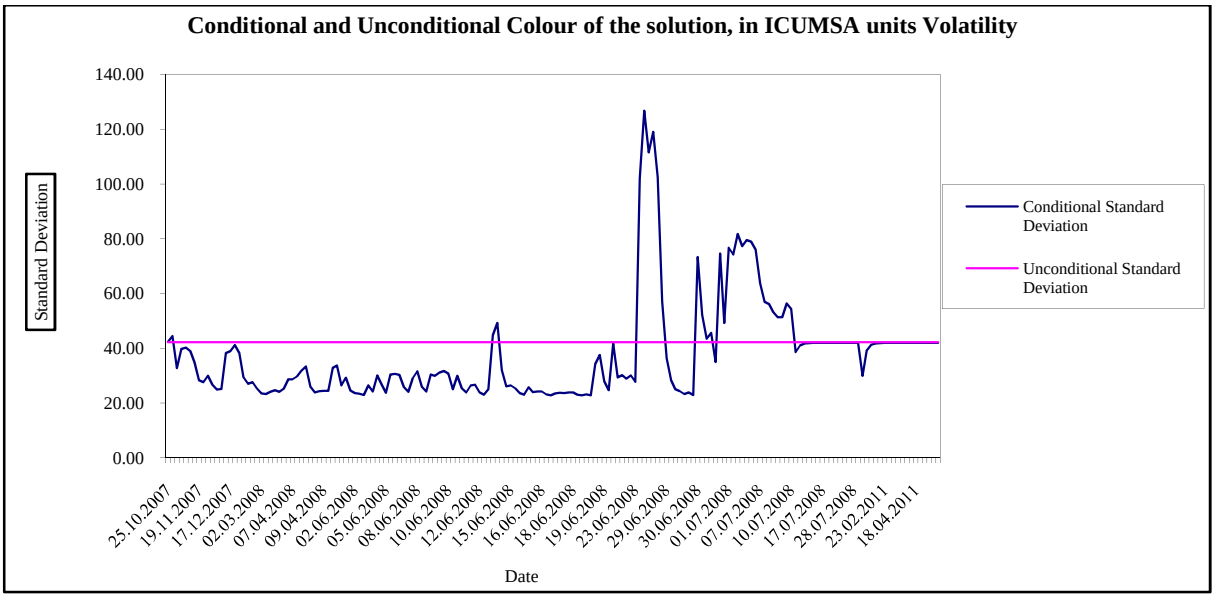


Figure 9. 10: Colour of the solution, in ICUMSA units content of White Sugar products for the Period October 2007 to May 2011.

Figure 9.10 shows the conditional and unconditional standard deviation of Colour of the solution, in ICUMSA units content over the period October 2007 to May 2011. Conditional standard deviations are over 20.00 during the sample period. As can be seen in Fig. 9.10, the deviation has a stable during the period October 2007 to June 2008 and volatility present at the period June 2008 to July 2008 then also stable. However, volatility in deviation is high in this time period.

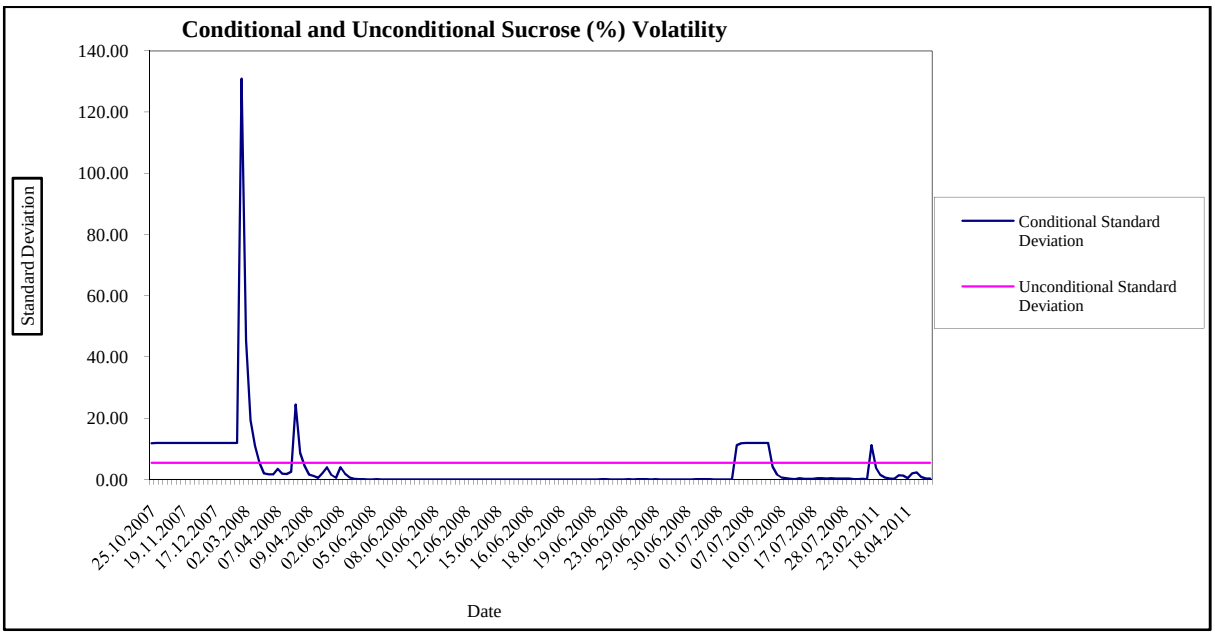


Figure 9. 11: Sucrose (%) content of White Sugar products for the Period November 2007 to October 2012.

