

Original Research Article

Artificial Neural Network (Ann) Forecast of University Growth: A Focus on College of Technology Education, Kumasi, University of Education, Winneba Admissions.

Abstract

The definition of growth can mention nature that growth can be take: Physical and Abstract. The growth of Academic institutions especially universities has become a major concern in Ghana. Growth of Academic institutions (Universities and Colleges) can take different dimensions. Some of these dimensions include the number of undergraduate admissions per each year, number of postgraduate admissions per each year, Number of Teaching Staff, infrastructure, logistics, and Research. In the Corporate strategic plan of University of Education (2015), the targets enshrined in it indicate that the University of Education would pursue non-reluctant growth strategy in all spheres of academic life including infrastructure growth, increase in enrollment of students and continuous pursuant of higher academic research. A focus shall be on the admissions of College of Technology Education, Kumasi, one of the University's campuses. This admission growth of the college shall be used as a proxy for the entire University of Education. The Neural Autoregressive (NAR) model is specified based on the Autoregressive (AR) five (5) in terms of the lag length and variables used. The AR had mean forecast error of 22.58 % whiles the NAR had a mean forecast error of 5.89 %. It is self-evident from the results that the College of Technology Education, Kumasi is growing in terms of students numbers. Future studies should be done on Faculty basis.

Keywords: Artificial Neural Network, Forecast, University Growth, Autoregressive, Neural Autoregressive

1.0 INTRODUCTION

Growth refers to a positive change in size, and/or maturation, often over a period of time. Growth can occur as a stage of maturation or a process toward fullness or fulfillment. The definition of growth can mention nature that growth can be take: Physical (e.g., growth in height, growth in an amount of money) and Abstract (e.g., a system becoming more complex, an organism becoming more mature) (wiki).

Growth occur to natural living things like Human beings and Plants. In the same way, institutions also grow. These institutions include Academic institutions , Health institutions, Financial institutions etc. The growth of Academic institutions especially universities has become a major concern in Ghana.

37 Growth of Academic institutions (Universities and Colleges) can take different dimensions.
38 Some of these dimensions include the number of undergraduate admissions per each year,
39 number of postgraduate admissions per each year, Number of Teaching Staff, infrastructure,
40 logistics, and Research. Different researchers may lay emphasis on different measure of growth
41 depending on the core objective of the research.

42 The University of Education has four main campuses. The University has since its inception
43 continued to graduate increasing number of quality students (Vice Chancellors Report, 2014). In
44 a sense it is direct to say that the University of Education is growing. However, growth of
45 students number comes with its own challenges: availability of teaching staff, Lecture rooms,
46 Laboratories and Student accommodation facilities.

47

48 The continuous increase in the number of students has rang the bell to ensure a commensurate
49 match of staffing to students number. This call for a good forecast of student enrollment to
50 enable easy planning.

51

52 **2.0 PROBLEM STATEMENT**

53 In the Corporate strategic plan of University of Education (2015), the targets enshrined in it
54 indicate that the University of Education would pursue non-reluctant growth strategy in all
55 spheres of academic life including infrastructure growth, increase in enrollment of students and
56 continuous pursuant of higher academic research.

57 Growth has its own challenges as already mentioned above. Besides, peculiar challenge to
58 increasing enrollment of students has fundamentally been the problem of infrastructure and
59 academic staffing. This means that whiles the university think of increasing enrolment it should
60 also think of these problems that have cast their shadows in advance.

