

# **FORECASTING PATIENT NEEDS IN A DONOR FUNDED HEALTH CARE PROJECT IN KENYA**

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**DECLARATION**

This project is my original work and has not been submitted for a degree award in any other university.

Signed.....

Date.....

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This project has been submitted for examination with my approval as university supervisor.

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## TABLE OF CONTENTS

DECLARATION .....	ii
TABLE OF CONTENTS.....	iii
LIST OF TABLES.....	v
LIST OF FIGURES .....	vi
DEDICATION.....	vii
ACKNOWLEDGEMENTS.....	viii
ABSTRACT.....	ix
CHAPTER ONE: INTRODUCTION.....	1
1.1 Background.....	1
1.2 Statement of the Problem.....	2
1.3 Objectives of the Study.....	5
1.4 Value of the Study .....	5
1.5 Outline of the Study .....	5
CHAPTER TWO: LITERATURE REVIEW .....	7
2.1 Introduction.....	7
2.2 Health Sector in Kenya.....	7
2.3 Malnutrition in Human Immunodeficiency Virus/Acquired Immune Deficiency Syndrome .....	8
2.4 Demand Forecasting .....	10
2.5 Demand Forecasting for Health Commodities .....	11
2.6 Demand Forecasting Practices .....	12
2.7 Review of Previous Studies .....	15
2.8 Univariate Box Jenkins Auto Regressive Integrated Moving Average.....	21
2.9 Summary .....	25
CHAPTER THREE: RESEARCH DESIGN AND METHODOLOGY .....	27
3.1 Introduction.....	27
3.2 Research Design.....	27
3.3 Data Collection .....	28

3.4	Data Analysis.....	28
CHAPTER FOUR: DATA ANALYSIS AND DISCUSSION .....		31
4.1	Introduction.....	31
4.2	Description of the Consumption Data.....	31
4.3	Forecasting for Nutrition Commodities .....	33
4.4	Factors that Influence the Selection of a Forecasting Strategy .....	34
4.5	Accuracy of the Current Forecasting Method.....	35
4.6	Un-differenced Auto Regressive Integrated Moving Average Model for the Actual Consumption Data .....	36
4.7	Differenced Auto Regressive Integrated Moving Average Model for the Actual Consumption Data .....	39
4.8	Summary .....	43
CHAPTER FIVE: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS .....		44
5.1	Summary .....	44
5.2	Conclusions.....	44
5.3	Recommendations.....	45
5.4	Limitations and Further Research.....	46
REFERENCES .....		48
ANNEXES .....		52
Annex I:	Actual Consumption and Forecasted Demand for Nutrition Commodities 2006-2011 .....	52
Annex II	Nutrition and Human Immunodeficiency Virus Project Structure.....	54
Annex III:	Research Questionnaire .....	55

## LIST OF TABLES

Table		Page
1	Summary of Research Design and Methodology .....	30
2	Summary Statistics for Actual and Forecast Consumption Data 2006 - 2011 .....	31
3	Output for the Actual and Forecasted Analysis of Variance .....	36
4	Grouping Information Using Tukey Method.....	36
5	Final Estimate of Parameters .....	40
6	Modified Box - Pierce (Ljung-Box) Chi Square Statistic .....	40
7	Forecasts from Period 72 (95 Percent Limits).....	41
8	Final Estimate of Parameters .....	41
9	Modified Box-Pierce (Ljung-Box) Chi-Square Statistic .....	41
10	Forecasts from Period 72 (95 Percent Limits) .....	42

## LIST OF FIGURES

Figure		Page
1	Time Series of Actual Versus Forecasted Total Metric Tons of Nutrition Commodity: 2006 – 2011.....	4
2	Flow Diagram of the Box – Jenkins Model Building Strategy.....	23
3	Summary Statistics for Actual Consumption Data.....	32
4	Summary Statistics for Forecast Consumption Data.....	33
5	Time Series of Actual Versus Forecasted Total Metric Tons of Nutrition Commodity 2006 – 2011.....	35
6	Time Series Plot of the Actual Consumption Data (Metric Tons).....	37
7	Autocorrelation Function of the Actual Consumption Data.....	37
8	Partial Autocorrelation Function of the Un-differenced Actual Consumption Series.....	38
9	Autocorrelation Function for Actual Consumption Differenced Once.....	39
10	Partial Autocorrelation Function for the Actual Consumption Differenced Once.....	39
11	Residual Autocorrelations Auto Regressive Integrated Moving Average (2, 1, 0) Model Fit for Actual Consumption.....	41
12	Residual Autocorrelations Auto Regressive Integrated Moving Average (0, 1, 2) Model Fit for Actual Consumption.....	42

## **DEDICATION**

I dedicate this study to the people who have given me a life full of love and support beyond measure or remembrance. My mum (Alice), dad (Joseph), sisters (Anne, Mary, Liz and Tess) and brothers (Eric, David and Tony).

God bless you all.

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## **ABSTRACT**

Forecasts are crucial for practically all economic and business decisions. The focus of this research paper is in the area of forecasting. The purpose of a forecast is to reduce the range of uncertainty within which management judgements must be made. The research approach adopted is a case study of the Nutrition and HIV Program (NHP), which is a donor funded public health project. The general objective of this study was to forecast the demand for patient needs in a donor funded project. Specifically, this study sought to explain the current method used, determine the factors that influence the selection of forecasting strategy, review and evaluate the accuracy of the current method and establish a more suitable forecasting method that can accurately predict demand for nutrition commodities. The findings from this research provide evidence that forecasts did influence decision making in the key functional areas of the project. Also, that strategy, government and donor policies were the main factors that affected the selection of a forecasting strategy. Further, the review and evaluation of the current forecasting method indicated that there was a significant difference between the actual and forecasted consumption. In order to establish a more suitable forecasting method, Univariate Box – Jenkins (UBJ) methodology was used and two models were tested and Auto Regressive Integrated Moving Average (ARIMA (0, 1, 2)) model provided a better fit and was chosen as the model of choice for a short run forecast horizon. The main conclusion drawn from this study is that, UBJ-ARIMA models are useful as benchmarks for forecasting and therefore they should be viewed as complements to a reliable forecasting process. This study recommends that public health projects need to consider adopting business forecasting methods that will provide a better glimpse of the future based on historical events rather than relying on disease morbidity data trends.

# CHAPTER ONE

## INTRODUCTION

### 1.1 Background

Over the past couple of decades, the use of computerized and improved statistical forecasting methods has greatly enhanced the productivity and effectiveness of forecasting in business, government and private sectors. This development is in part due to the uncertain and changing nature in competitive markets, global economic expansions, financial objectives, shifting demographics and operational environments facing the business enterprise. The clear need for improved planning to reduce costs and enhance customer satisfaction in manufacturing companies has, for instance increased the desire to apply better forecasting approaches to the planning and management of change in supply chain. Fortunately, for practicing forecasters, computer based techniques have greatly simplified the way they do their work. Ready access to data sources, spread sheet modelling and sophisticated quantitative methods have given rise to a wide variety of data-intensive techniques that are readily applied in a relatively short time at reasonable cost. Still, a forecast practitioner can easily be overwhelmed by a plethora of forecasting techniques that are not readily understood. Moreover, the manager or end user of the forecasting process is offered little guidance on how to make effective and appropriate use of these powerful (often inadequately documented) techniques in real world situations (Levenbach and Cleary, 2006).

Long term predictions are indispensable for planning and strategy. Makridakis (1996) notes in his paper on forecasting its role for planning and strategy that the most important lesson we have learned in the field of forecasting over the last two decades is that models which best fit available data are not necessarily the most accurate ones in predicting beyond this data. He continues and argues that correctly recognizing emerging changes in the business environment and accurately predicting future ones are prerequisites for future success. Recognizing and predicting such changes brings forecasting to the forefront of management and ironically turns its greatest weakness (the fact that the best model fit does not guarantee the most accurate after the fact forecasts) into a much needed strength as recognizing and predicting changes is becoming one of the most critical factors for developing foresight, formulating corporate strategies, planning effectively and in general succeeding in business (Makridakis, 1996).

McCarthy et al (2006), notes that the business environment has changed dramatically over the last two decades with increasing globalization, widespread adoption of information technology and the advent of e-business. Factors stemming from these environmental changes such as time based competition and product proliferation have a direct impact on forecasting practices and processes. Further, the change in computer over the 20 years from mainframes to personal computers, wide area networks, World Wide Web and astounding efficiency in software efficiency and effectiveness has been nothing less than amazing. Given all this however, accuracy has not improved and satisfaction with techniques, systems and management processes has not improved. McCarthy concludes that sales forecasting will not improve until companies commit the resources to create an adequately funded, cross functional sales forecasting process that is populated with personnel trained in the use of sales forecasting techniques (both qualitative and quantitative), packages and systems, properly measured and rewarded for performance; performance measured in terms of forecasting accuracy and its impact on customer satisfaction levels and supply chain costs (McCarthy, et al, 2006)

Up to recent times, business forecasting was most closely linked to economic and financial thinking. During the 1980s however, economic forecasting suffered from a lack of credibility, media ridicule and short comings in accuracy goals. Nowadays, the meaning of business forecasting has broadened considerably to include forecasting demand throughout a supply chain from supplier of raw material to consumer of finished goods. Called demand forecasting, it generally attempts to predict future customer demand for a company's goods and services. This new focus is nowadays directed more to forecasting the disaggregated elements of product demand for supplying warehouses, distributors, channels and consumers than to economic and financial-driven aggregates (Levenbach and Cleary 2006) This research will review the current methods used for demand forecasting by NHP with the purpose of making significant improvements to the process of forecasting in order to provide useful and relevant information to decision makers in management of project resources.

## **1.2 Statement of the Problem**

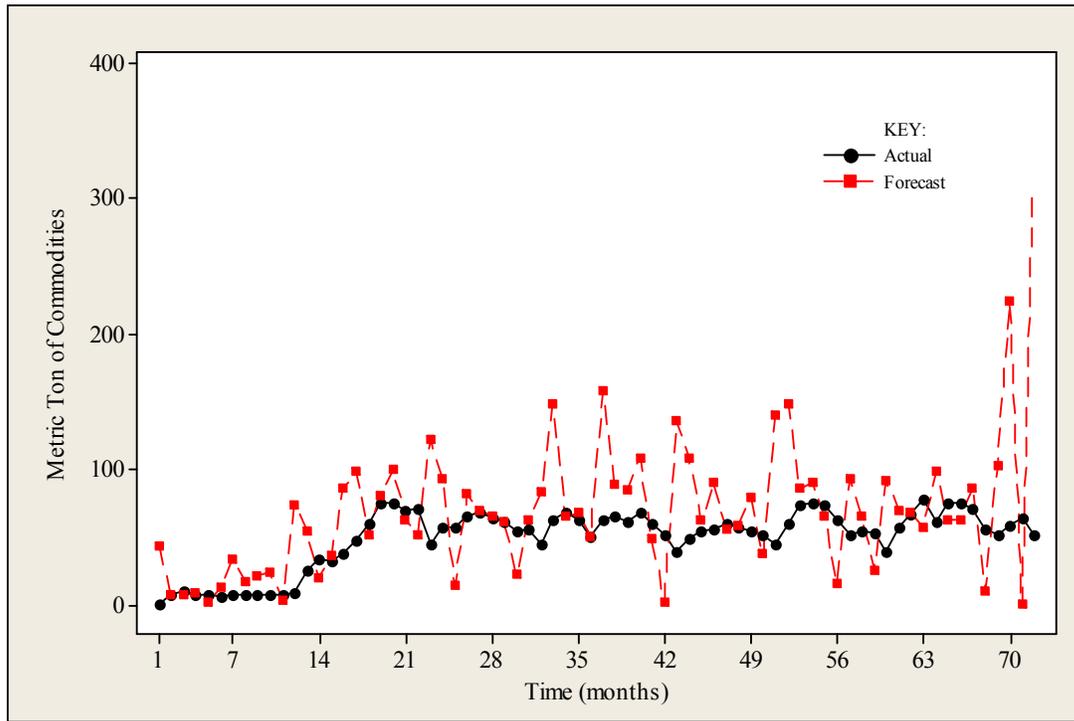
The purpose of the forecasting process is to identify and evaluate systematically all factors, which are most likely to affect the course of future events and provide a realistic view of the future (Hanke and Wichern, 2009). The future is not completely predictable, therefore the systematic structure of the forecasting process establishes the foundation on which the most important ingredient (human judgement and intuition) is based. Forecasting is important in

many types of organizations since predictions of future events must be incorporated into the decision making process. Any organization must be able to forecast in order to make intelligent decisions. Forecasting is a process that predicts future events or conditions in the presence of uncertainty (Bowerman, et al 2005) If future events represented only a quantifiable change from historical events, future events or chance could be readily projected through quantitative projections of historical trends in the future. The need for accurate forecasts is not limited to businesses only but rather cuts across to all institutions that provide goods or services, be they for profit or not for profit.

The Nutrition and HIV Quarterly Program Report for the period January 1, 2012 to March 31, 2012 indicates that the project among other activities supplies nutrition commodities to 619 health service points across 47 counties in Kenya for patients who are infected and affected by Human Immunodeficiency Virus/Aids Immune Deficiency Syndrome (HIV/AIDS). These commodities account for over 70 percent of the total budgetary allocation for the project. Therefore, successful implementation of project relies heavily on the ability to predict demand for nutrition commodities and services consequently, the ability to forecast demand for commodities that results in a low degree of variation between the actual and predicted consumption translates into savings for the project. The current method of forecasting relies on human judgement and intuition whereby an expert panel representing each of the core functional areas and project manager develop consensus based on service level coverage and historical trends of the project service data. The panel also takes into account the prevailing economic conditions within which the project operates. In order to determine whether there is need to improve the current forecasting technique used, monthly data on the forecast orders in Metric Tons (MT) of commodities delivered to health facilities or service points are compared against the actual consumption of commodities in MT by respective service point; the aggregate data for consumption and forecasts is shown in Annex I.

Figure 1 below shows the time series plots of the actual and forecast consumption for nutrition commodities over a period of 72 months from January 2006 to December 2011. Both curves show a gradual upward trend from the 1<sup>st</sup> to the 72<sup>nd</sup> month. The upward trend exhibited in both curves reflects the long run growth of the project.

Figure 1 Time Series of Actual Versus Forecasted Total Metric Tons of Nutrition Commodity: 2006 – 2011



The two curves of actual and forecasted consumption during the 72 month period exhibit unique characteristics. The upward trends of the actual and forecasted curves show a recurring up and down movements. The fluctuations for curve of actual consumption have duration of seven months when measured peak to peak and eight months when measured trough to trough. The cyclical fluctuations in the actual consumption represent the project business cycle with the peaks reflecting periods of expansion or increased service utilisation as a result of the scale up of project service points. The troughs, on the other hand typically represent periods of contraction occasioned as a result of poor inventory management practices that result in stock outs of the nutrition commodities. The forecast order curve is characterised by irregular fluctuations that are erratic movements as shown on the time series plot. These fluctuations follow no recognizable pattern; typically, many irregular fluctuations in time series are caused by unusual events mostly natural disasters such as, tsunamis and earthquakes. However, irregular fluctuations can also be caused by errors on the part of the time series analyst (ibid). It is the objective of this research to address the problem of trying to match an appropriate forecasting model to the patterns of time series data shown Figure 1. To be able to achieve this, this research will seek to improve the current forecasting methods and produce a time

series curve with a consistent pattern that will inform the forecasting process by utilizing a different forecasting method that will produce low variation between the actual consumption and the forecasted orders for nutrition commodities. A comparative analysis of the current and proposed forecasting methodology will also be done to determine if a significant difference exists from the outputs of these two methodologies.