Figure 9.11 shows the conditional and unconditional standard deviation of Sucrose (%) content over the period October 2007 to May 2011. Conditional deviations are over 0.01 during the sample period. The results indicate that the deviations stable trend between 2008 - 2011 and high spike at the January 20008. However, volatility in deviations is low in this time period. The deviations are stable behaviour during the period 2007-2011.

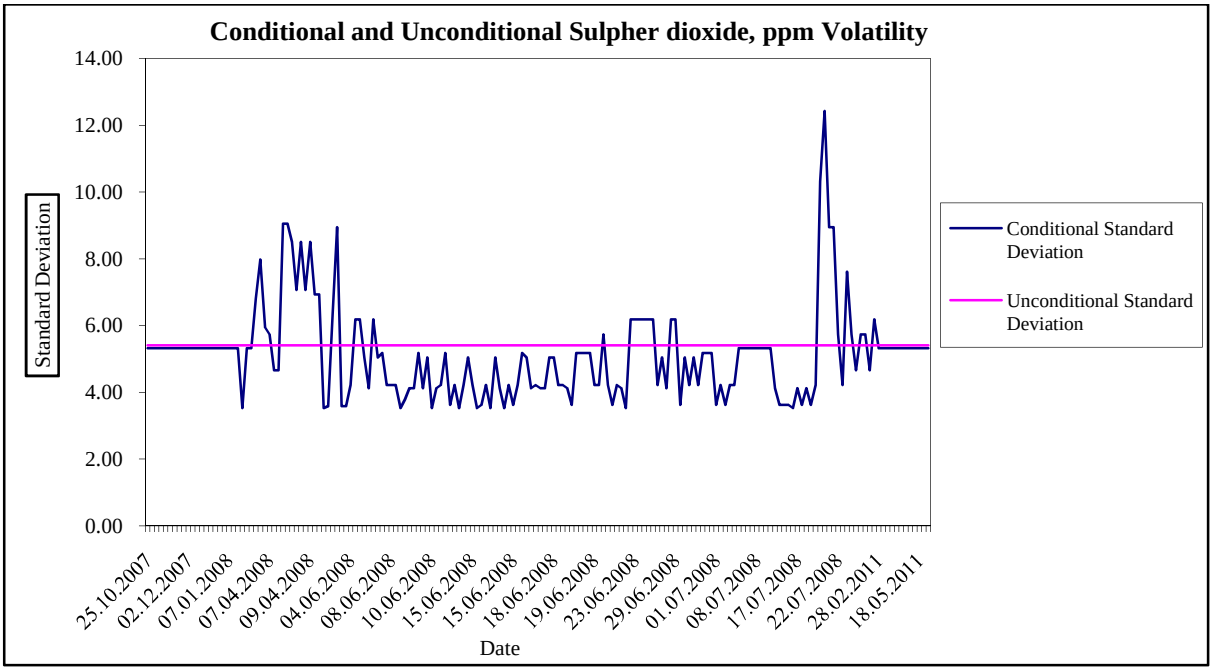


Figure 9. 12: Sulphur dioxide, ppm content of White Sugar products for the Period October 2007 to May 2011.

Figure 9.12 shows conditional and unconditional standard deviation of Sulphur dioxide, ppm content over the period October 2007 to May 2011. Conditional deviations are over 3.5 during the sample period. As can be seen in Fig. 9.12, the deviation has volatility during sample period. However, volatility in deviation is high in this time period. The deviation is spike behaviour during the period July 2008.

