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MODELING STUDENTS' PERFORMANCE IN QUANTITATIVE METHODS USING TIME SERIES ANALYSIS. THE CASE OF HND STUDENTS PURSUING PLM IN BOLGATANGA POLYTECHNIC

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ABSTRACT

This study was conducted with the aim of determining whether Procurement students in Bolgatanga Polytechnic have acquired a strong understanding of the mathematical/statistical concepts and their applications as required in Quantitative methods, a first-year course, using their end of semester examination scores. Time series analysis was applied on a historic data of students' examinations' score for eight consecutive years, from 2010/2011 academic year to 2017/2018 academic year.

The study revealed, from the preliminary analysis, that marks obtained by students in quantitative methods are skewed to the right, indicating that most students scored below the average mark of approximately 61.5%. This together with the high variability amongst the scores obtained indicate that students' performance in quantitative methods for the eight-year period was weak. The plots from the trends also showed vigorous fluctuations in the marks suggesting that students do not have firmer grips on the mathematical/statistical concepts and their applications, hence, the unstable nature in their scores over the period. The study further revealed, from the five years forecast into the future, that there would be very little increase in students' scores in the subject unless lectures handling this course and the students they teach modify their methods of lesson delivery and learning habits.

Keywords:Time Series Analysis, Linear trend model, Quadratic trend model, Autocorrelation Function, Partial Autocorrelation Function, Stationarity, Parameter Estimation, Parsimonious model and Differencing

1.0 Introduction

There is a continuous demand for statistical applications in a wide range of industries and businesses, as well as in local and central government and their associated services. One reason for this demand is the need for greater and deeper understanding of statistical and management science methodologies in today's businesses; with technology providing ever increasing amounts of data to be processed and interpreted. (Paul van kessel et al, 2014)

This module, Quantitative Methods for Procurement and Logistics Management students, aims at creating the awareness of the usefulness and applicability of basic descriptive statistics in daily live as students, office workers, small scale businessmen etc. It is also meant to equip Procurement and Logistics Management Students with some fundamental concepts in statistics, the elementary tools and applications of statistical techniques which are heavily used in business, marketing and other financial services. Kvanli et al. (2003). However, one most important question that needs answers is 'Do these students really gain a deeper understanding of these statistical concepts and their applications at the end of the course'?

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To answer this question, the study looked at the performance of Senior High School leavers at the West African Senior School Certificate Examinations (WASSCE) for the past three years and also collected marks obtained by students at the end of semester examinations for eight consecutive years and applied Time Series Analysis Techniques to analyze the data.

Many writers have opined that quantitative methods as a course is one of the most feared courses by many students who are required to take these courses at various stages during their studies at diploma and undergraduate programmes.

According to Richter (2007), grades obtained by students from the High Schools appeared to have impacted either positively or negatively on the academic performance of students enrolled in Business Administration program at a German university. Yousef D. A. (1993) on his part stated that majority of students in many parts of the world consider quantitative methods as the most difficult course among the business programs. He explained that students' grades and the course they offered at the High School level have significant impacts on their performance in quantitative courses at the undergraduate level. Mukherjee (2000) shared the same view as Yousef. He believed that the quantitative methods courses are seen as the challenging by most or all students in business colleges, whereas Brookshire and Palocsay (2005) argued that Introductory Management Science course is rather viewed as one of the most difficult courses in the business curriculum. However, Zimmer and Fuller believed that anxiety, attitude and computer experience are factors that affect undergraduates' performance in statistics.

Prospective students wishing to enter into any tertiary institution in Ghana to do a diploma or degree programmes are required to obtained at least a grade C6 pass in three core subjects including Core English Language and Core Mathematics as well as at least a grade C6 in any three of their elective subjects. However, majority of prospective students are unable to meet these entry requirements each year as a result of poor/weak performance in mathematics, especially in core mathematics at the West African Senior School Certificate Examinations (WASSCE). For instance, CitiFmonline.com carried analysis of students' performance in core mathematics at WASSCE 2016 as released by Rev. Nii Nmai Ollennu, Head of Ghana National Office of WAEC that out of a total of 274,262 candidates who sat for the examination that year, results of 234,871 candidates were released. Of this number, 77108 candidates representing 32.83% obtained grades A1 – C6. Also, 65,007 (27.68%) obtained grades D7 – E8 whilst 42,519 (18.09%) obtained grade F9. In effect, 107,526 (45.77%) of the candidates could not meet the university entry requirement in 2016. (CitiFmonline.com, 9th August 2016)

The WASSCE results for 2017 also indicated that 106,024 (37%) of candidates obtained grades D7 – E8 that year whilst 58,070 (20.27%) obtained F9. Thus, a total of 164,094 (57.27%) could not meet the university entry requirements. (Agnes, T.C, July 2017).

The 2018 WASSCE results indicated even worse performance by candidates in core mathematics as a total of 193882 (61.67%) could not meet the entry requirements. Indeed, 99,275 (31.58%) failed outright in core mathematics. (Isaac Yeboah, 2018).

The polytechnic's main source of students is the Senior High School graduates and this presupposes that most students admitted into the polytechnic may have weak background in mathematics.

2.0 Data and Source

The data is an existing examination record of HND students pursuing ***Procurement and Logistics Management*** programme in Bolgatanga Polytechnic. It represents marks obtained by the students in

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Quantitative Methods examination at the end of each of the two semesters at level 100. This course, Quantitative Methods, is a requirement for every student offering Business programme but vary slightly in content and extent of detail or difficulty from one Business programme to the other. Even though the number of students' enrolment into this programme vary from year to year, a total of 1165 data points was collected from the Examinations Unit of the Polytechnic for this study. There are three levels of assessments for students in this course: Class Assessment (20%), Mid Semester Examinations (20%) and End of Semester Examinations (60%). With the exception of the class assessment, the rest of the two level of assessments are controlled and this study make use of the sum of these three assessment levels.

