https://dx.doi.org/10.4314/dujopas.v9i4a.16
ISSN (Print): 2476-8316
ISSN (Online): 2635-3490
Dutse Journal of Pure and Applied Sciences (DUJOPAS), *Vol. 9 No. 4a December 2023*

A Study Pack Model for Course Materials Demand Forecasting

Peter I. Adoga

ICT Directorate,
National Open University of Nigeria,
Otukpo Study Centre,
Benue State,
Nigeria.

Email: padoga@noun.edu.ng

Abstract

This study seeks to provide a framework for developing course materials demand forecast modules in distance learning institutions. The Holt Winters Additive (HWA) forecast model was applied in predicting students' enrolment into multiple programmes. Multiple time series of the number of previously admitted students in each programme were discussed. An Initialization process was carried out for all the time series to define the initial values of the HWA model. The smoothing constants α, β, and γ were trained using the Statistical Package for Social Sciences (SPSS) in order to determine the best values and the one-step-ahead forecast for each time series was thereafter done using updated values of the Level (L_t), Trend (B_t) and Seasonal factor (S_t). To determine the demand for course materials in a forecast year, a study pack algorithm was formulated and applied on an organized collection of courses offered by students of each programme. A prototype of the demand forecast module was developed and tested using python programming language. This module can be integrated with Information Systems developed for course materials production and inventory management.

Keywords: Course Materials, Demand Forecasting, Distance Learning, Holt Winters, Time series.

INTRODUCTION

In distance education, the learners get very little opportunity to interact with the teachers in the classroom situations. This loss is compensated by a special kind of self-learning course materials developed to stimulate independent learning. Printed course materials constitute the mainstay of teaching through the distance education system (IGNOU, 2005). Self-Learning Print Materials (SLPMs) perform the functions of an effective, efficient and inspiring teacher in the distance learning situation (IGNOU, 2018). In recognition of the importance of course materials in Open and Distance Learning (ODL) Institutions, most ODL institutions have special units where all their course materials are processed. In the National Open University of Nigeria (NOUN), the Course Material Development Unit amongst others is responsible for timely printing of the required number of course materials based on students' trend of admission (NOUN, 2023a). There are three basic kinds of Open and Distance Learning institutions: single, dual and mixed mode ODL institutions. Single mode ODL are primarily set up to offer programmes of study at a distance. The Dual mode offers two modes with one using traditional classroom-based methods and the other using distance methods. Lastly, the

**Author for Correspondence*

mixed mode offers learners a wide choice of modes of study such as independent, group-based, or some combination (Commonwealth of Learning & Asian Development Bank, 1999). These ODL institutions most times offer wide range of programmes with thousands of students spread across many study centres in different locations. Every semester, there is need to distribute several course materials to these students at their different locations to enable them carry out their studies. The determination of the quantities of each of the study material required to service students' demand is a major problem largely because of the openness of these institutions.

Manufacturing firms in most developing countries predict product demand using subjective and intuitive judgments. When the forecast is inaccurate it may lead to production inefficiency and may result in over or under stock problem. Studies show that an improvement of demand forecasts and a reduction of total production costs can be achieved when systematic demand forecasting and production planning methods are applied (Yenradee *et al*., 2001). This research applies the Holt Winters Additive (HWA) model which is an extension of the exponential smoothing model first proposed by Brown (1959). This model is of great importance to industries because it has been found to generate reliable forecasts quickly and with application to wide range of time series (Hyndman & Athanasopoulos, 2018).

The Holt Winters method has been applied by many authors in solving real life problems in different areas. These authors used different methods in choosing the best forecast methods to apply and also in initializing the level, trend and seasonality of the model. Bermudez *et al*. (2010) described a Bayesian forecasting approach based on Holt Winters model, which allows for accurate prediction intervals. The model is useful in inventory control or demand analysis. Taylor (2008) presented time series methods for predicting intraday arrivals for lead times from a half hour ahead to two weeks ahead. Seasonal autoregressive integrated moving average method, periodic autoregressive modeling, extension of Holt Winters exponential smoothing for the case of two seasonal cycles, robust exponential smoothing based on exponentially weighted least absolute deviations regression and dynamic harmonic regression methods were considered. The results showed that the exponential smoothing method for double seasonality performed better than other tested models. Manideep & Sekar (2018) discussed an improvement of the additive Holt Winters method where the initial values for the level, trend and seasonal components as well as three smoothing constants were treated as decision variables. Their method was geared towards improving the Holt winters method by reducing the mean square error (MSE) and at the same time working for dataset values which contains zeroes.