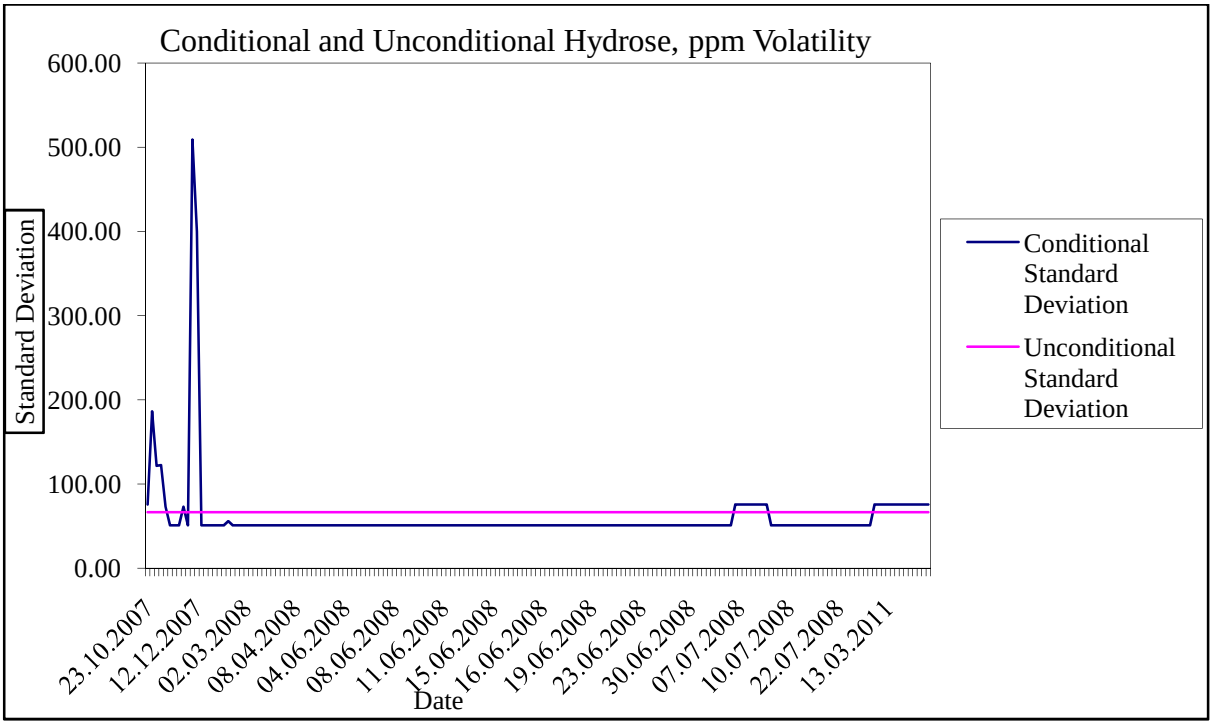


Figure 9. 13: Hydrose, ppm content of White Sugar products for the Period October 2007 to April 2011.

Figure 9.13 shows the conditional and unconditional standard deviation of Hydrose, ppm content over the period October 2007 to April 2011. Conditional deviations are over 50.00 during the sample period. The results indicate that the deviations are highly spike behaviour at the period November 2007. As can be seen in Fig. 9.13, the deviation has a stable trend between 2008 -2011. The deviation is low volatile during the period 2007–2011.

9.14: Comparison among three statistical technique

Comparison among two group Logistic & Probit Regression and Discriminant Analysis in classification groups for White Sugar.

Table 9. 8: Summary of statistics of Logit, Probit model and Discriminant function analysis.

		Logistic Regression		**Probit Regression**		**Discriminant analysis**	
Response variable	Independent Variable	p-value	GOF	p-value	GOF	p-value	GOF
Colour of the solution,	Moisture (%)	0.921	0.995	0.908	0.995	0.934	0.000
in ICUMSA units	Sucrose (%)	0.501		0.501		0.762	
Sulphated Ash (%)	Moisture (%)	0.038	1.000	0.058	1.000	0.010	-
	Sucrose (%)	0.370		0.459		0.925	

Note: GOF= Goodness-of-fit statistics.

From the above demonstrations of three different technique, Logit & Probit model and Discriminant function analysis, all of them provide are not equal predicted probability of the same variable which is given with the level of accepted range as prescribed by WFP, Dhaka. The level of significane of Goodness-of-fit statistics are >0.05 under Logit and Probit, respectively but all variables under Discriminant analysis are <0.05. Obviously, from these results, the Logit and Probit Model perform the better results in terms of the fulfill the assumptions. If in the case of assumptions fullfill in Discriminant analysis yields better results than logit and probit model.

Chapter (4 – 9) Summary

In this study, for statistical prediction we have studied the some food products sample data with some statistical technique as statistical quality control chart, parameteric one sample *t*-test and nonparametric one sample wilcoxon test, sign test, limited dependent variable model e.g. Logit, Probit and discriminant analysis model. We have also used autoregressive conditional heteroscedasticity (ARCH) model for statistical forecasting. We have used stata, Minitab and SPSS software to identify the best statistical technique of statistical quality control chart, parameteric one sample *t*-test and nonparametric one sample wilcoxon test, sign test, limited dependent variable model e.g. Logit, Probit, discriminant analysis model and ARCH model. After obtaining the result, comparing these several technique we observed that the Probit & Logit model is performed better than other model as fullfill the assumptions and technique. If in the case of normality assumptions fullfill, Discriminant analysis yields also better results. The results of one sample *t*-test and wilcoxon / sign test indicate that, in almost every case when the null hypothesis was false, the *t*-test performed same results with the Wilcoxon signed-rank/ sing test though normality assumptions was violated. But when H_0 was true the Wilcoxon signed-rank/ sign test perform efficient or more power predicted probability (p-value) than the *t*-test as fullfill the assumptions.

CHAPTER10: SUMMARY AND RECOMMENDATIONS

10.1 Introduction

This thesis is structured in ten chapters that address the introduction and background to the study, literature review that covers the historical prospective of quality control, limited dependent variable model, arch model, material and methods, results and discussions and culminates in the summary and recommendations. The chapter begins with a summary of the introduction focusing mainly on the background, problem statement, research objectives and rationale of the study. The summary on the quality of food underlines the global perspective with respect to the food quality physiochemical analysis parameters. The methodology has been summarized with regard to the study area, sampling procedure, data collection methods and using software, variable specification and models for data analysis.The summary on the presentation of the results of food qualily parameter among some food products as biscuit, complan, soft drinks, milk, parboiled rice, wheat soya blend, yellow split peas and white sugar for stake holder as well as researcher awareness. This culminates into recommendations that address the policy implications and areas for further research.

