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Forecasting Patient Needs in a Donor Funded Health Care Project in Kenya

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Forecasts are crucial for practically all economic and business decisions. The focus of this research paper is in the area of forecasting. 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 paper was to forecast the demand for patient needs in a donor funded project. Specifically, this paper sought to establish a suitable forecasting method that can accurately predict demand for nutrition commodities. 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 paper 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 paper 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.

Key words: Autocorrelation function, ARIMA, partial autocorrelation function, public health project, residual autocorrelations short run forecast, stationarity, UBJ, un-differenced

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Introduction

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 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 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).

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)

Nutrition and HIV Quarterly Program Report for January 1, 2012 to March 31, 2012 indicated 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 actual consumption of commodities in MT by respective service point; the aggregate data for consumption and forecasts is shown in Annex I.

Demand Forecasting Practices for Health Commodities

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).

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 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 'true' but unknown demand generation process. The benefits of forecast model selection will depend on the noise in the data (Fildes and Kingsman, 2011).

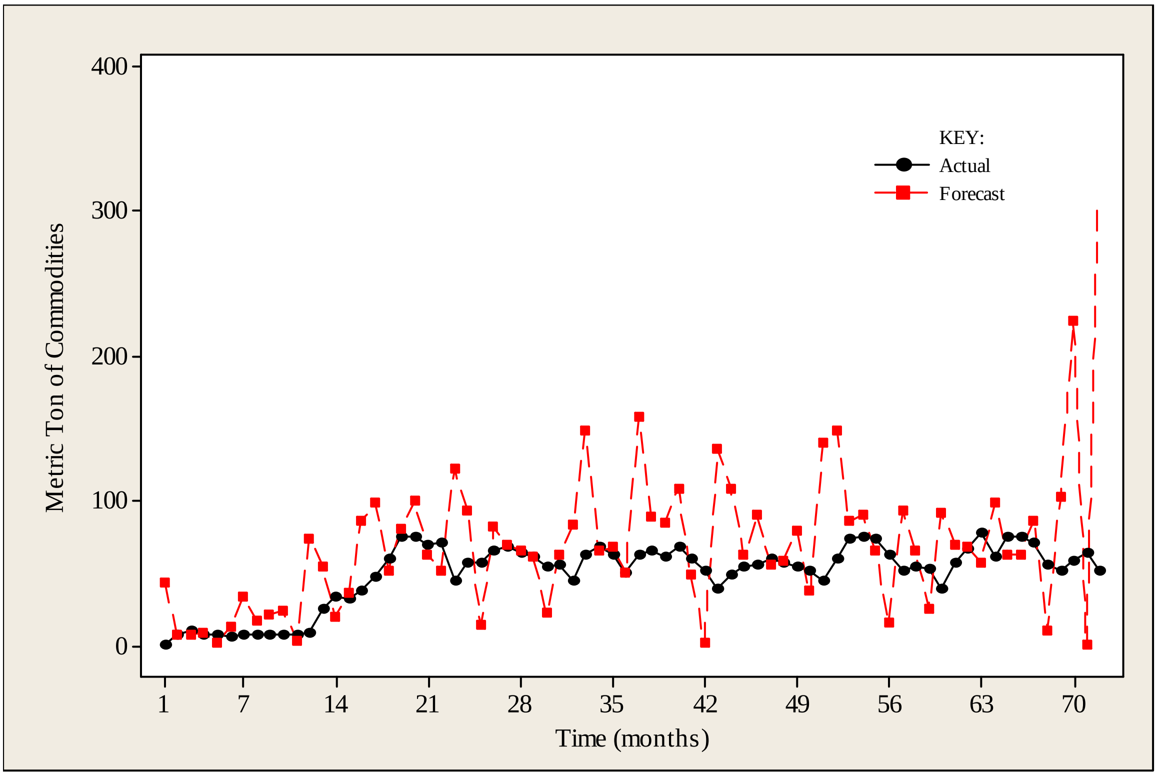
Haberleitner et al.(2010) in their paper on implementation of a demand planning system using advance order information, demonstrates the successful application of a supply chain forecasting system in the refractory industry which integrates the knowledge of partially known advance demand information. 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 management of supply chain using an alternative forecasting technique propose 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 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.