### **1.3 Objectives of the Study**

The general objective of this study was to forecast the demand for patient needs in a donor funded project. The specific objectives were to:

1. Explain the current forecasting method used to predict demand for nutrition commodities.
2. Determine the factors that influence selection of a forecasting strategy.
3. Review and evaluate the accuracy of the current method used to forecast demand for project nutrition commodities.
4. Establish a more suitable forecasting method that can be used to accurately predict demand for nutrition commodities.

### **1.4 Value of the Study**

This study will also help in advancing the understanding on how donor funded projects can combine different forecasting approaches to achieve accuracy and maximize effectiveness of their activities. Donor agencies, manufacturers, project managers and forecasters will benefit from this study through the application of more accurate forecasting techniques. Donor agencies and government will be able to accurately forecast, quantify the demand as well as identify funding gaps for essential services in the public health domain. Researchers and academics will benefit from the study through additional understanding. On the basis of this knowledge, this study is will extend the frontiers of knowledge in the area of demand forecasting practices for service based profit making and not for profit organisations.

### **1.5 Outline of the Study**

Chapter One provides a background to the study on forecasting patient needs on a donor funded project, the research problem, research objectives and significance of the study. Chapter Two is the review of literature around the subject of demand forecasting and current practices in this area. This chapter also outlines issues around forecasting demand in health and review empirical studies, identify knowledge gaps and highlight pertinent issues in application and use of appropriate methods to forecast demand. Chapter Three presents the research design and

methodology and outlines how the research will be conducted and the strategies to be used for sampling, data collection and analysis. These strategies will be guided by the objectives of the study.

Chapter Four looks at the findings from this study and is divided into three sub sections. Section one provides an overview of the current forecasting practices, while section two addresses the test of hypothesis that determines if a significant difference exists between the forecast orders and actual consumption and section three presents the proposed method and a comparative analysis with the current method. Chapter Five consists of summary, conclusions, limitations and further research and recommendations.

## **CHAPTER TWO**

### **LITERATURE REVIEW**

#### **2.1 Introduction**

This chapter covers literature review of the main issues surrounding current forecasting practices within industry, their use in predicting demand for commodities, accuracy of these demand forecasting methods and impediments to successful implementation of forecasting practices in industry. In addition, this chapter reviews past studies in demand forecasting with respect to objectives, methodology and analyses used and findings in these studies in order to identify the gaps within these studies.

#### **2.2 Health Sector in Kenya**

The second National Health Sector Strategic Plan (NHSSP) 2005 to 2010 notes that the vision for the sector is of an efficient, high quality health care system that is accessible, equitable and affordable for every Kenyan household. The mission of the health sector is to promote and participate in the provision of integrated and high quality curative, preventive, promotive and rehabilitative health care services for all Kenyans (Health Sector Reform Secretariat, 2005).

The Kenya health demographic survey of 2008/09 notes that since attaining independence, the government has prioritized the improvement of the health status of Kenyans. The Government of Kenya (GoK) recognises that good health is a prerequisite to socioeconomic development. A number of government policy documents and successive national development plans have stated that the provision of health services should meet the basic needs of the population, place health services within easy reach of Kenyans and emphasize preventive, promotive and rehabilitative services without ignoring curative services. Perhaps as a result of these policies, both infant mortality and life expectancy at birth, which are basic indicators of health status, have improved significantly (Ngigi and Macharia, 2006).

##### **2.2.1 Kenya Essential Package for Health**

The Kenya Essential Package for Health (KEPH) integrates all health programmes into a single package focused on improving health at different stages of the human lifecycle. In this approach, health programmes are centred on the different phases of human development and complement each other so that synergy and mutual reinforcement among programmes can be achieved. The KEPH approach also defines six service delivery levels level 1; the community

level is the foundation of the service delivery priorities because it allows the community to define its own priorities so as to develop ownership and commitment to health services. Levels 2 and 3 are, respectively dispensaries and health centres and maternity/nursing homes, which all primarily handle promotive and preventive care, but also some curative services. Levels 4 and 6 are the primary, secondary and tertiary hospitals which focus mainly on curative and rehabilitative aspects of the service delivery package. According to the Ministry of Public Health and Sanitation, Division of Health Information Systems (DHIS 2012) there are 8,496 health facilities in health sector in Kenya.

### **2.3 Malnutrition in Human Immunodeficiency Virus/Acquired Immune Deficiency Syndrome**

The AIDS is caused by HIV that weakens the immune system making the body susceptible to and unable to recover from other opportunistic diseases that could lead to death. Results from the Kenya AIDS Indicator Survey 2007, indicate that 7.4 percent of Kenyan adults aged 15 to 64 years are infected with HIV, the virus that causes AIDS. According to the survey, more than 1.4 million Kenyans are living with HIV/AIDS (National AIDS and STD Control Program, 2008).

The National AIDS Control Council (NACC) HIV sentinel survey of 2009 shows that Kenya is experiencing a mixed and geographically heterogeneous HIV epidemic. Its characteristics are those of both a generalised epidemic among mainstream population and a concentrated epidemic among most at risk population. The HIV epidemic affects all sectors of the economy. It is equally a developmental and an epidemiological challenge, encompassing identification and development of a series of appropriate sectoral responses and their applications at the local level. Nationally, most new infections (44 percent) occur in couples who engage in heterosexual activity within a union or regular partnership. Men and women who engage in casual sex contribute 20 percent of new infections, while sex workers and their clients account for 14 percent. Men who have sex with men and prison populations contribute 15 percent, and injecting drug users' account for 4 percent. Health facility related infections contribute 3 percent of new cases (National AIDS Control Council, 2006).

The success of Antiretroviral Therapy (ART) in the management of HIV/AIDS is highly dependent on the synergy drawn from adjunct clinical nutrition therapy. As Kotler (2000) notes in his article on nutrition altercations in HIV, malnutrition is a common complication of

HIV infection world-wide that promotes excess morbidity and mortality in the disease. It was one of the earliest complications of AIDS to be recognized and one of the most common diagnoses reported to public health authorities. The topic of nutrition and HIV has received considerable study and is considered by some as a paradigm of chronic inflammatory disease. The rationale for providing nutritional support to AIDS patients is the same as for other chronic progressive diseases. The assumptions underlying nutrition support are that malnutrition promotes adverse outcomes, that nutrition status can be improved through nutritional therapies and that such improvements improve outcomes (Kotler, 2000).

### **2.3.1 Nutrition and Human Immunodeficiency Virus Project**

The rationale for providing nutritional support to HIV/AIDS patients is based on the assumption that malnutrition promotes adverse outcomes and nutrition status can be improved through nutritional therapies and that such improvement improves effect of treatment outcomes for ART. The Kenya Medical Research Institute (KEMRI) randomized control trial of the impacts of food supplementation on malnourished adult ART clients findings, suggest that food supplementation delivered in clinical settings can confer significant benefits to malnourished and nutritionally vulnerable adults living with HIV (Muttunga et al, 2009).

The NHP is designed to address the issue of malnutrition in HIV/AIDS among those infected and affected by the disease in Kenya. The overall objective of this project is to improve the quality of life for People Living with HIV/AIDS (PLHIV) through provision of targeted nutrition services to clinically malnourished patients. Annex II shows the three tier structure of NHP which includes:

- (i) Donor and government level - this level represents the United States Government (USG) and GoK bilateral agreement for HIV/AIDS programs in Kenya. The funding mechanism for HIV/AIDS is through the Presidents Emergency Plan for AIDS Relief (PEPFAR). The prime focus at this level is health sector strategic planning. The prime accountability for the funding is Ministry of Medical Services (MoMS) and Ministry Public Health and Sanitation (MoH&S) and the United States Agency for International Development (USAID).
- (ii) Corporate level this consists of the project management board consisting of USAID program managers, project director, compliance officer, senior ministry officers and finance director. The board is accountable to USAID, MoMS and MoH&S). The prime focus of the board is the mission of the project, long terms goals and overall

effectiveness of the project. Its major concerns include project competitive positioning, values, growth and establishing appropriate financial controls. The board appoints a project manager or chief of party whose primary responsibility is to manage the project operations.

- (iii) Operational level - the prime focus at this level is achievement of the project targets, optimising resources and efficiency of operations. Project operations further categorised into support functions or shared services whose major concerns include budgeting and finance, procurement and human resource management. The core functional areas of the project include food manufacture, supply chain management, technical guidance, capacity building and monitoring and evaluation. Food manufacturers or processors are responsible for the production of nutrition commodities for the project. The SCM function ensures that materials and nutrition commodities are accessible by all project beneficiaries. Technical guidance represents the design function for the project for all operations and ensures project delivers quality products and services to all its customers. The capacity building arm focuses on enhancing skills of primary beneficiaries that is health care workers as well as the secondary beneficiaries the patients. The monitoring and evaluation function focuses on data collection, analysis, reporting and harnesses the use of information technology to enhance project operations. It also serves as the feedback loop and measures performance of the project activities. The core functional areas constitute the expert panel that is used in the development of forecasts for the project.

## **2.4 Demand Forecasting**

Levenbach et al (2006) define forecasting as a process that has its objective in predicting future events or conditions. More precisely, forecasting attempts to predict change in presence of uncertainty. Forecasting is all about change and chance. If future events represented only a quantifiable change from historical events, future events or chance conditions could be readily predicted through quantitative projections of historical trends in the future. However, there is much more to forecasting than projecting past trends; experience and intuitive reasoning quickly reveal that future events or chance conditions are not solely a function of historical trends. In addition, the commercial world goods and services are bought by individuals for innumerable reasons. Therefore, business forecasting must include other ingredients to complement quantitative projection techniques.

Demand forecasting is the ability to predict the future. The simplest forecasts occur in stable environments with plenty of good data. They depend on the future resembling the past - the closer the resemblance, the more accurate the forecast. When the future does not resemble the past, demand forecasting becomes especially critical. The process of forecasting becomes the vehicle to quantify the rate of change from the current state of supply and demand to another state of supply and demand. The change from one state to another state depends on human action and reaction to the possibility of change and hence is difficult if not impossible to simply calculate. The level of demand is based on a wide range of demand drivers and understanding the impact of each of these drivers on total demand is complicated. Forecasting in these conditions is as much an art as a science and requires wisdom as well as data (Levenbach, 2006).

Forecasting for demand management generally attempts to predict future customer demand for a firm's goods and services. More recently, demand forecasting has become much more focussed on disaggregate elements of product demand for supplying warehouses, distribution channels and consumers on economic and financially driven aggregates. Levenbach and Cleary (2006) note that it is generally recognized that accurate forecasts are necessary and provide significant improvements in manufacturing, distribution and the operations of retail firms. Over-time, the scope of business forecasting has broadened to include forecasting more detailed micro-elements of the demand for goods to supply to warehouses, distributors, brokers, channels, accounts and consumers. Demand-driven forecasting of the right amount of the right product in the right place at the right time is one of the underpinnings of demand forecasting for the supply chain. Therefore, demand forecasting is the process of predicting future customer demand for a firm's goods and services (Levenbach, 2006).

## **2.5 Demand Forecasting for Health Commodities**

One of the weakest links and one of the most vital for achieving both short and long-term gains in global health is the forecasting of demand for critical medical technologies, including vaccines, medicines and diagnostic products. Demand forecasting, which may seem at first glance to be a small piece of the very large puzzle of access to medical products, is of central importance. Many of the shortcomings in funding and functioning of health systems impede accurate forecasting of demand and without the ability to forecast demand with reasonable certainty and some assurance of a viable market, manufacturers cannot scale production capacity, make commitments to suppliers of raw materials or justify a business case for

investing in costly clinical trials and other activities to develop future products. National governments and international funders rely on demand forecasts for budgeting, while health programs and implementing agencies depend on forecasts to plan their supply chain logistics. Thus, in the high-level policy debates about the volume, duration and use of donor funds to support research and development and purchase essential health products, one key fact has often been overlooked if actions by the international community do not increase the ability to generate credible forecasts of demand if, in fact, those actions contribute to a situation of greater uncertainty, with higher stakes efforts to achieve greater access to life-saving and life-extending medicines will be undermined (Centre for Global Development, 2007).

The Global Health Forecasting Working Group notes that whether poor people in developing countries receive adequate health care depends in part on whether they have access to crucial medical technologies, such as drugs, vaccines and diagnostics. Despite increased donor funding and an array of new products, weak links in the global health supply chain continue to greatly restrict access to essential health products, including those needed to prevent and treat AIDS, malaria, Tuberculosis (TB) and other deadly diseases. One of the weakest links is in demand forecasting often more than a year in advance, which products will be purchased in what quantities. Predicting demand is tricky; it means figuring out ahead of time how much of which products governments, private consumers and donors will want to buy and how much they will be willing to pay, often even before these decisions have been considered. It is made trickier by the recent entry of many new sources of funding and advice, a broad range of new products and new actors in procurement. The lack of accurate forecasts has several damaging effects. It increases risks for suppliers, resulting in higher costs and supply shortages. It discourages firms from investing in research and development for new health products that poor people need and it creates obstacles for donors and national governments as they seek to spend aid effectively to improve health and save lives (Global Health Forecasting Working Group, 2007).

## **2.6 Demand Forecasting Practices**

Demand forecasting is inherently a customer focused activity. At the global health level, the purpose of forecasting demand is to influence the supply of medicines and health products. This means that suppliers, who are expected to make investment decisions based on these forecasts, are important customers of forecasts. Ensuring the appropriate availability of drugs and health commodities at an optimal price requires demand forecasting that has sufficient

certainty around funding and timing of orders to allow suppliers to confidently invest in production capacity. Therefore, demand forecasting is an iterative process and a critical part of the supply chain that links supply to demand so that consumers and service providers have products available when and where they need them (Sekhri, et al., 2006).

While the decision makers in the field of public health are conscious of the need for demand forecasts, few empirical studies have been carried out in this area. Barlas and Gunduz (2011), show from their study on demand forecasting and sharing strategies to reduce fluctuations and the bullwhip effect in supply using dynamic simulation note that a major structural cause of bullwhip is isolated demand forecasting performed at each echelon of the supply chain and that demand and forecast sharing strategies, for example collaborative planning, information systems like Point-of-Sale (POS), web-based transaction systems and Radio Frequency Infrared Devices (RFID) can significantly reduce bullwhip effect even though they cannot completely eliminate it (Barlas and Gunduz, 2011).

Estimating the value of improving forecasting accuracy for manufacturers is a topic of practical importance because manufacturers spend large sums of money in purchasing and staffing forecasting support systems to achieve more accurate forecasts. Fildes and Kingsman (2011) were able to develop a framework for incorporating demand uncertainty and forecast error in supply chain planning models. This framework examined the effect of demand uncertainty and forecast error on unit costs and customer service levels in supply chain including Materials Requirements Planning (MRP) type manufacturing systems. To illustrate the issues, the problem of estimating the value of improving forecasting accuracy was simulated. The results from this study show that unit cost increases exponentially with demand uncertainty, the benefits of improved forecasting increase with overall uncertainty but this depends on the relative sizes of the stochastic variation in demand generation process and the forecasting errors. In addition, that the mis-specification in choice of a forecasting model leads to increased forecast error and increased costs. There is no best method of forecasting; it will generally depend on the 'true' but unknown demand generation process. The benefits of the forecast model selection will depend on the noise in the data (Fildes and Kingsman, 2011).