10.2 Discussion and Implications of the study

It is apparent from the consequences that the selection of statistical technique should be data reliant. Researchers have often reminded scientists of the need for recognition of the properties of the data prior to selection of an estimation procedure. Each procedure numerically calibrates a model that is based upon a set of assumptions about the data.Violations of these underlying assumptions cause estimation problems for each technique and an improper estimation of model coefficients. The outcome indicate that various procedure for analyzing binary data are likely to differ in their recital under the following conditions: the distribution of the forecaster variables deviates considerably from normality. While these conditions are by no means exhaustive, the existence of conditions should caution the researchers that the choice of a particular technique should be made carefully.

Consistent with past studies, the performance of logit and probit was similar under the various conditions. Hence, a choice between these two may not be consequential (except in computational cost). However, the choice between logit or probit, LDA and OLS is still not straightforward. Hence, the researcher should first conduct some preliminary data analysis for

determine the statistical properties of the predictor variables. Perhaps part of the data could be analyzed by these techniques to determine which one is most appropriate. Alternatively, the researcher could transform the data to comply with the assumptions of a particular technique (Gessner, Malhotra, Kamakura, & Zmijewski, 1988).

10.3 Major findings of the study

Comparing the results, we observed that the Logit and Probit model outperforms other models and techniques as because they fulfill necessary assumptions as required. Also to compare of the two models (Logit & Probit), are approximately same as selection of criteria of best model. If in the case of normality assumptions fullfill, Discriminant analysis yields better results.

10.4 Summary

The chapter presents results of consumer and analyst awareness to food products. In order to verify whether production was under control condition or not we have adopted some control chart such as mean, range, standard deviation and EWMA chart for food products such purposes we have used several Shewhart Control Charts. The process producing the some food products are stable in control.

The results of process capability study of the given food analysis results reveals that, graphical values of parameters approaches very nearer to the magnitude of the analytical values and hence graphical approach could be treated as equivalent to analytical method. Graphical approach can be used to study the variability of foods analysis data. It is one of the tools to convey the results through which it is easy to make inference on the data. The approach helps a stakeholder in the food can make the assessment about the analyzed parameters. Thus, it also helps to process management and identifies opportunities for improvement quality and operational performance (Prabhuswamy & Nagesh, 2007). The estimation of process capability is one of the basic tasks of the statistical process control (SPC). The values of Cp, Cpk indices are very precise information on a process potential relating to the client's expectations. Correct determination of Cp, Cpk indices values by counting requires identification of a distribution size, at least as a general settlement whether it is a normal distribution or not. If it is a normal distribution, for the estimation of Cp,Cpk this can use a simple counting classic approach that is based on the rule of three standard

deviations. If it is not anormal distribution, the application of a classic approach leads to wrong results (Czarski, 2008).

Statistical methods, in particular designed and monitored control charts, enable graphical visualising measurements of processes. They also describe stability and repeatability of those processes. Using the statistical quality control (SQC) in food products allows for measuring, researching, estimating and controlling a few parameters of the product. A comparison of results with requirements, in order to state, whether with reference to every of these properties the unanimity was achieved is also possible. The statistical quality control of the process for the organization means preventing occurrence of defects, lets for minimizing losses thanks to the systematic identification and analysis of key-processes and the direct control (Dudek-Burlikowska, 2011).

Logistic regression was used to assess the impact of a physiochemical analysis parameter to identify the quality of food which was supplied by some foods sample produced industries. The full model containing physiochemical parameters were most of variables statistically insignificant, with P>0**.**05, indicating that the model was able to distinguish between foods samples which reported having and not having accepted range as prescribed by WFP, Dhaka and different food standard institution in a food sample. While some others were within unacceptable range. The *p*-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in chapter 4 to 9 with insignificant (P>0.05).

Chapter 4 to 9 shows estimates of the probit model for the factors influencing analyzed value among the foods producers or respective analyzer of the study. The full model containing physiochemical parameters was also statistically insignificant of most of the variables, with P<0**.**05, indicating that the model was able to distinguish between foods samples which reported having and not having accepted range as prescribed by WFP, Dhaka and different food standard institution in a food sample. While some other parameters were within unacceptable range. The *p*-values for pearson chi-square (χ^2) test of the goodness-of-fit statistics presented in chapter 4 to 9 with insignificant (P>0.05).

To find correct estimates of standard errors and p-values it is necessary to choose better model. To select the model, here, we consider two information criteria used to compare

models. In general, “smaller is better”: given two models, the one with the smaller AIC fits the data better than the one with the larger AIC. As with the AIC, a smaller BIC indicates a better-fitting model (stata, n.d.).

The Wilk‘s lambda is a measure of the overall statistical significance of the Linear Discriminant Functions and is statistically insignificant of most of the variables of food sample at the 5 percent level of probability for the Tests of Equality of Group Means of physiochemical parameters (refer to chapter 4 to 9). This implies that the group means for the independent variables are different on the discriminating function and that the differences in the mean discriminant score are greater than can be attributed to non-sampling error. While other some parameters are within unacceptable range as prescribe acceptable rang by WFP, Dhaka and different food standard institution in a food sample.