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 1st to the 72nd month. The upward trend exhibited in both curves reflects the long run growth of the project. 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.

It was the objective of this paper 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 sought 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. The objective of this paper was to establish a more suitable forecasting method that can be used to accurately predict demand for nutrition commodities.

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



Materials and Methodology

The UBJ-ARIMA model was employed in this paper; 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 Statistical Package of Social Sciences software was used.

A number of studies 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 two 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.

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

$$\left(1+\varphi_1 B+\varphi_1 B^2+\cdots+\varphi_p B^p\right)(1+\varphi_d B^d)X_t$$
$$\left(1-\theta_1 B-\theta_1 B^2-\cdots-\theta_q B^q\right)(1-\theta_d B^d)\varepsilon_t$$

where:

$\mathrm{BX}_t = \mathrm{X}_{t-1}$
$\mathrm{B}^2\,\mathrm{X_t} = \mathrm{X}_{t-2}$
$\mathrm{B}^3\,\mathrm{X_t} = \mathrm{X}_{t-3}$
$\mathrm{B^m}\,\mathrm{X_t} = \mathrm{X}_{t-m}$
p = degree of the auto-regressive part.
q = degree of moving average part.
d = degree of differencing.
ε_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:

$$W_t = \mu + \Sigma\Psi_\mathrm{i}(\mathrm{B})\mathrm{X}_{i,t} + \theta(\mathrm{B}) / \varphi(\mathrm{B})\varepsilon_t$$

where:
t = indexes time
B = is the backshift operator; that is, $\mathrm{BX}_t = \mathrm{X}_{t-1}$
W_t= is the response series or a difference of the response series.
$\varphi(\mathrm{B})$ = is the autoregressive operator,
$\varphi(\mathrm{B}) = \phi(\mathrm{B}) = 1-\phi_1 B-\phi_2 \mathrm{B}^2-\cdots-\phi_\mathrm{p}\mathrm{B^p}$
μ = the constant term.
$\theta(\mathrm{B})$ = the moving average operator,
$\theta(\mathrm{B}) = 1-\theta_1 B-\theta_2 \mathrm{B}^2-\cdots-\theta_\mathrm{q}\mathrm{B^q}$
$\mathrm{X}_{i,t}$ = the ^{i}th input time series or a difference of the ^{i}th input time series at time t.