3.2.0 Statistical Technique

Time series is an ordered sequence of values of a variable at equally spaced time interval and can also be described as a collection of observation made sequentially in time. Each of these sets of observations (Y_t) are recorded at a specific time (t). Time series occur in a variety of field ranging from Agriculture to Engineering. Many sets of data appear as time series, and these may include such series as; hourly observations made on the yield of chemical processes, a monthly sequence of goods sold in a supermarket and so on. Since the students' examinations' marks are recorded in this form Time Series Analysis is the most appropriate method for this study. This technique provided the study with summary statistics and simple descriptive measures of the main properties of the series such as the seasonal effects, trends, and test statistics. The normality test, for instance, was used to investigate the extent to which the data approximate a normal distribution by inspecting the coefficient of the skewness and kurtosis.
Skewness is the degree to which a data set departs from being symmetrical and was evaluated via the skewness statistic. As data becomes more symmetrical, its skewness value approaches zero. If the marks obtained by students is positively skewed or skewed right then the skewness has a value greater than 0 (the tail of such distribution points to the right) and indicates that majority of students obtained a score below the mean mark. The reverse case applies negatively skewed data and indicates that most students scored above the mean mark of the distribution.

Kurtosis on the other hand measures the degree to which a data set is peaked. Normally distributed data establishes the baseline for kurtosis not too flat or sharply peaked with a statistic of 0. A distribution with a sharper than normal peak will have a positive kurtosis value and is termed leptokurtic distribution, whereas, a platykurtic distribution has a flatter than normal peak and a negative kurtosis value.

3.1 Exploratory data analysis

The study conducted an exploratory data analysis on students' marks for the eight consecutive year period using mainly Minitab software and Gretl software, and the Box-Jenkins methodology of time series analysis was also applied. Some computations were made to first obtain the descriptive statistics in relation to the students' scores, followed by time series plots and a trend analysis.

3.2 Descriptive statistics of students' performance

Figure 3.2.1 below shows the grades obtained by students in quantitative methods for the eight-year period. The graph depicts an overall weak performance by students in the course. It can be seen that each year has a record of high number of students scoring from grade F to grade C. In particular, 2013 and 2014 recorded the worse grades.

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Figure 3.2.1: Plot of grades obtained by PLM students for eight consecutive years

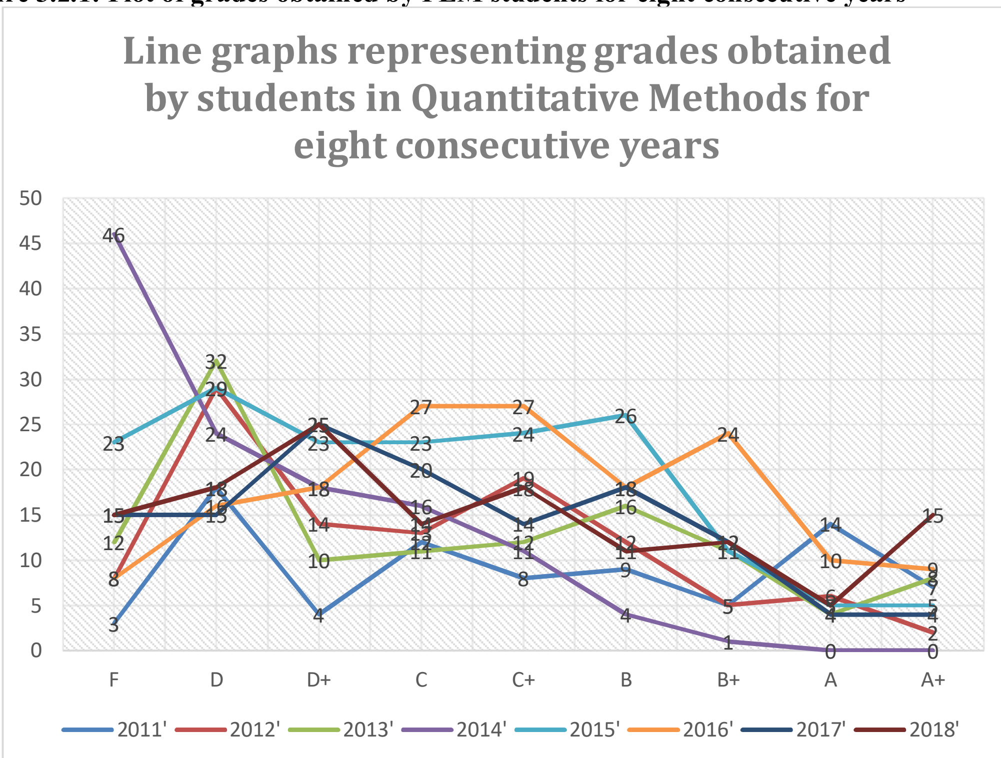

Table 3.2.a: Range of marks and the corresponding grades

85 - 100	A+		60 - 64	C
80 - 84	A		55 - 59	D+
75 - 79	B+		50 - 54	D
70 - 74	B		0 - 49	F
65 - 69	C+			

Table 3.2.b below represents the means and variances of marks obtained by students in the eight-year period. Comparing the means with their accompanying variances, it can be seen that students fared poorly in the course in 2013 and 2014 with respective means of approximately 60.5 and 52. The standard deviations for each year are above 10 marks but that of 2013 is approximately 15 marks. These are indications that marks scored by students were widely dispersed.

Table 3.2.c is ANOVA table and tests whether or not there are significant difference in the marks obtained by students in quantitative methods. It can be seen that the F-statistic = 15.12 with a p-value of 7.08493×10^{-19}, confirming that indeed there are significant differences in marks scored by students for the period under review.

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Table 3.2.b: Mean and variance of marks for each year

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
2011'	82	5478	66.80487805	194.208371
2012'	108	6543	60.58333333	124.1705607
2013'	117	7078	60.4957265	222.3728264
2014'	120	6273	52.275	104.3018908
2015'	169	10256	60.68639053	176.2522542
2016'	157	10404.89	66.27317197	119.8346706
2017'	127	7853	61.83464567	153.9168854
2018	134	8471	63.21641791	188.0204803

Table 3.2.c:

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	16826.26	7	2403.751439	15.1202836	7.08493E-19	2.018665
Within Groups	159929.1	1006	158.9752879			
Total	176755.4	1013				

Table 3.2.d below displays a summary statistic of students' performance in quantitative methods in Bolgatanga Polytechnic.

The minimum value in the data set was found to be 18 and maximum 95 whilst the arithmetic mean was 61.469 with accompanying standard deviation of 13.5234, indicating that the data is widely dispersed across the mean. The coefficient of variation of 21.5% also shows that the data has a very high variance. The students' mark distribution also exhibits positive skewness of 0.535 indicating that most of the marks scored are concentrated to the left of the mean and has a positive kurtosis value of 4.69 also indicating that the data is leptokurtic, thus, has a sharper than normal peak.