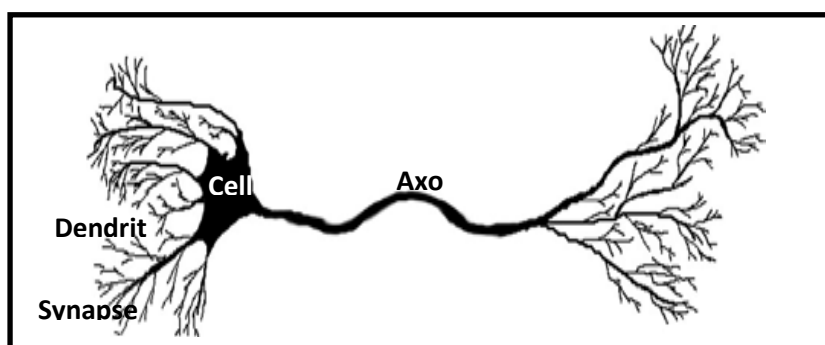
61 The question remains as to what level of infrastructure and staffing would meet the growth of
62 student enrollment. Technically the National Accreditation Board, Ghana, requires Lecturer to
63 Students ratio of 1:27. This means one lecturer should handle Twenty- seven students. To be
64 able to meet this ratio University of Education requires a good forecast of student enrollment.
65 The forecast will enable successful planning for academic staff as well as infrastructure .

66 As already mentioned, the University of Education has four campuses. To enable correct
67 forecast, a focus shall be on the admissions of College of Technology Education, Kumasi, one
68 of the University's campuses. This admission growth of the college shall be used as a proxy for
69 the entire University of Education.

70 Notably amongst better forecasting models is the Artificial Neural Network (ANN) model. The
71 model has been tried and tested to provide best forecast with the minimum possible error (Hadrat
72 YM, Eshun Nunoo Isaac K, and Effah Sarkodie E, 2015). Therefore, a forecast of the
73 university's growth shall be made using the Artificial Neural Network (ANN) model with
74 admissions data from the College of Technology Education, Kumasi.

75 **2.0 Literature on Artificial Neural Network (ANN)**

76 Artificial Neural Network (ANN) model is currently a popular forecasting technique in several
77 fields such computer science, engineering, economics, finance etc. ANNs have been used to
78 predict variables such as bond prices, exchange rates, stock returns, money supply, electricity
79 demand, construction demand, inflation rates and it forecasts have proven worthwhile etc
80 (Fernandez et al, 2000;Redenes& White, 1998;etc). The artificial neuron is a mimic of the
81 natural human neuron. The human brain, for example, contains approximately ten billion (10^{10})
82 neurons, each connected on average to ten thousand (10^4) other neurons, making a total of 10^{15}
83 synaptic connections (Larose, 2004).



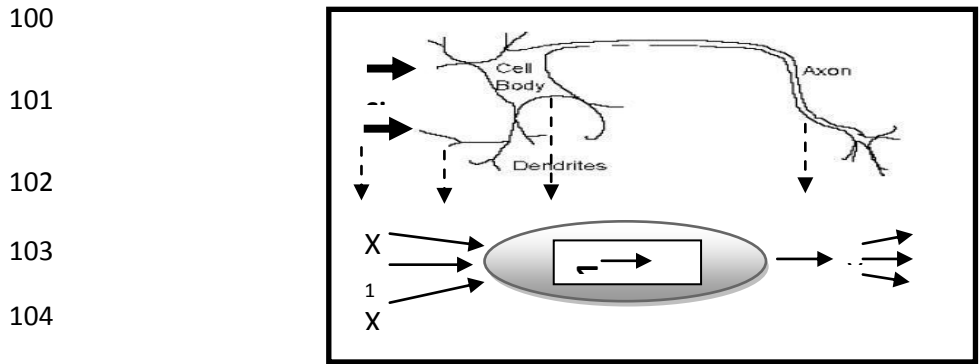
89 **Figure 1.**Biological Model of Human Neuron (artist's conception)

90 The human brain learns by experience: It receives information and recognizes the pattern; the
91 brain then generalizes and is able to predict based on the information received. It is this way of
92 information processing by the brain that the ANN model tends to mimic. Although ANN models
93 are too far from the way the human brain performs, by mimicking the basic features of the
94 biological neural networks, they have succeeded in doing certain jobs very well (Moshiri, 1997).

95

96

97 A mimic of the way biological networks perform may appear more than complex. Artificial
 98 neural networks represent an attempt at a very basic level to imitate the type of nonlinear
 99 learning that occurs in the networks of neurons found in nature.