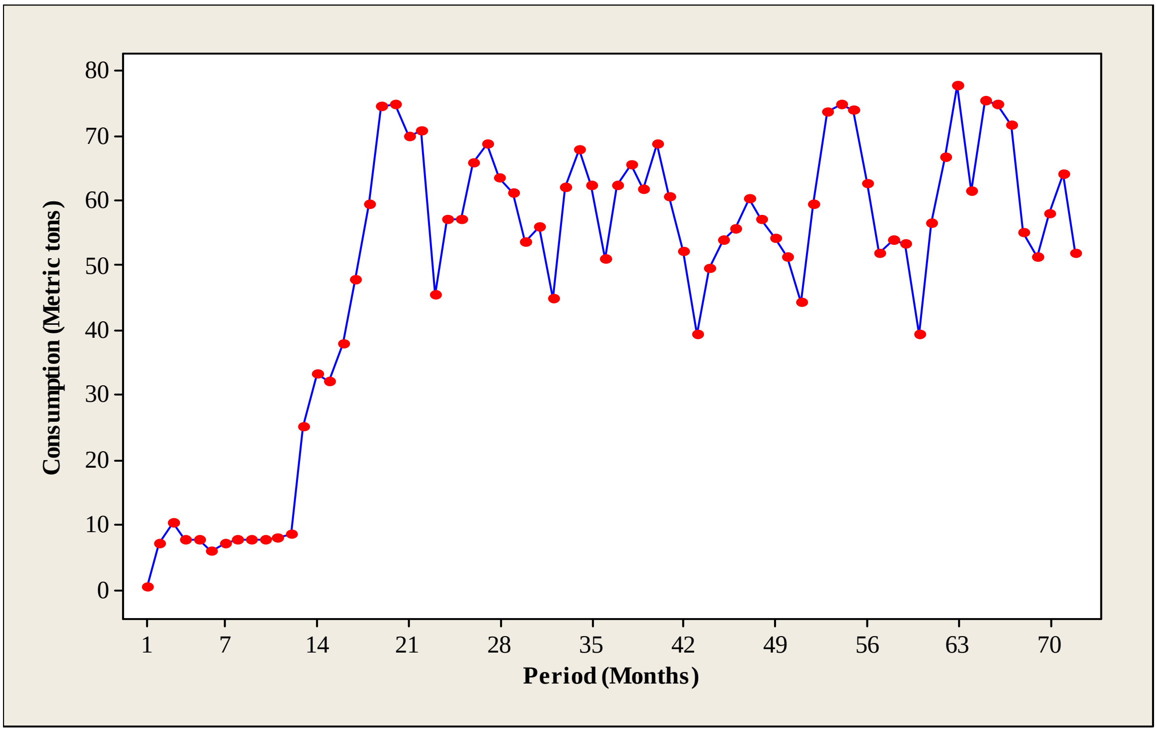
$\Psi_i(B)$ = is the transfer function for the ^{i}th input series modeled as a ratio of polynomials.
ε_t = random shock.
This model expresses the data as a combination of past values of the random shocks and the past values of other series.

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. Primary and secondary data was collected and used in this paper; 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.

Results and Discussion

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 2 below and the figure confirms that the data for actual consumption is not stationary as the series appears to grow and decline throughout the 72 month period.

Figure 2: 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 3 below. From Figure 3 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 4 below by the partial ACF. At this stage the actual consumption data needs to be transformed into stationary series by differencing. The transformation used to create a stationary consumption data series was differencing the original consumption series data. 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 5 below, whereas Figure 6 below shows the associated partial autocorrelation function.