A critical issue on the study of demand forecasting is the process of choosing appropriate level of aggregation that is dependent on the decision making process which the forecast is expected to support. Shin-Lian Lo et al (2008) in their study on forecasting for the Liquid Crystal

Display (LCD) market proposed a hierarchical forecasting methodology consisting of five steps. First, the three levels for LCD market are identified; second, several exogenously driven factors that significantly affect demand are identified at each level of product hierarchy; third, three forecasting approaches (regression analysis, transfer function and simultaneous equations model) are used to forecast demand at each hierarchical level. Fourth, various forecasting approaches (top-down, middle-out and bottom-up). The results, reveal that the middle level of LCD monitor product hierarchy is the best level to be forecast, and the best forecasting results of all levels can be obtained using the middle-out forecasting approach (Lo, Wang, and Lin, 2008). This study provides insights and strategies that can be used to forecast demand for products that are heavily influenced by changing technology and consumer preference. It is important to note that this study proposes a forecasting approach that includes all decision makers in the supply chain; manufactures, distributors and consumers.

Haberleitner et al.(2010) in their paper on implementation of a demand planning system using advance order information, demonstrates the successful application of a supply chain forecasting system in the refractory industry which integrates the knowledge of partially known advance demand information. This constitutes a flexible demand planning system that enables quick responses to market changes which are immediately reflected by customers' booking patterns. Refractory is the term given to a class of materials which are produced from non-metallic minerals and possess the capability to withstand heat and pressure. The paper was able to demonstrate that by using an easy to understand forecasting algorithm, accuracy can be increased for many planning segments in an industrial make to order manufacturing environment (Haberleitner et al, 2010).

Datta et al.(2007) in the paper on the management of supply chain using an alternative forecasting technique propose the adoption of an advanced forecasting technique; Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model with the aim to develop it as a decision support tool applicable to a wide variety of operations including Supply Chain Management (SCM). This model is based on advances in time series econometrics and is used to explicitly model volatility generally associated with supply chains. A Vector Auto-Regression (VAR) framework captures the dynamics of interactions that characterize multistage SCM. From a theoretical standpoint, such a model is expected to yield an accurate forecast, thereby reducing some of the operational inefficiencies (Datta, Granjer, Barari, & Gibbs, 2007). The paper proposes an innovative approach to management of supply chains

using GARCH model. While this contributes significantly to the forecasting body of knowledge, it is heavily oriented towards methods and techniques at the expense of future implications to management of organizations and how this translates to effective decision making.

## **2.7 Review of Previous Studies**

Forecasts are crucial for practically all economic and business decisions. Predictions of future events and conditions are called forecasts and the act of making such predictions is called forecasting (Bowerman, et al, 2005). Hanke et al. (2009), shows that the purpose of a forecast is to reduce the range of uncertainty within which management judgements must be made. This purpose suggests two primary rules to which the forecasting process must adhere first, the forecast must be technically correct and produce forecasts accurate enough to meet the firm's needs. Second, the forecasting procedure and its results must be effectively presented to management so that the forecasts are used in the decision making process to the firms advantage (Hanke and Wichern, 2009).

Demand forecasting is the ability to predict the future. The process of forecasting becomes the vehicle to quantify the rate of change from the current state of supply and demand to another state of demand (Bowerman et al, 2005). In the developed economies of the world namely the United States and Europe, the topic of demand forecasting has been widely published due to its significance to all decision makers in the supply chain, manufacturers, distributors and consumers. In Kenya, a few studies have been carried out broadly looking at both forecasting practices and demand forecasting in manufacturing and service based industries.

Long term predictions are indispensable for planning and strategy, yet little is known about their value, their limitations or the most appropriate way of making use of them. Makridakis (1996) in his paper on forecasting its role and value for planning strategy examines these issues and proposes two approaches to long term forecasting while illustrating their use to planning and strategy. The objectives of this paper were to identify and extrapolate critical long term trends while assessing their impact on society and firms and examine the analogy of the industrial and information revolutions and the specific consequences of the industrial revolution's five most important inventions in terms of the consequences of similar ones of the information revolution. The paper concludes by advocating that much needs to be done to integrate forecasting, on one hand and long term planning and strategy, on the other. The

purpose of such integration is to increase the ability of organizations to anticipate important forthcoming changes and their consequences and successfully adapt themselves to these changes as well as opportunities and dangers associated with them. The analogies used in this paper focussed on discoveries made during the industrial revolution, while they have shaped the long term planning and strategy in the developed world, they make the assumption that innovations and more life changing discoveries will continue to happen in these developed economies. It is clear more than ever that the emerging economies of Brazil, Russia, India and China will have a major impact on society and firms; it is these economies that will provide innovations and thereby influence long term planning and strategy of most firms in future (Makridakis, 1996).

The business environment has changed dramatically over the last two decades with increasing globalization, widespread adoption of information technology and the advent of e-business. Factors stemming from these environmental changes such as time based forecasting and product proliferation have a direct impact on forecasting practices and processes, thereby making it important to consider how forecasting management practices have changed since studies conducted in the 1980s (Mentzer and Cox, 1984) and 1990s (Mentzer and Kahn, 1995). McCarthy et al (2006) in the 20 year longitudinal study of forecasting practices present results of a survey designed to discover how sales forecasting management practices have changed over the last 20 years as compared to findings reported by Mentzer and Cox (1984) and Mentzer and Kahn (1995). The purpose of this research was to report the results of a 20 year retrospective study of sales forecasting management practices using the same measures applied by Mentzer and Kahn (1995) and Mentzer and Cox (1984), along with additional questions to obtain more detail on the impact of changing business environment on management and performance of forecasting in firms. The objectives of this study was to explore the familiarity of forecasting techniques used by managers, evaluate the level of satisfaction of forecasting techniques used to generate forecasts, identify the techniques used developing forecasts and determine the level of the accuracy of the forecasting methods used by the firms. A web based survey of forecasting executives was employed to explore trends in forecasting management, familiarity, satisfaction, usage and accuracy among companies in a variety of industries. The results revealed a decreased familiarity with forecasting techniques and decreased levels of forecasting accuracy. This study also revealed opportunities for future research in particular, the decline in familiarity with techniques and forecast accuracy over the past 20 years is alarming. Future research should delve into the reasons behind these trends and also focus on

the underlying causes of decreased forecast accuracy. However, the response rate for the web based questionnaires sent to 480 companies was low at 18 percent. Also, the study was biased to US manufacturing firms and efforts should have been made to include firms from Japan, Malaysia, Indonesia, Taiwan, Hong Kong South Korea and Singapore for a comprehensive global review (McCarthy et al, 2006).

Over the past three decades, significant advances have been made in developing sales forecasting techniques that more accurately reflect marketplace conditions. However, surveys of sales forecasting practice continue to report only marginal gains in sales forecasting performance. The forecasting literature suggests that the issue should be addressed by examining organizational factors in sales management. Davis and Mentzer (2007) in their paper on organizational factors in sales forecasting management, propose a theory based framework of organizational factors in sales management that integrates research on organizational climate capabilities, organizational learning and sales forecasting. The objective of this paper was to offer theory-based sales forecasting management framework to facilitate the exploration of the effects organizational factors in sales management. The paper proposed a model of sales forecasting management comprising four components sales forecasting climate, sales forecasting capability, performance outcomes and performance measurement. The authors proposed that a firm's sales forecasting climate influences its sales forecasting capability, which in turn determines performance outcomes.

The results of the content analysis verified the appropriateness of the sample for research purpose. Over 4,500 units of content that related to the conceptual framework were identified and every category of interest was represented in the analysis. The content analysis supported the conceptualization of sales forecasting as an organizational capability comprising two dimensions. A firm's expertise in information logistics and its ability to achieve shared interpretation appeared to be two distinct yet shared related, dimensions of sales forecasting capability. The role of executive leadership was reported in every firm to a significant element of sales forecasting climate. Executives, who were committed to sales forecasting as a key business process reinforced its importance through their behaviour. The outcome of sales forecasting management as a business performance driven by sales forecasting performance, this was a typical manager's reflection on the performance outcomes of sales forecasting. Secondary data comprising of texts of interviews collected from limited set of global manufacturing firms were used in this study and a further exploration of the feedback loops

described in the sales forecasting management framework would require longitudinal data to examine the effect of learning, which occurs over time, on improvements in sales forecasting capability and sales forecasting climate (Davis and Mentzer, 2007).

Demand forecasting is a crucial aspect of the planning process in supply chain companies. The most common approach to forecast demand in these companies involves the use of a computerized forecasting system to produce initial forecasts and the subsequent judgemental adjustment of these forecasts by the company's demand planners, ostensibly to take into account exceptional circumstances expected over the planning horizon. Making these judgements can involve considerable management effort and time, but do they improve accuracy and are some types of judgement more effective than others? Fildes et al (2009) address the issues of accuracy and effectiveness of forecasts in their empirical evaluation of effectiveness of forecasting and judgemental adjustments using data on more than 60,000 forecasts and outcomes from four supply chain companies. The objective of this paper was to evaluate the effects of the various types of judgemental adjustments on forecasting accuracy and the extent to which the resulting forecasts are unbiased and efficient. The findings of this analysis revealed that there were major differences in the forecasting accuracies obtained by the companies. It also showed the potential for improvements that could be achieved by focussing on more effective use of the available information and removal of consistent biases. Despite the large number of forecasts and adjustments examined in this study, there were a number of limitations.

First the data collected was just from four UK based companies and were one step ahead forecasts. In particular, given that managers in these organizations had minimal training in forecasting, one cannot be sure that these results can apply to companies with highly trained staff. Second, there is arguably no such thing as an objective statistical forecast - all forecasting involves some judgement, at least in the choice of statistical method used and the length of data history which it is fitted. Lastly, the finding that forecast adjustment reflects a general over optimism needs further investigation to determine its underlying causes (Fildes, et al 2009).

Forecasts are crucial for practically all economic and business decisions. However, there is a mounting body of empirical evidence showing that accurate forecasting in economic and business world is usually not possible. In addition, there is huge uncertainty as practically all economic and business activities are subject to events we are unable to predict. The fact that

forecasts can be inaccurate creates a serious dilemma for decision and policy makers. On one hand, believing that accurate forecasts are possible means succumbing to the illusion of control and experiencing surprises, often with negative consequences. The time has come for a new attitude towards dealing with the future. Makridakis et al (2009) in their paper on forecasting and uncertainty in the economic and business world, discuss limited predictability in the economic and business environment. The objective of this paper is to provide a framework that helps managers and policy makers plan and make decisions, formulate strategies in a complex world characterized by limited predictability, high level of uncertainty and future outcomes they cannot even conceive. The findings of this paper indicate that the conventional way of making future-oriented decisions involves first, making forecasts and then plans. However, this is not a universal prescription as is witnessed by the plethora of disasters experienced in forecasting in the corporate world (Hogarth and Makridakis, 1981). The key idea is not to develop precise plans for particular types of events but rather contingency plans for classes of events. That is to say, that assessment of uncertainty needs to be broad and allow for what has not been imagined previously. This paper suggests a systematic review of all activities and in particular, the definition of classes of events that could endanger or alternatively enrich the organization in major ways. The question would not be how to predict future values of these uncertain quantities, but how to generate ideas and develop strategies that could neutralise sources of threats. The key idea is not to believe any predictions about the future, but to develop plans that will be sensitive to surprises (Makridakis, et al, 2009). This paper proposes that we consider a change in behaviour based on forecasting outcomes and that planning should make contingencies for uncertainties in the future. However, it falls short of proposing a framework that can guide this process of change and also relies heavily on secondary data which can sometimes be subject to errors.

A study on forecasting sugar demand at Kenya National Trading Corporation (KNTC) by Chepkoit (1992) reported that sugar demand patterns could be modelled using forecasting techniques (decomposition methods) to develop forecasts for sugar depots across the country. The objective of this study was to formulate a methodology for forecasting sugar demand in each of the 34 KNTC depots around the country. The study came up with 34 models for each depot. The findings indicated that the models have high predictive power and therefore, could be used to forecast sugar demand at each respective depot. A comparison between actual and predicted sales revealed that individual models results were very close to actual sales and that the deviation between actual and predicted sales was minimal. This confirmed the strength of

the models to predict accurately and on this basis recommended to KNTC management that there was need to adopt these forecasting models to assist good decision making during production and distribution. The gaps identified in this study included the lack of skilled personnel to utilize and implement these models. Also, this study relied on secondary data which could be prone to errors. This study used the depots as the final point of consumption in the supply chain, instead of retail outlets, this was identified as a weakness since ideally consumption data from the retail outlets should be used to inform and develop forecasts (Chepkoi, 1992).

Nyanamba (2003) in her study on forecasting sales demand at Colgate Palmolive East Africa Limited concluded that use of statistical models produced better forecasts compared to subjective models. The objectives of this study included to develop a quantitative forecasting model for Colgate Palmolive East Africa which will improve the accuracy of forecasting for Colgate toothpaste, compare the results from the model develop against those obtained from the qualitative approach and make recommendations for implementation of these developed models. The findings from this study concluded that two statistical models namely time decomposition and Auto-Regressive Moving Average (ARMA) can be used to forecast sales for 11 millimeters and 50 millimeters with relatively better accuracy compared to the subjective methods used. These statistical models can be used to give a guideline that when combined with subjective expert opinion would yield significantly better or more accurate forecasts. This study identified a number of gaps the data used in the analysis was secondary, implying that the data was prone to errors and also the sales of toothpaste is a function of sales promotion, stock outs and rate of inflation in the economy. Therefore, a model that controls for these three factors should have been developed (Nyanamba, 2003).

Okelo (2007) in his study on forecasting short term demand for money transfer in Kenya Post Savings bank developed a regression analysis model using 66 monthly data points. The objectives of this study were to develop a short term forecasting model for money transfer services and validate the model by comparing current forecasting methods with the developed model. Regression analysis was used to forecast customers demand for western union money transfer services. The study found out that there was a strong correlation between the number of transactions handled and the period (month). In the case of inbound transactions, the regression model did not predict the customers demand level accurately using 66 data points. When tested through cross validation majority were found to give predictions that were

different from the actual recorded figures. This model was, however not recommended for predicting customer demand in the long term since the predictions made were inaccurate and was therefore was recommended for short term forecasting. The weaknesses identified in the study included the use of secondary data which was prone to errors. Also, the study did not control for the confounding factors that could affect money transfer services, for example sales promotions, media advertisements and inflation within the economy (Okelo, 2007).

## **2.8 Univariate Box Jenkins Auto Regressive Integrated Moving Average**

A model that describes the probability structure of a sequence of observations is called a stochastic process. A time series of  $n$  successive observations  $Z' = (z_1, z_2 \dots z_n)$  is regarded as a sample realization, from an infinite population of such samples, which could have been generated by the process. A major objective of statistical investigation is to infer properties of the population from those of the sample. For example, to make a forecast is to infer the probability distribution of a future observation from the population, given a sample  $z$  of past values. To do this, there is need to describe stochastic processes and time series and also the need for classes of stochastic models that are capable of describing practically occurring situations like demand for nutrition commodities. It is for this reason that the application of non-stationary ARIMA processes was used in this study.

An ARIMA model is an algebraic statement telling how observations on a variable are statistically related to past observations on the same variable. The model is extrapolative in nature and involves the projection of past patterns or relationships into the future. In the case of Univariate Box-Jenkins (UBJ) ARIMA model forecasting, past patterns are extrapolated within a single data series into the future. In this study, ARIMA model was used in-order to show how current observations of the actual consumption of nutrition commodities are related to the past actual consumption.

The UBJ-ARIMA models are especially suited to short term forecasting. Short term forecasting is emphasized because most UBJ-ARIMA models place major emphasis on the recent past rather than on the distant past. The long term forecasts from UBJ-ARIMA models are therefore less reliable than short term forecasts (Pankratz 1983).

