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Original Paper

On Analysis and Evaluation for Predicting Students' Academic Performance GPA Considering an Engineering Institution (Neural Networks' Modeling Approach)

Hassan M. H. Mustafa[1] & Hanafy M. Ali[2]

[1] Faculty of Engineering, Minia University, Egypt

[2] Banha University, Egypt

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Abstract

Predicting students' performance is one of the most important topics for learning contexts such as schools and universities, since it helps to design effective mechanisms that improve academic results. Educational Institutions face numerous challenges today in providing quality and student-centric education to Students Individual learners prefer their own strategies originated from diverse learning styles. Learning style models may include collective strategies for mental, emotional, and physiological components. On the basis of such components, this piece of research suggests a specific quantified learning style preferred by learners in engineering education. By following average learners' achievements (marks) at specific courses closely related to the specialization, interesting analytical results for Grade Point Average (GPA) evaluation are obtained. Moreover, an ANN model with supervised learning is presented to simulate diverse learning styles performance. Accordingly, optimal guided advise is suggested in fulfillment of probabilistically best GPA of graduated engineers. Obtained simulation results are well supported by the findings of experimental case study.

Keywords

Artificial Neural Networks, Learning Style Model, Individual differences, Prerequisite Courses, Engineering Education

1. Introduction

Universities play a remarkable role in the development of a country by producing skilled graduates for the country. Graduation rate is low as compared to the enrollment rate in the higher education institutions. Academic failure is main reason for non-degree completion (Ahmad & Shahzadi, 2018).

Generally, the field of learning is currently affected by international technologically growing Community. In recent time, the need for the application of machine learning in the educational frontier has become crucial. Accordingly, most educationalists including educational administrators and researchers have adopted various machine-learning methods aiming to improve students' retention, predict students' performance, mitigate students' dropout rate as well as position them to make better decisions in curriculum design and admission policy in their higher education institutions (Akpofure, 2020). Interestingly, as fhe goal for contributing improvinent and success pf higher education quality, there are various reasons/ factors for enhancement "students' academic performances based on the acheived grades at previous years" studied courses. during the of human capital creation is an issue of continuous analysis (Albarka, 2019).

Specifically, this research considers ANN modelling to support recent increasing attention paid by many educationalists regarding students' characteristics such as learning styles, their impact on educational systems' performance. Additionally, they now recognize that conventional ways used to perform forecasting of educational systems' performance are facing increasing challenges as how students' individual characteristics can be supported by learning systems. Systematic investigations to face such challenges are motivated by educational theories, which make learning easier for students and thus, improve their learning performance (2007). This paper considers courses at engineering colleges, which fit the individual characteristics of students to improve Students' Grade Point Average (GPA). In other words, enhancement of end educational objectives (GPA) is motivated by individual students' teaching styles (preferences) adopted with their own diverse learning styles. Obviously by better matching of students' learning preference (style) associated with teaching style (courses and methodology), would inevitably improve GPA. Herein, a modified approach is presented for better forecasting of Students' GPA at engineering education. Individual learner style model may include collective strategies for mental, emotional, and physiological components (Keefe, 1987). On the basis of such components, preferable learning styles adopted by students at engineering education are quantitatively measured. Directing engineering learners towards optimal choice for one of diverse engineering specializations is an interesting and challenging educational issue. Recent educational findings reveal increased understanding of the importance of Data-driven decision-making (DDDM) (2009). Accordingly, (DDDM) discipline has been implemented to improve students' achievement. That is, by monitoring data about average students' achievements (marks) at two sets of prerequisite subjects, interesting analytical results for (GPA) evaluation are obtained. Considering two sets of prerequisites are: (Mathematics and physics) & (Engineering drawing, and Mechanics). Both data sets are used for implementing DDDM discipline, which associate closely to electrical and mechanical Engineering specializations respectively.

