Projecting Student Population Using Artificial Neural Network

Annie O. Egwali, Ph.D.* and Macdonald I. Enabulele, M.Sc.

Department of Computer Science, Faculty of Physical Sciences. University of Benin, PMB 1154, Benin City, Nigeria.

Email: annie.egwali@uniben.edu
Telephone: 07033247730

ABSTRACT

Many Nigerian universities are beset with the need for expansion but lack effective planning techniques to effectively utilize the meager finance available to plan towards expansion of facilities in order to accommodate the ever-increasing number of students' population. In the quest to design effective strategic plans to guide the utilization of the limited funds allocations made available by the federal government, many Nigerian universities adopt statistical approaches like the ratio technique for making population projections. However, such statistical means are based on unrealistic assumptions and are not very suitable for predicting population growth due to the intrinsic chaos of population growth. This research work explores the use of Artificial Neural Networks in generating accurate student population projections from trends in student demographic data and implements a proposed model that achieves this purpose in a case study university. Results show that the proposed system has a better predictive accuracy than the ratio technique.

(Keywords: prediction, education, expansion, population, neural network, growth, projection)

INTRODUCTION

The demand for higher education in Nigeria, especially university education is becoming increasingly and unpredictably high, and of all the candidates applying for admission every year in Nigeria, only about 5.2% to 15.3% get admitted every year, resulting to about 84.7% to 94.8% of the candidates never getting admitted into Nigerian universities (Anyebe, 2014). These lapses are as a result of the fact that Nigerian universities lack the capacity to accommodate this large enrollee or applicant population (Ogunu, 2008) because they are plagued with the need for expansion. These universities lack the capacity to accommodate the ever-increasing population of Nigerian youths desperately seeking higher education. A fundamental requirement for such an expansion is funding. Despite UNESCO's recommendation to allocate 26% of national expenditure to education, a close look at Nigeria's expenditure on education reveals that Nigerian government expends just between 4% and 16% annually on education. Notwithstanding the insufficiency of funds provided by the Federal Government, proper planning can cause such funds to be effectively directed towards expansion of facilities to accommodate larger number of students.

The situation is further marred by the misuse or wastage of the meager funding by university leadership, which if well harnessed can be effectively directed towards expansion of facilities to accommodate larger number of students. Anyebe (2014) attributes this misuse to lack of effective planning as a result of several factors which include the inaccuracy of statistical data, and the use of mediocre means of preparing planning and forecasting data. Many Nigerian universities adopt statistical approaches like the ratio technique for making population projections. Whereas such statistical means are based on unrealistic assumptions and are not very suitable for predicting population growth due to the intrinsic chaos of population growth (Keilman et al., 2002; McKeown, 2009).

Population projection is a "best-guess" calculation of the number of people expected to be available at a future date, based on what we know about the current population size and what we expect to happen to births, deaths, and migration (Chapin and Diaz, 2007; Speth et al., 2010). Population projections are always set on a "conditional" future because we can never be certain about the assumptions we use in the projection. An estimate attempts to define the whole number of people or inhabitants in a region (Kirch, 2008) for a specific time in the past, such as a period midway between the last two census counts – an "intracensal estimate", or for a specific date at or near the present. While a projection, on the other hand, is a prediction about future population levels, conditioned upon a set of assumptions. The accuracy of the projection is directly affected by the validity of the assumptions underlying a projection which can be unsupervised (e.g. cohort-component method (Zhang et al., 1998), ratio techniques (Raymondo, 1992), mathematical extrapolation techniques (Lorenz and Egelhaaf, 2008) and economic-demographic models (Chapin and Diaz, 2007)) or supervised (e.g., Artificial Neural Network); accurate assumptions yield accurate projections.

Over the years, several within the domain of supervised projections, several researches have been undertaken. Folorunsho et al. (2010) applied a backward propagation Artificial Neural Network (ANN) and aimed at handling incomplete and inconsistent population data. A data set corresponding to twelve different age groups which included corresponding target values was used to train the neural. Prediction simulations were done using different Neural Network topologies and the topology with the best result was identified. The results of the simulation were compared with results of the traditional cohort component population model.

Findings revealed that the ANN model gave more accurate predictions than the cohort component model. For instance, unlike the cohort component model which uses a base population and is dependent on the population change rate, the ANN model allowed for anticipated deviations from past trends and explicitly includes the components of population change in generating predictions. Furthermore, distinctively, the cohort component model carries out population predictions under a closed population cohort where the effect of migration to population change is almost zero, whereas the neural network uses activation functions and hidden neuron layers to learn and extract progressive and meaningful features from highly complex and nonlinear data. Also the ANN model is more robust and fault tolerant in the face of missing data than the cohort component model.

