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Choosing a Forecast Model for Prediction of Students' Enrolment in Multiple Programmes of the National Open University of Nigeria: Towards Course Materials Production Planning

Choix d'un modèle de prévision de l'inscription des étudiants à plusieurs programmes de l'Université nationale ouverte du Nigeria : La planification de la production des supports de cours

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Abstract

Budgeting for highly capital-intensive activities such as course material development, hiring of facilitators and conduct of examinations in Open and Distance Learning (ODL) institutions rely greatly on the number of students admitted yearly. The need for an effective forecast model for the prediction of students' enrolment in ODL institutions can therefore not be overlooked. In this study, we tested seven different exponential smoothing forecasting models on *sampled data of students' admission into the National Open University of Nigeria (NOUN) programmes for a period of 16 years, in view of finding a single forecast method that will be effective in forecasting future enrolment of students into all programmes of NOUN. The students' enrolment data were collected twice a year corresponding to admissions made in each semester of the year as practiced in NOUN, forming a time series with 32 observations for each programme. The stationary R^2, MAPE and MAE goodness-of-fit measures obtained from the methods were compared to obtain the best performing model. The Holt Winters Additive model performed better than others with a mean stationary R^2 of 0.583 and a very low mean standard error (SE) of 0.127 for the sampled programmes, hence it was chosen as the forecast model for prediction of future outcomes. The result of this work is useful in describing the pattern of students' enrolment in NOUN over the past years and for forecasting of student population in each programme offered in NOUN.*

Keywords: Students enrolment forecasting, Exponential smoothing model, SPSS, time series analysis, Open and Distance Learning.

Résumé

La budgétisation d'activités à forte intensité de capital telles que le développement de matériel de cours, l'embauche de facilitateurs et la conduite d'examens dans les établissements d'enseignement ouvert et à distance (EOD) dépend fortement du nombre d'étudiants admis chaque année. La nécessité d'un modèle de prévision efficace pour prédire le nombre d'étudiants dans les établissements d'enseignement ouvert et à distance ne peut donc pas être négligée. Dans cette étude, nous avons testé sept modèles différents de prévision par lissage exponentiel sur un échantillon de données relatives à l'admission des étudiants dans les programmes de l'Université nationale ouverte du Nigeria (NOUN) sur une période de 16 ans, afin de trouver une méthode de prévision unique qui soit efficace pour prévoir les inscriptions futures des étudiants dans tous les programmes de NOUN. Les données relatives aux inscriptions des étudiants ont été collectées deux fois par an, ce qui correspond aux admissions effectuées au cours de chaque semestre *de l'année, comme cela est pratiqué à NOUN, formant ainsi une série temporelle de 32 observations pour chaque programme. Les mesures stationnaires R2, MAPE et MAE de qualité d'ajustement obtenues à partir des méthodes ont été comparées pour obtenir le modèle le plus performant. Le modèle additif de Holt Winters a donné de meilleurs résultats que les autres, avec un R2 stationnaire moyen de 0,583 et une erreur type moyenne très faible de 0,127 pour les programmes échantillonnés, et il a donc été choisi comme modèle de prévision des résultats futurs. Le résultat de ce travail est utile pour décrire le modèle d'inscription des étudiants à NOUN au cours des dernières années et pour prévoir la population étudiante dans chaque programme offert à NOUN.*

Mots-clés : Prévision des inscriptions des étudiants, modèle de lissage exponentiel, SPSS, analyse des séries temporelles, enseignement ouvert et à distance.

Introduction

Forecasters have in time past provided answers to questions such as, how much rainfall is expected in a forecast year, how much an economy will grow over a period of time, what direction a stock markets will take, the rate of call arrival at call centers, etc., using different forecasting methods. There is also growing interest in the area of student enrolment forecasting because of its importance in school administration and management. Forecasting of students enrolment into a school is the first step towards successful income and expenditure planning. This is because there is direct relationship between student population and their demand for services and products such as Course Materials.

Hillier & Lieberman (2001) discussed two main types of forecasting methods; the Statistical forecasting methods which uses historical trends to predict future outcomes and the judgmental forecasting methods which on the other hand solely uses expert judgment where historical data is not readily available. Most statistical forecasting methods use time series which are historical data from a series of observations of some quantity of interest, over time. The Moving Average model and the Exponential Smoothing model of forecasting are the most commonly used statistical forecasting methods. There are however, many more sophisticated methods for forecasting the expected values of random variables, for example the Box-Jenkins and ARIMA models, but these methods are not popular for production applications, in which forecasts for many items are required (Murty, 2006). In this research work, we shall focus more on the exponential smoothing methods considering their usefulness in the nature of problem we wish to solve.

According to Murty (2006), the exponential smoothing method introduced and popularized by Brown R.G in 1959, is perhaps the most popular forecast method in practice. There are several variations of the exponential smoothing method. They can be categorized into non-seasonal and seasonal exponential models. The Statistical Package for Social Sciences version 25 (SPSS 25) provides tools for executing the simple, Holt's Linear trend, Brown's linear trend and Damped trend non-seasonal exponential models. It also provides simple, Holt Winters additive and Holt Winters multiplicative seasonal exponential models which were all tested in this work. The Holt Winters additive seasonal model which was chosen in this work is preferred when a time series has a linear trend with a relatively constant seasonal pattern (Hyndman & Athanasopoulos, 2018), such that the level, growth rate and the seasonal pattern may be slowly changing over time.