105 **Figure 2.**Natural and artificial neurons (a relational sketch)

106 As shown in figure 2, a natural neuron uses the synapses located on the dendrite to gather inputs
 107 (signals) from other neurons and combines the input information, generate a nonlinear response
 108 (“firing”) when some threshold is reached, which it sends to other neurons using the axon.
 109 Similarly, the artificial neuron collects inputs (x_i) from input neurons, attaches weights and
 110 combines them through a combination function such as summation (\sum). It is then activated by a
 111 function (usually nonlinear) to produce an output response (y), which is again sent to other
 112 neurons.

113
 114
 115 **3.0 Model Specification**

116 The main objective of the study is to forecast University growth using the ANN method. The
 117 Neural Autoregressive (NAR) model is specified based on the Autoregressive (AR) five (5) in
 118 terms of the lag length and variables used. The ANN model is constructed with twenty (20)
 119 hidden layer units and one (1) output layer unit. The ANN transfer function is also the tan-
 120 sigmoid function in the hidden units and the linear function in the output unit. The model is
 121 specified as:

122 **NAR (5):**
$$F_h = b_h + \sum \beta_{hj} \left(\text{tansig} \left(b_j + \sum \gamma_{ji} p_{t-i} \right) \right), \quad i = 1, \dots, 12 \quad j = 1, \dots, 20 \quad h = 1 \quad (1)$$

123 where p_{t-i} are past values of the dependent variable, γ_s and β_s are hidden and output layer
 124 weights respectively and the (\mathbf{b}_s) are the biases.

125 **4.0 Estimation and Forecasting**

126 The model uses the data up to 2013/2014 academic year for estimation and uses 2015/2016 for
 127 future forecasts. This was to ensure that at least the 2015-2018 forecasts are compared to their
 128 respective actual values.

129 **5.0 Data type and Source**

130 The study uses time series data (1993-2015) on admissions obtained from the college of
 131 Technology Education, University of Education, Winneba.

132
 133 **6.0 Results and Discussion**

134 The table below shows the forecast results of the Neural Autoregressive (NAR) which represents
 135 the ANN. For comparison sake one traditional econometric model (AR) which possess similar
 136 structure like the NAR is also estimated and used. From the table it could be observed that both
 137 the AR and the NAR provided different forecasts. However, forecasts of the Nar were closer to
 138 the actual for the various years. The AR had mean forecast error of 22.58 % while the NAR
 139 had a mean forecast error of 5.89 %.

140 **Table 1. The Summary of Forecast Results**

141

<i>Year / Month</i>	<i>AR (12) Forecasts</i>	<i>% FE(AR)</i>	<i>NAR (12) Forecasts</i>	<i>% FE (NAR)</i>	<i>ACTUAL</i>
2015/16	2341	-7.69	2598	2.44	2536
2016/17	3997	10.75	3633	0.67	3609
2017/18	4456	64.67	3100	14.56	2706
2018/19	5421	****	3564	****	****
		22.58*			5.89*

142 ****Figures that are yet to be determined. *Average percentage forecast error that excludes figures of
 143 2019. Source: Author's construction 2018

144
 145 The NAR forecasts indicates that the College of Technology Education, Kumasi would double
 146 its admission figure by 2018/19 academic year. That is by students size the college of
 147 Technology Education is expected to grow rapidly as per the annual forecasts provided by the
 148 NAR.

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150 **7.0 CONCLUSION AND RECOMMENDATIONS FOR POLICY**

151 It is self-evident from the results that the College of Technology Education, Kumasi is growing
152 in terms of students numbers. The growth moreover looks very rapid as indicated by the figures.
153 This implies that the products (programmes) of the College of Technology Education, Kumasi
154 are increasingly demanded by prospective University graduates. It is also an indication that the
155 facilities of the college in terms of lecture halls, residential facilities, library and ICT have to be
156 expanded to meet the increasing number of students in the college. Further, the college has to
157 increase both academic and non-academic staff. this will prevent high student-lecturer ratio.

158

159 **9.0 FOR FUTURE STUDIES**

160 Future studies should be done on Faculty basis. This will enable comparative growth amongst
161 the various faculties in the college and by that provide Faculty based needs accordingly. If
162 possible, program based analysis would be very beneficial.

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