This thesis has explored the impact of type of food products on testing for ARCH effects and on the estimation of ARCH models for food products analysis data. Our sample comprises physiochemical and microbial analysis data for food produtcs. The results of the food products forecasts reveal that biscuits, soft drinks, milk, yellow split peas, parboiled rice and sugar are forecasted to volatility of 3, 3, 3, 2, 6 analytical parameters respectively. The usual unit root tests results of the Dickey–Fuller test (DF) presented in thesis reject the null hypothesis of most food qualitative variable indicating that series are stationary. Hence, food qualitative analysis data are appropriate for this technique of food products analysis as expected.

10.5 Findings for food processors and relevant researchers

All statistical procedures have underlying assumptions, some more stringent than others. In some cases, violation of these assumptions will not change substantive research conclusions. In other cases, violation of assumptions will undermine meaningful research. Establishing that one's data meet the assumptions of the procedure one is using is an expected component of all quantitatively-based journal articles, theses and dissertations (Garson, 2012).

For all publications, the assumptions of each statistical procedure are needed as indicated in an "Assumptions" section. This thesis provides a general discussion of the most common data and technique assumptions.

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Government mechanism should continuously monitor the food products quality in Bangladesh on a regular basis for necessary analysis of the contents of food products. For this purpose regular sample analysis data should be collected and necessary statistical analysis should be done. Attempt will be ended to construct partnerships with relevant academic and research institutions to conduct investigate and to generate information and data. This relevant organization should maintain as data bank of food products produced in our country for necessary further statistical analysis will be done.

10.6 Limitations

Non-sampling error may occur due to not storage of the data in the laboratory for research purpose. Also Institutes/ Supplier Company do not require for some type of micronutrient analysis, so such type of data are not available.

10.7 Further research

Future analysis using repeated observations (or panel data) may be needed to examine the relationship between food acceptability and food quality variables in order to control for unobserved specific heterogeneity and to see if the food quality gap persists over time. To the extent that specific norms drive part of the difference in food quality, as our results suggest, panel data analysis would help to show whether those norms are changing over time or not.

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APPENDICES

Appendix 1: Technical Specifications of:High Energy Biscuits (HEB)

Table 2: List of compulsory tests and reference method

No	Tests	Requirements	Reference method *(or equivalent)*
1	Moisture content	Max. 4.5 %	AOAC 925.10, 2002
2	Organoleptic characteristic (color, smell and taste)	Typical color, Pleasant smell and palatable taste.	Sensorial inspection
3	Broken biscuits	Max. 5.0 % broken (by weight)	Visual inspection
4	Protein	Min. 9 g/100g	AOAC 981.10
5	Fat	Min. 15.0 g/100g	AOAC 963.15, 2000
6	Sugar (total)	10.0-19.0 g/100g	AOAC 920.189
7	Crude fibre	Max. 2.3 g/100g	AOAC 962.09
8	Ash (total)	Max. 3.5 g/100g	ISO 2171.2000
9	Melamine	Max. 2.5mg/kg	http://www.who.int/foodsafety/fs_management/Melamine_methods.pdf
10	Aflatoxin M1	< 0.5 ppb	AACC 45-16
11	Peroxide value	Max. 10 meq/kg fat	AOAC 965.33
12	Vitamin A-Retinol	Min. 250 mcg/100g	AOAC 960.45
13	Iron	Min. 11 mg/100g	AOAC 945.40
14	Mesophillic aerobic bacteria	< 10,000 cfu/g	ICC No 125 AACC 42-11
15	Coliforms	< 10 cfu/g	AOAC 2005.03
16	Escherichia coli	Absent in 1g	AOAC 991.14
17	Salmonella	Absent in 25g	AACC 42-25B
18	Staphylococcus aureus	< 10 cfu/g	AACC 42-30B
19	Bacillus cereus	< 10 cfu/g	AOAC 980.31
20	Yeasts and moulds	< 100 cfu/g	ICC No 146
21	GMO *(only if required)*	Negative (< 0.9% of GMO material)	

4.4 Microbiology

The following levels of microbiological contamination in the finished product shall not be exceeded:

Table 2: Limit of micro-organisms in **HEB**

Microorganisms	Maximum levels
Mesophyllic aerobic bacteria	10,000 cfu per g
Coliforms	10 cfu per g
Escherichia coli	0 per 10 g
Salmonella	0 per 25g
Staphylococcus	<10 cfu per g
Bacillus cereus	10 per g
Enterobacter sakazakii	0 per 10 g
Yeasts and moulds	100 per g

FORTIFIED BISCUITS - India

This is not a regular WFP commodity.

Product

Required shelf-life: minimum 9 months.

Proposed **recipe** for required finished product:

- Wheat Flour: 60-67.5%
- Sugar: 20%
- Vegetable oil: 7.5-10%
- Soya flour: 5-10%
- Leavening agent (sod. Bicarb & Ammon. Bicarb.) as required
- Vitamin premix: as required
- Mineral premix: as required
- Vanilla flavor: as required (no other flavor accepted)

Notes:

- The ingredients used for the manufacture of micronutrient fortified biscuits, shall conform to the standards laid down under the Prevention of Food Adulteration Act, 1954.
- The finished product shall have the nutritional value and Vitamin content/levels as indicated in specs.
- Biscuits shall be processed, according to the product specifications provided in specs
- Micro nutrient fortified biscuits shall be of rectangular shape, of approximate dimensions L 5.5 cm/W 3.5 cm, H 0.7 cm , 12 pcs of each in a pack of 75 gms at the time of delivery, shall be dry, in good and sound condition, fit for human consumption and free from bad smell, infestation and any poisonous or deleterious substances in amounts hazardous to health.