Maliki et al. (2011) did a comparative study of Regression Model and ANN Model for the prediction of electrical power generated in Nigeria. And concluded from findings that neural networks are better at identifying patterns or trends in data and well suited for prediction or forecasting needs. Rafael et, al (2014) proposed a framework that used Generalized Feed Forward Neural Network GFFNN in designing a framework for predicting student enrollment population. In their work, a comparison was made on the prediction accuracy of ANNs with the prediction accuracy of the statistical prediction models; Linear Regression (LR) and Auto Regression (AR) on the basis of their Mean Absolute Percentage Errors (MAPE) and found that ANN Model performed better in the time series analysis of students' enrollment in tertiary institutions.

Skolpadungket et al. (2014) applied Evolutionary ANN in forecasting stock returns from a dataset containing the following independent variables; twelve month time lag of changing inflation (CPI), default yield spread, term yield spread, federal fund rate, Industrial product, money quantity and unemployment rate, monthly dividend splits and adjusted returns from ten selected stocks of the U.S. stock market namely; Alcoa (AA), Boeing (BA), Caterpillar (CAT), Dupont (DD), Disney (DIS), General Electric (GE), General Motor (GM), Honeywell (HON), HP (HPQ) and IBM (IBM) and the corresponding stock returns as dependent variables. Their work aimed at establishing the superiority of Evolutionary ANN models over linear regression models for the prediction of stock returns. Their findings revealed that Evolutionary ANN had higher predictive accuracy than linear regression models. They however highlighted for further research there was a need for improvements in the predictive time Evolutionary ANN and that Evolutionary ANN need to be improved to work on computers with low processing power.

Oduyemi et al. (2015) applied ANNs in estimating the operating maintenance cost of existing buildings from a ten-year historical data about the engineering cost, building material cost, budget and finance cost, management and administration cost, building user behavior cost and skilled labor cost of buildings. His findings revealed that the ANN architecture with topological structure 6-7-1 (6-input variables, 7-nodes in the hidden layer, 1-output) gave best results and generalized the data optimally to produce better outputs for unforeseen relationships in the data set.

Günay (2015) applied ANN in predicting the annual gross electricity demand of Turkey using a data set consisting of predicted values of the socio-economic indicators; Population, GDP per capita, inflation as well as climatic conditions. In his work, the annual gross electricity demand of Turkey was modeled by multiple linear regression and ANNs as a function of population, gross domestic product per capita, inflation percentage, unemployment percentage, average summer temperature and average winter temperature. Next, the future values of the statistically significant variables were predicted by time series ANN models, and these were simulated in a multilayer perceptron ANN model to forecast the future annual electricity demand.

His findings revealed that the model successfully forecasted the annual gross electricity demand for the future years yielding a gross demand of 460TWh for the year 2028. The results were also found to be superior to the official predictions (done by Ministry of Energy and Natural Resources of Turkey). His work showcased the capability of ANNs in identifying complex unforeseen relationships existing between the socio-economic indicators; Population, GDP per capita, inflation and gross electricity demand and the ability of ANNs to make highly accurate predictions of any of the above variables using the identified relationships.

There is a dearth of research work that applies neural network in handling the intrinsic chaos of population change in Nigeria universities. The ratio technique assumes fertility, mortality, and net migration rates for successive years must be identical or proportional and projected to remain equal or proportional over time (Hedeen, 1966). Hence in the case of a university system, admission rate (fertility), Graduation rate (mortality) and outward transfer rate (net migration) must be identical or proportional and projected to remain equal or proportional overtime. However, in reality, student population dynamics do not conform to this assumption.

According to Anyebe (2014), the insatiable demand for university education in Nigeria has brought about an exponential increase in student admission. Available evidence also shows that tertiary enrolment growth rates are quite inconsistent. Therefore, as trends in graduate output are generally affected by earlier changes in the composition of enrolment (Ogunu, 2008), it therefore follows that this inconsistent growth rate of two major components of student population change would also result in inconsistent overall student population growth rates annually.

Making well informed strategic plans for expansion cannot be achieved without a means of accurately forecasting student population size. A population projection system capable of handling the intrinsic chaos of population change in Nigeria universities will bolster the academic planning process, by assisting academic planners, Deans and Directors in making well informed decisions on matters concerning student population size and expansion plans. Statistical means of population projection like the ratio technique are based on unrealistic assumptions and are not very suitable for predicting population growth due to the intrinsic chaos of population growth (Keilman et al., 2002; McKeown, 2009).