Szmit & Szmit (2012) applied extended versions of the traditional Holt Winters method for the development of predicted templates and intruder detection. Mean Absolute Error (MAE) was used as a measure of accuracy. Kalekar (2004) discussed the Multiplicative Seasonal Model and the Additive. The research used error measures such as Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE) for validating the model. Dimitrov *et al*. (2015) used Holt Winters method in forecasting the monthly volume of tourism receipts in Bulgaria. Based on the results, the forecast achieved with best fit model is that the trend of increase is preserved. Heydari *et al*. (2020) investigated the use of additive and multiplicative Holt Winters model to predict environmental variables such as temperature, precipitation, and sunshine hours. Best values of α, β and γ were chosen based on the performance of MAPE values. Ribeiro *et al*. (2019) used the Holt Winters additive and multiplicative time series to forecast Brazilian natural gas production. Results showed the multiplicative method had a better performance within the 95% confidence interval. Nurhamidah *et al*. (2020) applied Holt

Winters exponential smoothing additive model on the data of passengers departing Hasanudin Airport in 2009-2019 and the results showed the existence of trends and seasonality in the passenger's number. Trull *et al.* (2020) proposed a new initialization method based on the adaptation of the traditional methods developed for a single seasonality. The initialization method for the level, trend, and seasonality in multiple seasonal Holt Winters models with an additive and multiplicative trend were determined by the analysis.

The major gap in all the literatures reviewed which this research seeks to breach is the lack of standardized frameworks for course materials demand forecasting. This research work therefore proposes an effective early forecast system for course materials demand prediction. This will help Managements of ODL institutions to improve on their budgeting system as well as provide sufficient time to meet up production, storage and distribution of course materials.

MATERIALS AND METHODS

Study Area

The National Open University of Nigeria (NOUN) was selected amongst other Open and Distance Learning institutions based on accessibility of data needed for this research. It is headquartered in University Village, Plot 91, Cadastral Zone, Nnamdi Azikiwe Expressway, Jabi, Abuja, Nigeria. NOUN has eight (8) faculties, thirty six (36) departments, over one hundred (100) academic programmes, two thousand seven hundred (2700) courses, over one hundred (100) study centres and over 500,000 students making it the largest university in Nigeria in terms of student enrolment and the largest Open and Distance Learning institution in West Africa. The study centres serve as physical locations where students can access their course materials and other support services (NOUN, 2023b). NOUN runs two semesters a year and admits students every semester. The admitted students begin their studies with first semester courses irrespective of the time of the year they are admitted. This means that students admitted at entry levels 100L, 200L, 700L or 800L will always begin their studies with first semester courses of their respective levels. NOUN provides instruction to its students remotely through a variety of ways including the use of self-learning course materials. One of the challenges faced by NOUN is the need to ensure timely production and distribution of these course materials to students who are not physically present on campus to support their learning process. These challenges are largely caused by inefficient demand forecasting which in turn leads to poor production planning and inventory management.

Best Forecast Model Selection Process

Data of students admitted into each programme of NOUN from 2004- 2019 were collected from the Management Information System Unit and reorganized to suit the purpose of the research. This data was collected twice each year corresponding to admissions made each semester as practiced in NOUN. The time series data were analyzed on the Statistical Package for Social Sciences (SPSS 25) using the following steps:

- Seasonal Decomposition test was carried out on each of the time series. Results showed existence of seasonality and trend in all sampled time series.
- Forecast of future outcomes of each time series data were done using the following seven Exponential Smoothing Models: 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. This was done in order to choose the best model for forecasting of future outcomes.
- The Stationary R^2, MAPE and MAE values obtained from each tested forecast model were recorded and used to measure the accuracy of the models. The HWA model

performed better than other tested models and was chosen as the best forecast model for predicting students' enrolment into NOUN programmes. Adoga *et al*. (2023) discussed the forecast model selection process in detail.