According to many educational experts; Artificial Neural Network (ANN) models are highly recommended for predicting student grade point averages rather than other statistical models (Gorr, Nagin, & Szczypula, 1994). Realistic simulation using ANN with (supervised learning paradigm) is suggested to measure quantitatively diverse learning styles performance with dependence upon learning rate values. Accordingly, by motivation of his or her preference (learning style model) optimal directing advise is provided to students in fulfillment of probabilistically best GPA of graduated engineers. Interestingly, obtained simulation results are supported well by experimentally presented case study statistical analysis of students' individual differences. Furthermore, an ANN feed-forward model has been presented for recognizing students' learning styles (Villaverde, Godoy, & Amandi, 2006). Therein, adaptation of courses' content to individual students' characteristics (learning styles) is suggested to enhance end educational objectives (learning performance).

More recently, another novel approach has been suggested for predicting students' performance. It is based on six variables observed at high school adopting data mining technique. Those variables include: grade point average (GPA), standardized test scores, age, gender, credit hours enrolled, and current college GPA (Mohammed, 2010). Interestingly, presented ANN model gives attention to simulation of student's personality indicator that influences his/her way of learning after Myers-Briggs Type Indicator (MBTI) (Briggs Myers, 1962). That MBTI is based on Jung's theory of psychological types (Jung, 1923). According to one dichotomy flowing MBTI (extroversion/introversion), presented ANN learning model is realistically referred to orientation of students' individual characteristics and personality. Conclusively, interesting comparative results for learning performance of mechanical Versus electrical specializations are presented. Moreover, prediction of GPA values for any specialization seems to be estimated well by comparison of obtained simulation results with average marks of specified prerequisite subjects (at presented case study).

The rest of this paper is organized as follows. In the next section, a general educational model based on ANN is presented along with mathematical descriptions for two diverse neural network learning paradigms. Furthermore, brief mathematical analysis for students' individual differences is introduced. At the third section, complete sets of obtained results are given, including computer simulation results after running the suggested ANN model. Additionally, revealed findings after experimental measurements of the case study are presented. At the fourth section, conclusion and suggestions for future work are introduced. Finally, the paper is appended by three appendices (I, II, and III). APPENDIX I includes graphical statistical experimental results for GPA. APPENDIX II provides score results for two sets of prerequisites. At APPENDIX III, a simplified macro level flowchart describing algorithmic steps for running the suggested computer program of ANN learning model.

2. Generalized Model of Education

Referring to Figure 1 shown in below, it depicts an illustrated generalized simple block diagram for an ANN learning/teaching process model. Which realistically presents a comprehensive simulation process for the two diverse learning paradigms. Both concerned with interactive tutoring /learning process as well as self-organized learning. The first paradigm is concerned with classical (supervised by tutor) learning observed at our classrooms (face to face tutoring). Accordingly, this paradigm proceeds interactively via bidirectional communication process between a tutor and his learner(s) (Hassan, 2008). The second paradigm performs self-organized (unsupervised) tutoring process (Fukaya, kitagwa, & Okabe, 1987; Haykin, 1999; Hebb, 1947).

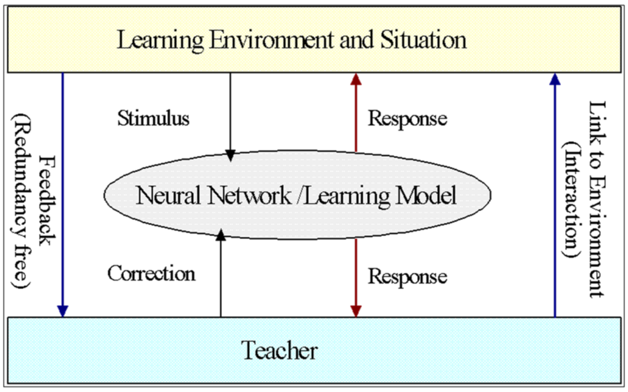

Figure 1. Illustrates Generalized Simple Block Diagram for Interactive ANN Model Teaching / Learning, Adapted from Mustafa and Ayoub (2009)

Regarding to the above presented ANN model, Figure 2 introduces realistically the two mathematical formulae for both diverse learning paradigms. In more details, firstly is concerned with classical supervised by a tutor observed in our classrooms (face to face tutoring). Accordingly, this paradigm proceeds interactively via bidirectional communication process between a teacher and his learners (supervised learning).