Selecting a suitable forecast model from the wide range of available methods is a major problem faced by many forecasters. According to Arsham (2015), using visual comparison of several forecasts models to assess their accuracy and choosing the best model is a widely used approach in model selection. In such approach, the original values of a time series variable and the predicted values from different forecasting methods are first plotted on the same graph, thus facilitating a visual comparison. Another method for choosing the best forecast model available in literature is the comparison of the goodness-of-fit measures obtained from different models. Such fit measures include Mean Absolute Error (MAE), Root Mean Square Error of Prediction (RMSEP), Root Mean Square Error (RMSE), Mean Absolute

Percentage Error (MAPE), Mean Absolute Scaled Error (MASE), Mean Squared Error (MSE), R-Squared values etc.

The National Open University of Nigeria offers wide range of programmes across its eight faculties with over Five Hundred Thousand students spread across over One Hundred Study Centres nationwide. Every Semester, there is need to distribute thousands of distinct printed Course materials to these students at their different locations to enable them study and prepare for examination. In recognition of the importance of Course Materials in Open and Distance Learning Institutions, most ODL institutions have special units where all their Course Materials are processed. In NOUN, the Course Material Development Unit (CMDU) amongst others is responsible for timely printing of the required number of Course Materials based on students' trend of admission (National Open University of Nigeria, 2023). To be able to produce and distribute adequate number of Course Materials within a budget year and to reduce the incidences of non-availability of some Course Materials at the Study Centres when demanded by students, there is need to employ effective Decision Support Systems with inbuilt forecast models that can effectively predict students' enrolment within such periods (Adoga et al., 2022a). This research outlines the procedures involved in choosing an effective forecast model which is the first and probably the most technical step in the series of activities leading to accurate forecast of students' enrolment into different programmes of NOUN.

Related Works

Lazar & Lazar (2015) applied different methods to forecast enrolment of the two categories of students admitted to University of Petroleum-Gas (UPG) of Ploiesti. They tested several trend functions using the relevant tools in Ms EXCEL program. The R-Squared values obtained from the test for each category of students were compared. A forecast was also made using extrapolation based on average change. The result of the work showed a decrease in the trend manifested in recent years, thus, a projected 25% decrease in the number of admitted students over the next five years was made. Chen (2015) developed an integrated enrolment forecast model aimed at studying the variables affecting student enrolment and to aid in accurate forecasts. The study first applied ARIMA methodology and then linear regression analysis and lastly three model selection criteria were used to determine the best ARIMA and linear regression models. The values of R- squared and MAPE were used in making judgment and choosing of the best model. Yang et al. (2020) proposed the whale optimization algorithm and support vector regression (WOASVR) algorithm combined with whale optimization algorithm (WOA) and support vector regression (SVR) for forecasting of student enrolment and teacher statistics. The research used the data of student and teacher population between 1991 and 2018 to test the performance of the proposed model. The forecast power of the WOASVR approach was compared with five other models: ARIMA, ETS, TBATS, GRIDSVR, and PSOSVR. The WOASVR model performed better than other tested models indicating that it is a better method for predicting student enrolment and teacher statistics. Chen et al. (2019) developed statistical models to predict international undergraduate student enrolment at a Midwest university. They developed a Seasonal Autoregressive Integrated Moving Average model with input variables to estimate future enrolment. One problem they encountered was insufficient records of international undergraduate enrolment to support a high quality time series model as common with higher institutions records. The enrolment data was therefore collected semester wise to bridge the gap and to reflect seasonality. They were of the view that instead of tracking back 40–50 years of enrolment data, introducing seasonality into the model will allow researchers to conduct a robust time series analysis by analyzing 15 to 20 years of the enrolment data instead of hunting for 40-50 years data to no avail. Lavilles & Arcilla (2012) in their paper added a forecasting module to the school management system to help in predicting the number of students expected to enroll in a subject. The simple moving average of order 3, Simple Exponential Smoothing and Double Exponential Smoothing statistical models were tested in the work using MAPE as the fit criteria. Results showed about 58% of subjects had least average MAPE when Double Exponential Smoothing is applied with varying alpha and beta, while Simple Exponential Smoothing was used for the remaining subjects with alpha having least MAPE.

Barman & Hasan (2017) analyzed the most appropriate time series forecasting methods on the short term and long term considering many available options like the Moving Averages method, Linear Regression with Time, Exponential Smoothing, Holt‘s Method, Holt-Winter‘s Method etc. MSE, MAPE, MAD were used in the paper as measures of accuracy on sampled data. Test results showed Holt Winters Multiplicative Forecasting Method gave less forecasting errors for the set of analyzed data, it was hence adopted as the most appropriate forecasting method in the research. Kuzmin et al. (2017) also made a case for the use of the Holt Winters model to forecast product mixes in the upmarket sector. The research compared RMSE and MAE values obtained from different forecast models and chose the model with the best values as the most effective model for forecasting product mixes in the upmarket sector. Tularam & Saeed (2016) explored the natures of statistical predictors by presenting time series analyses for oil prices data. To determine the best model, six model selection criteria were applied and the appropriate time series to which to apply the exponential smoothing (ES), Holt Winters (HW) and ARIMA models was chosen. The MSE, RMSE, MAE, MAPE and Theil's U-statistic were used as the model selection criteria. Results showed ARIMA forecast yielded the smallest values for the six selection criteria indicating that it is the best of the three methods. Odame et al. (2014) used Holt Winters Multiplicative model to forecast assisted childbirths at the Teaching Hospital in Ashanti, Ghana. The study applied Holt Winters methods to the dataset of number of quarterly assisted deliveries at Hospital (KATH) from 2000-2011. The Holt Winters multiplicative and additive forecasting models were applied on the data. The Multiplicative model reported lower values of RMSEP, RMSE, MAPE and MASE than the Additive model. The multiplicative model passed the Shapiro-Wilks test in addition and was hence chosen as the best forecast model for the research work.