Applying the Holt Winters Additive Model

Let our time series be denoted by $y_1, y_2, \ldots y_n$ with m seasonal period (m=2 for our biannual data), then:

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

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

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 while α, β, and γ are constants that take a value between 0 and 1. We are interested in the forecast of all the time series at same point i.e at point where t and h are the same for all the time series. Let the programmes be denoted by programme 1 (p_1) to programme z (p_z) with each of them having distinct time series data. We therefore have multiple time series for p_1-p_z. We formulate the Holt winters additive equations for each programme time series as shown in Table 1 in line with equations 1 and 2.

Table 1: The multiple time series of programmes and their equations.

Programmes	Time series	Holt Winters Additive	h-step-ahead forecast
p_1	$y(p_1)_1, y(p_1)_2, \ldots y(p_1)_n$	$Y(p_1)_t = L(p_1)_t + S(p_1)_t + \varepsilon(p_1)_t$	$\hat{Y}(p_1)_{t+h}(t) = L(p_1)_t + B(p_1)_t h + S(p_1)_{t+h-m}$
p_2	$y(p_2)_1, y(p_2)_2, \ldots y(p_2)_n$	$Y(p_2)_t = L(p_2)_t + S(p_2)_t + \varepsilon(p_2)_t$	$\hat{Y}(p_2)_{t+h}(t) = L(p_2)_t + B(p_2)_t h + S(p_2)_{t+h-m}$
.	.	.	.
.	.	.	.
p_z	$y(p_z)_1, y(p_z)_2, \ldots y(p_z)_n$	$Y(p_z)_t = L(p_z)_t + S(p_z)_t + \varepsilon(p_z)_t$	$\hat{Y}(p_z)_{t+h}(t) = L(p_z)_t + B(p_z)_t h + S(p_z)_{t+h-m}$

Initializing the Holt Winters Additive Method

We define the starting values of L_t, B_t and S_t for each time series p_1 to p_z

- The initial value of the level of the time series is given by:

$$l_0 = \frac{1}{m}(y_1 + y_2 + \cdots + y_n) \quad (6)$$

- The initial values for the trend of the time series is determined by:

$$b_0 = \frac{1}{n}\left[\frac{y_{m+1} - y_1}{m} + \frac{y_{m+2} - y_2}{m} + \cdots + \frac{y_{m+n} - y_n}{m}\right] \quad (7)$$

- Finally, the initial values for the HWA seasonal factor is determined by:

$$s_n = y_n - l_0 \quad (8)$$

Where: l_0 , b_0 and s_n are the initial values of the time series' level, trend and seasonal factor respectively. The initial values of level, trend and seasonal factor for the multiple time series are determined from equations 6 – 8 as shown in Table 2.

Table 2: The initialization equations for the level, trend and seasonal factor.

Time series	Level	Trend	Seasonal Factor
p_1	$l_0(p_1) = \frac{1}{m}(y(p_1)_1 + y(p_1)_2 + \cdots + y(p_1)_n)$	$b_0(p_1) = \frac{1}{n}[\frac{y_{(p_1)m+1} - y_{(p_1)1}}{m} + \frac{y_{(p_1)m+2} - y_{(p_1)2}}{m} + \cdots + \frac{y_{(p_1)m+n} - y_{(p_1)n}}{m}]$	$s_n(p_1) = y(p_1)_n - l_0(p_1)$
p_2	$l_0(p_2) = \frac{1}{m}(y(p_2)_1 + y(p_2)_2 + \cdots + y(p_2)_n)$	$b_0(p_2) = \frac{1}{n}[\frac{y_{(p_2)m+1} - y_{(p_2)1}}{m} + \frac{y_{(p_2)m+2} - y_{(p_2)2}}{m} + \cdots + \frac{y_{(p_2)m+n} - y_{(p_2)n}}{m}]$	$s_n(p_2) = y(p_2)_n - l_0(p_2)$
.	.	.	.
.	.	.	.
p_z	$l_0(pz) = \frac{1}{m}(y(p_z)_1 + y(p_z)_2 + \cdots + y(p_z)_n)$	$b_0(p_z) = \frac{1}{n}[\frac{y_{(p_z)m+1} - y_{(p_z)1}}{m} + \frac{y_{(p_z)m+2} - y_{(p_z)2}}{m} + \cdots + \frac{y_{(p_z)m+n} - y_{(p_z)n}}{m}]$	$s_n(p_z) = y(p_z)_n - l_0(p_z)$

Determination of the Best Values of α, β, and γ

SPSS was used to forecast future values of each time series using different combinations of α, β and γ. The Sums of Squared Errors from the different forecast trials were compared in view of finding the combinations of values that will produce the least errors. The SPSS GRID command was used to set the start, end, and increment values of α, β, and γ to 0.1, 0.6 and 0.1 respectively. The iteration produced α = 0.6, β = 0.1 and γ = 0.1 as the best values of the smoothing parameters. These values of α, β, and γ were therefore used to compute the h-step-ahead forecast for each time series using equation 2 and the initial values of L_t, B_t and S_t obtained from equations 6-8 respectively.