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Table 3.2 d: Descriptive Statistics of marks obtained in quantitative methods

Description	Statistic
Mean	61.46918
Standard Error	0.396206555
Standard Deviation	13.52336
Sample Variance	182.8812742
Kurtosis	4.693012441
Skewness	0.534638146
Minimum	18
Maximum	95
Sum	71711.6
Count	1165

3.3 Trend Analysis

Trend analysis fits a general trend model, thus, the linear, quadratic or exponential growth models to the time series data. This procedure is often used to fit trend when there is no seasonal component to the series. The trend most accurate to describe the series would be determined using the measures of accuracy, MAPE, MAD and MSD. The model with the minimum measure of accuracy is what best describes the series.

3.3.1 Trend Models

The trend models for the series would be build using the following preliminary data analysis:

- ***Linear Trend Model;*** is estimated using the Ordinary Least Square estimation with a general model of $y_t = \beta_0 + \beta_1 t + e_t$ $\quad (3.3\ a)$,

  where y_t is the projected value of the y variable for a selected value of t, β_o is the constant intercept; β_1 represents the average change from one period to the next.

- ***Quadratic Trend Model;*** which accounts for a simple curve is of the form

  $$y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + e_t \quad (3.3\ b)$$

- ***Exponential Growth Trend Model;*** accounts for exponential growth or decay. Mathematically,

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$$y_t = \beta_0 * \beta_1^t * e_t \qquad (3.3\ c)$$

3.3.2 Measures of Accuracy

Three measures of accuracy of the fitted model are computed, MAPE, MAD, and MSD for each of the simple forecasting and smoothing methods. For all three measures, the smaller the value, the better the fit of the model. These statistics are used to compare the fits of the different methods.

- *Mean Absolute Percentage Error (MAPE);* measures the accuracy of fitted time series values, specifically in trend estimation. It usually expresses accuracy as a percentage and is defined by,

  $$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left| \frac{At-Ft}{At}\right| \qquad (3.3\ d),$$

  where A_t is the actual value, F_t equals the fitted value, and n equals the number of observations.

- *Mean Absolute Deviation (MAD)*; expresses accuracy in the same units as the data, which helps conceptualize the amount of error. The mean deviation is a measure of how much the fitted value of the data is likely to differ from the actual value. The absolute value is used to avoid deviation with opposite sides cancelling each other out. Its mathematical form is,

  $$MAD = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t| \qquad (3.3\ e).$$

- *Mean Squared Deviation (MSD);* measures the square forecast error, error variance and also recognize that longest errors are disproportionately more expensive than small errors. It is expressed mathematically as,

  $$MSD = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t|^2 \qquad (3.3\ f).$$

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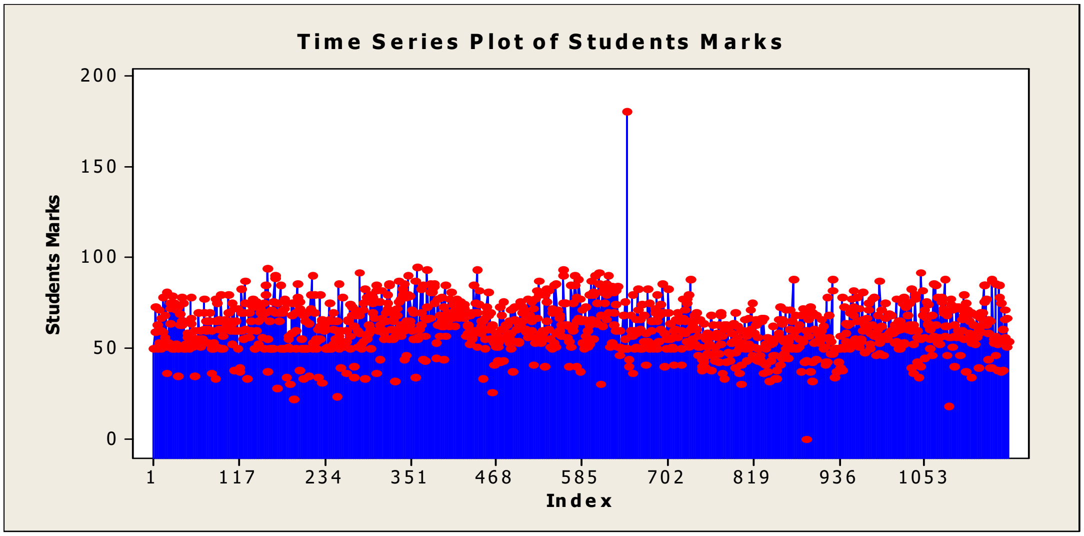
3.3.3 Time Series Plot

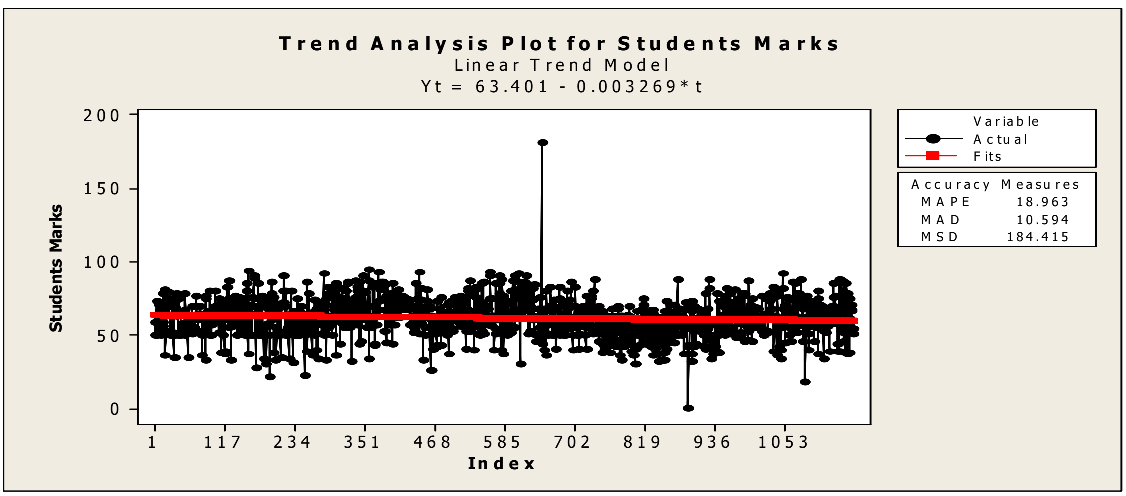
Figure 3.3.1: Time Series Plot for students' marks in quantitative method



The plot in Figure 3.3.1 shows the fluctuation pattern of students' marks with respect to time. It can be observed, generally, from the figure above that increasing trend in the plot is significantly sharp between 819 and 1053. Students' marks however, took a significant downward turn at 702, 468 and 819 respectively. The generally increasing pattern in the time graph shows a gradual change of the mean whilst the sharper fluctuations over time shows an unstable variance suggesting the series is not stationary.