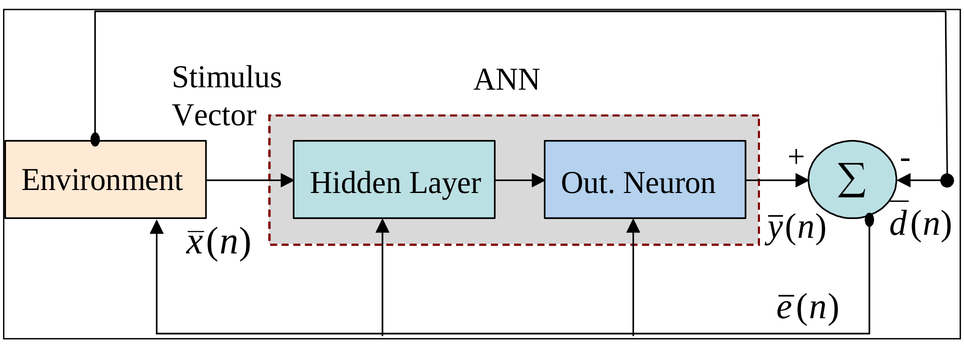

Figure 2. Detailed of ANN Block Diagram Simulating Two Diverse Learning Paradigms

The error vector $\bar{e}(n)$ at any time instant (n) observed during learning processes is given by:

$$\bar{e}(n) = \bar{y}(n) - \bar{d}(n) \tag{1}$$

Where $\bar{e}(n)$ … is the error correcting signal that adaptively controls the learning process,

$\bar{y}(n)$ … is the output obtained signal from ANN model, and $\bar{d}(n)$ … is the desired numeric value(s).

Moreover, the following four equations are deduced to illustrate generalized interactive learning process. These equations are commonly well valid for either guided with a teacher (supervised) or self-learning without a teacher (unsupervised):

Equation (2) considers the scalar product of two vectors the input vector (X) and internal weight vector (W) computed at the time instant (n). It is noticed that both are associated to neuron (k), and each has the same dimension (number of vector's components). The output of this neuron is given by equation (3). Which originated from the hyperbolic tangent function deduced from classical sigmoid function. Equation (4) computes the error value which controls the guided learning process (supervised with a teacher) and so it does not valid in case of unsupervised (learning without a teacher). Additionally, the synaptic dynamical changes at two subsequent time instances (n) & (n+1) are given by learning law given by equation (5).

$$V_k(n) = X_j(n) W_{kj}^T(n) \tag{2}$$

$$Y_k(n) = \varphi(V_k(n)) = (1 - e^{-\lambda V_k(n)}) / (1 + e^{-\lambda V_k(n)}) \tag{3}$$

$$e_k(n) = \left| d_k(n) - y_k(n) \right| \tag{4}$$

$$W_{kj}(n+1) = W_{kj}(n) + \Delta W_{kj}(n) \tag{5}$$

Where X is input vector and W is the weight vector. φ is the activation function. Y is the output. e_k is the error value and d_k is the desired output. Note that $\Delta W_{kj}(n)$ is the dynamical change of weight vector value. Above four equations are commonly applied for both learning paradigms: supervised (interactive learning with a tutor), and unsupervised (learning though student's self-study). The dynamical changes of weight vector value specifically for supervised phase is given by:

$$\Delta W_{kj}(n) = \eta e_k(n) X_j(n) \tag{6}$$

Where η is the learning rate value during the learning process for both learning paradigms. At this case of supervised learning, instructor shapes child's behavior by positive/ negative reinforcement Also, Teacher presents the information and then students demonstrate that they understand the material. At the end of this learning paradigm, assessment of students' achievement is obtained primarily through testing results.