In the most general form, UBJ-ARIMA model is defined as:

$$(1 + \varphi_1 B + \varphi_1 B^2 + \dots + \varphi_p B^p)(1 + \varphi_d B^d)X_t$$

$$(1 - \theta_1 B - \theta_1 B^2 - \dots - \theta_q B^q)(1 - \theta_d B^d)\varepsilon_t$$

where:

$$BX_t = X_{t-1}$$

$$B^2 X_t = X_{t-2}$$

$$B^3 X_t = X_{t-3}$$

$$B^m X_t = X_{t-m}$$

p = degree of the auto-regressive part.

q = degree of moving average part.

d = degree of differencing.

$\varepsilon_t$  = random shock or 'white noise' and  $\varepsilon_t \sim N(0, I\sigma^2)$  independent and identically distributed

Specifically, the mathematical model is written as:

$$W_t = \mu + \sum \Psi_i(B)X_{i,t} + \theta(B) / \varphi(B)\varepsilon_t$$

where:

t = indexes time

B = is the backshift operator; that is,  $BX_t = X_{t-1}$

$W_t$  = is the response series or a difference of the response series.

$\varphi(B)$  = is the autoregressive operator,

$$\varphi(B) = \phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$$

$\mu$  = the constant term.

$\theta(B)$  = the moving average operator,

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q$$

$X_{i,t}$  = the  $i$ th input time series or a difference of the  $i$ th input time series at time t.

$\Psi_i(B)$  = is the transfer function for the  $i$ th input series modeled as a ratio of polynomials.

$\varepsilon_t$  = random shock.

This model expresses the data as a combination of past values of the random shocks and the past values of other series. Box and Jenkins propose a practical four step procedure for finding a suitable model and these steps are:

Step 1: Differencing the series so as to achieve stationarity – a homogeneous non-stationary series of degree d is differenced d times to achieve stationarity if mean changes over time.

Plots of actual consumption correlogram are examined at each stage until the correlogram dampens.

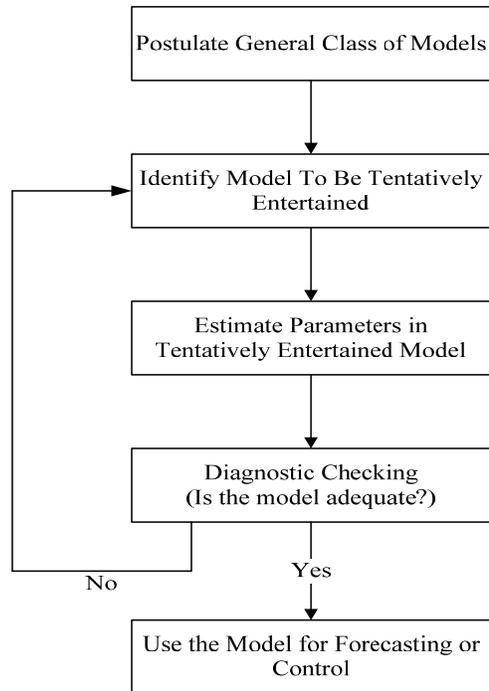
Step 2: Identification of a tentative model - a tentative model with the appropriate orders of Auto Regressive (AR) and Moving Average (MA) components, the Auto Regressive Moving Average (ARMA) (p, q) model for the differenced series ( $w_t$ ) is identified. Through an examination of estimated actual consumption autocorrelations and partial-correlations of the model that seems likely to provide parsimonious and statistically adequate representations, the consumption data is fitted into the series. The ARMA (p, q) model for the differenced series ( $w_t$ ) implies an ARIMA (p, d, q) model for the integrated original un-differenced series  $z_t$ . Original values ( $z_t$ ) are recovered by integration of the differenced series.

Step 3: Estimation - at this stage precise estimates of the coefficients of the model chosen at the identification stage above are determined. Various estimation methods are employed to estimate the parameters (mean and some AR and/or MA coefficients) of the identified model. Approximate t-values for each coefficient, absolute correlations coefficients, Adjusted Root Mean Squared Error (RMSE) and Mean Absolute Percent Error (MAPE) are used to check the model for stationarity and invertibility.

Step 4: Diagnostic checking - some diagnostic checks are utilized to help determine if the estimated model is statistically adequate. Furthermore, the results at this stage also indicate how the model could be improved. If the model is found to be inadequate, then go back to the identification step; or otherwise proceed with forecasting.

To determine if the model developed is statistically adequate, that is, test whether random shocks are independent, estimation step residuals are analyzed through autocorrelation, Bartlett's approximate formula to estimate standard errors of the residual autocorrelations and use of t-tests to test the null hypothesis  $H_0: \rho_k(\varepsilon) = 0$  for each residual autocorrelation coefficient. Some other tests include residual plots for heteroskedasticity test, approximate  $\chi^2$ -test (the Ljung-Box Q-statistic), Akaike Information Criterion (AIC), Schwartz Bayesian Criterion (SBC) or Bayesian information Criterion (BIC), Durbin's h-test, and Lagrange-Multiplier (LM) tests. If the residuals are randomly distributed, this implies that the tentative model is correct and therefore can be used for forecasting. Figure 2 below shows the four steps discussed above.

Figure 2      Flow Diagram of the Box – Jenkins Model Building Strategy



Source: Box, G.E.P., Jenkins, G.M., and G.C. Reinsel, Time Series Analysis: Forecasting and Control (4<sup>th</sup> ed.,)

The UBJ-ARIMA model was employed in this study. A single-series UBJ-ARIMA forecasting model was based only on past values of actual consumption commodities data. Forecasted values were generated using the parameter estimates produced in the estimation process. The UBJ-ARIMA models were used because they are flexible and usually contain relatively few parameters compared with econometric models and thus, inexpensive and simpler to construct. The UBJ approach has some advantages over many other traditional single-series methods. First, the concepts associated with UBJ models are derived from a solid foundation of classical probability theory and mathematical statistics. Second, ARIMA models are a family of models, not just a single model and there is a strategy that guides the analyst in choosing one or more appropriate models from this larger family of models (Pankratz, 1983). Third, it can be shown that an appropriate ARIMA model produces optimal univariate forecasts (no other standard single-series model can give forecasts with a smaller forecasted error variance) (Pankratz, 1983). The actual consumption commodities data from January 2006 to December 2011 were used to develop UBJ-ARIMA model while the data for March to May 2011 was utilized for cross-validation. In order to do the above mentioned analysis ARIMA procedure in the Statistical Package of Social Sciences (SPSS) software was used.

In a number of studies, Granger and Newbold (1986) show that forecasts from simple ARIMA models have frequently outperformed larger, more complex econometric systems for a number

of economic series. Although it is possible to construct ARIMA models with only a few years of monthly historical data, the best results are usually obtained when at least five to 10 years of data are available particularly if the series exhibits strong seasonality. A major drawback of ARIMA models is that, because they are univariate, they have limited explanatory capability. The models are essentially sophisticated extrapolative devices that are of greatest use when it is expected that the underlying factors causing demand for products, services, revenues and so on will behave in future much in the same way as in the past. In the short term, this is often a reasonable explanation however, because these factors tend to change slowly, data tend to show inertia in the short term. A significant advantage of univariate ARIMA models is that they can be developed in a relatively short time. Much more time is usually required to obtain and validate historical data than to build the model (Levenbach, 2006) .

## **2.9 Summary**

The role of forecasting is critical in developing a body of knowledge to help executives in their task of developing an effective foresight about the future as possible. Forecasters and strategists will have to work closely together to bring successes to tomorrow's firms. In such a collaborative effort, forecasters must concentrate their efforts on identifying long-term trends and appropriate analogies affecting the entire economy as well as specific industries.

A review of empirical studies relating to forecasting practices reveals that there has been considerable improvement in tools and techniques used in forecasting. The growth of the information technology has increased and led to an increase in software efficiency and effectiveness. However, this has not translated into better performance, more accurate forecasts and better planning for organizations. As Fildes notes, there is need for more work in forecasting that considers the role of organizational arrangements on forecasting practices and performance (Fildes, et al., 2003).

Today global health programmes will attain their objectives only if products appropriate to the health problems in low and middle income countries are developed, manufactured and made available when and where they are needed. Achieving this requires mobilizing public and private resources for more and better products to diagnose, prevent and treat HIV/AIDS, TB, malaria, childhood illness and reproductive health problems. But, more money is just part of the story; weak links in the global health value chain are constraining access to essential products. One of the weakest links and one of the most vital for achieving both short term and

long term gains in global health is the forecasting of demand for critical technologies in health, including vaccines, medicines and other diagnostic products. Demand forecasting, which may seem at first glance to be simple, is of central importance. Many of the shortcomings in funding and functioning of health systems impede accurate forecasting of demand and without the ability to forecast demand with reasonable certainty and some assurance of a viable market, manufacturers cannot scale production capacity and make commitments to suppliers of raw materials or justify business case for investing in health. From the research presented here, it is clear that demand forecasting is a critical element of managing supply chains to avoid costly errors of oversupply or under performance, which contribute to the bullwhip effect. To achieve this, studies have recommended a cross functional approach to forecasting and information sharing across key elements of the supply chain. This approach allows for informed judgemental adjustments to statistical forecasts of the demand for products thereby reducing the political influence and replacing it with reliable and accurate forecasts, which inform decision making.

## **CHAPTER THREE**

### **RESEARCH DESIGN AND METHODOLOGY**

#### **3.1 Introduction**

This chapter describes and outlines the research methods used in order to achieve the objectives outlined in Chapter One. Specifically, this chapter describes the research design, population of the study, sampling design, data collection, data analysis and methodology employed.

#### **3.2 Research Design**

The research strategy that was used in the empirical research is a case study. Cooper and Schindler (2008) describe a case study as a powerful research methodology that combines individual and sometimes group interviews with record analysis and observation. Researchers extract information from company brochures, annual reports, sales receipts, newspaper articles, along with direct observation and combine it with interview data from participants. The objective is to obtain multiple perspectives of a single organization, situation, event or process at a point in time or over a period of time (Cooper and Schindler, 2008). This research was concerned with an in-depth study of demand forecasting in NHP where forecasting practices, methods and their accuracy are not obvious. The unit of analysis was the functional areas involved in management and planning of the supply chain in NHP.

The general objective of this study is to advance understanding of forecasting the demand for nutrition commodities (patient needs) for NHP. In essence this study is primarily quantitative in nature, and the research strategy that will be used is case study. Cooper (2006) indicate that the case study approach provides the focus that is required, emphasizes the depth of study, is based on the assumption that reality can only be understood through social constructions and interactions and that the context in which phenomena is under study is situated is complex.

In order to achieve objective one, that is an explanation of the current forecasting method used; this was done to understand the basis of the current forecasting method, this study sought to establish the factors influencing selection of a forecasting strategy. This was done by use of a data collection instrument that collected information on the forecasting practices and the factors considered in selection of a forecasting strategy. This analysis supported achieving objective two.

Determining the accuracy of the current forecasting method, which is objective three was determined from analysis of forecast orders and actual consumption monthly consumption data

from January 2006 to December 2011. The Analysis of Variance (ANOVA) was used to determine if a significant difference exists between the actual consumption and forecasted orders. The process of establishing a more suitable method for forecasting demand involved the analysis of the time series plot of actual consumption data in order to summarize its components as a prelude to the selection of a suitable model for forecasting. The iterative Univariate Box –Jenkins (UBJ) approach, was used in the development of a suitable model and hence achieve objective four.

### **3.3 Data Collection**

Primary and secondary data was collected and used in this study. Primary data was collected using a questionnaire, while the project's quarterly reports provided secondary data. In particular, the data on the variables of interest was the actual consumption of commodities and forecast orders of commodities in MT.

### **3.4 Data Analysis**

In this study, a number of statistical techniques were used to analyze the data since the research purpose focus was on description of current practices, and developing a more suitable forecasting method. The techniques used included both descriptive and inferential statistics. Descriptive statistics included graphs, measures of location (mean, mode, and median) and measures of dispersion - these measures were used to describe the collected data. Inferential statistics included correlation analysis and ANOVA. These were used to establish association between variables and test the formulated hypothesis.

For objective one that is, explaining the current forecasting methods used to predict demand for nutrition commodities, a description of the current forecasting method was done. This review focused on the steps and methodology used in the process of forecasting.

For objective two, that is the determination of factors that influence selection of a forecasting strategy, the questionnaire (see Annex III) was used to collect primary data on the factors that influence the forecasting process. The questions in section three and four of the questionnaire focused on collecting data on external and internal environmental factors and the forecasting practices, respectively. This questionnaire targeted the respective project functional area heads namely finance, SCM, monitoring and evaluation and food manufacture.

The third objective, which is to review and evaluate the accuracy of the current method used to forecast demand for project nutrition commodities; one way ANOVA was used to determine if there is a significant difference between the actual consumption and forecasted orders. To be able to determine whether a significant difference exists between the actual and forecasted total consumption of nutrition commodities, an assumption was made that the sample data represents an infinite population of commodities that could have been consumed. Hence, the hypothesis that no difference exists between the actual and the forecasted total MT of nutrition commodity, where  $\mu$  denote the mean infinite population of all MT of nutrition commodity that could be delivered to the project service points, then:

$$H_0 \mu_A = \mu_F$$

$$H_a \mu_A \neq \mu_F$$

where:

$\mu_A$  = population mean of the actual total MT consumed

$\mu_F$  = population mean of the forecasted total MT of commodities delivered

Objective four, to establish a more suitable forecasting method that can be used to accurately predict demand, the study utilized UBJ methodology. Through UBJ methodology identification, fitting and checking was done using ARIMA model and forecasts were done directly from the form of the fitted model (Hanke and Wichern, 2009).

Table 1 Summary of Research Design and Methodology

Objective	Data	Purpose	Analysis	Display
1. Profiling the current forecasting methods used to predict demand for nutrition commodities	Not applicable	Describe the current approach used	Not applicable	None
2. Determine the factors that influence selection of a forecasting strategy.	Primary data	Identify factors that influence the selection of the current method and the forecasting practices	Questionnaire	Summary table of the responses
3. Review and evaluate the accuracy of the current method used to forecast demand for project nutrition commodities	Secondary data: (actual and forecasted consumption data)	Determine if significant difference exists between actual and forecasted consumption	ANOVA	<ul style="list-style-type: none"> <li>• Time series plot (figure 1)</li> </ul>
4. Establish a more suitable forecasting method that can be used accurately predict demand for nutrition commodities	Secondary data: (actual consumption data)	Develop more suitable forecasting method	UBJ ARIMA	<ul style="list-style-type: none"> <li>• Scatter plot</li> <li>• Autocorrelation plots</li> </ul>

## CHAPTER FOUR

### DATA ANALYSIS AND DISCUSSION

#### 4.1 Introduction

This chapter deals with data analysis and discussion of the results. First, the chapter describes the data and also discusses the current method used for forecasting and the factors that influence forecasting strategies used by NHP. Under data description the actual consumption data is described, and thereafter the accuracy of the current forecasting method is discussed.

#### 4.2 Description of the Consumption Data

The actual and forecast consumption data was for the period January 2006 to December 2011. The statistics discussed below are mean, mode, standard deviation, coefficient of variation skewness and kurtosis. The analysis proceeds with a descriptive statistics of the actual consumption data as shown in Table 2 below shows the summary statistics of the data.