The general trend models are now fitted in search of one that best describes the data

Figure 3.3.2: Linear Trend Plot for students' marks



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From the above plots the Linear Trend Models is derived as $Yt = 63.401 - 0.003269t$ whilst the derived Quadratic Trend Model below is $Yt = 61.80 + 0.00496t - 0.000007t^2$

Figures 3.3.2 above and 3.3.3 below show the linear and quadratic models respectively. In each of the figures, round dotted lines represent the actual values of students' marks whereas the square dotted lines represent the fitted values based on the various models

Figure 3.3.3: Quadratic Trend Plot for students

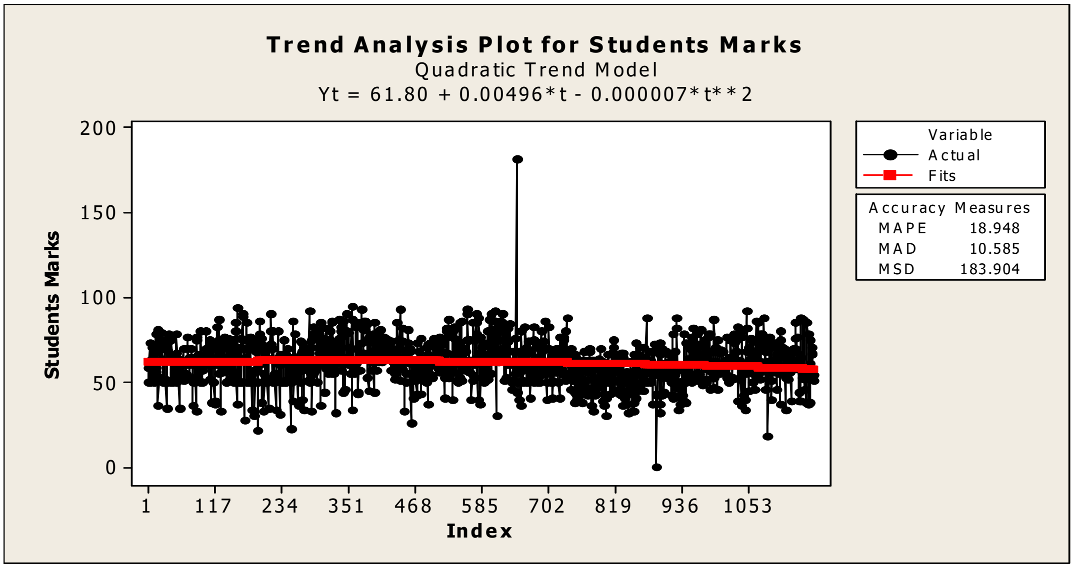

Table 3.3.3: Measures of Accuracy for Trend in marks

Model	MAPE	MAD	MSD
Linear	**18.963**	**10.594**	**184.415**
Quadratic	**18.948**	**10.585**	**183.904**

From **Table 3.3.32** the most appropriate model to describe the trend in students' performance in quantitative methods is the one with minimal errors. A closed observation of the errors produced by two models, the quadratic model has the minimum MAPE, MAD and thus, is considered to be the best model in describing the trend in students' performance in quantitative methods.

4.1 Further Analysis

Further analysis was conducted and checks made on the Autocorrelation Function (ACF) plots and those of the Partial Autocorrelation Function (PACF). It can be observed that with 95% confidence interval the data appears not stationary. The ACF is dying down slowly with significant spikes at lags 1 and 2 of the PACF as illustrated in Figures 4.1(a) and (b)

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Figure 4.1(a) Autocorrelation Function (ACF)

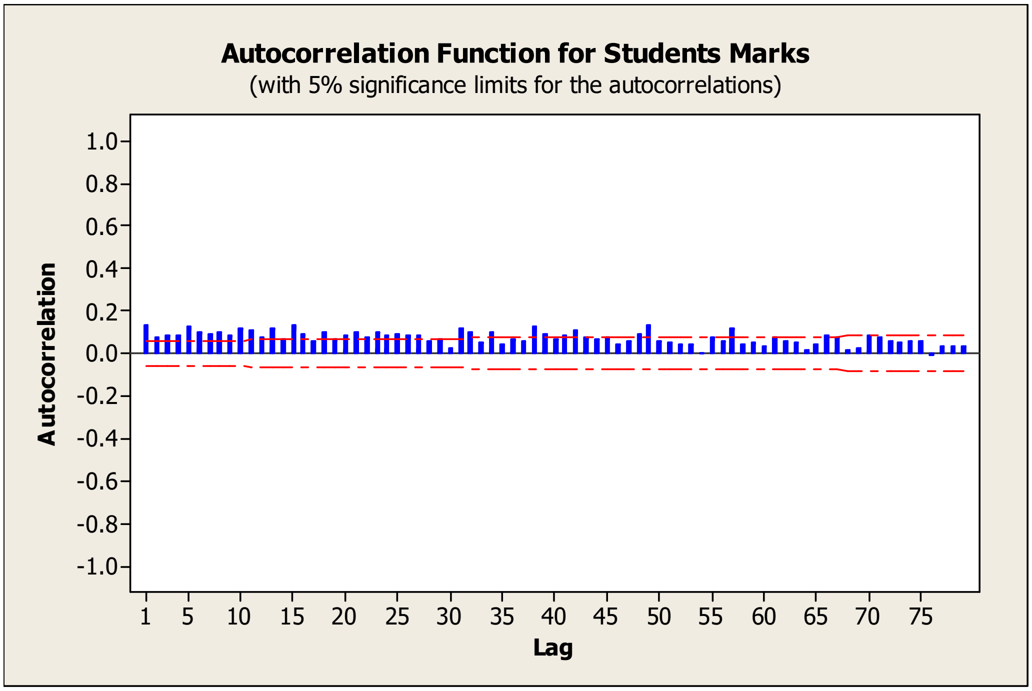
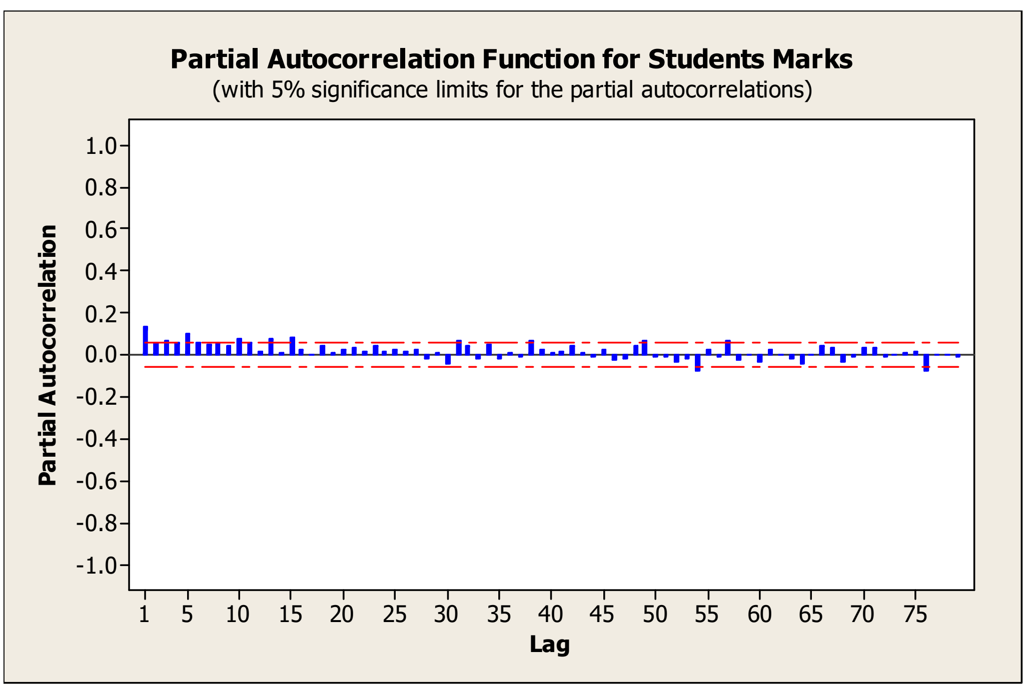


