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A Neural Network Students' Performance Prediction Model (NNSPPM)

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***Abstract* - In the academic industry, students' early performance prediction is important to academic communities so that strategic intervention can be planned before students reach the final semester. This paper presents a study on Artificial Neural Network (ANN) model development in predicting academic performance of engineering students. Cumulative Grade Point Average (CGPA) was used to measure the academic achievement at semester eight. The study was conducted at the Faculty of Electrical Engineering, Universiti Teknologi MARA (UiTM), Malaysia. Students' results for the fundamental subjects in the first semester were used as independent variables or input predictor variables while CGPA at semester eight was used as the output or the dependent variable. The study was done for two different entry points namely Matriculation and Diploma intakes. Performances of the models were measured using the coefficient of Correlation R and Mean Square Error (MSE). The outcomes from the study showed that fundamental subjects at semester one and three have strong influence in the final CGPA upon graduation.**

Keywords – Prediction; Engineering fundamentals; academic performanc;, ANN model.

I. INTRODUCTION

Students' performance prediction seemed to be of dire important to most academic institutions of higher learning. This led to many researches in prediction work that included students from different background and academic areas such as MBA students, nursing students and that of Computer background students. However the predicator variables or the independent values were mostly dealt with demographic profiles. Data collected were mostly from survey forms based on the students' former background education, residency region, gender and Scholastic Aptitude Test (SAT) scores. Statistical Package for Social Sciences (SPSS) has been very popular indeed among past researchers that utilizes Linear Regression, Data Mining Technique and Decision Trees. Artificial Neural Network (ANN) came into the picture for students' performance prediction quite recently [1, 2]. These NN models also considered demographic background as inputs to the model. The study presented herewith however only considered the Grade Point (GP) of fundamental subjects scored by the students at first semester as inputs without considering their former background education or family background. Once the students are accepted into the Program based on merits set by the Faculty of Electrical Engineering UiTM, then every help should be offered to help students to perform in their study before graduation so as to provide students with basic keys into their future lives. Thus such novel effort from academic lecturers is in line with the philosophy of the Universiti which states that every individual student has the ability to attain excellence through the transfer of knowledge and assimilation of moral values so as to become professional graduates capable of developing knowledge, self, society and nation [3-5]. This paper describes the development of ANN to predict performance of bachelor degree engineering students based on intakes from Matriculation and Diploma level entries.

II. DATA COLLECTION AND NEURAL NETWORK MODEL DEVELOPMENT

Data of Matriculation and Diploma level intake students were compiled in Excel format which included student identity number, gender, CGPA at semester eight, GP of subjects scored at semester one and semester three for Matriculation students. As for the Diploma students the Grade Points of subjects start at semester three onwards. Such Diploma students have a direct entry into semester three of the Program due to credit exemption for courses in semester one and two.[6] Such data was collected from Students Information Management System (SIMS) in UiTM developed to store students' academic information until graduation. Such software helps academic advisors to keep track on students' achievement right from the very start of Program.

The most important data is the identity number of students as that number will be traced to get final CGPA at semester eight. There were a total of 391 matriculation students from three batches namely from July 2005, 2006 and 2007. The Diploma students totalled up to 505 from July 2006, 2007 and 2008. There were seven (7) subjects attempted by students at semester one but for this study we omitted subjects like Co-curriculum and Laboratory work as input or independent variables. At semester three we again omitted Laboratory work and Tamadun Islam as such subjects do not form basic foundation to higher courses along the path of program.

III. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) is a biological inspired intelligent technique that is generally made of a number of highly interconnected processing elements units or nodes whose functionality is loosely based on animal neuron. The processing ability of the network is stored in the inter-unit connection strengths, or weights, obtained by a process of adaptation to, or learning from a set of training patterns. Neural Network (NN) can be used to predict future events based on historical data. Data history performance of past Electrical Degree students were used to train in order to get the targeted output or final CGPA8.

A. NN architecture

ANN consists of three layers namely input, hidden and output layers. The hidden layer may consist of one or two hidden layers and theoretically there is no basic research on how many hidden layers are adequate for such network. The hidden layers actually determine the size of the network which implies that the bigger the size of the network, the more time will be consumed to train the network [7].