However, for unsupervised paradigm, dynamical change of weight vector value is given by:

$$\Delta W_{kj}(n) = \eta Y_k(n) X_j(n) \tag{7}$$

In equation (7), it is noticed that $\{e_k(n)\}$ given in the supervised learning equation (6) is obviously replaced -when considering- self-organized / unsupervised learning by $\{Y_k(n)\}$ at any arbitrary time instant (n) during the learning process.

2.1 Students' Individual Differences

Experimental analysis and evaluation of observed students' different achievements might be measurable either using a set of comparative performance curves or statistically. Similarly, simulation results of students' individual differences might be evaluated using learning performance curves or statistical measurable parameters (Hassan, 1998, 2004). In this subsection, mathematical formulation is adopted so that deferent learning response (convergence) times of individual students are comparable (on the average). More specifically, referring to previously published research work (Hassan, 2005; Tsien, 2000, 2001), individual learning diversity is considered based upon Hebb's rule of coincidence detection (Haykin, 1999; Tsien, 2001). Therein, the angle detected between synaptic (training) weight vector and an input (stimulus) weight vector denoted by α. Ideally, at one extreme, the best students' learning achievement attained if α =0, i.e. complete coincidence detection learning occurs. Consequently, in case if (tan (α) equals zero), that results in gain factor λ value equals infinity as ($\lambda = \frac{1}{\tan\alpha}$). Conversely, on other extreme value, impossible coincidence detection learning occurs, when the value of angle α equals Π/2. In other words, students' learning achievement equals zero as the value of tan (α) equals ∞. Furthermore, by referring to Hassan (2004), normalized students' learning achievement ranging between two extremes (ideal till zero), is given by the derived equation of Hebb's rule as follows:

$$y = (1 - e^{-\lambda t}) \tag{8}$$

This equation performs analogously, in agreement with gain factor (slope) presented by classical sigmoid function given by the equation:

$$y(t) = \frac{1}{1 + e^{-\lambda t}} \tag{9}$$

More precisely, equation (8) performs closely similar to odd sigmoid function given as:

$$y(t) = \frac{1 - e^{-\lambda t}}{1 + e^{-\lambda t}} \tag{10}$$

For $0 \le t \le \infty$

Following above equation (8), at Figure 3 three performance learning curves are mathematically presented considering three different gain factor values (λ_1 & λ_2, and λ_3). These three diverse curves based on two memorizing and forgetting learning factors (Haykin, 1999) resulting in corresponding values of tan (α) ranging from zero to ∞. So, they illustrate-on the average-three diverse students' individual differences as follows. Normal individual level of learning performance is given by equalized forgetting and learning factors (angle α = Π/4), it is represented by curve (Y_2) (Hassan, 2004). However, curve (Y_1) represents lower level of individual learning performance. This indicates that value of angle between synaptic weight vector and an input vector given by (α < Π /4). Conversely, the curve (Y_3) indicates better level of individual learning performance that exceeds the normal level of learning at curve (Y_2) (Π /4 < α). As an illustrative example, at Figure 3 in fulfillment of desired achievement (normalized) value (Y=0.9), three different cases (shown as three learning curves denoted by Y_1&Y_2 and Y_3). The three-learning convergence (response) times (t_1 & t_2, and t_3) have corresponding to values of relative time units (2 & 2.6, and 3.5) as suggested at Mustafa and Ayoub (2009). They are corresponding to three performance learning curves denoted by (Y_1 & Y_2 and Y_3) respectively.