Figure 3 Autocorrelation Function of the Actual Consumption Data

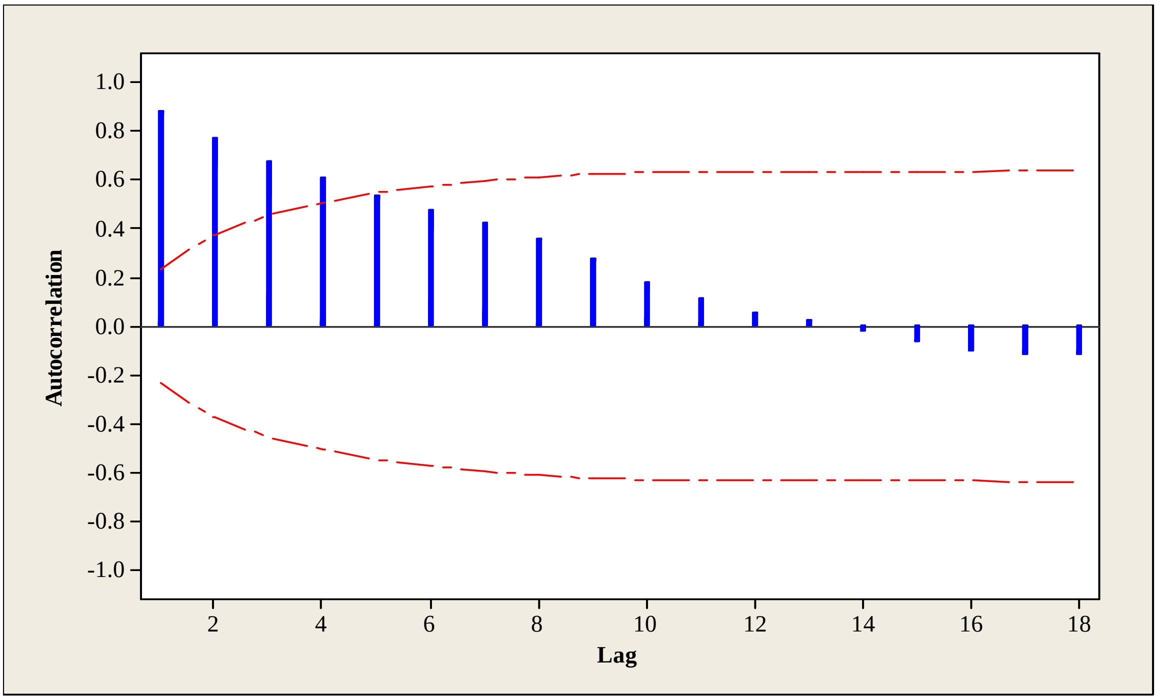


Figure 4 Partial Autocorrelation Function of the Un-differenced Actual Consumption Series