Materials and Methods

Here we discuss the method of data collection, sampling strategy, method of data analysis and specification of the general procedures followed in carrying out this study.

Data Collection

The number of students that enrolled in various programmes of NOUN from 2004 – 2019 formed the primary data used in this research. The population for the study is all the programmes offered in NOUN since its resuscitation in 2002. There were a total of 94 programmes mounted collectively from 2004 – 2019. During the period, we observed that some programmes were discontinued shortly after they were mounted while some were newly introduced. The sample for the study therefore comprised 45 programmes that have been mounted for at least ten years. The samples were chosen in such a manner as to satisfy the rule of thumb that in time series analysis more observations or data points are always preferable but at the very least, a time series should be long enough to capture the phenomena of interest. The length of a time series can vary, but are generally at least 20 observations long and many models require at least 50 observations for accurate estimation (McCleary et al., 1980). Hyndman & Kostenko (2007) also estimated the minimum sample size requirement for Holt Winters seasonal forecasting methods to be m+5 observations, where m is the seasons per year. That is 9 observations for quarterly data, 17 for monthly and 7 for the biannual data used in this study. Our data was sourced from the Management Information Systems units of NOUN.

The data of students' enrolment were collected twice each year corresponding to admissions made each semester as practice in NOUN. The 16 years data (2004- 2019) therefore formed a time series with 32 observations for each programme.

Data Analysis

The resultant 45 time series data were analysed on the Statistical Package for Social Sciences version 25 (SPSS 25) using the following steps:

- The data was first transcribed in computer readable form for statistical analysis as shown partly in appendix 1.
- Seasonal Decomposition test was carried out on each of the time series. Results showed existence of seasonality and trend in all 45 time series data.

- Forecast of future outcomes of each time series data were done using the following seven Exponential Models: Simple non-Seasonal (SN), Holt's non-Seasonal (HN), Brown's Linear trend non-Seasonal (BLT), Damp Trend non-Seasonal (DT), Simple Seasonal (SS), Holt Winters Additive seasonal model (HWA) and Holt Winters Multiplicative (HWM seasonal model). This was done in order to choose the best model for forecasting of future outcomes. Figures 1-3 show the outputs of the Holt Winters Additive forecasting method carried out on the time series.
- The Stationary R^2, MAPE and MAE values obtained from each tested forecast model were recorded and used to measure the accuracy of the model. Tables 1 – 4 show the comparison of the fit criteria obtained from the different tested models.

The Holt Winters Additive Model

If $y_1, y_2, \ldots y_n$ denote a time series with m seasonal period then:

$$Y_t = L_t + S_t + \varepsilon_t \qquad (1)$$

$$\hat{Y}_{t+h}(t) = L_t + B_t h + S_{t+h-m} \qquad (2)$$

Where:

Y_t denotes the observations (actual data) and t is an index denoting a time period (t=1,2,…,n)

$\hat{Y}_{t+h}$ is the forecast at h periods ahead, h is the step ahead forecast (the period to be predicted).

$L_t = \alpha(Y_t - S_{t-m}) + (1-\alpha)(L_{t-1} + B_{t-1})$ = Estimate of the Level of the series (3)

$B_t = \beta(L_t - L_{t-1}) + (1-\beta)B_{t-1}$ = Estimate of the trend of the series (4)

$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-m}$ = Estimate of the Seasonal factor of the series (5)

ε_t is the forecast error.

α, β, and γ are constants that take a value between 0 and 1.

The Holt Winters additive model is formulated, initialized and solved using the above equations or using Software packages like SPSS, R, Microsoft Excel, Python programming etc.