Table 2 Summary Statistics for Actual and Forecast Consumption Data 2006 - 2011

Statistic	Actual Consumption	Forecast Consumption
N	72.00	72.00
Mean	49.65	70.17
Median	55.85	65.00
Mode	-	65.00
Minimum value	0.22	0.00
Quartile 1	40.72	34.38
Quartile 3	64.00	90.69
Maximum value	77.91	360.33
Range	77.69	360.33
Inter Quartile Range	23.29	56.31
Standard deviation	22.02	54.99
Variance	484.96	3023.78
Coefficient of variation	44.36	78.37
Skewness	-1.02	2.37
Kurtosis	-0.12	10.37

The results of the summary statistics of actual and forecast consumption in MT are shown in Table 2 above. The mean actual and forecast consumption during the period was 49.65 MT and 70.17 MT, respectively. The most frequent actual consumption recorded was 65 MT for the forecasted consumption. In general, the results above indicate that the forecast consumption tended to exceed the actual consumption. The maximum forecast consumption was 360.3 MT compared to the maximum actual consumption of 77.91 MT. This results reveal

that the variability of the actual consumption varied by 22.02 MT while forecast consumption varied by 54.99 MT, indicating a higher value in the latter.

The coefficient of variation indicates a high absolute spread for the forecast consumption to a reasonable spread for the actual consumption. The coefficient of variation for the forecast consumption was 78.37 percent indicating variability than the actual consumption of 44.36 percent. The measurement of symmetry shows that the actual consumption is negatively skewed, while the forecast consumption is positively skewed. The actual consumption data as displayed in Figure 3 below indicates negative kurtosis since the curve has light tails and flatness. This data has an outlier that affects the location and variability of the distribution. In addition, the forecast consumption data indicates a positive kurtosis where the tails are heavier and the peak is higher compared to the actual consumption data.

The box plot in Figure 3 below indicates that the actual consumption data had only one outlier and that most of the consumption values are spread closer to the mean. However, the box plot on Figure 4 below illustrating the spread of the forecast consumption data has two outliers notable is also the fact that the whiskers are much shorter indicating that the range of values of the forecast consumption was less compared with the actual consumption data.

Figure 3 Summary Statistics for Actual Consumption Data

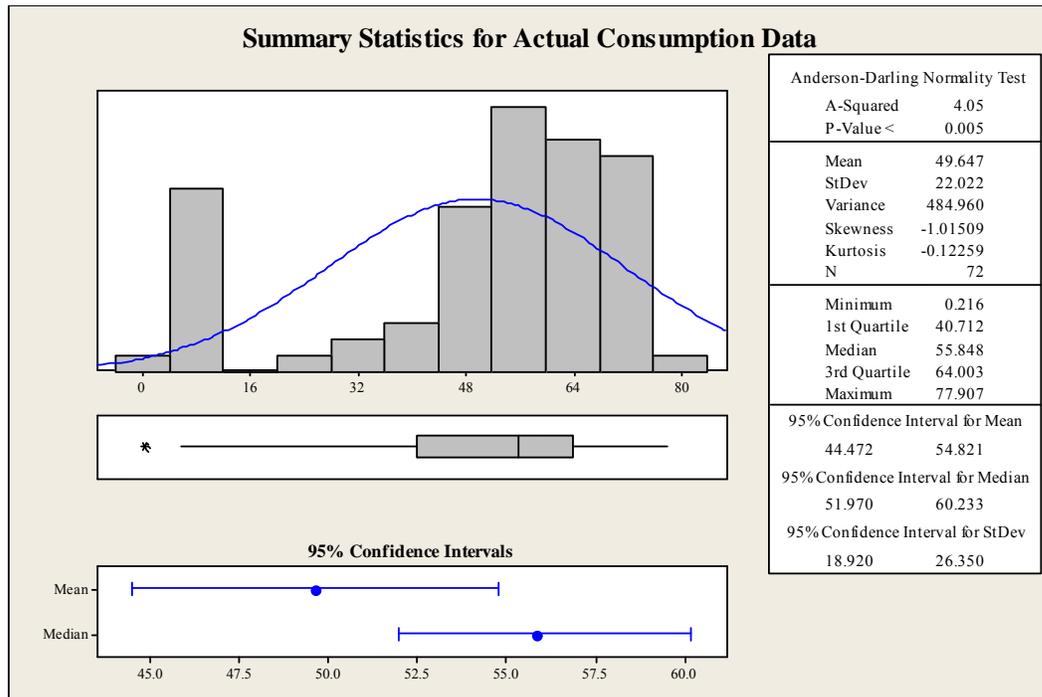
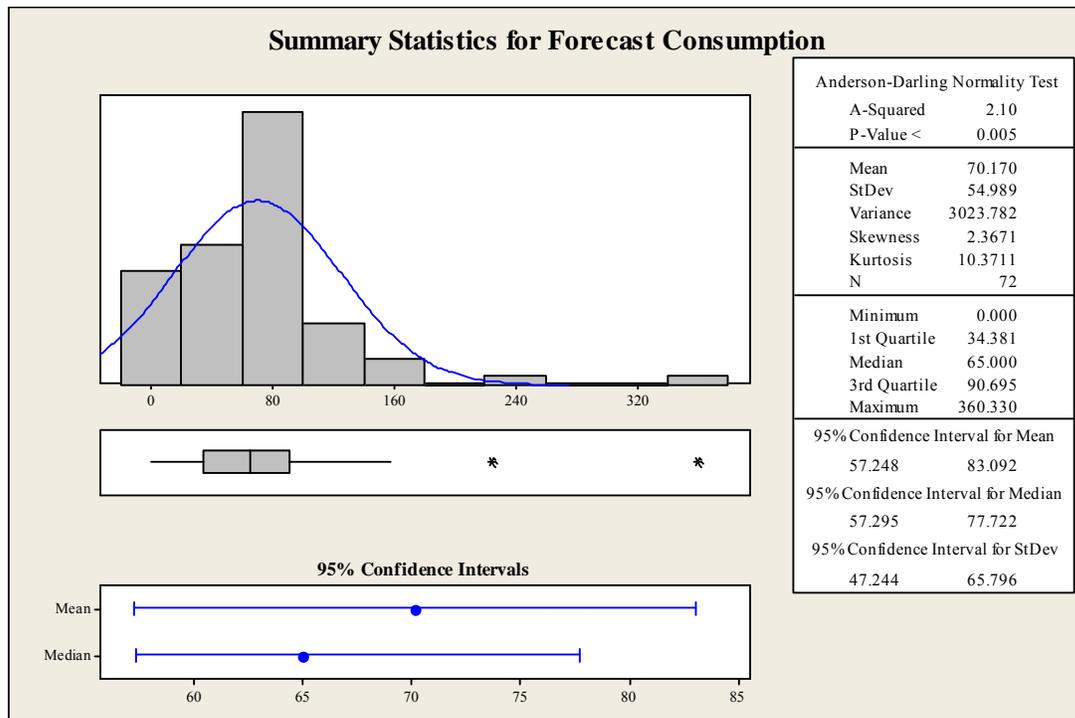


Figure 4 Summary Statistics for Forecast Consumption Data



### 4.3 Forecasting for Nutrition Commodities

Nutrition services in Kenya are provided as a mix of both preventive and curative service. However, nutrition care services for people living with HIV/AIDS are predominantly curative in nature. The NHP uses the patient morbidity standard treatment method due to the lack of national consumption data on nutrition services, rapid expansion of nutrition service points and insufficient resources based on estimated needs for these services. Morbidity data refers to the estimated incidence or prevalence rates of health conditions occurring within a defined population group. The morbidity method uses standard treatment guidelines or treatment protocols and the projected number of patients expected to receive treatment or services. Therefore, this method forecasts the quantity of health commodities demanded for treatment or diagnosis of specific diseases based on projections of the incidence of those diseases.

The first step to determining demand for nutrition commodities involves the development of assumptions to guide the process of forecasting. These assumptions are drawn from the Kenya AIDS Indicator Survey, Kenya Demographic Health Survey and national data based on the Estimates Projection Package (EPP) that shows the number of people living with HIV in need of ART. The second step in this process of developing forecasts involves estimating the

number of treatment episodes based on the morbidity data. For example, NHP data suggests that the incidence of moderate malnutrition in adults living with HIV is approximately 30 percent, while 5 to 10 percent of adults are severely malnourished. These proportions inform the estimation of treatment episodes for each nutrition problem based on the patient demographic data. The final step of this process involves the quantification of these forecasts into nutrition commodities required for each nutrition problem. This is then followed by the process of making adjustments for growth and attrition of patients during the treatment period. The costs of the final estimated quantities are determined and posted into a budget. These forecasts are generated at the beginning of the fiscal year and are reviewed quarterly; the development of annual forecasts is done by a team consisting of the project director, monitoring and evaluation manager, supply chain manager, capacity building and technical guidance officer.

#### **4.4 Factors that Influence the Selection of a Forecasting Strategy**

The questionnaire (see Annex III) was used to collect data on the factors that influence the selection of a forecasting strategy for NHP. The questionnaire was administered to the heads of the core project functional areas namely monitoring and evaluation, finance, SCM and food manufacture. The purpose of this questionnaire was to identify the factors that influence the selection of a forecasting method and understand the forecasting practices within the project. All the four respondents were in the middle management position in the project structure and thus were key decision makers in the project and all had been with the project for more than two years. Finance and supply chain manager had been with the project for over six years.

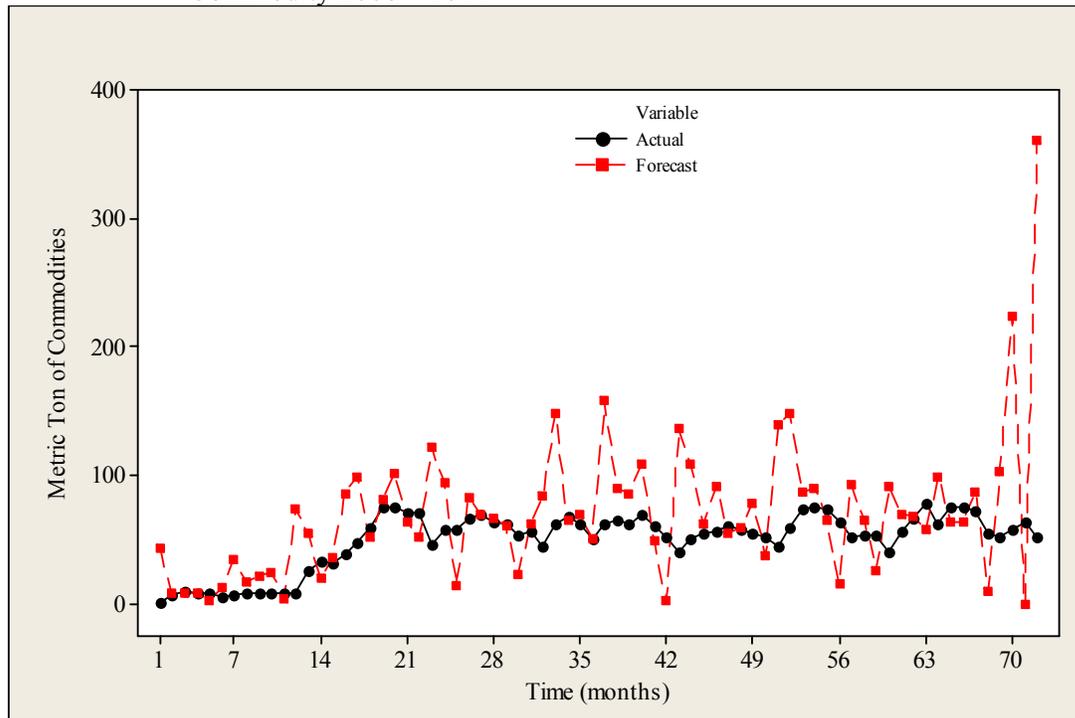
The donor and government policies were reported as the external factors which determined the choice and selection of a forecasting method. Strategy was considered as the most important factor within the internal environment governing choice of a forecasting method. All the respondents reported that the project has a formalised and centralised forecasting function and the methods considered most relevant were computer based, judgemental and combination of computer based and judgemental methods. The qualitative methods used by the project include jury of executive opinion, cross-functional teams and survey of patient needs. Likewise, the quantitative forecasting techniques used by the project are simple averages and trend line analysis. Credibility was considered to be the most important criteria used to determine effectiveness of the forecasting method used. The amount of data and inventory turnover were considered to be important while accuracy of the forecasting method was considered to be

somewhat important. The extent to which forecasts influence decision making in the functional areas namely monitoring and evaluation, procurement, food manufacture, SCM was reported as very significant.

#### 4.5 Accuracy of the Current Forecasting Method

A comparative analysis of the actual and forecasted consumption was done to determine if there is a significant difference between these two consumption levels.

Figure 5 Time Series of Actual Versus Forecasted Total Metric Tons of Nutrition Commodity 2006 – 2011



The characteristics of the two curves in Figure 5 above show that there is notable difference between the actual consumption and the forecasted demand for the nutrition commodities. However, to be able to determine whether a significant difference exists between the actual and forecasted total consumption of nutrition commodities, an assumption was made that the above values represent samples from an infinite population of commodities that could have been consumed. Hence, the hypothesis that no difference exists between the actual and the forecasted total MT of nutrition commodity, where we let  $\mu$  denote the mean infinite population of all MT of nutrition commodity that could be delivered to the project service points, then:

$$H_0 \mu_A = \mu_F$$

$$H_a \mu_A \neq \mu_F$$

where:

$\mu_A$  = population mean of the actual total MT consumed

$\mu_F$  = population mean of the forecasted total MT of commodities delivered

The ANOVA was used to determine if a significant difference exists between the means of the actual and forecasted consumption and thereby test the hypothesis that no difference exists between the actual and the forecasted total MT of nutrition commodity.

Table 3 Output for the Actual and Forecasted Analysis of Variance

Source	Sum of Squares	Degrees of Freedom	Mean Square	F	p – value
Factor	15,163	1	15,163	8.64	.004
Error	249,121	142	1,754		
<b>Total</b>	<b>264,284</b>	<b>143</b>			

Table 4 Grouping Information Using Tukey Method

	N	Mean	Grouping*
Forecast	72	70.17	A
Actual	72	49.65	B

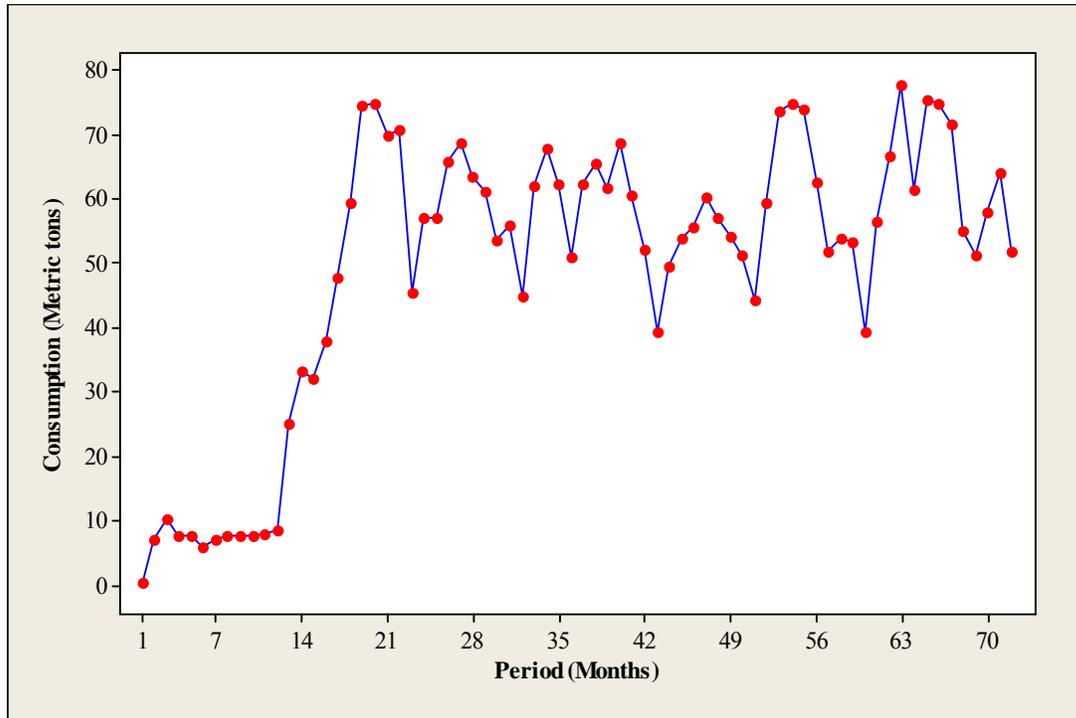
\*Means that do not share a letter are significantly different

In Table 3 above the heading source is used for the source variation column and factor identifies the treatments row. The p-value and the F-value were, respectively 0.004 and 8.64. This means that the null hypothesis ( $H_0$ ) is rejected that the actual and forecasted consumption means are equal. This implies that there was a significant difference between the means of the actual and forecasted consumption. Since ANOVA results suggested that there was a significant difference between the actual and forecasted consumption, the next step involved identifying the specific differences in the forecasts. In order to identify these differences, pairwise comparison was done using Tukey’s studentized range test as shown in Table 4. Results from the test show that there was a significant difference between the actual and forecasted consumption. Under the grouping column in Table 4, these two variables share different letters A and B.