Table 3 Test Inputs of the Holt Winters Additive Module.

Date	Early_Childhood_Edu_Bed (p_1)	English_Education_Bed (p_2)	Criminology_and_Security_Studies_BSc (p_3)
01-Jun-04	44	101	302
01-Dec-04	44	101	303
01-Jun-05	59	112	387
01-Dec-05	60	113	388
01-Jun-06	75	123	472
01-Dec-06	78	92	858
01-Jun-07	93	103	943
01-Dec-07	72	83	926
01-Jun-08	88	94	1009
01-Dec-08	89	95	1010
01-Jun-09	104	105	1094
01-Dec-09	66	53	472
01-Jun-10	81	63	555
01-Dec-10	29	24	315
01-Jun-11	45	35	399
01-Dec-11	154	295	1607
01-Jun-12	169	305	1692
01-Dec-12	105	185	1101
01-Jun-13	121	195	1185
01-Dec-13	191	341	2232
01-Jun-14	206	351	2317
01-Dec-14	284	432	2926
01-Jun-15	299	443	3010
01-Dec-15	233	305	2128
01-Jun-16	248	314	2211
01-Dec-16	158	193	1286
01-Jun-17	174	202	1369
01-Dec-17	224	194	1462
01-Jun-18	239	204	1545
01-Dec-18	214	141	1227
01-Jun-19	229	151	1311
01-Dec-19	273	168	1297

The HWA forecast model was tested using data of students' enrolment into three programmes (p_1, p_2 and p_3) as a prototype of other programmes in NOUN. Table 3 shows the time series data of students' enrolment into p_1, p_2 and p_3 collected twice a year from 2004-2019 which was used as input of the system. The data is used by the HWA module to forecast enrolment into the programmes in the first half of 2020. The data was split into two parts for training and testing purpose. Forecast done using the training data was compared with the test data and the Mean Squared Error (MSE) and Root Mean Square Error (RMSE) were determined for each forecast.

The Study Pack Algorithm

Study pack refers to the list of courses offered by students of each programme and level in a distance learning institution. Having determined the number of students that will enroll into the programmes at entry levels in a forecast year from the Holt Winters additive forecast discussed above, we proceed to determine the quantities of each course material needed to service students' demand in a forecast year.

Since each student is issued one material per course, the numbers of each course material in the study pack required to service the demand of students admitted in the first semester in p_1, p_2... p_z equals F_{p_1}, F_{p_2}... F_{p_z} respectively. To find the total number (T_{Course_Code}) of course materials needed to service the demand of students of p_1, $p_2 \dots p_z$ in first semester of the forecast year, we sum the corresponding F_{p_1}, $F_{p_2} \dots F_{p_z}$ for each course:

$$T_{Course\_Code} = \sum_{i=1}^{z} F_{p_i} \qquad (9)$$

For second semester, the number of returning students is deterministic and is given by C_{p_1}, $C_{p_2} \dots C_{p_z}$ respectively. So the total number (N_{Course_Code}) of course materials needed to service the demand of students of p_1, $p_2 \dots p_z$ in second semester: $N_{Course\_Code} = \sum_{i=1}^{z} C_{p_i}$ (10)
The study packs of three programmes (p_1,p_2 and p_3) presented in Tables 4 – 6 are used to illustrate the performance of the study pack algorithm. These study packs were extracted from the respective faculties' handbooks of NOUN.

Notations of the Study Pack Algorithm
z = number of programmes offered in the institution which may or may not share same courses.
p_i = a unique programme.
F_{p_i} = the forecast number of students that will enroll in p_i, for i = 1 to z.
C_{p_i} = the current number of students enrolled in p_i, for i = 1 to z.