$$y = (1 - e^{-\lambda t})$$

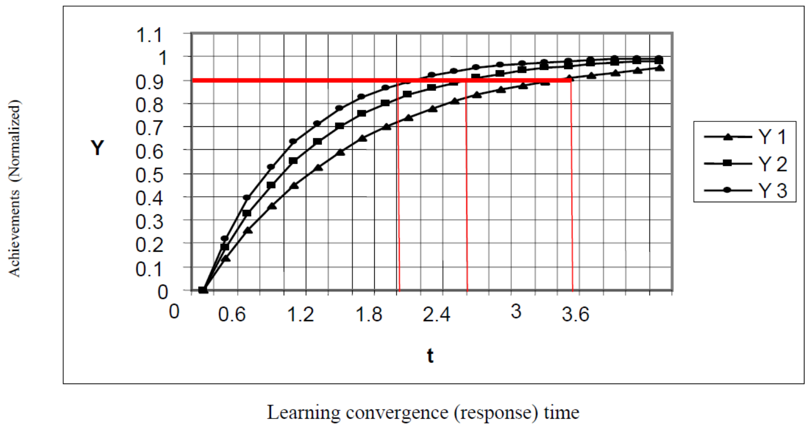

Figure 3. Illustrates Three Different Learning Performance Curves Y_1&Y_2 and Y_3 that Converge at Time t_1, t_2, and t_3 Considering Different gain Factor Values λ_1 & λ_2 ,and λ_3, Respectively, Adapted from Hebb (1947)

3. Results

In this section obtained simulation results are presented after running of a computer program with a simplified flowchart shown at APPENDIX III. Considering (MBTI) the following subsections introduce simulation of students' individual characteristics based on the dichotomy (extroversion/introversion). An extrovert attitude represents interaction with learning environment is relevantly simulated by learning rate (subsection 3.1). Whereas learner's introvert's preferred focus is on his/her own thoughts and ideas (Gain factor). Interestingly, as neurons' number contributing to learning process varies inside brain, that is analogously represents internal (individually) learner's brain state (introvert attitude). So, this number implicitly simulates different individual student's needs and characteristics. Such as prior knowledge, motivation, cognitive traits, and learning styles (subsection 3.2).

3.1 Simulation of Students' Extrovert Attitude (Learning Rate)

However, learners have different needs and characteristics such as prior knowledge, motivation, cognitive traits, and learning styles. Recently, increasing attention is paid to characteristics such as learning styles, their impact on learning, and how these individual characteristics can be supported by learning systems. These investigations are motivated by educational theories, which argue that providing courses which fit the individual characteristics of students makes learning easier for them and thus, increases their learning progress. It worth noting that learning performance associated with diverse learning / teaching environments comprise the dichotomy (extroversion/introversion). Both represent external and internal environmental learning conditions, including: teaching methodology, adopted educational technology, learning styles, prior knowledge, motivation, and cognitive traits. At Figure 4 in below, the effect of continuous increase of the learning rate (starting from **η =0.1** till **η =0.7**) on students' achievements (on the average), is graphically represented.

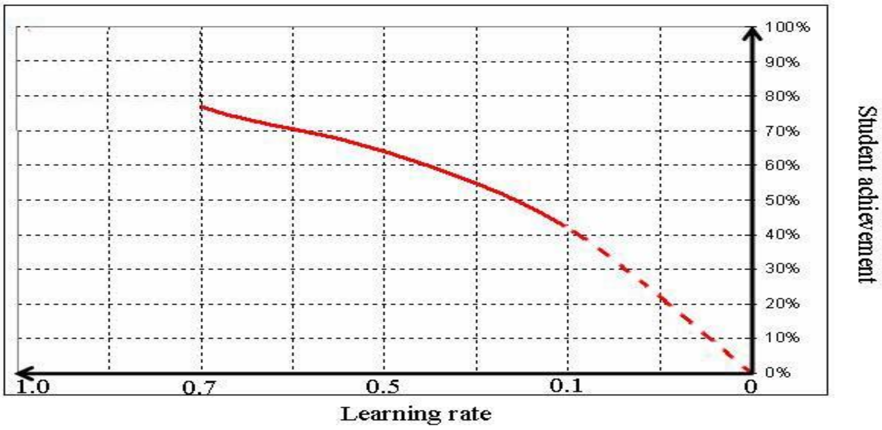

Figure 4. Illustrates the Effect of Continuous Learning Rate Values η Increase on Average Students' Achievement