It is obvious that reliance on assumed fixed student population growth rates would only result in ineffective strategic plans that do not accommodate the inconsistencies in student population dynamics and consequently, inefficient use of meager financial resource allocations. Hence, this research work centers on the application of predictive data mining to historical student demographic data in order to obtain population projections for use in academic planning. It analyses the existing method used by the University of Benin academic planners in making population projections for expansion planning. It further explores the use of ANNs in generating accurate student population projections from trends in student demographic data. A Neural Network based decision support system is proposed and implemented that can generate population projections from historical student demographic data for academic planners. The proposed decision support system is compared with the existing technique in order to ascertain its efficiency.

MATERIALS AND METHODS

In this research study, two types of surveys were conducted: (i) to elicit data from several academic planners about student population projection techniques currently used by Nigerian higher education institutions; (ii) to ascertain the current population projection methodology adopted in the University of Benin.

Table 1: Number of Respondents per University School Name.

University	Number of Respondents	Percent	Valid Percent	Cumulative Percent
Benson Idahosa University	4	14.3	14.3	14.3
Delta State University	4	14.3	14.3	28.6
Federal University Kashere Gombe	3	10.7	10.7	39.3
Federal University Lokoja	3	10.7	10.7	96.4
Igbinedion University Okada	4	14.3	14.3	64.3
University of Benin	4	14.3	14.3	78.6
University of Uyo	1	3.6	3.6	82.1
University of Uyo	2	7.1	7.1	89.3
Wellspring University	3	10.7	10.7	100.0
Total	28	100.0	100.0	

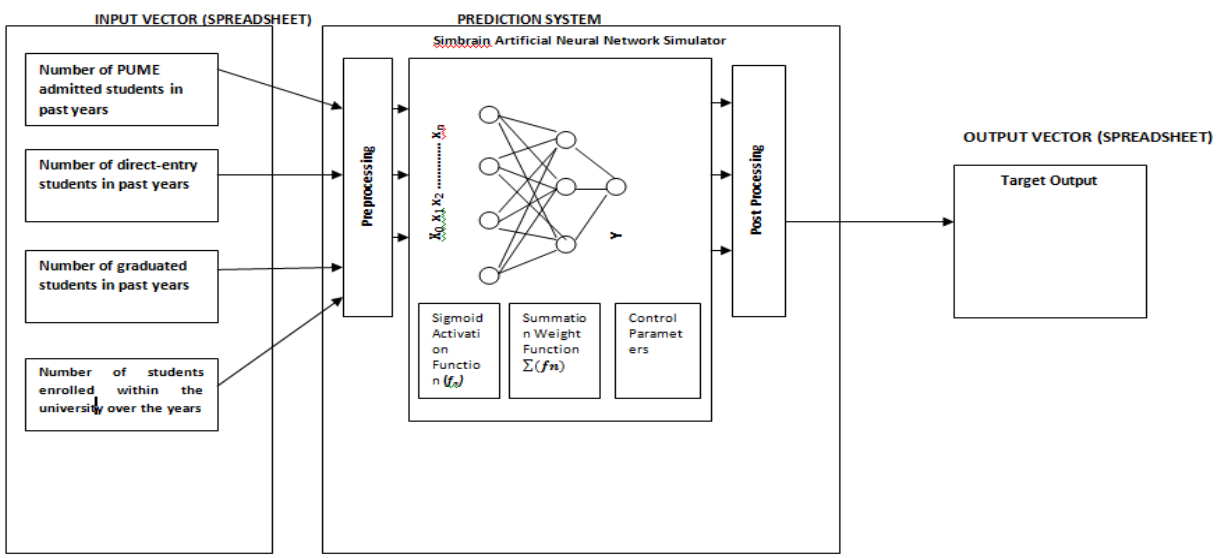

Figure 1: The Proposed Neural Network Based Student Population Projection System Architecture/

Research Design

The study commenced with the administration of questionnaires designed to elicit information about currently adopted student population projection technique to academic planners across eight Nigerian universities namely, Benson Idahosa University, Delta State University, Federal University Kashere Gombe, Federal University of Lokoja, Igbinedion University Okada, University of Benin, University of Uyo and Wellspring University. The first section of the questionnaire includes higher education institution category and academic planner field of specialization. The second part elicits data about the frequency at which student population projection is carried out, the student population projection methodology adopted by the Educational institution as well as the reason for preference of the adopted methodology. The third section analyses the respondents' perception of the usability of the adopted methodology, the long term and short-term prediction accuracy of the adopted methodology.

Response Rate

Target respondents were academic planning directors and members of staff of academic planning units and departments in the nine universities. A total of twenty responses were collected across the nine universities as shown in Table 1.

Data Analysis Method

In this work, the Simbrain ANN simulation tool which is a Visual Basic.NET based ANN simulator developed by Yoshimi (2008) was used to train our data, simulate a backward propagation ANN and to generate the population projections. The proposed system architecture shown in figure 1 is an ANN Based Student Population Projection System for academic planners in tertiary institutions in Nigeria. The ease of use of this tool as well as the Microsoft visual studio IDE made it a tool of choice for training input vectors and making predictions in this project.