Required Nutritional composition (per 100 gms):

- Energy: 450-460 kcal
- Protein: 10.6-12.4 g
- Fat: 12-14.4 g
- Total carbohydrates: 67.2-72.4 g
- Fibre and others: 5.0-6.0 g (incl. a maximum Moisture content of 3.5%)
- Vitamins and Minerals: as premixed

Micronutrients: (per 100g of finished product)

- Thiamin [B1]: 0.9 mg (as Thiamin Mononitrate)
- Riboflavin [B2]: 0.9 mg (as Riboflavin)

Appendix 2: Technical Specifications for Dried Whole Milk

Table 1: List of compulsory tests and reference methods

No	Tests	Requirements	Reference methods *(Or equivalent)*
1	Organoleptic characteristic	White or slightly yellow, no impurities or coloured particles. Typical smell and taste.	Sensorial examination
2	Moisture	Max. 3.0%	ISO 5537:2004
3	Protein in milk solids-non-fat*	Min. 34.0%	ISO 8968-1:2014
4	Fat	26.0- 42.0%	ISO 1736:2008
5	Titratable acidity (ml- 0.1 N NaOH)	Max. 18 ml/10 g solids-non-fat	ISO 6091:2010
6	Lactates (in non-fat dry matter)	Max. 150mg/100g	ISO 8069:2005
7	Phosphatase test	Negative	ISO 11816-1:2013
8	Insolubility index	Max. 0.5 ml (at 24 °C)	ISO 8156:2005
9	Scorched particles	Max. 15 mg (i.e. at least disc B)	ISO 5739:2003
10	Total bacterial count	Max. 50000 cfu/g	ISO 4833-1:2013
11	Coliforms	Negative in 1 g	ISO 4831:2006
12	Melamine	Max. 1.0 mg/kg	

** The water content does not include water of crystallization of the lactose; the milk solids-not-fat content includes water of crystallization of the lactose*

5. PRODUCT SPECIFICATIONS

5.1 Minimum requirements:

- Fat: minimum 26 %
- Moisture: maximum 3 %
- Titratable acidity (of non-fat dry matter) ADPI:
  + in ml of decinormal sodium hydroxide solution: maximum 3
  + in lactic acid: maximum 0,15 %
- Lactates (in non-fat dry matter): maximum 150 mg/100 g
- Additives: none
- Phosphatase test: negative, i.e. maximum 4 ig of phenol/g of reconstituted milk
- Insolubility index: maximum 0,5 ml (at 24 °C)
- Burnt particles: maximum 15 mg, i.e. at least disc B
- Micro-organisms: maximum 50 000/g,
- Coliform test: negative in 0,1 g, in accordance with Regulation (EC) No 1080/96 (OJ L 142, 15.6.1996, p. 13),
- Buttermilk test: negative
- Whey test: negative
- Taste and smell: clean
- Appearance: white or slightly yellow, no impurities or coloured particles
- Antimicrobial substances: negative

5.2 Contaminants

Whole Milk powder shall be free from objectionable matter; not contain any substances originating from micro-organisms or any other poisonous or deleterious substances such as anti-nutritional factors, heavy metals or pesticide residues, in amounts which may represent a hazard to health.

Product		Moisture	Milk Fat	Milk protein in milk solids not fat	Titrable acidity (ml 0.1N NAOH / 10 gm solids not fat)	Insolubility index	Total ash on dry weight basis
(i)	Whole milk powder	Not more than 4.0 percent m/m	Not less than 26.0 percent m/m	Not less than 34.0 percent m/m	Not more than 18.0	Not more than 2 ml	Not more than 7.3 percent
(ii)	Partly skimmed milk powder	Not more than 5.0 percent	Not less than 1.5 percent m/m and not more than 26.0 percent m/m	Not less than 34.0 percent m/m	Not more than 18.0	Not more than 2 ml	Not more than 8.2 percent
(iii)	Skimmed milk powder	Not more than 5.0 percent	not more than 1.5 percent m/m	Not less than 34.0 percent m/m	Not more than 18.0	Not more than 2 ml	Not more than 8.2 percent