Results and Discussion

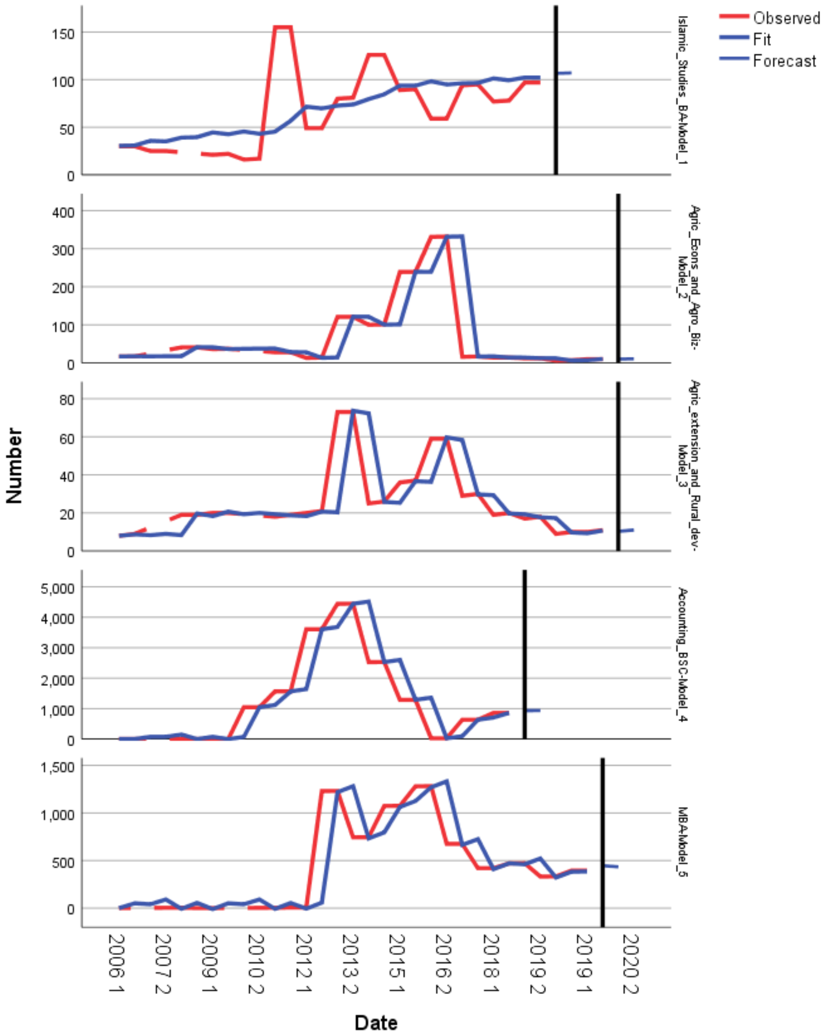

Figure 1: The output of the Holt Winters Additive forecast carried out on the time series data of 5 programmes across different faculties of NOUN.

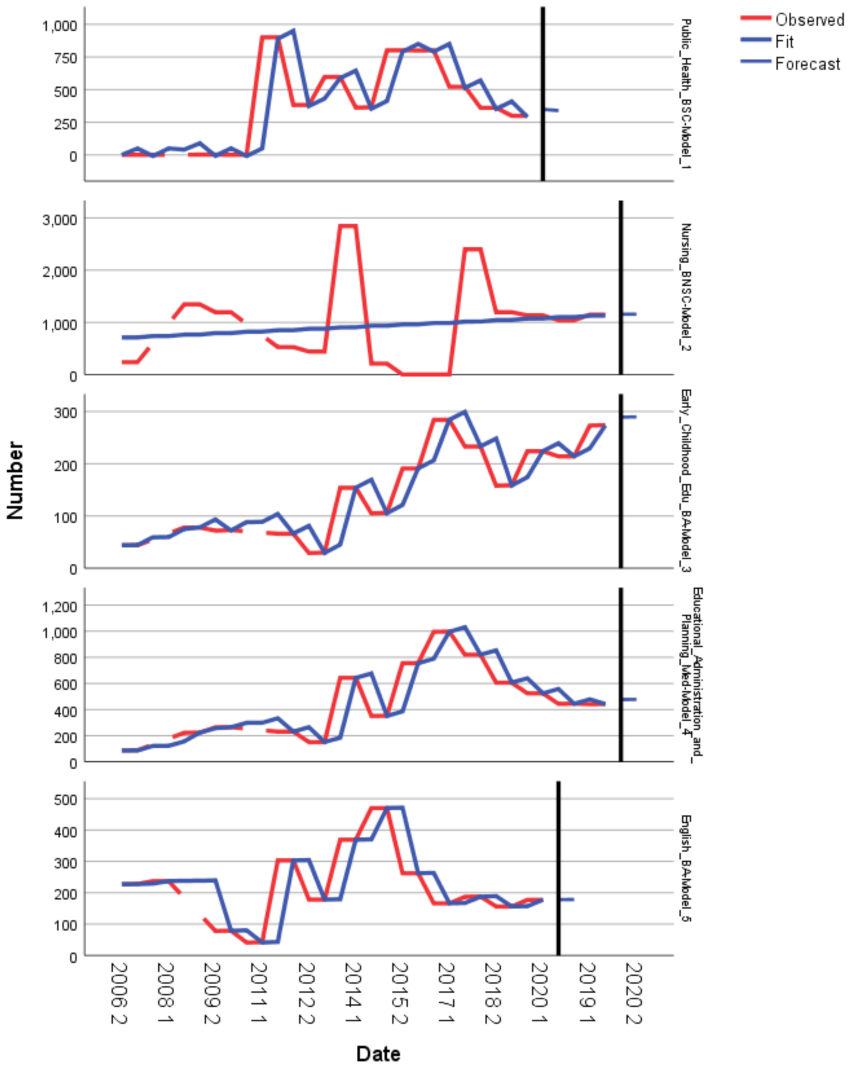

Figure 2: The output of the Holt Winters Additive forecast carried out on the time series data of another 5 programmes across different faculties of NOUN.