The architecture is made up of three components, the input vector component, the prediction system component and the output vector component. The prediction component contains a preprocessing and post processing sub component, a Backward Propagation ANN Component that utilizes a sigmoid activation function and a summation weight function. The input vector is a spread sheet file representing a dataset of historical student population records that could either be prepared manually or spooled from a relational database system.

For this project, Input vector file was made up of five columns containing historical values for the number of students admitted via PUME, the number of students admitted via direct entry, the total number of students enrolled within the university system across all levels, the number of graduating students and the total student population of the university. The system represented each of these columns as variables. Each of these variables were modeled to reflect the components of population change; with the number of students admitted via PUME and the number of students admitted via direct entry representing births, the number of graduating students representing deaths, migration was not represented because the case study university did not allow interschool transfer of students.

The total number of students enrolled within the university system across all levels was used to represent the base population. The four columns of the dataset corresponding to the number of students admitted via PUME, the number of students admitted via direct entry, the total number of students enrolled within the university system across all levels and the number of graduating students were used as independent variables of the dataset while the last column which contained the total student population of the university was used as the dependent variable of the data set.

The Simbrain ANN simulation tool was used to simulate a Backward Propagation ANN that adopts a sigmoid activation function and a weight summation function for predictive analysis. The system takes as input, the input vector and uses records for ten years out of the available fourteen-year record for training. During training, data in the input vector is normalized by an embedded preprocessing module. This normalization optimizes the speed of the training process by scaling the training data to a range that can be effectively handled by the sigmoid transfer function.

After preprocessing is complete, the ANN learns patterns or relationships that exist within the training data set. These relationships are represented by a set of optimal weights that interconnect the nodes. Using these weights, the prediction systems can calculate sets of target values using normalized values of the independent variables in the test set. The new target values are then validated by a comparison with the target values of the test set (the remaining four records of the input vector). The weights that generate predictions closest to the target values in the test data are identified and reserved as optimum weights. The optimum weights are then used to make a projection for the following year.

The backward propagation ANN return target variable predictions iteratively using the steps in the following algorithm:

Begin

1. *Initialize the weights that connect inputs to hidden layer 1*
2. *Multiply the input vectors with their connecting weights*
3. *Compute the total weighted input*
4. *Threshold the total weighted input by tansig to get output for the first hidden layer*
5. *Use the output for the first hidden layer as the input for second hidden layer*

6. Initialize the weights that connect hidden layer 1 to hidden layer 2

7. Repeat step 2 and 3

8. Threshold the total weighted input by logsig to get output and input for second hidden layer and output layer respectively

9. Initialize the weights that connect hidden layer 2 to output layer

10. Repeat step 2 and 3 to get the output values

11. Threshold the total weighted output by purelin to get the actual output values

12. If the output values are equivalent to the target values Then Go To step 19 Else

13. Compute EA // EA is the difference between the actual values and the target values.

14. convert EA to EI// EI is the rate at which error changes as the total input received by a unit is changed.

15. Compute EW // EW is the error derivatives of the weights (i.e. that is how the error changes as each weight is increased)

16. Multiply those EAs of those output units and add the products

17. Compute EAs for other layers by repeating step 12 to 15 // movingrom layer to layer in a direction opposite the way activities to propagate.

18. Repeat 2 to 13

19. Stop

20. End

The different components of the neural network apply the algorithm. The weighting factors (independent variables) are represented by input neurons, with each neuron initialized to a relative random weight that gives the input the impact it needs on the processing components summation function. Weights are adaptive coefficients within the network that determine the intensity of the input signal as registered by the artificial neuron. They are modified in response to various training sets. The processing component of the summation function then computes the weighted sum of all the inputs by adding up the dot products of the input vector values and the weights to yield a single number. A sigmoid function "tansig" is then used to approximate this summation. Sigmoid functions have logistic regression properties which enable them model complex nonlinear relationships. Sigmoid function derivatives are continuous hence it is easy to compute their derivatives and this property facilitates an easy gradient descent towards an optimum weight (Deepthi and Kumar, 2011). The approximation of the weighted sum by the sigmoid function yields the output of the hidden layer. This output is then acted upon by an activation function "log sig" to allow the summation output vary with time (Perez et al., 2000).