Figure 4.1(b): Partial Autocorrelation Function for students' marks



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4.2 Tests for Stationarity

A stationary process has a mean and variance that do not change over time and the process does not have trends. To proceed with the estimation of an ARIMA model, the series is required to be stationary, as such this study employed the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test for evidence of stationarity in students' marks in quantitative methods.

- **Augmented Dickey-Fuller Test**

For the ADF test, we test the hypothesis that;

H_0: the series is not stationary.

H_1: the series is stationary.

At 95% significance level, a p-value less than 0.05 means a rejection of H_0, meaning the series is stationary, otherwise the H_0 is upheld.

- **Kwiatkowski, Phillips, Schmidt and Shin Test**

The KPSS test has a reverse hypothesis to the ADF test hence;

H_0: the series is stationary.

H_1: the series is not stationary.

This means that at 95% significance level, a p-value less than 0.05 means we reject H_0 and say the series is not stationary, otherwise it is stationary.

Table 4.2: ADF and KPSS Test for Stationarity of Production

TEST	TEST STATISTIC	P-VALUE
ADF	3.33849	0.9998
KPSS	1.19383	0.470

From the KPSS test values on table 4.2 above**,** at 5% significance level, the conclusion is that the series is *not stationary* since the p-value (0.470) is greater than 0.05. However, the ADF test with a reverse null hypothesis indicates that the data is stationary with p-value 0.9998. In all, the data is concluded to be non-stationary based on the evidence of the time plot, correlogram and KPSS test, hence needed to be difference.

4.2.1 Achieving Stationarity

As a result of the *not stationary* nature of the data, there was the need for it to be differenced in order to obtain stationarity before building any model. Since the series has an exponential growth trend and

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increasing variance over time it was necessary to transform the data by taking the logarithm of the series and then difference it. A time plot of the transformed data is examined and tested for stationarity.