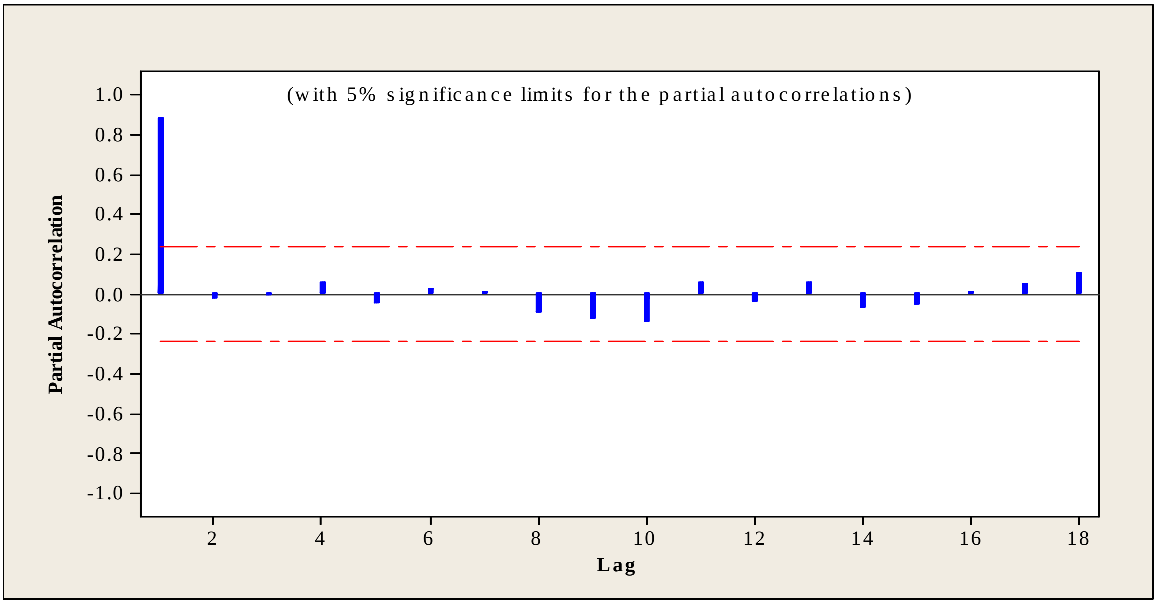


Figure 5 Autocorrelation Function for Actual Consumption Differenced Once

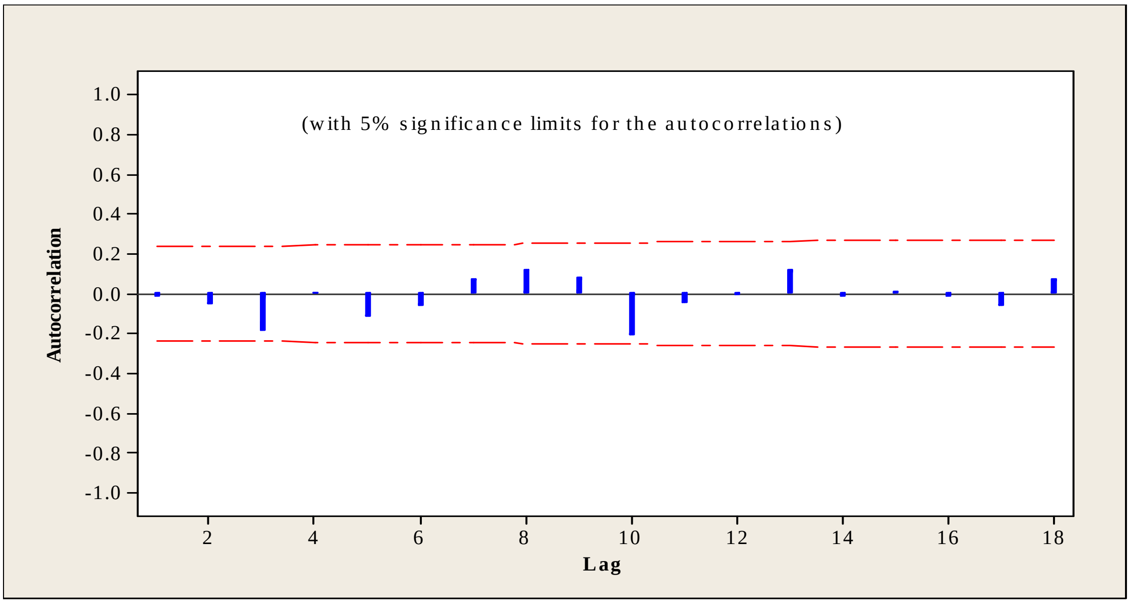
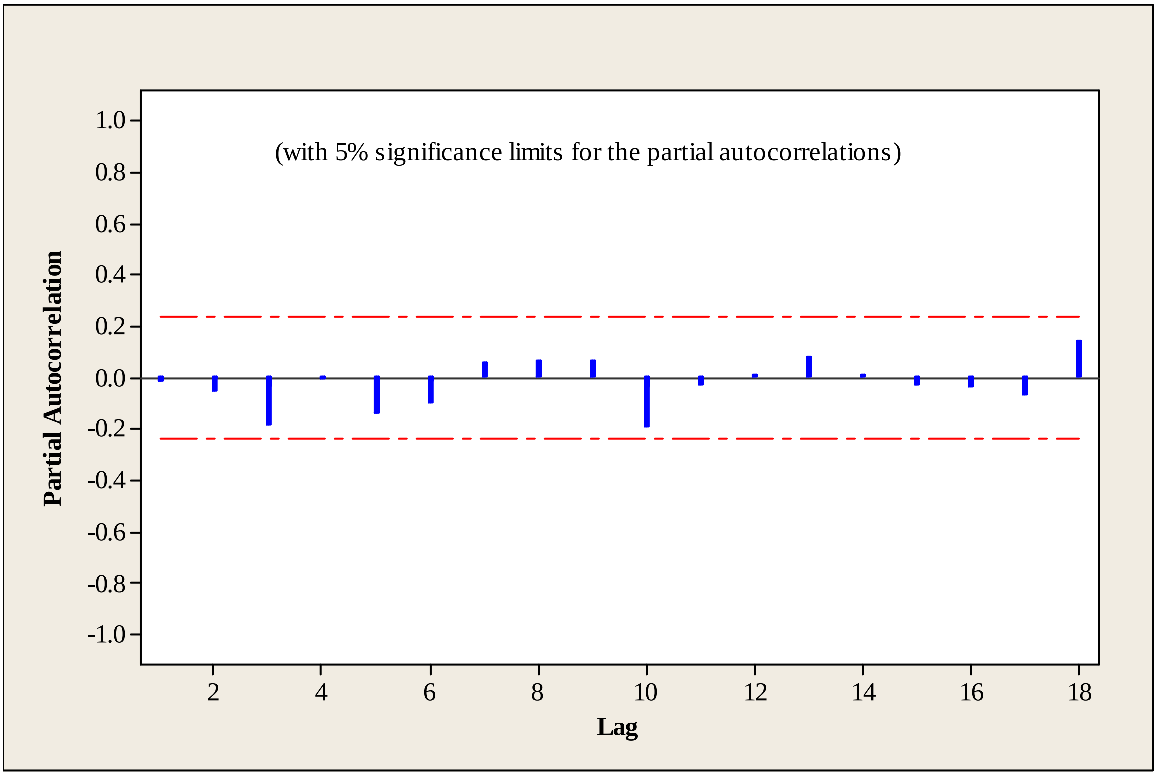