At Figure 5, illustrates statistical distribution for students' normalized achievements. The shown bell shape probabilistic curve indicates similarity of the distribution to be Gaussian (natural). Considering two different extrovert attitudes represented as external environmental learning conditions (learning rates **(η =0.1**) & **(η =0.5**)). Accordingly, learning rate (**η =0.1**) seems relevant to simulate a week case of educational environmental conditions. However, learning performance according to higher rate (**η =0.5**) simulates a case of environmental conditions with better applicable educational methodology. Interestingly, obtained results after computer running with learning rate **η =0.5** agrees with experimentally obtained case study results. Agreement between both (simulation and experimental) sets of tabulated results is clearly shown at Tables 1 & 2.

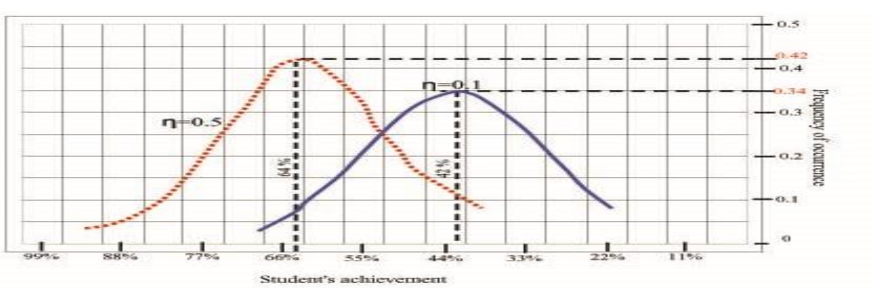

Figure 5. Illustrates Simulation Results Presented by Statistical Distribution for Students' Achievements Versus the Frequency of Occurrence for Various Achievements Values, at Different Learning Rate Values (η =0.1& η =0.5)

Table 1. Simulation Results for Students' Grade Point Average (η =0. 5)

Poor 35%	Fair 50%	Good 65%	V.G. 75%	Excel. 90%
0.06	0.25	0.4	0.24	0.05

3.2 Simulation of Students' Introvert Attitude (Gain Factor)

Referring to Myers-Briggs Type Indicator (MBTI) students' introvert suggested herein to represent individual student's characteristics and personality. That is simulated by various gain factor (slope) values and different neurons' number as well, contributing to the learning process.

In Figure 6, a set of performance curves is shown for general normalized ANN learning model, It represents considers various gain factor values (denoted by λ parameter). By changing values of this parameter, results in various response time (speeds) in reaching optimum (desired) achievements in accordance with the following equation:

$$y(n)= (1-\exp(-\lambda_i(n-1)))/ (1+\exp(-\lambda i(n-1))) \quad (11)$$

where λ_i represents one of gain factors (slopes) for odd sigmoid function given by equation (10) and n represents the response time expressed in number of cycles (epochs).

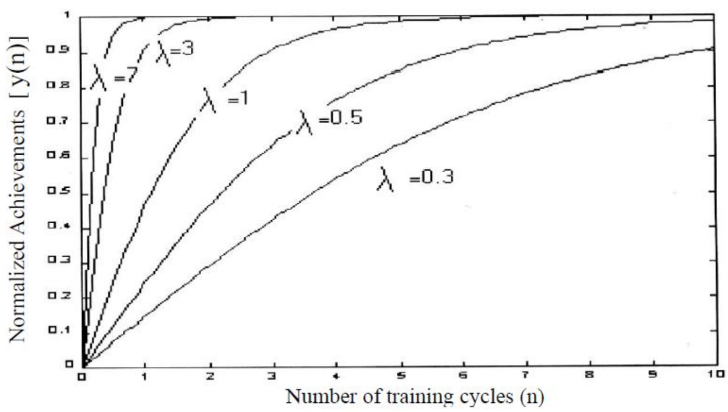

Figure 6. A Set of Learning Performance Curves of Model with Various Values of Gain Factor (λ) Versus Learning Response Time