The result of the summation function stage is transformed into a working output through an algorithmic process known as the threshold or transfer function "purelin". Here the summation total is compared with the threshold to determine the neural output. If the sum is greater than the threshold value, the processing component generates a signal otherwise an inhibitory signal is generated. The scaling and limiting is a post processing activity in which the output of the transfer function (the transfer value) is multiplied by a scale factor and then added to an offset value. Limiting is the mechanism which ensures that the scaled result doesn't exceed an upper or lower bound. The error function calculates the difference between the current output and the desired output and transforms this difference to match the network architecture. Some architectures use the error, some square the error and retain its sign while some cube the error depending on the purpose of the neural network. The output of the error function also called the current error is then fed into the learning function which scales the value and multiplies the value against each in coming connector weight of a previous layer to modify or adapt them for backward propagation to that previous layer. The output of the projection system is spreadsheet containing the input vector, optimal weights and the projected output.

Simbrain Neural network Simulator User Interface

The Simbrain Neural Network Simulator user interface is depicted in Figure 2.

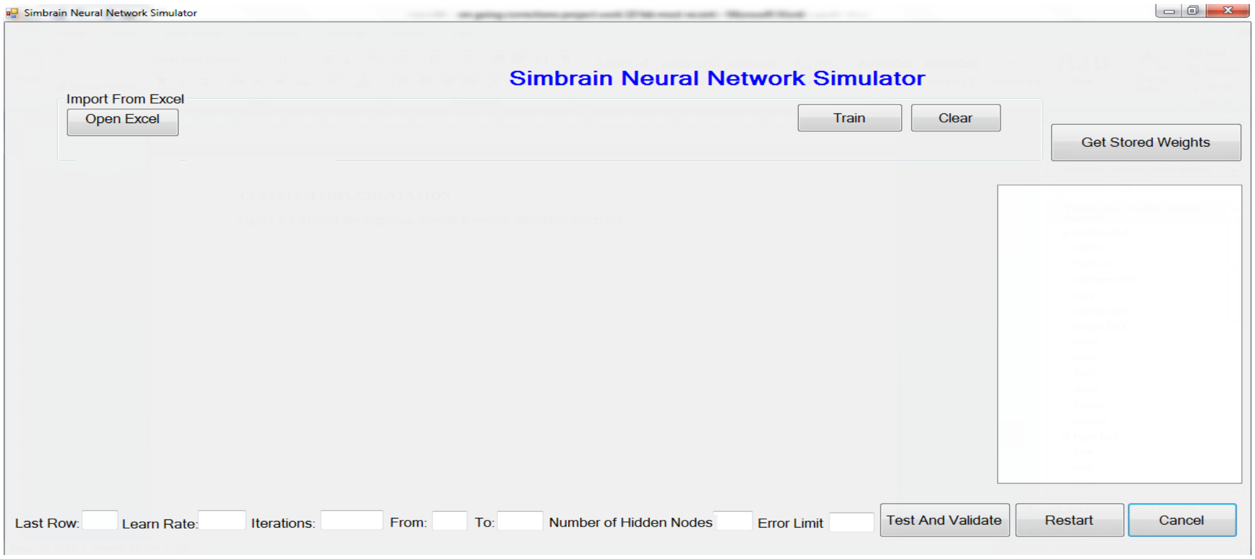

Figure 2: The Simbrain Neural Network Simulator User Interface.

Table 2: Population Projection Methodology Adoption Frequency.

Methodology		Number of Respondents	Percent	Valid Percent	Cumulative Percent
Valid	Cohort component	6	21.4	21.4	21.4
	Mathematical Extrapolation Technique	3	10.7	10.7	32.1
	Ratio Technique	19	67.9	67.9	100.0
	Total	28	100.0	100.0	

The user interface contains the open excel button that allows a user to access and import a stored excel spread sheet file containing an input vector matrix. Also included is the control parameter form that allows users to specify control parameters that define the topological structure of the neural network to be simulated. The 'last row value' allows the user to specify the number of records contained in the input vector.

The input vector used for this implementation contains contained twenty-five records including the column header record. Therefore the value 25 was specified for the implementation. The 'learn weight' is a constant between 0 and 1 that defines the rate at which weight bias changes are made during backward propagation. For this simulation, a learning rate of 0.25 was used. The 'iterations value' specifies the number of backward propagation iterations to perform. For this simulation, 1000 iterations were specified.

The 'from and to values' allow users specify the range of input vector records to use for training. The 'number of hidden nodes value' allows users specify the number of hidden nodes for their network. For this simulation six hidden nodes were selected. 'Error limit' value allows the user to specify the root mean square error value at which to terminate training. The 'restart button' allows a user to restart a training session for a selected input vector. 'Cancel button' allows a user to cancel a training session. The 'get stored weight button' causes optimum weights generated after training to be displayed. The 'train button' allows the user to commence a training session after supplying the input vector and control parameters. The 'clear button' enables the user to clear out displayed weights and results.