#### 4.6 Un-differenced Auto Regressive Integrated Moving Average Model for the Actual Consumption Data

To develop a forecasting model for a short-run forecast horizon for the consumption data, the actual consumption data from January 2006 to December 2011 was used. The first step in the development of ARIMA model data was a visual inspection of actual consumption data as shown in Figure 6 below. The graph above confirms that the data for actual consumption is not stationary as the series appears to grow and decline throughout the 72 month period.

Figure 6 Time Series Plot of the Actual Consumption Data (Metric Tons)



In addition to the visual inspection of the actual consumption data, the Sample Autocorrelation Function (ACF) was examined to determine if the data was stationary as shown in Figure 7 below. From Figure 7 below, the sample autocorrelation fail to die out rapidly and the actual consumption curve depicts typical non stationary data. The same information is shown in Figure 8 below by the partial autocorrelation function. At this stage the actual consumption data needs to be transformed into stationary series by differencing.

Figure 7 Autocorrelation Function of the Actual Consumption Data

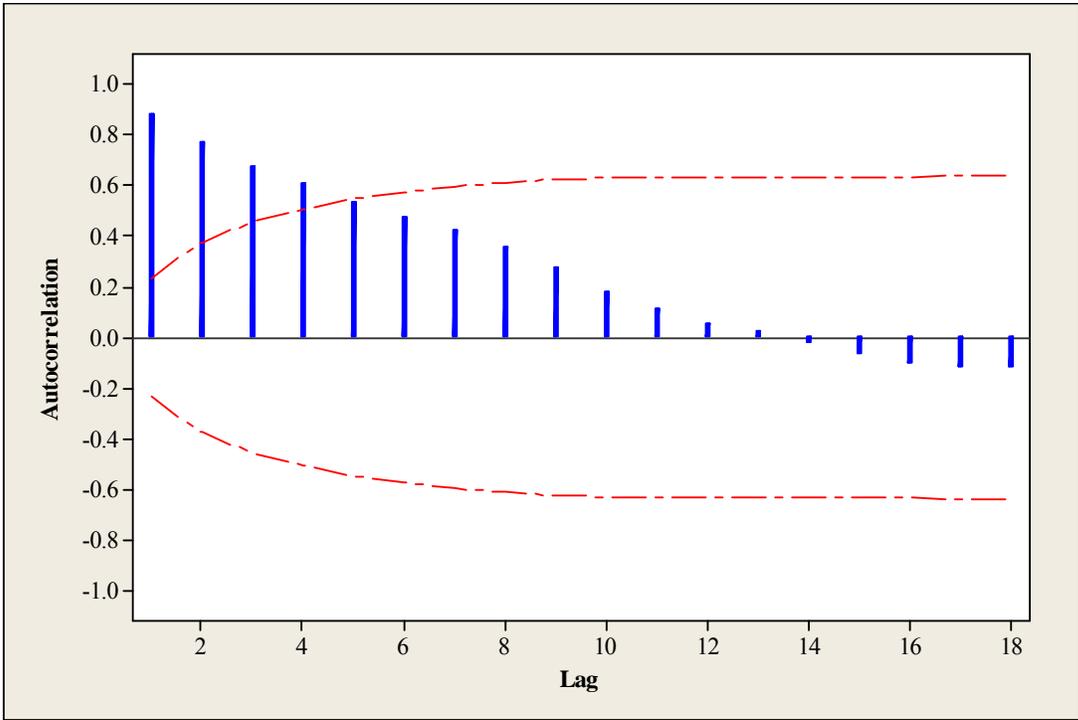


Figure 8 Partial Autocorrelation Function of the Un-differenced Actual Consumption Series

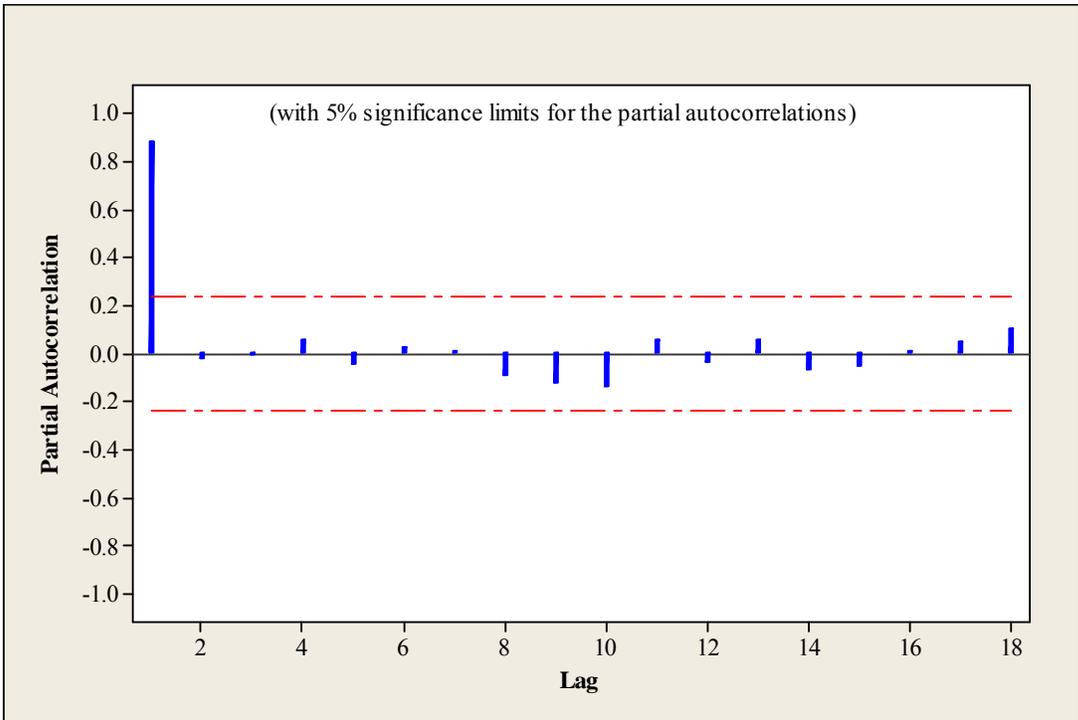


Figure 9 Autocorrelation Function for Actual Consumption Differenced Once

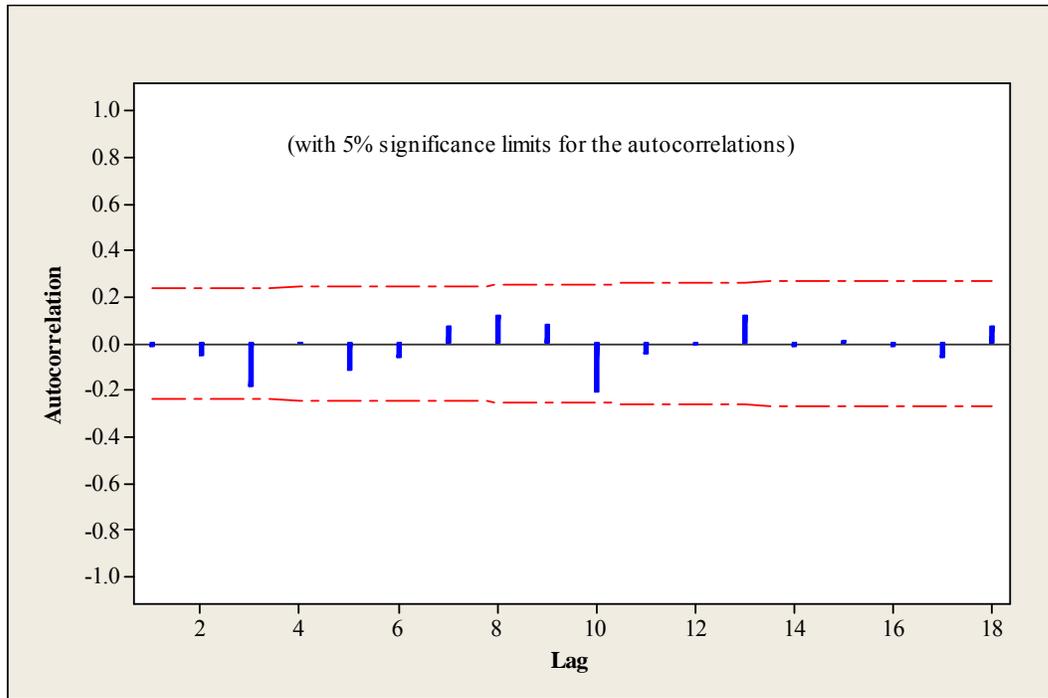
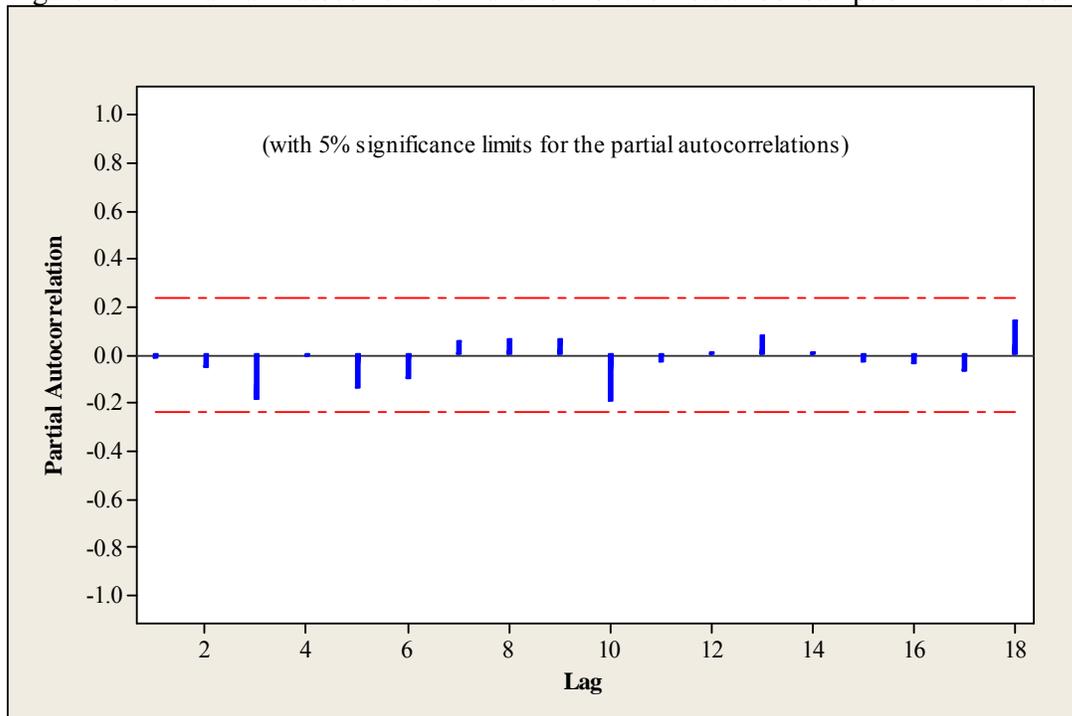


Figure 10 Partial Autocorrelation Function for the Actual Consumption Differenced Once



#### 4.7 Differenced Auto Regressive Integrated Moving Average Model for the Actual Consumption Data

The transformation used to create a stationary consumption data series was differencing the original consumption series data. Differencing refers to finding the successive changes in the values of the data series. Since most time series data are differenced once to achieve stationarity, (Wainaina, 1993) the actual consumption data series for this analysis was differenced once, that is, the original series was replaced by a series of differences and is shown in Figure 9 above, whereas Figure 10 above shows the associated partial autocorrelation function.

Comparing the autocorrelations as illustrated in Figure 9 above with their error limits, the only significant autocorrelation was at lag 2. Similarly, only lag 2 partial autocorrelation as shown on Figure 10 was significant. The autocorrelations appear to cut off after lag 2, indicating moving average MA (2) behaviour. At the same time, the partial autocorrelations appear to cut off after lag 2, indicating autoregressive AR (2) behaviour. Neither pattern appears to die out in a declining manner at low lags. Based on these observations, both ARIMA (2, 1, 0) and ARIMA (0, 1, 2) models will be fitted to the actual consumption data. A constant term will be included in each model to allow for the fact that the series of differences appears to vary about a greater level than zero.