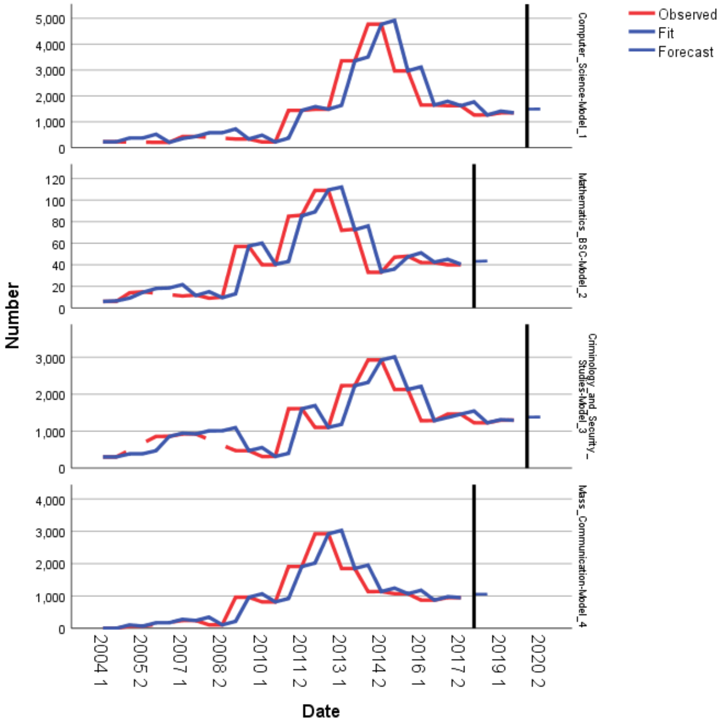

Figure 3: The output of the Holt Winters Additive forecast carried out on the time series data of another 4 programmes across different faculties of NOUN.

Figures 1-3 show the trends and patterns of some programmes time series data when the Holt Winters Additive model was used to forecast future values of the series. These trends and patterns were obtained for each of the seven forecast models applied on all the programmes. The trends and patterns obtained from the HWA model shows existence of seasonality in all the times series. Although a large number of the time series appear to be correlated as seen in their trends and patterns, it was extremely difficulty to completely study their individual properties and relationships using their patterns, considering the large number of time series data tested in this research. To reduce error in the best model selection process therefore, the numeric goodness-of-fit values obtained from the seven tested forecast models for each time series were compared and analyzed as shown in Table 1.

Table 1: Comparing the stationary R^2 values obtained from the 7 forecast models applied on each of the 45-time series data.

		stationary R^2 values								
SN	Time Series (Programmes)	Simple non-seasonal Model	Brown non-seasonal Model	Damp Trend	Holt non-seasonal Model	Simple Seasonal Model	Holt Winters Additive Model	Holt Winters Multiplicative Model	**Best value**	Best Method of Estimation
1	B.Sc. Public Health-Model_1	-0.003	0.419	0.003	0.5	0.656	0.658	0.67	0.67	Holt Winters Multiplicative Model
2	B.A (ed)Early Childhood Education-Model_2	-0.033	0.387	0	0.52	0.605	0.644	0.594	0.644	Holt Winters Additive Model
3	B.A (ed) French Education-Model_3	0.14	0.623	0.327	0.69	0.846	0.855	0.853	0.855	Holt Winters Additive Model
4	B.A (ed) Primary Education-Model_4	-0.003	0.366	-0.003	0.5	0.58	0.588	0.566	0.588	Holt Winters Additive Model
5	B.A (ed) English Education - Model_5	-0.003	0.383	-0.003	0.5	0.605	0.61	0.594	0.61	Holt Winters Additive Model
6	B.A English-Model_6	-0.003	0.328	-0.003	0.5	0.61	0.61	0.61	0.61	Simple Seasonal Model
7	B.A French International	0.045	0.542	0.046	0.52	0.698	0.698	0.685	0.698	Holt Winters Additive Model

	Studies - Model_7									
8	B.A Islamic Studies-Model_8	0.021	0.487	0.146	0.57	0.681	0.727	0.724	0.727	Holt Winters Additive Model
9	B.Agric Agricultural Economics and Agro-Business-Model_9	0	0.354	0	0.5	0.569	0.569	0.569	0.569	Simple Seasonal Model
10	B.Agric Agricultural Extension and Rural Development-Model_10	-2.20E-05	0.447	0	0.5	0.655	0.655	0.659	0.659	Holt Winters Multiplicative Model
11	B.Sc.(ED) Agricultural Science-Model_11	-3.72E-05	0.411	-3.09E-05	0.5	0.652	0.652	0.644	0.652	Simple Seasonal Model
12	B.Sc.(ED) Biology-Model_12	-0.015	0.386	-8.65E-05	0.51	0.553	0.571	0.49	0.571	Holt Winters Additive Model
13	B.Sc.(ED) Chemistry-Model_13	-0.003	0.386	-0.001	0.5	0.616	0.62	0.569	0.62	Holt Winters Additive Model
14	B.sc Integrated Science Edu-Model_14	0.001	0.468	-0.004	0.52	0.616	0.619	0.62	0.62	Holt Winters Multiplicative Model