RESULTS AND DISCUSSIONS

The elicited data was analyzed by observing a projection methodology adoption frequency table generated by SPSS statistical tool (See Table 2) and a pivot table of methodology distributions across the visited universities generated using Microsoft office excel (See Table 3). Table 2 reveals the ratio technique to be the most used student population projection technique as 67.9% of the twenty-eight academic planners across the eight universities used the ratio technique in making student population, 21.4% used the cohort component method and 10.7% used the Mathematical Extrapolation technique.

Table 3 shows that the nineteen respondents who adopted the ratio technique in table 2 reside in six of the visited universities, the six respondents who adopted the cohort component methodology reside in three of the visited universities while the three respondents who adopted the mathematical extrapolation technique reside in one of the visited universities.

Making Projections

To make a projection, for the years ahead, the input vector shown in Table 4 is supplied to the system and the control parameters are filled in as shown in Figure 3 that student demographic records were not stored electronically but rather in hard copy format and that the university did not allow interschool transfers.

Next the number of input columns is specified. Based on this input, Simbrain uses the first four columns of the input vector as independent variables and uses the last column to represent the target output. Once these inputs have been specified, the train button was selected to simulate the ANN and generate the projected output.

Prediction Results

Table 4 shows actual values as well as predicted values obtained using the ratio technique and the proposed system for a six-year period from the 2008/2009 session to the 2013/2014 session.

Table 3: Projection Methodology Distribution across Universities.

PROJECTION METHODOLOGY DETAILS	SCHOOL COUNT
⊟Cohort component	**6**
Benson Idahosa University	4
Federal University Lokoja	1
Igbinedion University Okada	1
⊟Mathematical Extrapolation Technique	**3**
University of Uyo	3
⊟Ratio Technique	**19**
Delta State University	4
Federal University Kashere Gombe	3
Federal University Lokoja	2
Igbinedion University Okada	3
University of Benin	4
Wellspring University	3
⊟(blank)	
(blank)	
Grand Total	**28**

Table 4: System Input Vector.

SESSION	Admitted Students	Graduated Students	Enrolled students	Direct Entry	Total Population
90/91	2900	2465	16124	1641	19686
91/92	3246	2759	16537	2205	19437
92/93	3592	3053	16961	2166	19924
93/94	3938	3347	17396	2025	20463
94/95	4284	3641	17842	2190	21053
95/96	4630	3935	18300	1907	21696
96/97	4976	4229	18769	2152	22390
97/98	5322	4523	19250	2338	23137
98/99	5668	4818	19744	2577	23935
99/00	6014	5112	20250	1679	24785
00/01	6360	5406	20769	1773	25687
01/02	6706	5700	21302	2355	26641
02/03	7052	5994	21848	2657	27647
03/04	5559	4725	22408	1887	28705
04/05	5188	4135	20457	2295	28440
05/06	5526	4423	20982	2530	29723
06/07	5836	4712	20667	1648	37216
07/08	6201	4999	20357	1841	27505
08/09	6538	5287	20051	2253	29733
09/10	6875	5574	20246	2484	28068
10/11	6703	5862	20623	2212	27581
11/12	6535	5325	21546	2319	23650
12/13	6371	5608	22398	2119	22970
13/14	6211	5889	21222	2065	24150