Figure 4.2: Time Series Plot of Differenced students' marks

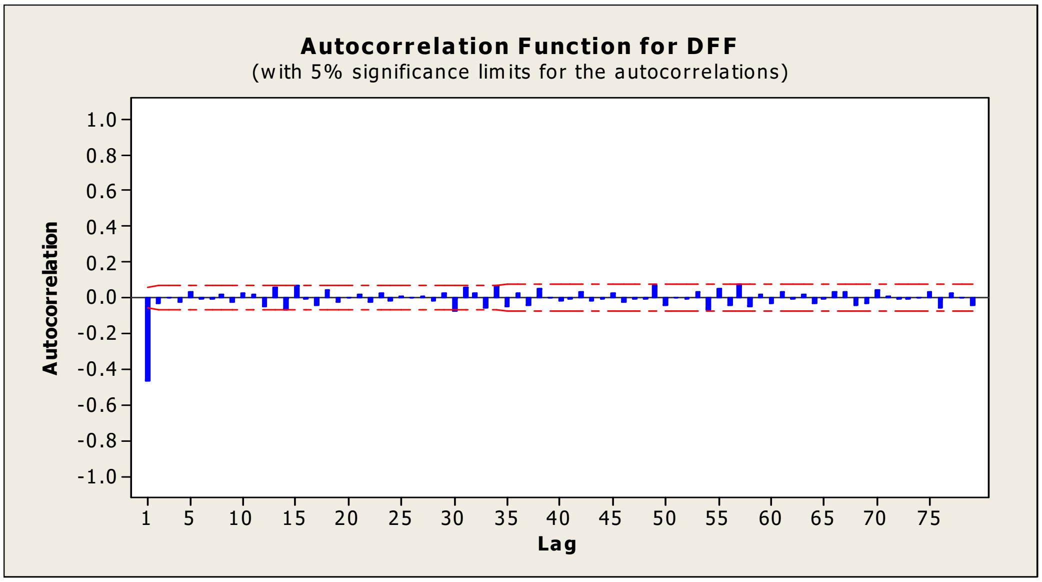

Figure 4.3: PACF of the Differenced students' performance

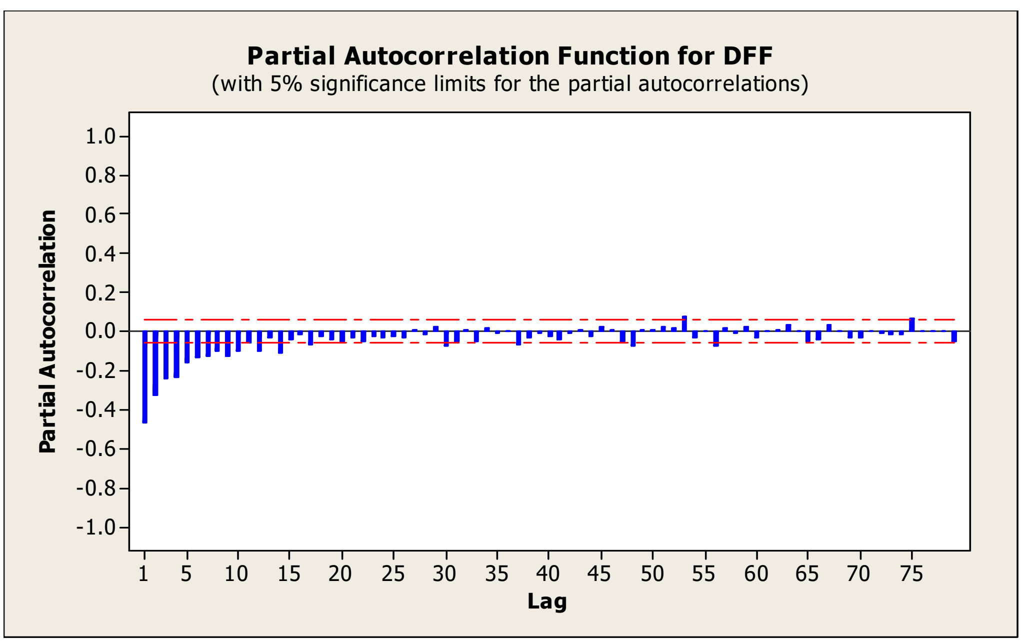

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Figure 4.3 shows the correlogram of the differenced students' marks data. It shows a rapid decay indicating stationarity. The stationarity of the differenced data however, must be confirmed by performing the ADF test and the KPSS test once again. The results in Table 4.3 below show that both tests confirm stationarity after first differencing

Table 4.3: ADF and KPSS Test for Stationarity of Differenced students' marks

TEST	TEST STATISTIC	P-VALUE
ADF	-7.33344	4.029e-11
KPSS	0.0496	0.470

4.3 The Box-Jenkins Method of Modelling Time Serie

The Box-Jenkins methodology (Box & Jenkins, 1976) is a step-wise statistical method used in analysing and building forecasting models which best represents a time series. This method of forecasting implements knowledge of autocorrelation analysis based on autoregressive integrated moving average models.
The methodology makes great use of historical time series data, is logically and statistically accurate and increase forecasting accuracy
The procedure is of four distinct stages namely; Identification, Estimation, Diagnostic checking, Forecasting.

4.3.1 Model Identification

Once stationarity of the series is achieved the important thing was to choose model which best describes the series. This was done by considering how many autoregressive (p) and moving average (q) parameters are necessary to yield an effective but still parsimonious model of the process (has the fewest parameters and greatest number of degrees of freedom among all models that fit the data). In practice, the numbers of the p or q parameters very rarely need to be greater than 2 and the primary tools for doing this are the ACF and the PACF. The sample autocorrelation plot and the sample partial autocorrelation plot are compared to the theoretical behaviour of these plots shown below.

Table 4.3.1: Theoretical Behaviour of the ACF and PACF for Model Identification

PROCESS	ACF	PACF
AR(p)	Tails off	Cut off after the order p of the process
MA(q)	Cut off after the order q of the process	Tails off
ARMA(p, q)	Tails off	Tails off

The general ARIMA model that best suits the series is the ***ARIMA (p, 1, q)***. Thus, it is important to identify which order of ***p*** and ***q*** best describes the series. The sinusoidal ACF in Figure 4.3 above, with a significant spike at lag 1 suggests ***MA (1)*** behaviour. Similarly, the significant spikes at lag 1

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of the differenced PACF suggest ***AR (1)***. Table 4.3.2 shows the suggested models with their respective AIC and log likelihood**.**

4.3.2 Model identification

Model	AIC	Log likelihood
Arima(1,1,1)	**9320.72**	**-4657.36**
Arima(2,1,1)	**9321.98**	**-4656.99**
Arima(3,1,1)	**9323.59**	**-4656.8**
Arima(4,1,1)	**9325.14**	**-4656.57**
Arima(5,1,1)	**9326.44**	**-4656.22**
Arima(6,1,1)	**9328.41**	**-4656.21**
Arima(7,1,1)	**9330.32**	**-4656.16**
Arima(8,1,1)	**9332.31**	**-4656.16**
Arima(9,1,1)	**9334.09**	**-4656.04**
Arima(10,1,1)	**9335.34**	**-4655.67**

The most appropriate model for the series is the one with the minimum Akaike Information Criteria (AIC) and log likelihood. Thus, by an inspection of all the competing models in table 4..3.2 the ARIMA (1, 1, 1) model has the minimum values and therefore the best model for forecasting.

4.3.3 Parameter Estimation

Table 4.6 below displays estimates of the parameters of the ARIMA (1, 1, 1) model. The parameters of both MA(1) and AR(1) are significant at 5% levels with coefficients and p-values of ***(-0.9624, 0.0262)*** and ***(0.0337, 0.00823)*** respectively. less than 0.05 indicates the significance of the parameters.

Table 4.3.3: Parameter Estimates for ARIMA (1, 1, 1)

Type	Coefficient	Standard error	Z value	P-value
AR 1	0.0337	0.0305	-1.737	0.00823
MA 1	-0.9624	0.0083	-2.223	0.0262

4.3.4 Model Diagnosis

To ensure that the selected model is the best model that suits the data the following diagnostics are performed.

4.3.4(i) Residuals Plots

The patterns of the residuals over time around the zero mean as seen in figure 4.8 below indicates that the residuals are random and independent of each other, thus, indicating that the model is fit.