Assumptions of the Study Pack Algorithm

i. The number of old students moving from one level to another or from one semester to another is deterministic and corresponds to the population of students at the current level at the time of the forecast.
ii. Each programme must have an organized Study Pack.

Table 4: Study Pack of 100L B.A. (Ed) Early Childhood Education (p_1)

SN	Code	Course title	Unit	Status	Semester	Demand
1	GST101	Use Of English And Communication Skills I	2	core	1	Fp_1
2	GST105	History And Philosophy Of Science	2	core	1	Fp_1
3	GST107	The Good Study Guide	2	core	1	Fp_1
4	EDU111	Introduction To Foundations Of Education	2	core	1	Fp_1
5	ECE121	Child Development	2	core	1	Fp_1
6	ECE113	Introduction To Philosophy Of Early	2	core	1	Fp_1
7	ECE123	Health Care In The Early Years	2	core	1	Fp_1
8	PED122	Primary English Curriculum And Methods	2	Core	1	Fp_1
9	PED144	Primary Mathematics Curriculum Methods	2	Core	1	Fp_1
10	GST102	Use Of English And Communication Skills Ii	2	Core	2	Cp_1
11	ECE110	Childhood Education In Traditional African	2	Core	2	Cp_1
12	ECE112	Origin And Development Of E.C.E	2	Core	2	Cp_1
13	ECE120	Development Of Appropriate Skills In	2	Elective	2	Cp_1
14	PED112	Reading In Early Childhood An Primary	2	Core	2	Cp_1
15	EDU112	Professionalism In Teaching	2	Core	2	Cp_1
16	EDU114	History Of Education In Nigeria	2	Core	2	Cp_1
17	PED130	Introduction To Social Studies	2	Elective	2	Cp_1

Table 5: Study Pack of 100L B.Sc Criminology and Security Studies (p_2)

SN	Code	Course Titles	Units	Status	Semester	Demand
1	GST101	Use of English and Communication	2	C	1	Fp_2
2	GST105	History and Philosophy of Science	2	C	1	Fp_2
3	GST107	The Good Study Guide	2	C	1	Fp_2
4	CSS111	Introduction to Sociology	3	C	1	Fp_2
5	CSS121	Introduction to Psychology	3	C	1	Fp_2
6	CSS133	Introduction to Criminology I	3	C	1	Fp_2
7	CIT101	Computer in Society	2	C	1	Fp_2
8	POLIII	Element of Political Science	3	E	1	Fp_2
9	ECO121	Principles of Economics	3	E	1	Fp_2
10	PCR111	Introduction to Peace Studies	3	E	1	Fp_2
11	GST102	Use of English and Communication	2	C	2	Cp_2
12	CSS152	Introduction to Nigerian Criminal Law	3	C	2	Cp_2
13	CSS112	Sociology of Law	3	C	2	Cp_2
14	CSS132	Ethnography and Social structure of	3	C	2	Cp_2
15	CSS134	Geography of Nigeria	3	E	2	Cp_2
16	CSS136	Introduction to Criminology II	3	C	2	Cp_2
17	CIT102	Application Software Skills	2	C	2	Cp_2
18	POL126	Citizen and the State	3	E	2	Cp_2
19	PCR114	Introduction to Conflict Resolution	3	E	2	Cp_2

Table 6: Study Pack of 100L B.A. (Ed) English Education (p_3)

SN	Code	Course Title	Unit	Status	Semester	Demand
1	GST 101	Use of English and Communication Skills I	2	C	1	Fp_3
2	GST 105	History and Philosophy of Science	2	C	1	Fp_3
3	GST 107	The Good Study Guide	2	C	1	Fp_3
4	EDU 111	Foundations of Education	2	C	1	Fp_3
5	CIT 101	Computers in Society	2	C	1	Fp_3
6	ENG 121	The Structure of Modern English I	2	C	1	Fp_3
7	ENG 113	Intro. to Nigerian Literature I	2	C	1	Fp_3
8	ENG 111	Introduction to Literature and Literary	3	C	1	Fp_3
9	ENG 141	Spoken English	3	C	1	Fp_3
10	GST 102	Use of English and Communication Skills II	2	C	2	Cp_3
11	EDU 112	Professionalism in Teaching	2	C	2	Cp_3
12	EDU 114	History of Education in Nigeria	2	C	2	Cp_3
13	ENG 122	The Structure of Modern English II	2	C	2	Cp_3
14	ENG 114	Intro. to Nigerian literature II	2	C	2	Cp_3
15	ENG 162	Elements of Drama	2	C	2	Cp_3
16	ENG 172	Intro. to Poetry	3	C	2	Cp_3