15	B.sc(Ed) Mathematics Education-Model_15	-0.002	0.375	-0.002	0.5	0.581	0.584	0.566	0.584	Holt Winters Additive Model
16	B.Sc.(ED) Physics-Model_16	-0.002	0.381	-0.002	0.5	0.621	0.623	0.635	0.635	Holt Winters Multiplicative Model
17	B.sc Accounting-Model_17	-0.003	0.454	0.101	0.5	0.2	0.205	0.183	0.5	Holt non seasonal Model
18	B.Sc. Computer Science-Model_18	-0.005	0.413	0.026	0.5	0.371	0.378	0.273	0.5	Holt non seasonal Model
19	B.Sc. Cooperative Management-Model_19	0.018	0.505	0.051	0.53	0.697	0.702	0.704	0.704	Holt Winters Multiplicative Model
20	B.Sc. Criminology and Security Studies-Model_20	-0.006	0.353	-0.001	0.5	0.563	0.572	0.52	0.572	Holt Winters Additive Model

stationary R^2 values

SN	Time Series (Programmes)	Simple non-seasonal Model	Brown non-seasonal Model	Damp Trend	Holt non-seasonal Model	Simple Seasonal Model	Holt Winters Additive Model	Holt Winters Multiplicative Model	**Best value**	Best Method of Estimation
21	B.sc Entrepreneur Business Management-Model_21	-3.61E-05	0.393	0.008	0.5	0.444	0.442	0.458	0.499	Holt non seasonal Model
22	B.sc Environmental studies and resources Mgt-Model_22	-0.003	0.439	0.055	0.5	0.305	0.311	0.168	0.5	Holt non seasonal Model
23	B.Sc. Mass Communication-Model_23	-0.005	0.399	-0.001	0.5	0.449	0.458	0.45	0.5	Holt non seasonal Model
24	B.Sc. Mathematics-Model_24	-0.007	0.369	-0.007	0.5	0.536	0.542	0.502	0.542	Holt Winters Additive Model
25	B.Sc. Maths and Computer Science-Model_25	-0.001	0.394	-0.001	0.5	0.637	0.637	0.467	0.637	Holt Winters Additive Model
26	B.sc Peace Studies and Conflict Resolution-Model_26	-0.001	0.312	-0.002	0.5	0.616	0.622	0.591	0.622	Holt Winters Additive Model

27	B.sc Political Science-Model_27	-0.003	0.449	0.101	0.5	0.166	0.173	0.148	0.501	Holt non seasonal Model
28	B.Sc. Tourism Studies-Model_28	-0.004	0.359	-0.004	0.49	0.541	0.54	0.545	0.545	Holt Winters Additive Model
29	B.sc (Ed) Business Education-Model_29	-0.003	0.405	0.003	0.5	0.457	0.462	0.39	0.501	Holt non seasonal Model
30	B.NSc. Nursing -Model_30	0.097	0.548	0.119	0.58	0.714	0.711	0.711	0.714	Simple Seasonal Model
31	M.ED. Administration and Planning-Model_31	-0.004	0.391	-0.002	0.5	0.613	0.619	0.565	0.619	Holt Winters Additive Model
32	M.ED. Educational Technology-Model_32	-0.012	0.403	-0.001	0.51	0.638	0.651	0.604	0.651	Holt Winters Additive Model
33	M.ED. Science Education-Model_33	-0.019	0.401	-0.019	0.51	0.613	0.63	0.586	0.63	Holt Winters Additive Model
34	M.Sc. Mass Communication-Model_34	-0.003	0.427	-0.001	0.5	0.641	0.647	0.641	0.647	Holt Winters Additive Model
35	M.Sc. Information	-0.022	0.37	-0.022	0.51	0.566	0.585	0.544	0.585	Holt Winters Additive Model

	Technology-Model_35									
36	M.Sc. Peace Studies and Conflict Resolution-Model_36	-0.013	0.446	0.066	0.57	0.63	0.698	0.69	0.698	Holt Winters Additive Model
37	Masters in Public Administration-Model_37	-0.001	0.324	-0.001	0.5	0.568	0.569	0.6	0.6	Holt Winters Multiplicative Model
38	Masters in Business Administration-Model_38	-0.003	0.391	-0.003	0.5	0.613	0.615	0.62	0.62	Holt Winters Multiplicative Model
39	PGD. Agricultural Extension Management-Model_39	-0.002	0.384	-7.03E-06	0.51	0.611	0.614	0.605	0.614	Holt Winters Additive Model
40	PGD. Criminology and Security Studies-Model_40	-0.007	0.46	0.112	0.57	0.657	0.716	0.706	0.716	Holt Winters Additive Model
41	PGD. Education-Model_41	-0.072	0.48	0.024	0.55	0.603	0.667	0.63	0.667	Holt Winters Additive Model
42	PGD. Information	-0.023	0.379	-0.001	0.51	0.494	0.522	0.424	0.522	Holt Winters Additive Model

	Technology-Model_42									
43	PGD. Peace Studies and Conflict Resolution-Model_43	-0.013	0.363	0.006	0.52	0.498	0.51	0.373	0.515	Holt non seasonal Model
44	PGD. Business Administration-Model_44	-0.019	0.383	-0.019	0.56	0.536	0.55	0.535	0.555	Holt non seasonal Model
45	PGD. Public Administration-Model_45	-0.013	0.373	-0.006	0.5	0.569	0.583	0.568	0.583	Holt Winters Additive Model