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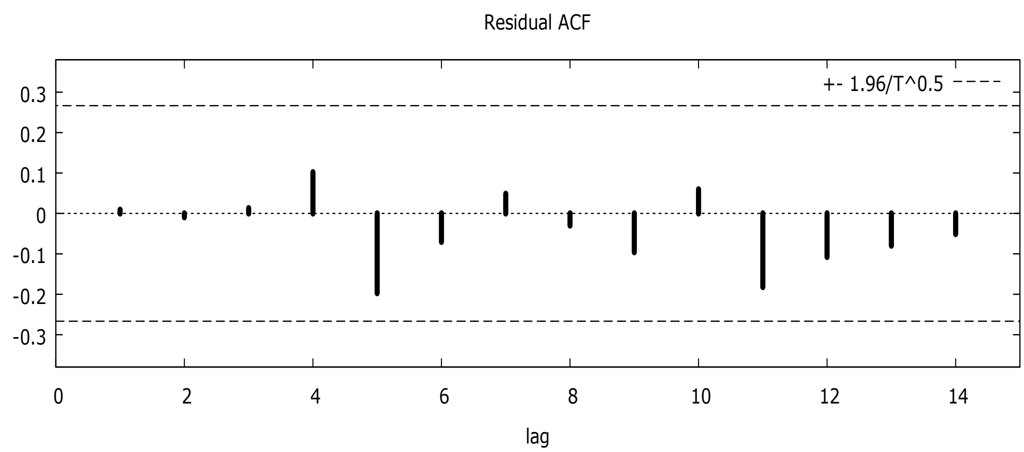
Figure 4.3.4: Plot of Residual ACF and PACF



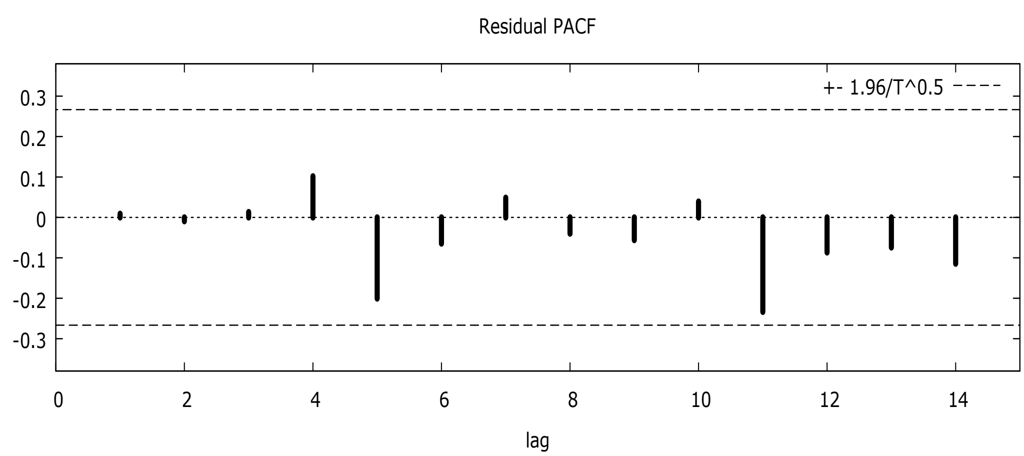


Figure 4.3.4 shows all autocorrelation spikes within the 95% confidence interval. This means that there is no correlation between residuals indicating that they are accurate and the model is adequate.

4.3.4(ii) The Normal Q-Q Plot

The Normal Q-Q Plot is another diagnostic check on the residuals to determine whether it follows the normal distribution. This is done by using the normal probability plot (Q–Q plot). It is a plot a plot based on estimates of the quantiles. The normal Q-Q plots is used to compare the distribution of a sample to a theoretical distribution. If most of the points are in line and closer to the normal line, then the model is a good fit.

The Q-Q plot in Figure 4.9 below shows all points along the normality line except for one outlier hence the model is deemed fit.

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Figure 4.3.5 a: The Normal Q-Q Plot

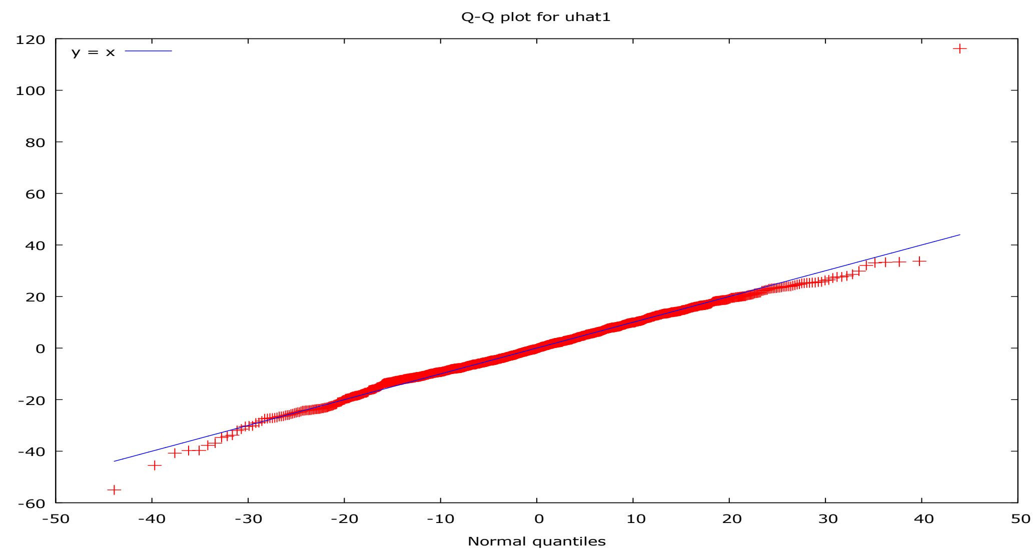
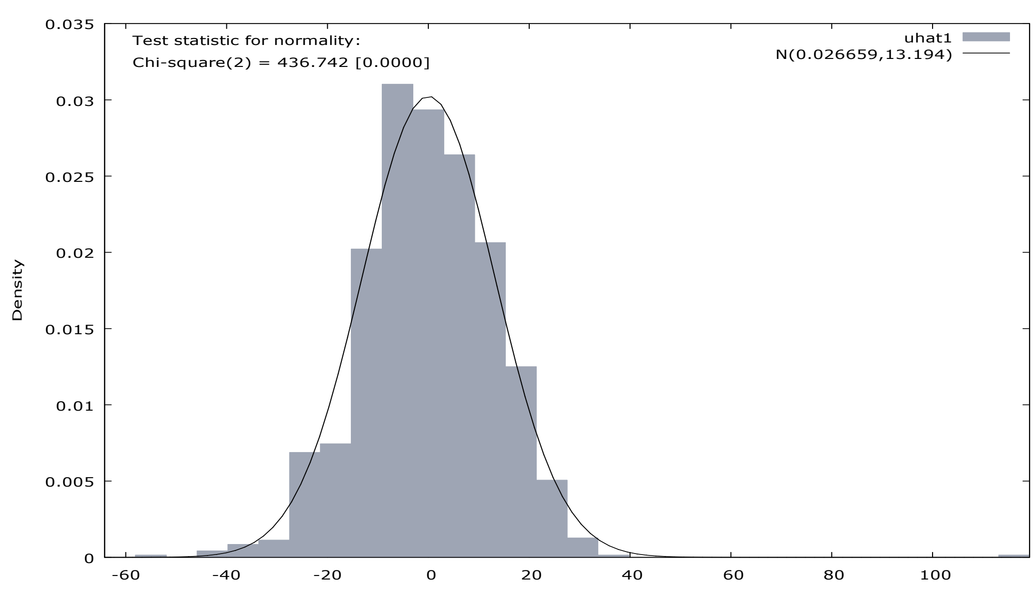