In Tables 4-6 the demand for first semester courses corresponding to the predicted number of students that will enroll in the programmes is given as Fp_1, Fp_2 and Fp_3 while the demand for second semester courses corresponding to the number of students currently enrolled in the level and who will be moving to the next level/semester is given as Cp_1, Cp_2 and Cp_3 respectively. Equations 9 and 10 were applied accordingly to determine the demand for each course material required to service demand within the forecast period.

Coding Using Python Programming

Python programming was used to develop a prototype of the demand forecast module. Smoothen time series data of the three programmes were stored in a comma-separated values (csv) file and imported into python integrated development environment (IDE) using "pandas" tool. Using our determined optimum values of α = 0.6, β = 0.1 and γ = 0.1, the Holt Winters Additive model was applied to the data and a 1-step-ahead-forecast for each of the time series was obtained. The python "pymysql" tool was used to write the forecast results of each programme to the corresponding records of the programme in an already created SQL database table. The SQL "groupby" query was then used to determine the total number of each course material needed for each programme using their unique course codes.

RESULTS AND DISCUSSION

Test Results of the Holt Winters Additive Module

Table 7: Output of the HWA Module

Predicted B.A. (Ed) Early Childhood Education (p_1)	Predicted B.A. (Ed) English Education (p_2)	Predicted B.Sc Criminology and Security Studies (p_3)
271.7442	164.4213	1342.9970

Table 7 shows the outputs of the HWA module. The outputs show the forecast values of students' enrolment into programmes p_1, p_2 and p_3 for a succeeding semester. In addition to the test earlier carried out during the process of model selection, the performance of Holt Winters Additive Model on the data was measured using python programming to determine the MSE and RMSE. Furthermore, the Scatter Index (SI) test given by ($SI = \frac{RMSE}{Average\ observed\ values} * 100$) was used to compare the RMSE with the predicted values. RMSE values of 29.685, 16.784 and 48.563 were obtained for forecast of p_1, p_2 and p_3 respectively with good Scatter Index values of 20.89%, 9.40% and 3.95%. The obtained SI values show a good performance of the HWA model as outlined by Boukarta (2020).

Test Results of the Study Pack Module

Table 8: Outputs of the Study Pack module

Course_code	Forecast_Demand
CIT101	1506
CIT102	1297
CSS111	1342
CSS112	1297
CSS121	1342
CSS132	1297
CSS133	1342
CSS134	1297
CSS136	1297
CSS152	1297
ECE110	273
ECE112	273
ECE113	271
ECE120	273
ECE121	271
ECE123	271
ECO121	1342
EDU111	435
EDU112	441
EDU114	441
ENG111	164
ENG113	164
ENG114	168
ENG121	164
ENG122	168
ENG141	164
ENG162	168
ENG172	168
GST101	1777
GST102	1738
GST105	1777
GST107	1777
PCR111	1342
PCR114	1297
PED112	273
PED122	271
PED130	273
PED144	271
POL111	1342
POL126	1297

Table 8 shows the outputs of the study pack module. Results show the quantities of each course material required to service students' demand in a forecast year. Results obtained from the study pack module were accurate and reliable in line with the assumptions of the study pack algorithm. There was no accurate data of past demand for each course material to compare the test results with. This is however not regarded as a problem but a major motivation of the research work.

CONCLUSION

In this study, we discussed an algorithm for easy application of the HWA model in forecasting students' enrolment into multiple programmes of an ODL institution. The predicted number of enrolled students is further used to compute the demand for various course materials in a forecast period using a study pack algorithm. The model was applied on data of students' enrolment in NOUN programmes from 2004 – 2019. The HWA forecast model and the study pack algorithm were finally coded using python programming language. The Study pack method of determining the quantities of course materials needed in a forecast period is effective and will aid greatly in the timely determination of Economic Order Quantities (EOQ) or Economic Production Quantities (EPQ) whenever there is need to order or produce course materials for ODL students. Early forecast of students' population in ODL institutions will lead to improved course material production and distribution planning and affect the general service delivery in the Institutions.

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