Table 2: Models with best stationary R^2 Values

SN	Forecast model	No of cases	Percentage (%)
1	Holt Winters Additive model	25	55.55556
2	Holt Winters Multiplicative model	7	15.55556
3	Holt nonseasonal model	9	20
4	Simple Seasonal model	4	8.888889

Table 1 shows the stationary R^2 values obtained when the Simple non-Seasonal, Holt's non-Seasonal, Brown's Linear trend non-Seasonal, Damp Trend non-Seasonal, Simple Seasonal, Holt Winters Additive seasonal model and Holt Winters Multiplicative forecast models were tested on each of the programmes time series data. For each time series, the best forecast model was determined and recorded. This was done by comparing the stationary R^2 values obtained from each forecast model when applied on a single time series data and choosing the model with the highest positive stationary R^2 value. The stationary R^2 is a measure that compares the stationary part of the model to a simple mean model. A high positive stationary R^2 value implies that the model under consideration is better than the baseline model.

The overall performance of each forecast model was thereafter determined as shown in Table 2. Results showed that the Holt Winters Additive seasonal model produced the best stationary R^2 values in 55.6% of the sampled programmes, Holt Winters Multiplicative model produced the best stationary R^2 values in 15.6% of the sampled programmes, Holt nonseasonal model produced the best stationary R^2 values in 20% of the sampled programmes while Simple Seasonal model produced the best stationary R^2 values in 8.9% as shown in Table 2..

Table 3: comparing the MAPE values of the forecast models in cases where there were ties in stationary R^2 values

		Mean Absolute Percentage Error (MAPE)			
SN	Time Series (Programmes)	simple seasonal model	Holt Winters Additive	Holt Winters Multiplicative	Best method
1	B.A English	27.456	27.717	27.656	simple seasonal model
2	B.A French International Studies	95.308	93.696	125.326	Holt Winters Additive
3	B.Agric Agricultural Economics and Agro-Business	91.905	92.787	92.866	simple seasonal model
4	B.Sc.(ED) Agricultural Science	37.914	39.441	39.998	simple seasonal model
5	B.Sc. Maths and Computer Science	34.344	33.875	202.204	Holt Winters Additive
6	B.Sc. Tourism Studies	38.296	38.108	38.674	Holt Winters Additive

Table 3 shows six cases where two or more forecast models produce the same stationary R^2 values. Where two or more models produced same best stationary R^2 values, the Mean Absolute Percentage Error (MAPE) fit criteria was used to resolve the tie. The model with the lowest MAPE was chosen among the ties as shown in Table 3.

Table 4: Showing the MAE fit statistics of the four top models when applied on the 45-time series data

Forecast Model	Mean	SE	Min	Max	Percentile						
					5	10	25	50	75	90	95
HWA	105.745	152.755	2.934	672.073	4.282	6.413	14.514	45.639	136.996	351.552	546.132
HWM	119.226	171.341	2.984	789.485	4.295	7.059	16.824	58.142	146.122	405.257	568.22
HN	109.667	158.269	2.934	713.489	4.273	6.49	15.071	48.869	137.314	364.071	551.965
SS	106.057	155.36	2.954	677.746	4.259	6.356	14.456	44.842	143.263	343.166	563.767

Finally, the obtained Mean Absolute Error (MAE) values for the top four best performing models were recorded and compared as shown in Table 4 to validate our choice of the best model. The mean values of MAE shown in Table 4 are the average values of MAE when each of the four top models is used to forecast all the 45 sampled time series data. In addition to the MAE validation, a mean stationary R^2 of 0.583 and a very low standard error (SE) of 0.127 were obtained when Holt Winters additive model was tested on the entire 45 time series data. This shows a good performance of the Holt Winters Additive model on all the time series data. The Holt Winters additive model was therefore chosen as the best forecast model for forecasting students' enrolment into NOUN programmes.

Conclusion and Recommendations

Choosing an effective forecast method for multiple time series using traditional approach can be daunting and most times prone to errors if not carefully managed. The approach adopted in this research is simple and reliable while working with large number of correlated time series. Comparing numeric goodness-of-fit values for our 45 distinct time series data is no doubt easier and less prone to errors than using any other method to evaluate and compare such large number of time series data. The determination of Holt Winters Additive method as the best forecast model for future students' enrolment in NOUN implies that the enrolment pattern of NOUN displayed a relatively constant seasonality over time.

Accurate forecast of student population will have great implication on Course Material production and distribution planning, hiring of Facilitators, Examination booklets production planning and also help in income and expenditure projections in NOUN and other ODL institution with similar structure. Choosing an effective forecast model is the first and probably the most technical step in the series of activities leading to accurate forecast of students' enrolment into different programmes of NOUN. The results of this study will therefore be of great benefit to researchers, software developers and others non expert forecasters wishing to predict students' enrolment into NOUN programmes for several purposes. The chosen HWA forecast model in this research was applied in Adoga et al. (2022 a,b) to determine the demand of course materials needed in a succeeding year and to develop a decision support system for Course Materials production and inventory management in NOUN.

It is therefore the recommendation of this study that to ensure accurate and reliable forecast of students' enrolment into various programmes of NOUN in future, the Management of NOUN and relevant stakeholders should employ the Holt Winters additive technique as it produced better goodness-of-fit values and generally performed better than other tested time series models.