Taking into consideration various number of neurons contribute to the learning process, internal learners inside brain state is represented by this number realistically. Accordingly, students' individual characteristics, such as his/her prior knowledge, motivation, cognitive traits, and learning styles are all simulate realistically by various neurons' number, along with different gain factor values. Interestingly, as the number of neurons increases, the learning time response decreases. Obviously, that implies improving of student's learning performance as the speed needed for reaching optimum achievements (desired) increases. As well, increase of gain factor values results in improving of student's learning performance. That is well illustrated at Figure 7 in below.

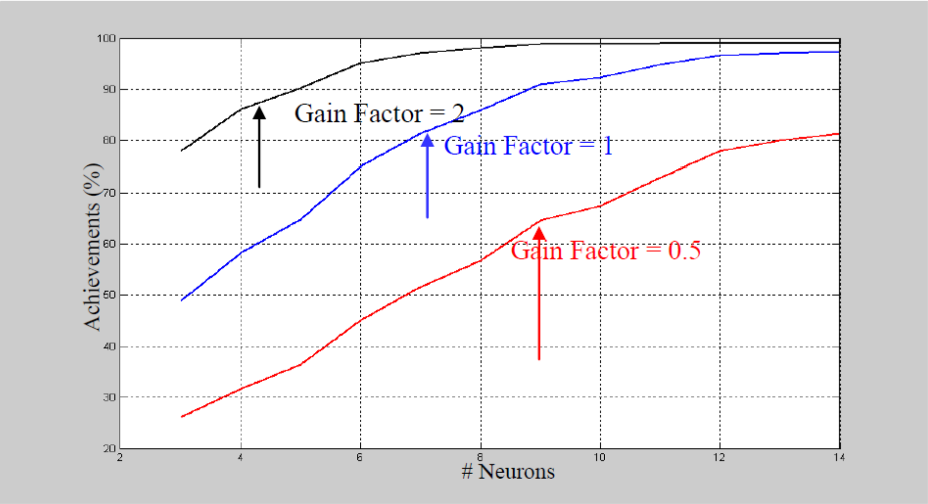

Figure 7. Illustrate Students' Learning Achievement for Different Gain Factors and Various Number of Neurons (Measured for Learning Rate Value = 0.3, and after Number of Training Cycles = 300)

3.3 Experimental Results (For the Case Study)

This subsection presents experimental results obtained given in tabulated forms (Tables 2, 3, 4, and 5). In Tables 2 & 3, Normalized distribution values for Students' GPA, and Students' achievements at two prerequisite courses are given respectively. Correlation Coefficients of Electrical Engineering prerequisites are shown at Table 4, Moreover these Coefficients for Mechanical Engineering are given at Table 5.

Table 2. Normalized Values of Students' GPA Referring to Appendix I

Grade specialization	Poor	Fair	Good	Very Good	Excellent
Electrical	0.08	0.12	0.44	0.28	0.08
Mechanical	0.08	0.11	0.27	0.43	0.11

Table 3. Normalized Distribution Values for Students' Achievements at Two Prerequisite Courses Referring to Appendix II

Grade specialization	Poor	Fair	Good	Very Good	Excellent
Electrical	0.08	0.2	0.32	0.28	0.12
Mechanical	0.08	0.16	0.27	0.38	0.11

The following Tables 4 & 5, presents results of statistical analysis for correlation coefficients of suggested case study:

Table 4. Correlation Coefficients of Electrical Engineering Department

Variables	Math. /GPA	Phys. / GPA	Prerequisite / GPA
Correlation value	0.61	0.65	0.66

Table 5. Correlation Coefficients of Mechanical Engineering Department

Variables	Mechanics / GPA	Eng. Drawing /GPA	Prerequisite / GPA
Correlation value	0.5	0.57	0.59

3.4 Analysis of the Results

The results of the experimental work showed considerably high correlation between learning style and student results. Tables 4 & 5 depict this correlation. Moreover, Tables 2 & 3 show considerably good results for students who properly chosen their majors according to the results of the prerequisites. That means the proper choice of specialization that fits high marks in the prerequisite courses leads to better grade point average. The higher marks student achieves in the prerequisites, the better are the final student GPA.