Figure 4.3.5.b: Normality graph



4.3.5 Ljung-Box Q Statistics

A check of the overall model adequacy is made using the Ljung-Box Q statistics. With a p-value of 0.560 which is way greater than 0.05 indicates that the model is generally adequate.

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Table 4.3.5: Ljung-Box Q Statistics

Model	Statistics	DF	Sig.
ARIMA (1, 1, 1)	14.526	16	0.560

4.3.6 Forecasting

Since the model checks out to be of good fit, we can now forecast for future values in this instance, the next 5 observations

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
1167	60.49650	43.60796	77.38505	34.66771	86.32530
1168	60.71566	43.78420	77.64712	34.82123	86.61010
1169	60.72305	43.77812	77.66799	34.80801	86.63810
1170	60.72330	43.76560	77.68101	34.78873	86.65787
1171	60.72331	43.75288	77.69375	34.76927	86.67736
1172	60.72331	43.74015	77.70647	34.74981	86.69681
1173	60.72331	43.72744	77.71918	34.73037	86.71626
1174	60.72331	43.71474	77.73189	34.71094	86.73568
1175	60.72331	43.70204	77.74458	34.69153	86.75510
1176	60.72331	43.68936	77.75727	34.67213	86.77450

Figures 4.3.6 represents the forecasted model. It can be seen from the forecasted graph that the growth or increase is very little over the five-year period.

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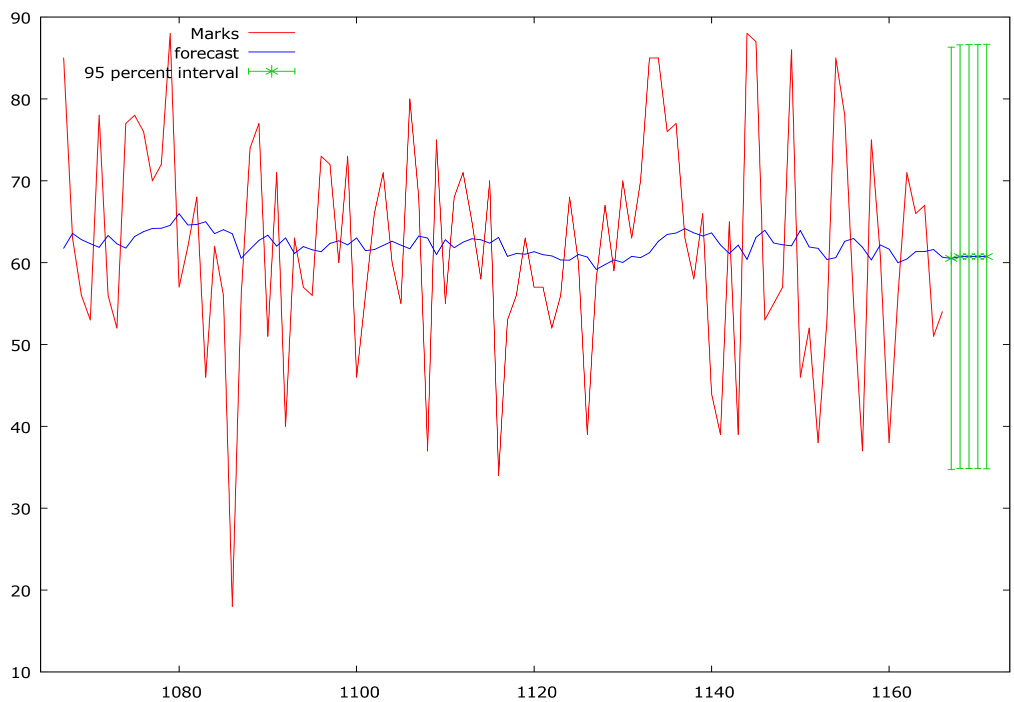
Figure 4.3.6: The graph for the five-year forecasted model of students' marks



4.4 4

4.4 Discussions of results/conclusion

From the descriptive statistics, in Table 3.2 it is observed that students' marks are skewed to the right, indicating that most of the values are concentrated at the left of the mean and this means that majority of the students scored below the average indicating weak performance. Again, since the peakness demonstrated a leptokurtic shape with a coefficient of kurtosis = 4.693 it shows that most of the scores are spread to the extreme sides of the curve also exhibiting weak performance and lack of concrete mathematical/ statistical concepts and their related applications

Figure 3.3.1 shows an upward and downward trend with high and low peak indicating an irregular or random trend with the series showing a generally increasing trend.

*Figure 3.3.2- Figure 3.3.***3** describe various trend models of the series and the best trend descriptor per the measures of accuracy in *Table 3.3.3* is the quadratic l model.

Secondly, even though the data was transformed by way of differencing to achieve stationarity and the tests of best fit also confirmed that the final model was adequate for the forecast, the five years predicted outcomes showed very little increase in students' scores over time. Thus, further demonstrating that improvement of students' performances in the Quantitative methods is likely stagnate in the future if the course lecturers do not introduce innovations in the methods of lessons delivery as well as students modifying their mode of learning.

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5.0 Recommendations/Suggestions

Based on the findings of this study, couples with the fact that many students gain admissions to pursue HND programme with weak grades from WASSCE in mathematics, the study commends/suggests the following:

- Lecturers should endeavour and ensure that students are given frequent exercises/assignments in the course and should diligently mark such exercises/assignments and provide feedback to students on same. This would afford students the opportunity to gain adequate understanding on the concepts and application of the course
.
- Students who are also found to be weak in the course should be encourage to take extra tuition outside the normal hours allocated for the course. This would allow them to acquire the requisite mathematical concepts and application.

- Module leaders or lecturers should provide students with adequate list of credible reading material and references on the course so that students can do further studies and research on their own.

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