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Appendix 1: Transcribe time series data of 25 of the 45 programmes for a period of 2004 -2019

Year	Public_Health_BSC	Early_Childhood_Edu_BA	French_Edu_BA	Primary_Education	English_Education	English_BA	French_International_Studies	Islamic_Studies_BA	Agric_Econs_and_Agro_Biz	Agric_extension_and_Rural_dev	Agricultural_Science_EDU	Biology_EDU	Chemistry_EDU	Integrated_Science_Edu	Mathematics_Education	Physics_EDU	Accounting_BSC	Computer_Science	Cooperative_Management	Criminology_and_Security_Studies	Entrepreneur_Business_Mgt	Environmental_studies_and_res_Mgt	Mass_Communication	Mathematics_BSC	Maths_and_Computer_Science
01-Jun-04	0	44	6	106	101	0	0	0	17	8	15	7	3	3	19	3	0	226	442	302	3	67	0	0	0
01-Dec-04	0	44	6	107	102	0	1	0	17	9	16	7	3	3	19	4	0	226	443	303	4	67	0	0	1
01-Jun-05	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
01-Dec-05	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
01-Jun-06	0	78	4	126	92	227	15	30	41	19	35	34	13	21	30	5	0	205	284	858	428	198	1	6	74
01-Dec-06	1	78	5	126	93	228	16	30	41	19	35	34	13	22	31	6	0	206	285	859	428	198	1	6	74
01-Jun-07	1	72	2	169	83	237	11	25	36	20	47	44	15	9	34	8	2	431	486	925	790	197	68	14	120
01-Dec-07	1	73	2	169	84	237	11	25	37	20	47	44	15	10	35	9	3	431	487	925	790	197	68	15	120
01-Jun-08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
01-Dec-08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
01-Jun-09	2	66	1	155	53	78	12	21	28	18	28	28	11	6	19	8	2	334	363	471	628	197	242	11	75
01-Dec-09	2	66	2	156	53	79	12	22	28	19	28	29	11	6	19	8	3	335	364	471	628	198	242	12	76
01-Jun-10	1	29	0	34	24	41	8	16	13	20	9	15	5	7	13	4	1	220	194	314	344	117	108	9	39
01-Dec-10	1	30	1	34	25	42	9	17	14	21	9	15	5	7	13	5	1	221	194	315	344	118	109	10	40
01-Jun-11	900	154	13	282	295	303	114	155	121	73	92	145	42	29	72	29	1046	1440	552	1607	2337	674	962	57	261
01-Dec-11	901	154	14	283	295	303	114	155	121	73	92	146	43	29	72	29	1047	1441	552	1608	2337	674	962	57	262
01-Jun-12	383	105	4	192	184	178	15	49	100	25	35	110	31	17	47	13	1566	1486	217	1100	2546	660	817	40	147
01-Dec-12	383	106	5	192	185	178	15	49	101	26	36	110	31	18	48	14	1567	1487	218	1101	2546	660	817	40	147
01-Jun-13	597	191	8	375	341	369	41	80	239	36	88	214	45	24	97	42	3607	3357	463	2232	6013	1566	1912	85	277
01-Dec-13	597	191	8	375	341	369	42	81	239	37	89	214	45	25	97	43	3607	3358	464	2233	6013	1567	1912	86	278
01-Jun-14	363	284	9	597	432	470	49	126	331	59	119	285	63	27	123	46	4443	4771	581	2926	7665	2227	2923	109	289
01-Dec-14	364	284	9	597	433	470	49	126	332	59	120	285	63	28	123	46	4444	4771	581	2926	7666	2227	2923	109	290
01-Jun-15	801	233	14	454	304	262	49	89	16	29	106	195	34	19	72	34	2528	2968	334	2126	4103	1679	1849	72	164
01-Dec-15	801	233	15	455	304	262	50	90	17	30	106	196	35	19	73	35	2529	2968	335	2127	4104	1679	1850	73	165
01-Jun-16	800	158	3	258	192	166	41	59	14	19	66	148	25	13	51	16	1288	1648	150	1284	1174	985	1137	33	91
01-Dec-16	801	159	4	258	192	166	42	59	14	20	66	148	26	14	51	17	1288	1648	150	1285	1174	985	1138	33	92
01-Jun-17	522	224	8	262	194	187	16	94	12	17	67	153	33	0	52	20	26	1621	411	1461	2776	834	1071	47	92
01-Dec-17	522	224	8	263	194	188	17	95	12	18	67	153	33	0	52	21	27	1622	412	1461	2777	835	1072	48	93
01-Jun-18	361	214	5	212	141	156	17	77	6	9	18	138	26	15	36	18	636	1264	31	1226	1079	566	871	42	56
01-Dec-18	361	214	5	213	141	156	18	78	7	10	18	138	26	16	37	18	636	1265	32	1227	1080	566	872	42	56
01-Jun-19	300	273	8	240	168	177	12	97	10	10	18	144	24	13	38	14	861	1346	41	1296	469	599	950	40	70
01-Dec-19	300	274	9	240	168	177	12	97	10	11	19	145	24	14	39	14	862	1346	41	1297	469	600	950	40	70