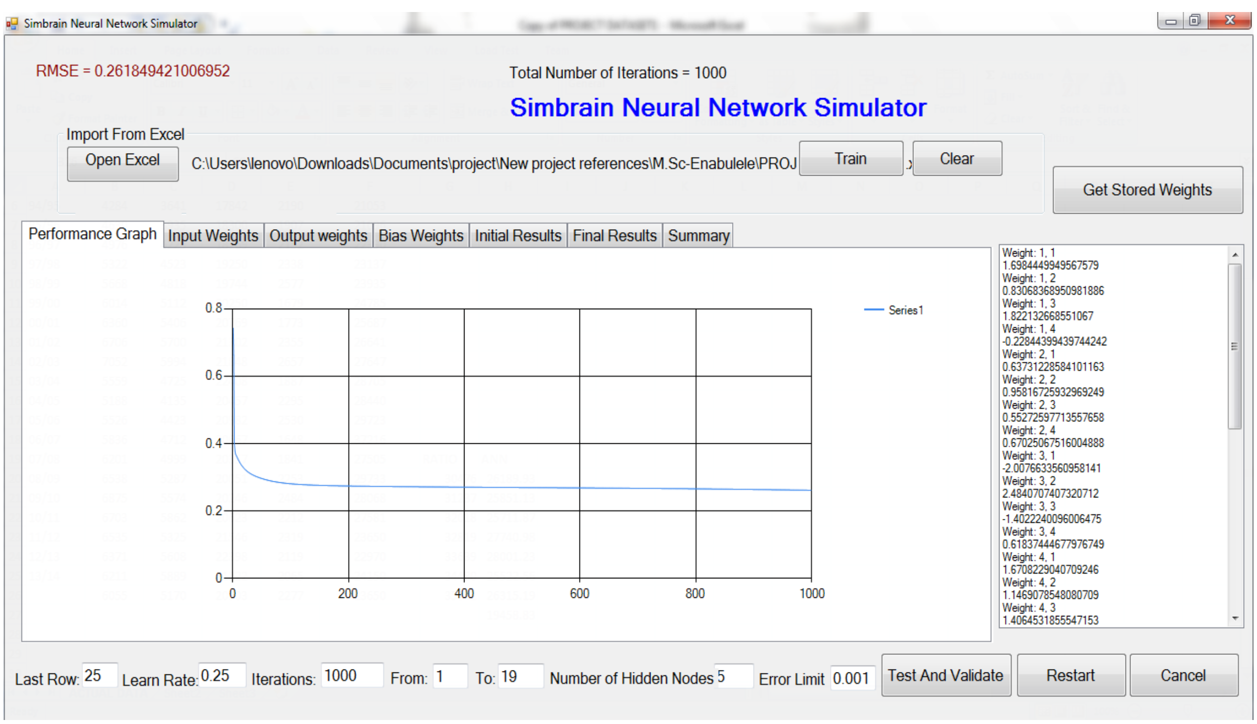

Figure 3: The Simbrain Neural Network Simulator with Control Parameters.

Table 4: Prediction Results.

Session	Ratio Predictions	Actual Population	Neural Network Predictions
08/09	30476	29733	26189.93231
09/10	31237	28068	25851.13029
10/11	32018	27581	25711.87098
11/12	32819	23650	27740.97658
12/13	33639	22970	28001.22504
13/14	34480	24150	25522.55517

Table 5: Mean Deviation of Predictions from Actual Values.

Ratio Prediction Deviation	Mean Deviation For Ratio Technique	Neural Network Deviation	Mean Deviation for Neural Network
743	6419.5	3543.067685	477.615
3169	6419.5	2216.869714	477.615
4437	6419.5	1869.129024	477.615
9169	6419.5	-4090.976583	477.615
10669	6419.5	-5031.225045	477.615
10330	6419.5	-1372.555175	477.615

Predictive accuracy is measured by how much the prediction by both techniques deviate from actual population values for the six-year period. Table 5 shows values for the deviations and mean deviation of results obtained using both techniques. From table 5, we see that the predictions obtained using the ratio techniques have larger mean deviations from the actual population values than the results of the proposed system. Therefore, it can be concluded that the proposed system has a better predictive accuracy than the ratio technique.

CONCLUSION

Amidst insufficient funding for the Nigerian educational sector, the demand for higher education in Nigeria is still on the rise. It is possible to achieve greater access to university education in Nigeria, if areas of waste are curbed and resources conserved are directed towards expanding the existing facilities to accommodate an increased number of students in Nigerian universities (Anyebe, 2014). To achieve this goal, academic planners need to use highly accurate student population data to design effective strategic plans to guide the utilization of limited funds allocations made available by the federal government. This research project has been able to establish ANN as a possible means through which academic planners can obtain accurate student population projections for planning. However, to successfully adopt the system, observed lapses like the disorganization of student population data and the storage of such data in hard copy format need to be addressed.

Student population details need to be stored electronically in databases. Furthermore, the database system should integrate and organize student population data from University admissions board, Exams and records department and the academic planning. Taking these steps would facilitate easy access to student population data for use with ANN systems.

REFERENCES

1. Anyebe, C.C. 2014. "Nigerian University and Manpower Development in a Changing World". Retrieved from: www.ccsenet.org/journal/index.php/hes/article/viewFile/33736/19452

2. Chapin T. and C. Diaz. 2007. "Local Government Guide to Population and Estimation Techniques". Retrieved from https://www.google.com/url?sa=t&rct=j&q=&esrc=s&sourc e=web&cd

3. Dayhoff, J.E. 1990. "Neural Network Architecture: An Introduction". Retrieved from https://catalyst.library.jhu.edu/?q=%22Dayhoff%2C+Judith

4. Deepthi, D. and K. Kumar. 2011. "Novel Approach to Unsupervised Pattern Recognition". *International Journal for Advances in Computer Science*. 2:1.

5. Diogo, F.P., R.S.O. Flávio, and B.L.N. Fernando. 2008. "Multi-Objective Abilities in the Hybrid Intelligent Suite for Decision Support". Retrieved from http://ieeexplore. ieee.org/xpl/freeabs_all.jsp?arnumber=4634378.