The simulation technique using artificial neural networks (ANN's) produced results that are in good agreement with the results produced by the case study. The input to the network is the marks obtained in the prerequisites (learning style) and the output is the GPA achieved. Figure 7 shows the effect of the gain factor and the learning rate on the results.

4. Conclusion

1- Students who might wish to attain better learning performance have to follow up Data-driven decision-making in accordance with their achievements in the prerequisite courses.

2- Considering the learning style that incorporates various student characteristics can greatly improve learning outcomes. Directing learners to proper specialization in view of their achievements in the prerequisite courses is a promising trend for achieving better learning performance results.

3- ANN modelling results in very interesting results in the field of learning and learning styles.

4- For future extension of presented research work, it is highly recommended to consider more elaborate investigational analysis and evaluations for GPA phenomena. That is by considering other effective parameters on students' learning performance, rather than prerequisite courses, such as age, gender, credit hours enrolled, etc.

5- Moreover, obtained results are realistically applicable for other engineering specializations such as chemical, architect, and civil.

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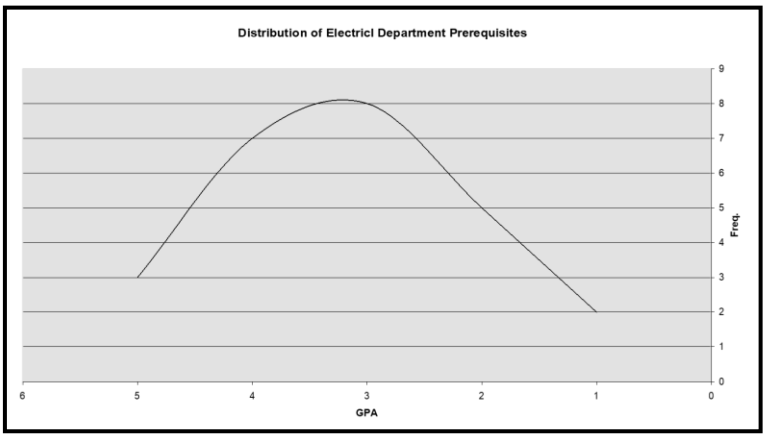
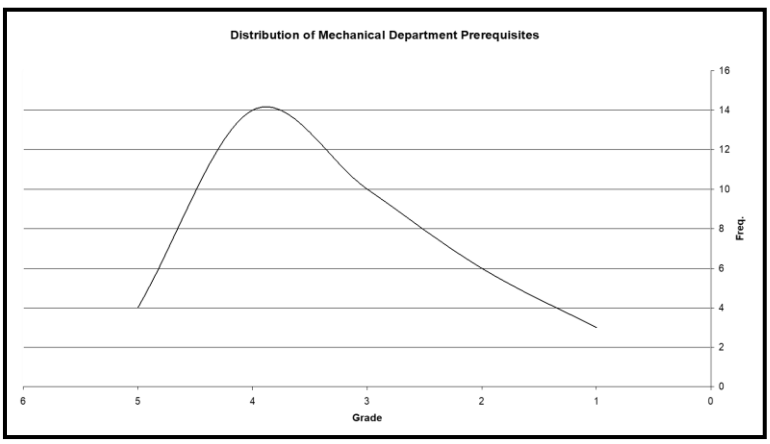
APPENDIX I

The figure below illustrates two distributions of experimentally obtained students' GPA results for Electrical and Mechanical Majors presented at A, B, respectively.



(A)



(B)

APPENDIX II

The shown figure in below presents a simplified macro level flowchart describing in brief algorithmic steps for realistic simulation learning program using Artificial Neural Networks. After running that program, three graphs time response results are obtained as shown at Figure 8.