Figure 2 Partial Autocorrelation Function for the Actual Consumption Differenced Once



Comparing the autocorrelations as illustrated in Figure 5 above with their error limits, the only significant autocorrelation was at lag 2. Similarly, only lag 2 partial autocorrelation as shown on Figure 6 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 were fitted to the actual consumption data. A constant term was 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:

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

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

Tables 1 to 6 and Figures 7 and 8 illustrate the outputs for both models. Based on these observations both models fit the data equally well. The residual Mean Squares (MS) were:

ARIMA (2, 1, 0): $s^2 = 82.08$

ARIMA (0, 1, 2): $s^2 = 81.99$

Also, it is important to note that for both models none of the parameters were significant given the high p-values. Figures 7 and 8 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 were not significant, as indicated by the large p-values for each model. Moreover, the one step ahead forecasts provided by the two models were nearly the same.

Table 1 Final Estimate of Parameters

Type	Coefficient	Standard Error Coefficient	T-Value	P- Value
AR 1	-0.0095	0.123	-0.08	0.938
AR 2	-0.0529	0.123	-0.43	0.669
Constant	0.7730	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 2 Modified Box - Pierce (Ljung-Box) Chi Square Statistic

Lag	12	24	36	48
Chi-Square	9.800	16.700	25.200	33.900
Degrees of Freedom	9.000	21.000	33.000	45.000
P-Value	0.368	0.726	0.832	0.888

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Table 3 Forecasts from Period 72 (95 Percent Limits)

Period	Forecast	Lower	Upper	Actual
72	52.4220	34.6618	70.1823	
73	53.8374	28.8400	78.8348	
74	54.5666	24.5297	84.6035	

Figure 7 Residual Autocorrelations Auto Regressive Integrated Moving Average (2, 1, 0) Model Fit for Actual Consumption