Appendix 3: Technical Specifications for Parboiled Rice

Table 1: List of compulsory tests and reference method

No	Analyses/tests	Limit	Reference method *(or equivalent)*
1	Moisture	**14.0%** m/m max.	ISO 711-2009
2	Short grain (≤ 6.2 mm)	**30.0%** m/m min.	*Visual examination*
3	Whole kernels	**65.0%** m/m max.	*Visual examination*
4	Total Brokens **(***including Brokens not passing through sieve No. 7 and Small brokens***)**	**23.0%** m/m max.	*Visual examination*
5	Small brokens	**1.5.0%** m/m max.	*Visual examination*
6	Red and/or Under milled kernels	**6.0%** m/m max.	*Visual examination*
7	Yellow kernels	**2.5%** m/m max.	*Visual examination*
8	Black kernels	**0.6%** m/m max.	*Visual examination*
9	Total partly black and Peck kernels	**4.25%** m/m max.	*Visual examination*
10	Partly black kernels	**2.75%** m/m max.	*Visual examination*
11	Damaged kernels	**1.5%** m/m max.	*Visual examination*
12	White glutinous rice	**2.5%** m/m max.	*Visual examination*
13	Undeveloped, Immature kernels, Other seeds and Foreign matter *(singly or combined)*	**0.85**% m/m max.	*Visual examination*
14	Paddy	**10grains/kg** max.	*Visual examination*
15	Milling degree	**Ordinarily milled**	*Visual examination*
16	GMO (***only if required***)	**Negative** (< 0.9% of GMO material)	

Appendix 4: Technical Specifications for the manufacture of: Super Cereal Wheat Soya Blend with Sugar.

Table 3: List of compulsory tests and reference methods

No	Tests	Requirements	Reference method *(Or equivalent)*
1	Moisture	Max. 10.0%	ISO 712: 2009
2	Protein	Min. 14.0 g/100g flour (N x 6.25)	AOAC 981.10
3	Fat	Min. 6.0 g/100g flour	AOAC 954.02
4	Crude fibre	Max. 3.8 g/100g flour	AOAC 962.09
5	Total ash	Max. 4.5 g/100g flour	ISO 2171:2007
6	Peroxide value	Max. 10.0 meq/kg fat	AOAC 965.33
7	Urease index	Max. 0.20 pH units	AOCS Ba 9-58 (1997)
8	Particle size	- 95% must pass through a 600 microns sieve. - 100% must pass through a 1,000 microns sieve	
9	Organoleptic (smell, taste, color)	Pleasant smell and palatable taste, typical color	Sensorial inspection
10	Consistency (Bostwick flow rate)	Min. 55mm /30s for 15% dry matter porridge	WFP's SOP http://foodqualityandsafety.wfp.org
11	Vitamin A	2780-4170 IU/100g flour	AOAC 992.04
12	Iron	10.2-15.2 mg/100g flour	AOAC 944.02
13	Calcium	360-550 mg/100g flour	AOAC 984.27
14	Potassium	620-920 mg/100g flour	AOAC 984.27
15	Aflatoxin (total)	Max. 20 ppb (total of B1, B2, G1, G2)	AOAC 972.26
16	Mesophyllic aerobic bacteria	< 100,000 cfu/g flour	ICC No 125
17	Coliforms	< 100 cfu/g flour	AOAC 2005.03
18	Salmonella	0 cfu/25g flour	AACC 42-25B
19	Escherichia Coli	< 10 cfu/g flour	AOAC 991.14
20	Staphylococcus aureus	< 10 cfu/g flour	AACC 42-30B
21	Bacillus cereus	< 50 cfu/g flour	AOAC 980.31
22	Yeasts and moulds	< 1,000 cfu/g flour	ICC No 146
23	GMO *(only if required)*	Negative (< 0.9% of GMO material)	

Appendix 5: Technical Specifications for Canada Yellow Split Peas

Table 3: List of compulsory tests and reference methods

No	Parameters	Recommended level	Reference methods*
			ICC No 110
1	Moisture:	**15% max**	ISO 712-2009
2	Purity	**99% min**	
3	Whole peas	**0.5% max**	
4	Heat damage	**0.05% max**	
5	Other damage	**0.5% max**	
6	Foreign matter	**0.5% max**	
7	Other colour	**2% max**	
8	Insect damage	**0.3% max**	
9	Broken	**2% max** through a 10/64 RH screen	
10	Cooking test	**45-60 minutes** (no soaking)	
11	Organoleptic	**Clean and bright appearance, Natural smell**	
12	Live insect	**Nil**	*Visual*
13	Aflatoxin	**20 ppb max**	ISO 16050
14	GMO (only if required)	**Negative**	

** Or equivalent*

Appendix 6: Technical Specifications for: White Sugar, ICUMSA 45

7. ANALYTICAL REQUIREMENTS

No	Item	Limit	Method
General requirements			
1	Polarization	99.7% min	ICUMSA method GS 2/3-1(1994), AS 4185:1994
2	Moisture content	0.06% max	ICUMSA method 2/1/3/9-15
3	Invert sugar content	0.04% max	ICUMSA (1997) GS 2/3-5
4	Conductivity ash	0.04% max	ICUMSA method GS 2/3-17(2002)
5	Colour of the solution	45 ICUMSA units max	ICUMSA method GS 2/3-10(2007)
Microbiological		*Max (cfu/g)*	
6	Total bacteria	100	ICUMSA Methods Book – GS2/3-41 (1994); GS2/3-47 (1994)
7	E. Coli	30	ICUMSA Method GS 2/3-43 (1998)
8	Mould	25	ICUMSA Method GS 2/3-47 **(1998)**
Chemical contaminants and toxins		*Max (mg/kg)*	
9	Sulphur dioxide (SOsub2)	15	ICUMSA Method GS 2/3/9-25 (2007), AOAC 952.13
10	Arsenic (As)	0.5	UMSA Method GS 2/1/3-27 (1994), AOAC 997.15
11	Lead (Pb)	0.5	ICUMSA (1998) GS 2/3-35 / NMKL 135 (1990) / EN 1988-2 (1998)

Appendix 7: Technical Specifications for: Soft Drinks.