If  $Y_t$  denotes the actual consumption then the differenced series is  $\Delta Y_t = Y_t - Y_{t-1}$ . The two models are:

$$\text{ARIMA (2, 1, 0): } \Delta Y_t = \phi_0 + \phi_1 \Delta Y_{t-1} + \phi_2 \Delta Y_{t-2} + \varepsilon_t$$

$$\text{ARIMA (0, 1, 2): } \Delta Y_t = \mu + \varepsilon_t - \omega_1 \varepsilon_{t-1} - \omega_2 \varepsilon_{t-2}$$

#### 4.7.1 Auto Regressive Integrated Moving Average (2, 1, 0): Model for Actual Consumption

Table 5 Final Estimate of Parameters

Type	Coef	SE Coef	T	P
AR 1	-0.0095	0.123	-0.08	0.938
AR 2	-0.0529	0.1233	-0.43	0.669
Constant	0.773	1.075	0.72	0.475

Differencing: 1 regular difference

Number of observations: Original series 72, after differencing 71

Residuals: SS = 5581.11 (back-forecasts excluded)

MS = 82.08                      DF = 68

Table 6 Modified Box - Pierce (Ljung-Box) Chi Square Statistic

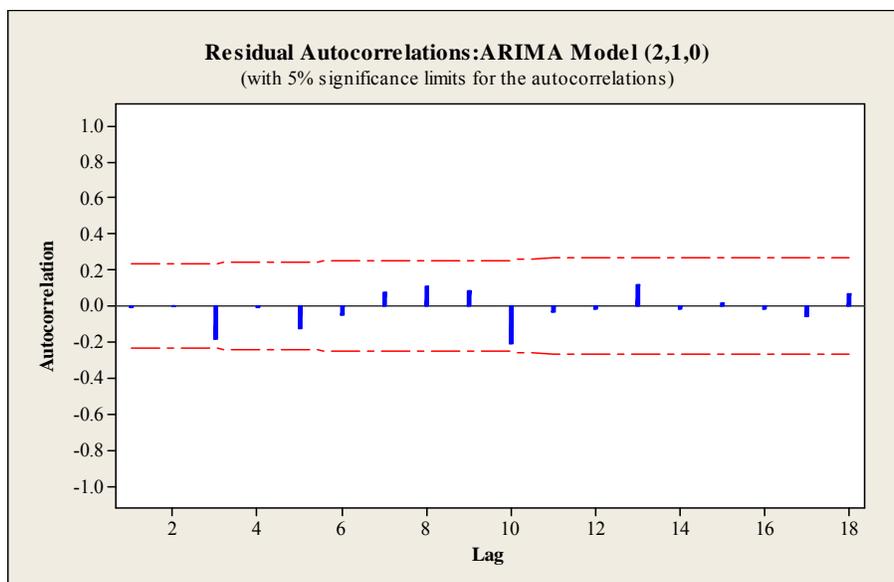
Lag	12	24	36	48

Chi-Square	9.8	16.7	25.2	33.9
DF	9	21	33	45
P-Value	0.368	0.726	0.832	0.888

Table 7 Forecasts from Period 72 (95 Percent Limits)

Period	Forecast	Lower	Upper	Actual
72	52.422	34.6618	70.1823	
73	53.8374	28.84	78.8348	
74	54.5666	24.5297	84.6035	

Figure 11 Residual Autocorrelations Auto Regressive Integrated Moving Average (2, 1, 0) Model Fit for Actual Consumption



#### 4.7.2 Auto Regressive Integrated Moving Average (0, 1, 2) Model for Actual Consumption

Table 8 Final Estimate of Parameters

Type	Coef	SE Coef	T	P
MA 1	0.0375	0.1227	0.31	0.76
MA 2	0.0686	0.1229	0.56	0.579
Constant	0.73	0.961	0.76	0.45

Differencing: 1 regular difference

Number of observations: Original series 72, after differencing 71

Residuals: SS = 5575.13 (back-forecasts excluded)

MS = 81.99 DF = 68

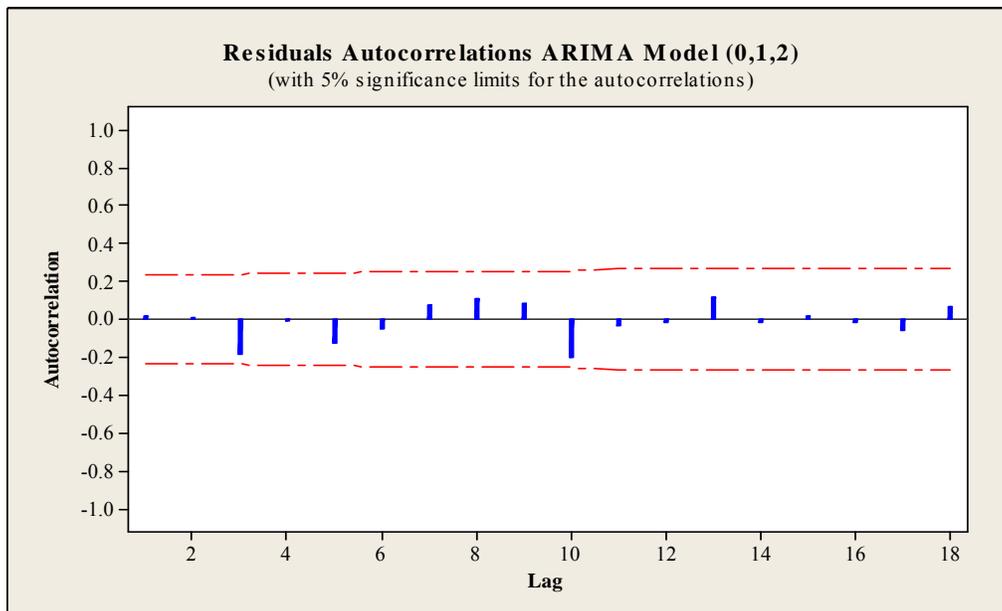
Table 9 Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Lag	12	24	36	48
Chi-Square	9.7	16.8	25.2	33.8
DF	9	21	33	45
P-Value	0.374	0.725	0.833	0.889

Table 10 Forecasts from Period 72 (95 Percent Limits)

Period	Forecast	Lower	Upper	Actual
72	52.7004	34.9497	70.4512	
73	54.2858	29.6492	78.9223	
74	55.0158	25.7118	84.3199	

Figure 12 Residual Autocorrelations Auto Regressive Integrated Moving Average (0, 1, 2) Model Fit for Actual Consumption



Tables 5 to 10 and Figure 11 and 12 illustrate the outputs for both models. Based on these observations both models fit the data equally well. The residual Mean Squares (MS) are:

$$\text{ARIMA (2, 1, 0): } s^2 = 82.08$$

$$\text{ARIMA (0, 1, 2): } s^2 = 81.99$$

Also, it is important to note that for both models none of the parameters are significant given the high p-values. Figures 11 and 12 show that there is no significant autocorrelations for both ARIMA (2, 1, 0) and ARIMA (0, 1, 2). The Ljung-Box Q statistics computed for groups of lags  $m = 12, 24, 36,$  and  $48$  are not significant, as indicated by the large p-values for each model. Moreover, the one step ahead forecasts provided by the two models are nearly the same.

The ARIMA model (0, 1, 2) is adopted on the basis of a slightly better fit. To check the forecast using this model for period 73 is carried out as follows:

$$Y_t = Y_t + \mu + \varepsilon_t - \omega_1 \varepsilon_{t-1} - \omega_2 \varepsilon_{t-2}$$

where  $\mu = 0.73$

$$\omega_1 = 0.0375$$

$$\omega_2 = 0.0686$$

therefore,

$$Y_{73} = Y_{72} + 0.73 + 0.0375(Y_{72} - Y_{71}) - 0.0686(Y_{72} - Y_{71})$$

$$Y_{73} = 51.8499 + 0.73 + 0.0375(51.8499 - 64.1043) - 0.0686(51.8499 - 64.1043)$$

$$Y_{73} = 51.8499 + 0.73 - 0.45954 + 0.84065$$

$$Y_{73} = 52.961$$

The forecast agrees with the result on Table 10; the prediction interval for the actual is 52.7 – 70.45.

#### 4.8 Summary

In this chapter, four steps were followed to develop a UBJ–ARIMA short run forecast model for the actual consumption series. Two models were tested and even though both were statistically significant, the ARIMA (0, 1, 2) model provided a better fit over ARIMA (2, 1, 0) model. To check the forecast for period 73 against the calculated values, revealed similar results compared to those from the analysis, that is calculated forecast 52.9 compared to 52.7 MT from the output on Table 10.

In principle, therefore the forecasts developed from this model should be used to support the process of forecasting especially with regard to allocation of resources for food manufacture and supply chain. Thus, while the work reported in this chapter offers a foundation for improving the actual consumption forecasts, the difficulty of making precise forecasts using the model developed is a limitation for nutrition commodity forecasting for the project.

## **CHAPTER FIVE**

### **SUMMARY, CONCLUSIONS AND RECOMMENDATIONS**

#### **5.1 Summary**

The main objective of this study was to forecast the demand of nutrition commodities in a donor funded project. The specific objectives were to explain the current forecasting method used to predict demand for nutrition commodities, determine the factors that influence the selection of a forecasting strategy, review and evaluate the accuracy of the current method used to forecast demand for nutrition commodities and establish a more suitable forecasting method that can accurately predict demand for nutrition commodities.

Forecasting is all about change and chance; if future events represented only a quantifiable change from historical events, future events or chance conditions could be readily predicted through quantitative projections of historical trends in the future. However, there is much more to forecasting than projecting past trends, experience and intuitive reasoning quickly reveal that future events or chance conditions are not solely a function of historical trends (Levenbach, 2006).

Many of the shortcomings in funding and functioning of health systems impede accurate forecasting of demand and without the ability to forecast demand with reasonable certainty and some assurance of a viable market, manufacturers cannot scale production capacity, make commitments to suppliers of raw materials or justify a business case for investing in costly clinical trials and other activities to develop future products. National governments and international funders rely on demand forecasts for budgeting, while health programs and implementing agencies depend on forecasts to plan their supply chain logistics. Thus, in the high-level policy debates about the volume, duration and use of donor funds to support research and development and purchase essential health products, one key fact has often been overlooked if actions by the international community do not increase the ability to generate credible forecasts of demand if, in fact, those actions contribute to a situation of greater uncertainty, with higher stakes efforts to achieve greater access to life-saving and life-extending medicines will be undermined (Centre for Global Development, 2007).

#### **5.2 Conclusions**

The external factors that affect the selection of forecasting method are donor and government policies. Within the internal environment of the project, strategy was reported to have the

strongest effect on selection of a forecasting strategy. The forecasting practices indicated that there was a formalised and centralised forecasting function within the project and credibility of the forecasting method was considered to be the most important criteria used to determine effectiveness of the forecasting method used. Also, forecasts did influence decision making in the functional areas namely monitoring and evaluation, procurement, food manufacture and SCM.

The review and evaluation of the accuracy of the current forecasting method was done using ANOVA and it indicated that there was a significant difference that the actual and forecasted consumption means are not equal. This implies that there was a significant difference between the means of the actual and forecasted consumption, since ANOVA results indicated that there was a significant difference between the actual and forecasted consumption of nutrition commodities.

To establish a more suitable forecasting method that can be used to accurately predict demand for nutrition commodities, UBJ methodology was used to develop a forecasting model for a short-run forecast horizon for the consumption using the actual consumption data from January 2006 to December 2011. Two models were tested and even though both were statistically significant, ARIMA (0, 1, 2) model provided a better fit over ARIMA (2, 1, 0) model. To check the forecast for period 73 against the calculated values, revealed similar results compared those from the analysis. In summary, UBJ-ARIMA models are useful as benchmarks for forecasting and therefore they should be viewed as complements to reliable forecasting.

### **5.3 Recommendations**

The greatest gains made in forecasting would result from research focused on forecasting management practices while there undoubtedly will be some improvements in available methodologies, it is management's knowledge and use of existing methods in the specific organizational context that hold greatest promise (Davis and Mentzer, 2007).

Based on the finding and conclusions, the following recommendations can be made first, public health projects such as NHP tend to adopt blindly forecasting methods that do not inform future events. The morbidity method is widely used across the health sector, even though it produces results that tend to over estimate the demand for medical commodities. Therefore, the managers of public health projects need to consider adopting business forecasting methods that

will provide a better glimpse of the future based on historical events rather than relying on disease morbidity data trends.

Second, forecasts influence decision making in the project functional areas, therefore the project need to invest in building capacity within respective functional areas on the use of quantitative forecasting approaches that can be combined with past experience and intuitive reasoning to provide more informative forecasts. Third, the current method of forecasting used by NHP is not accurate and therefore a new methodology needs to be adopted that considers both external and internal factors in the projects operating environment. The UBJ – ARIMA method can be adopted to complement the forecast process for nutrition commodities in the short term as it is more reliable.

Finally, the environment within which public health projects operate is dynamic given the nature of diseases, new and emerging best practices in health service delivery and demands placed on these projects by donors. It is therefore important that the donor agencies of these projects have some basic understanding of forecasting practices so that resources can be effectively utilized. This will translate to donors having an objective input regarding project expenditures rather than being at the mercy of implementing partners who in turn justify their expenditures on morbidity disease trends.

#### **5.4 Limitations and Further Research**

This study was limited in several respects; the main limitation was the non–availability of data on forecasting practices within donor funded projects. The questionnaire was administered to four respondents who represent each of the projects core functional areas. However, due the small sample of respondents, this research was not able to identify the factors that influence the selection of a forecasting method in such donor funded projects. It is important to note that the performance of a project can be attributed to its forecasting practices. Another limitation is that this study was not able to show the link between the forecasting practices and the outcome with respect to accuracy of the forecasting methods used.

From the results of this study, further research is necessary in developing more accurate forecasting methods. The areas of potential improvements are:

1. Since this study was focussed on one project, a study needs to be done to determine the factors that influence the selection and choice of a forecasting method within the projects in the health sector.
2. The forecasting model developed in this study needs to be improved; one way could be to develop a model based on the variation between actual and forecasted consumption. Also, since the dynamic specification of UBJ-ARIMA models are not flexible enough, probably an Error-Correction Model (ECM) could be used which incorporates dynamic behavior and achieves long-run equilibrium.
3. Advanced Box and Jenkins using intervention models can be used since these models are preferred when exceptional external events affect the variable to be predicted; such is the environment in which most donor funded projects operate.

## REFERENCES

- Barlas Y. and Gunduz B. "Demand Forecasting and Sharing Strategies to Reduce Fluctuations and Bullwhip Effect in Supply Chains." *Journal of the Operational Research Society* 62 No. 3 (2011) pp 458–473.
- Bermudez J. D. Segura J. V. and Vercher E. "Improving Demand Forecasting Accuracy Using Nonlinear Programming Software." *Journal of the Operational Research Society* 57 No. 1 (2006) pp 94–100.
- Bowerman B. L. O'Connell R. T. and Koehler A. B. *Forecasting, Time Series and Regression*. Brooks/Cole Cengage Learning 2005.
- Box G. E. P. Jenkins G. M. and Reinsel G. C. *Time Series Analysis*. New Jersey: John Wiley and Sons Inc. 2008.
- Center for Global Development. *A Risky Business: Saving Money and Improving Global Health Through Better Demand Forecasts*. Washington DC: Center for Global Development 2007.
- Chepkoi C. K. *A Methodology for Forecasting Sugar Demand: The Case of Kenya National Trading Corporation*. Unpublished MBA Project University of Nairobi 1992.
- Cooper D. R. and Shindler P. S. *Business Research Methods*. Boston: McGraw Hill 2008.
- Datta S. Granjer C. W. J Barari M. and Gibbs T . "Management of Supply Chain: An Alternative Modelling Technique for Forecasting." *Journal of the Operational Research Society* 58 No. 11 (2007) pp 1459-1469.
- Davis D. F. and Mentzer J. T. "Organizational Factors in Sales Forecasting Management." *International Journal of Forecasting* No. 23 (2007) pp 475 - 495.
- Donald P. K. "Nutritional Alterations Associated With HIV Infection." *JAIDS Journal of Acquired Immune Deficiency Syndromes* 2000: 25:S81–S87.
- Faucheux C. "Comments on Forecasting: Its Role and Value for Planning and Strategy." *International Journal of Forecasting I* No. 12 (1996) pp 539-554.
- Fildes R. and Kingsman B. "Incorporating Demand Uncertainty and Forecast Error in Supply Chain Planning Models." *Journal of the Operational Research Society* 62 No. 3 (2011) pp 483-500.
- Fildes R. Bretschneider S. Collopy F. Lawrence M. Stewart D. Winklhofer H. and Moon M. A. "Researching Sales Forecasting Practice" *International Journal of Forecasting* 19 (2003) pp 27-42.
- Fildes R. Konstantinos N. Crone S. F. and Syntetos A. A. "Forecasting and Operational Research: A Review." *Journal of the Operational Research Society* 59 No. 9 (2008) pp 1150–1172.