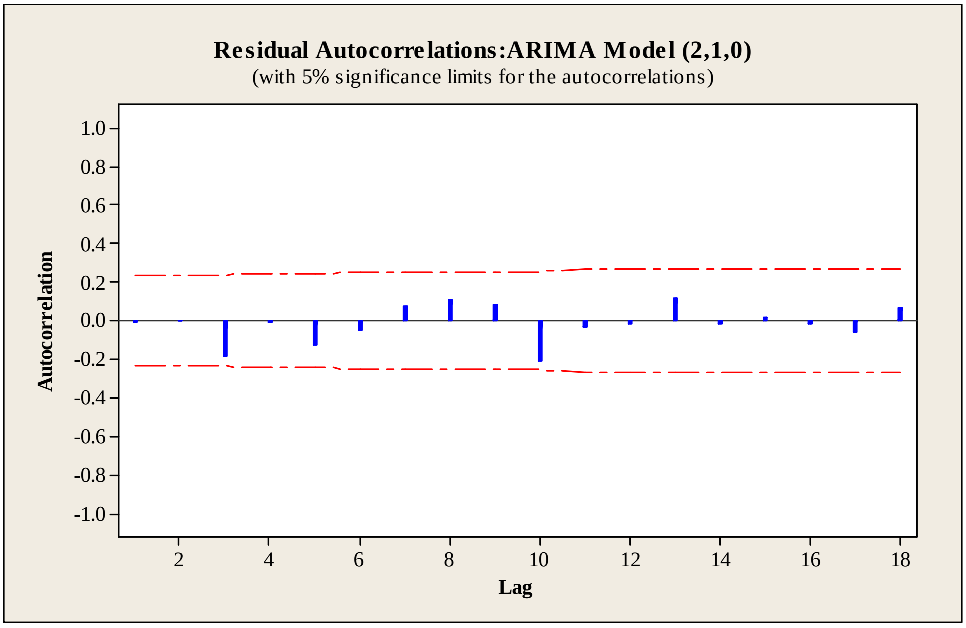


Table 4 Final Estimate of Parameters

Type	Coefficient	Standard Error Coefficient	T-Value	P-Value
MA 1	0.0375	0.1227	0.31	0.760
MA 2	0.0686	0.1229	0.56	0.579
Constant	0.7300	0.9610	0.76	0.450

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

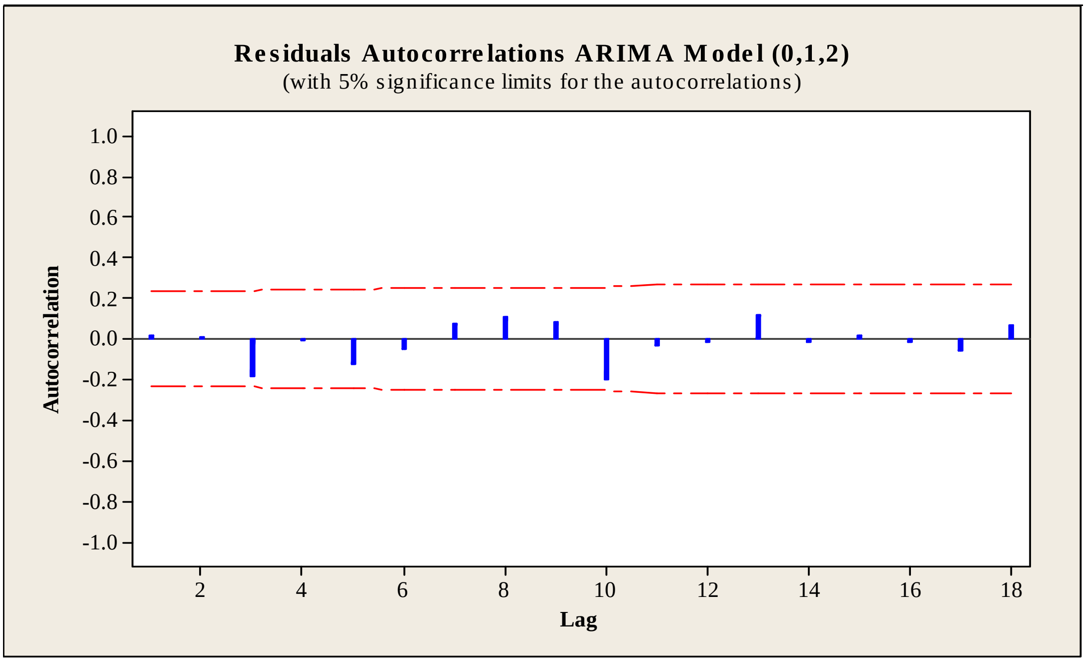
Table 5 Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Lag	12	24	36	48
Chi-Square	9.700	16.800	25.200	33.800
Degrees of Freedom	9.000	21.000	33.000	45.000
P-Value	0.374	0.725	0.833	0.889

Table 6 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 8 Residual Autocorrelations Auto Regressive Integrated Moving Average (0, 1, 2) Model Fit for Actual Consumption



The ARIMA model (0, 1, 2) was adopted on the basis of a slightly better fit. To check the forecast using this model for period 73 was 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 in Table 6; the prediction interval for the actual is 52.7 – 70.45.

Conclusion

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.

Based on the finding, 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. 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.

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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

Year	Month	Actual Total (Metric Tons)	Forecast Total (Metric Tons)
	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
	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