BDS 1727 : 2003

4.2 Appearance- The non - carbonated , non – alcoholic ready to drink beverages shall be free from insect and rodent contamination , skins (skums) and practically free form other extraneous matter. Clear carbonated beverages shall be of sparkling clarity and shall remain so when stored under normal conditions. Cloudy beverages shall be reasonably stable.

4.2.2 Flavour- The non - carbonated, non - alcoholic ready to drink beverages shall be balanced , pleasant and characteristic flavour. The beverages of the flavored type shall be free form off flavours and off odours .

4.2.3 Sugar content- In the case of non - carbonated, non-alcoholic ready to drink beverages sweetened by adding sugar alone except by adding dry ginger ale and spiced beverages the production being tested after removal of nitrogen shall record a Brix hydrometer value of not less than 5 degrees at 20^0C .

NOTE: The gas volume is the amount of nitrogen the water will absorb at the normal atmosphere pressure at 15.56^0C.

4.3 The material shall conform to the requirements given in Table 1 & Table-2

TABLE-1 REQUIREMENTS FOR NON-CARBONATED, NON-ALCOHOLIC READY TO DRINK BEVERAGES.

SL.NO	NAME OF THE INGREDIENTS	REQUIREMENTS	METHOD OF TEST REF TO
1	Sugar	Conforming to BDS 361 : 1994*	
2	Caffeine	200 mg/1	RDA
3	Niacin, Max	35 mg/1	"
4	Riboflavin, Max	20 mg/1	"
5	Vitamin B6,Max	10 mg/1	"
6	Vitamin B12, Max	10 mcg	"
7	Pantothanic Acid, Max	10 mg/1	"
8	Taurine, Max	2000 mg/1	"
9	Glucuronolactone, Max	1200 mg/1	"
10	Inositol, Max	100 mg/1	"
11	N_2 gas Max	As per GMP	"

* Specification for Vacum pan suger (Plantation white)

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TABLE 2 : REQUIREMENTS FOR NON – CARBONATED, NON - ALCOHOLIC READY TO DRINK BEVERAGES.

SL. NO	CHARACTERISTIC	REQUIREMENTS	MEHOD OF TEST REF, TO		
			Appendix of BDS	Clause No of BDS 1010: 1982*	Appendix of BDS 1123 : 2002**
(1)	(2)	(3)	(4)	(5)	(6)
i)	Arsenic, mg/kg, Max	0.01	-	14	-
ii)	Lead, mg/kg, Max	0.01	-	15	-
iii)	Copper, mg/kg, Max	1.0	-	16	-
iv)	Iron, mg/kg, Max	1.0	App.k of BDS 739:1994+	-	-
v)	Standard plate count per ml, Max	50	-	8	-
vi)	Coliform count per ml	0	App. M. of BDS 860:2000++	-	-
vii)	Yeast and mould count per ml, Max	2	App. E of BDS 1123 : 2007 **	-	E

* Method for sampling and test for processed fruits and vegetables in cans containers
** Specification for Carbonated bevegroges Ondronziza
\+ Specification for Infant milk food (First Revision)
++ Specification for Whole milk powder and Skim milk powder

4.4 Desirable characteristics- The material may not also contain any phenolic compoud , surface active agent, pesticide, mineral oil and polynuclear aromatic hydrocarbon at a level of 0.001 mg / l

5. PACKING

The non - carbonated, non - alcoholic ready to drink beverages shall be filled in glass or food grade PET containers or cans made of aluminium food grade .

5.2 All containers shall be clear and free from chips, cracks and any other defects, Bottles shall be hermetically sealed with new and clear crown closures and shall be lined internally with a suitable disc made of any harmless material. The PET container shall be sealed along one or more edges and shall not leak after it is filled with the product all containers shall be subjected to sanitizing before filling process.

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Appendix 8: Permission Letter for using of data.

"জীবনের জন্য বিজ্ঞান"

খাদ্য বিজ্ঞান ও প্রযুক্তি ইনস্টিটিউট

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সূত্র নং- ৩৯.৩৪৫.০৩১.০৪.০০.০০৬.২০১০. ৮৬ তারিখ ঃ ০৬/০৭/২০১০ ইং।

অফিস আদেশ

আপনার ২৭/৬/২০১০ ইং তারিখের আবেদন পত্রের বরাতে নির্দেশক্রমে মোঃ আনোয়ার হোসেন, এসওকে জানানো যাচ্ছে যে, আপনাকে পিএইচডি প্রোগ্রামের জন্য আইএফএসটির এডহক এনালাইসিস ডাটা ব্যবহারের অনুমতি দেয়া হলো।

৬/৭/১০

(খঃ আঃ লোকমান হেকিম)
প্রশাসনিক কর্মকর্তা (ভারঃ)

প্রাপক,
জনাব মোঃ আনোয়ার হোসেন
বৈজ্ঞানিক কর্মকর্তা
গবেষণা উন্নয়ন বিভাগ
বিসিএসআইআর
ঢাকা।