6. Folorunsho. O., A. Akinwale, O. Asiribo. and T. Adeyemo. 2010. "Population Prediction Using Artificial Neural Network". *African Journal of Mathematics and Computer Science Research*. 3(8):155- 162.

7. Gunay, E. 2015. "Forecasting Annual Gross Electricity Demand by Artificial Neural Networks using Predicted Values of Socio-Economic Indicators and Climatic Conditions: Case of Turkey". *Elsevier Journal*. 92–101.

8. Hedeen, J.E. 1966. "Population Projection; A Demographic Procedural Manual for Planning Practitioners". Retrieved from: https://archive.org/details/populationprojec00hede

9. Jain, A. 2003. "Frost Prediction using Artificial Neural Networks: A Temperature Prediction Approach", MS. Thesis, Artificial Intelligence Center, University of Georgia: Athens, GA. 2003:18- 21.

10. Keilman, N., D.Q. Pham, and A. Hetland. 2002. "Why Population Forecasts Should be Probabilistic - Illustrated by the Case of Norway". *Demographic Research Journal*. 6:409-454.

11. Kirch, W. 2008. *Encyclopedia of Public Health.,* 2:120-141. Springer Science and Business Media: Berlin, Germany.

12. Kuan, C.M. and H. White. 1994. "Artificial Neural Networks: An Econometric Perspective". *Econometric Review*.13:1-91,139-143.

13. Lorenz, S. and M. Egelhaaf. 2008. "Curricular Integration of Simulations in Neuroscience Instructional and Technical Perspectives". *Journal of Brains, Minds, and Media*, 3:198.

14. Maliki, O., A. Agbo, A. Maliki, L. Ibeh. and C. Agwu. 2011. "Comparison of Regression Model and Artificial Neural Network Model for the Prediction of Electrical Power Generated in Nigeria". *Advances in Applied Science Research, Pelagia Research Library*. 2(5):329-339.

15. McKeown, R. 2009. "The Epidemiologic Transition: Changing Patterns of Mortality and Population Dynamics". *American Journal of Lifestyle Medicine (AJLM)*. 1:3.

16. Oduyemi. O., M. Okoroh, and A. Dean. 2015. *Developing an Artificial Neural Network Model for Life Cycle Costing in Buildings*. Association of Researchers in Construction Management. 843-852.

17. Ogunu, M.A. 2008. 'The Development of University Education in Nigeria: A Statistical Analysis". Retrieved from: http://www.unilorin.edu.ng/journals/education/ije/dec1990/the%20development%20of%20university%20education%20in%20nigeria%20%20a%20statistical%20analysis.pdf

18. Perez, P., A. Trier, and J. Reyes. 2000. "Prediction of PM2.5 Concentrations Several Hours in Advance using Neural Networks in Santiago, Chile". *Journal of Environmental Research*. 34:1189-1196.

19. Rafael, A., D. Pietro, H. Francisco. and L. Beatrice. 2014. "A Multi-Objective Evolutionary Approach to Concurrently Learn Rule and Data Bases of Linguistic Fuzzy-Rule-Based Systems" retrieved from: http://sci2s.ugr.es/gfs/pdf/2009-alcala-IEEETFS.pdf

20. Raymondo, J. 1992. *Population Estimation and Projection: Methods for Marketing, Demographic, and Planning Personnel*. Greenwood Publishing Group. 190.

21. Skolpadungket, P., K. Dahal, and N. Harnpornchai. 2014. "Forecasting Stock Returns using Evolutionary Artificial Neural Network". *IEEE Journal*. 1:186 – 189.

22. Zhang, G., B.E. Patuwo, and M.Y. Hu. 1998. "Forecasting with Artificial Neural Networks: The State of the Art". *International Journal of Forecasting*.14:35-62.

ABOUT THE AUTHORS

Dr. (Mrs.) Egwali Annie Oghenerukevbe, is an Associate Professor in the Department of Computer Science, Faculty of Physical Sciences. University of Benin, Benin City. Nigeria. Her area of interests includes Network Security, E-commerce, Electronic Marketing and Information Technology, Software Engineering, Gender studies, To date, she has supervised several undergraduate and postgraduate students. She is a member of International Network for Women Engineers and Scientists (INWES), Nigerian Computer Society (NCS) and Third World Organizations of Women Scientists (TWOWS).

Enabulele Macdonald, is a lecturer in the Department of Computer Science, Faculty of Physical Sciences. University of Benin, Nigeria. He holds a Masters degree in Software Engineering. His research interests are in the areas of Information Technology and Software Engineering.

SUGGESTED CITATION

Egwali, A.O. and M.I. Enabulele. 2018. "Projecting Student Population Using Artificial Neural Network". *Pacific Journal of Science and Technology*. 19(2):118-129.

Pacific Journal of Science and Technology