- Fildes R. Goodwin P. Lawrence M., and Konstantinos N. "Effective Forecasting and Judgemental Adjustments: An Empirical Evaluation and Strategies for Improvement in Supply Chain Planning." *International Journal of Forecasting* 25 (2009) pp 3-23.
- Food and Nutrition Technical Assistance 2 Project. *Review of Kenya's Food by Prescription Program*. Washington DC: Academy for Educational Development, 2009.
- Glenngård A.H. and Maina T. M. "Reversing the Trend of Weak Policy Implementation in the Kenyan Health Sector. A Study of Budget Allocation and Spending of Health Resources Versus Set Priorities." *Health Research Policy Systems* 2007.
- Global Health Forecasting Working Group. *A Risky Business: Saving Money and Improving Global Health Through Better Demand Forecasts*. Washington DC: Center For Global Development 2007.
- Goodwin P. and Robert F. "Forecasting in Supply Chain Companies: Should You Trust Your Judgement?" *Operations Research Society* 24 No. 3 (2011) pp 159-167.
- Goodwin P. Fildes R. Lawrence M. and Konstantinos N. "The Process of Using a Forecasting Support System." *International Journal of Forecasting* 23 (2007) pp 391–404.
- Haberleitner H. Meyr H. and Taudes A. "Implementation of a Demand Planning System Using Advance Order Information." *International Journal of Production Economics* 128 (2010) pp 518-526.
- Hanke J. E. and Wichern D. W. *Business Forecasting*. 9. New Jersey: Pearson Prentice Hall 2009.
- Health Policy Initiative. *Investing Wisely: Health Policy Initiative Helps Kenya to Improve Health Financing Policies and Systems*. Nairobi September 2009.
- Health Sector Reform Secretariat. *Reversing the Trends: The Second National Health Sector Strategic Plan of Kenya 2005–2010*. Nairobi: Ministry of Health 2005.
- Jones V. D. Bretschneider S. and Gorr W. L. "Organizational Pressures on Forecast Evaluation: Managerial, Political, and Procedural Influences." *Journal of Forecasting* 16 No. 4 (1997) pp 241 - 254.
- Kenya Food Security Steering Group. *The 2009 to 2010 Short Rains Season Assessment Report*. Nairobi 2010.
- Kenya National Bureau of Statistics, and Macro ICF. *Kenya Demographic Health Survey 2008 - 2009*. Calverton Maryland 2010.
- Lawrence M. O'Connor M. and Edmundson B. "A Field Study of Sales Forecasting Accuracy and Processes." *European Journal of Operational Research* 122 (2000) pp 151-160.
- Lawrence M. Goodwin P. O'Connor M. and Onkal D. "Judgmental Forecasting: A Review of Progress Over the Last 25 Years." *International Journal of Forecasting* No. 22 (2006) pp 493– 518.

- Levenbach H. and Cleary J. P. "Forecasting: Practice and Process for Demand Management." In *Forecasting Practice and Process for Demand Management* by Hans Levenbach and James P. Cleary xxiii. California. Thomson Brooks/Cole 2006.
- Lo S. L. Wang F. K. and Lin J. T. "Forecasting for the LCD Monitor Market." *Journal of Forecasting* 27 (2008) pp 341-356.
- Makridakis S. "Forecasting: Its Role and Value for Planning and Strategy." *International Journal of Forecasting* 1996 pp 513-537.
- Makridakis S. Hogarth R and Gaba A. "Forecasting and Uncertainty in the Economic and Business World." *International Journal of Forecasting* 25 2009 pp 794–812.
- McCarthy T. M. Davis D. F. Golicic S. L. and Mentzer J. T. "The Evolution of Sales Forecasting Management: A 20-Year Longitudinal Study of Forecasting Practices." *Journal of Forecasting* 25 (Wiley InterScience) 2006 pp 303–324.
- Meade N.. "Evidence for the Selection of Forecasting Methods." *Journal of Forecasting* 19 (2000) pp 515-535.
- Muttunga J. D. L L. Bukania M. Z. Munia E. and Kilonzo B. Randomized Controlled Trial of the Impacts of Food Supplementation on Malnourished Adult ART Clients and Adult Pre-ART Clients in Kenya. *Clinical Trial Nairobi Kenya Medical Research Institute* 2009.
- National AIDS Control Council. HIV Sentinel Surveillance Prevalence Data Nairobi Unpublished 2006.
- National AIDS and STD Control Program. Kenya AIDS Indicator Survey 2007 Nairobi Ministry of Health 2008.
- Ngigi A. and Macharia D. Kenya Health Sector Policy Overview Paper. Nairobi 2006.
- Nyanamba J. O. A Methodology for Forecasting Sales Demand for Toothpaste: The Case of Colgate Palmolive. Unpublished MBA Project University of Nairobi 2003.
- O'Connor M. W. R. and Griggs K. "Does Updating Judgmental Forecasts Improve Forecast Accuracy?" *International Journal of Forecasting* 16 (2000) pp 101–109.
- Okelo G. O. Forecasting Short Term Demand for Money Transfer Services in Kenya Post Savings Bank. Unpublished MBA Project University of Nairobi 2007.
- Pankratz A. *Forecasting with Univariate Box Jenkins Models: Concepts and Cases*. New York: John Wiley and Sons 1983.
- Sekhri N. et al. Principles for Forecasting Demand for Global Health Products. *Global Health Forecasting Working Group Background Paper*. Centre for Global Development, Washington DC 2006 pp 1-3.

Sprague L. G. and Wacker J. G. "Forecasting Accuracy: Comparing the Relative Effectiveness of Practices Between Seven Developed Countries." *Journal of Operations Management* No. 16 (1998) pp 271 - 290.

USAID Kenya Health Programs. <http://kenya.usaid.gov/programs/health/projects> (accessed November 5, 2011).

Wainaina G. An Analysis of Corn Basis Movements in Mississippi. Unpublished PhD Thesis Mississippi State University 1993.

World Bank. Kenya Economic Update. Turning the Tide in Turbulent Times. Nairobi: Poverty Reduction and Economic Management Unit Africa Region June 2011.

## ANNEXES

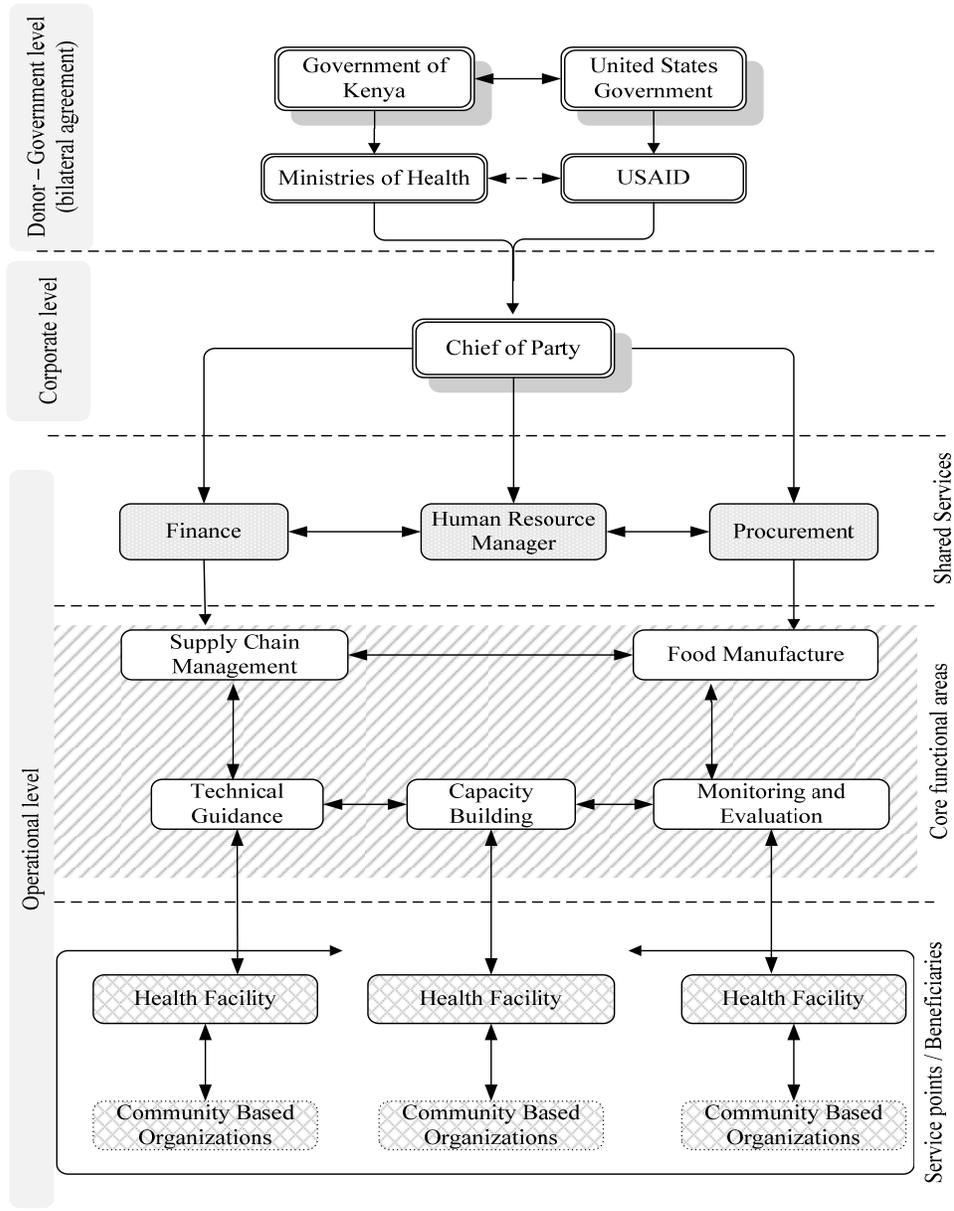
### Annex I: Actual Consumption and Forecasted Demand for Nutrition Commodities 2006- 2011

Year	Month	Actual Total (Metric Tons)	Forecast Total (Metric Tons)
2006	January	0.2160	42.755
	February	6.8498	7.78
	March	10.2229	7.65
	April	7.4542	8.75
	May	7.4508	1.8
	June	5.8028	12.95
	July	6.8792	33.70
	August	7.4616	16.448
	September	7.4490	21.75
	October	7.4659	24.08
	November	7.7398	3.95
	December	8.3886	74.30
2007	January	14.4085	54.13
	February	15.6725	19.875
	March	15.3385	36.43
	April	18.226	85.775
	May	22.954	98.78
	June	28.589	51.650
	July	35.983	81.265
	August	36.0955	100.745
	September	33.6075	62.840
	October	33.981	51.05
	November	22.677	122.375
	December	27.425	93.705
2008	January	34.198	14.33
	February	39.6395	81.89
	March	41.2525	69.89
	April	38.2025	65.7
	May	36.2705	60.89
	June	31.65	22.63
	July	34.023	62.60
	August	27.629	84.20
	September	37.812	148.00
	October	47.355	65.00
	November	43.6555	68.60
	December	35.937	50.60
2009	January	43.565	157.60
	February	46.8955	89.30
	March	44.237	85.30
	April	48.2335	108.10
	May	43.8665	48.80
	June	37.3015	2.50
	July	28.03	136.20
	August	34.543	108.00
	September	38.8595	62.10
	October	39.1805	90.96
	November	41.6185	55.28
	December	40.068	58.54
2010	January	38.152	78.69
	February	35.8505	37.55
	March	31.33	139.82

Year	Month	Actual Total (Metric Tons)	Forecast Total (Metric Tons)	
	April	41.193	148.45	
	May	51.6615	86.45	
	June	52.1285	89.90	
	July	53.182	65.20	
	August	44.931	15.70	
	September	37.5775	92.70	
	October	39.3295	65.00	
	November	38.602	26.00	
	December	29.8905	91.20	
	2011	January	56.6424	69.804
		February	66.76995	68.481
		March	77.90655	56.943
April		61.6326	98.154	
May		75.5334	63.057	
June		75.0525	63.081	
July		71.65905	86.784	
August		55.2006	10.1925	
September		51.32265	103.062	
October		58.0974	224.160	
November		64.1043	0.000	
December		51.8499	360.330	

Source: NHP Quarterly Program Reports

## Annex II Nutrition and Human Immunodeficiency Virus Project Structure



Source: NHP Work Plan 2008

### **Annex III: Research Questionnaire**

#### Section 1: Project Functional Area

Please tick the most appropriate functional area

1. Which functional area of the project do you work?

- Finance; (1)
- Capacity building; (2)
- Supply chain; (3)
- M&E; (4)
- Food manufacture (5)

#### Section 2: About Yourself

Please tick the most appropriate information about yourself

2. Your position in the project

- Top Management (1)
- Middle Management (2)
- First level supervisor (3)
- Non Managerial position (4)

3. Your Gender

- Male (1)
- Female (2)

4. Your age in years

- Less than 25 (1)
- 25 – 35 (2)
- 36 – 47 (3)
- 48 – 54 (4)
- More than 54 (5)

5. Your highest level of education

- Diploma (1)
- University/College degree (2)
- Master's Degree (3)
- PhD (4)
- Other (please specify) (5) [Click here to enter text.](#)

6. Number of years worked in organization or project

- Less than 1 year (1)
- 1 – 2 years (2)
- 3 – 5 years (3)
- 6 – 10 years (4)
- Over 10 years (5)

Section 3: External and Internal Environment

7. To what extent do the following external and internal environments affect the project's choice of a forecasting method? (please tick appropriate box)

External environment

	+5 Strong effect	+4 Moderate effect	+3 Weak effect	+2 No effect
(i) Government Policy	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(ii) Donor	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(iii) Fiscal policies(taxation)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(iv) Political	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Internal environment

	Strong effect	Moderate effect	Weak effect	No effect
(v) Leadership	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(vi) Strategy	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(vii) Structure	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(viii) Culture	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Section 4: Forecasting Practices

8. Is there a formalized and centralized forecasting function for the project?

- Yes (1)                       No (2)

9. Which forecasting methods are relevant to you in this project/ business (rate each method as 1= not important to 5 extremely important)

	+5 Extremely important	+4 Importan t	+3 Somewhat important	+2 Little importanc e	+1 Not Importan t	NA
(i) Computer based methods	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(ii) Judgmental methods	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(iii) Combinations of the above two	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(iv) Simulation	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Other (please specify)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

10. If subjective (judgmental) methods are used for forecasting, please select the forecasting technique used in this project?

- Jury of executive opinion (1)
- Cross functional teams (2)
- Survey of patient needs (3)
- Expert opinion (4)
- Past patient number analysis (5)
- Other (please specify)(5): [Click here to enter text.](#)

11. If quantitative methods are used for forecasting, please select the technique used to develop forecasts in this project.

- Naïve (1)
- Simple averages (2)
- Moving averages (3)
- Exponential smoothing (4)
- Trend line Analysis (5)
- Simple Regression(6)
- Box – Jenkins time series (7)

12. Which of the following criteria would you use to determine the effectiveness of the forecasting method used? (Please rate each criteria as +1= not important to +5 extremely important)

	+5 Extremely important	+4 Important	+3 Somewhat important	+2 Little importance	+1 Not Important
(i) Accuracy	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(ii) Credibility	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(iii) Patient satisfaction	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(iv) Ease of Use	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(v) Inventory turnover	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(vi) Amount of data required	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(vii) Cost	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(viii) Overall savings to project	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

13. Which of the following forecast timing horizon is most important to you? (Please rate each time period as +1= not important to +5 extremely important)

	+5 Extremely important	+4 Important	+3 Somewhat important	+2 Little importance	+1 Not Important	NA
(i) Monthly	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(ii) Quarterly	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(iii) Semi-annual	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(iv) Annual	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(v) Other (please specify)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

14. To what extent do the forecasts influence decision making and planning in the following functional areas?

	+5 Very Significant	+4 Significant	+3 Somewhat significant	+2 Slightly significant	+1 Not significant	NA
(i) Finance	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(ii) Procurement	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(iii) Food Manufacture	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(iv) Supply chain management	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
(v) Monitoring &evaluation	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

(vi) Capacity building

15. Please provide any additional comments on forecasting and forecasting methods used by the project.