In the hidden layers, the output of a layer becomes the input to the following layer. The transfer function of a neuron converts the input to the output of the neuron. Multilayer neural networks are quite powerful tools used in solving many different problems compared to single layer.

B. Data Pre-processing

The data collected was divided into training and testing data. Data was commonly divided into 50/50 or 60/40 or 70/30 in terms of percentage of training and testing purposes in the simulation work. In this paper, the data was divided into 70/30 ratio as such division gave the highest coefficient of correlation, R. Then the data was normalized between 0 and 1 or -1 to 1.

C. Learning Algorithm

Learning is actually the process of adaptation or modifying the connected weights between neurons as a result of the mismatch between the targeted output and the desired output of such NN in response to the input fed at the input layer[7]. There are many techniques commonly used in the learning algorithms which include Gradient Decent Backpropagation, Radial Basis Function and the fastest known technique called Levenberg –Marquardt (LM).

Thus NN is designed using the fastest technique so as to get the minimum error between targeted and predicted value of output. There is no basic rule of choosing the learning rate, the momentum rate and the number of hidden layers in any network. It is rather trial and error process and up to the designer of the network. The Learning Rate (0-1) helps to converge the ANN training process while the Momentum Rate (0-1) helps to accelerate the training process in the simulation. The learning algorithms used in this study was LM which seemed to be the fastest training algorithms with memory reduction features [8, 9].

The activation or transfer function used in the hidden layers are log sigmoid or "logsig" while in the output layer is mainly pure linear or "purelin". The training will stop when Minimum Square Error or MSE is obtained, which is the minimum error between targeted and predicted. MSE is given by:

$$MSE = \frac{1}{n}\sum_{i}^{n}(y_p - y_i)^2 \tag{1}$$

The initial model was firstly trained and tested with 391 data for Matriculation students. The input parameters only considered Grade Point (GP) of subjects scored at semester one while the output is CGPA8 [5]. The subjects considered include Circuit Theory, Fundamental Electronics, Signals and Systems, Mathematics Communication Theory and CGPA1. Subsequently, the model was further tested with input parameters by considering GP of subjects attempted at semester three for the same 391 students. From the earlier findings, six inputs gave better results (minimum MSE) than three inputs therefore the following model will only discuss six input parameters instead of three [5]. The model was further extended with another set of 505 data of Diploma students that joined at semester three of the Program whereby such students sat for the same subjects as that of Matriculation students. Such Diploma students are given credit exemption for subjects in semester one and two.

Table I and II show the input and output parameters of NN and the NN properties of the developed Model respectively.

TABLE I. INPUT AND OUTPUT PARAMETER

Input Parameters	Output Parameter
Digital Systems Signal and Systems 2 Mathematics 2 Materials CGPA3 English 1	CGPA8

From Table I, the subjects chosen as inputs at semester three included Digital Systems, Signals and Systems 2, Material Science, Mathematics 2, English 1 and CGPA3. From Table 2, the LR was 0.6 and MR was 0.95 for both models DataMaxSem3 and DataDipSem3. It was found that Coefficient of Correlation, **R=0.9774** and **MSE=0.0409** for Matriculation students and **R= 0.9245** and **MSE=0.0488** for Diploma students.

TABLE II. NN MODEL CONFIGURATION

Items	DataMaxSem3 (6 inputs)	DataDipSem3 (6 inputs)
Network Configuration	'logsig', 'logsig','purelin' [17, 35, 1]	'logsig', 'logsig','purelin' [17, 35, 1]
Learning Rate	0.6	0.6
Momentum Rate	0.95	0.95
Training Technique	Lavenberg Marquardt (lm)	Lavenberg Marquardt (lm)
Training Goal	1.00E-03	1.00E-03
Coefficient of Correlation	0.9774	0.9245
Training Patterns	273	355
Testing Patterns	118	150
No. of Variables	6	6
Mean Square Error (MSE)	0.0409	0.0488

IV. RESULTS AND ANALYSIS

Fig. 1 and 2 show the results obtained for the matriculation students (Semester one). Fig. 1 shows the Performance at minimum Mean Squared Error (MSE) for the Matriculation students. From Fig. 1, it can be seen that the best validation performance was at **MSE= 0.05544** [5].

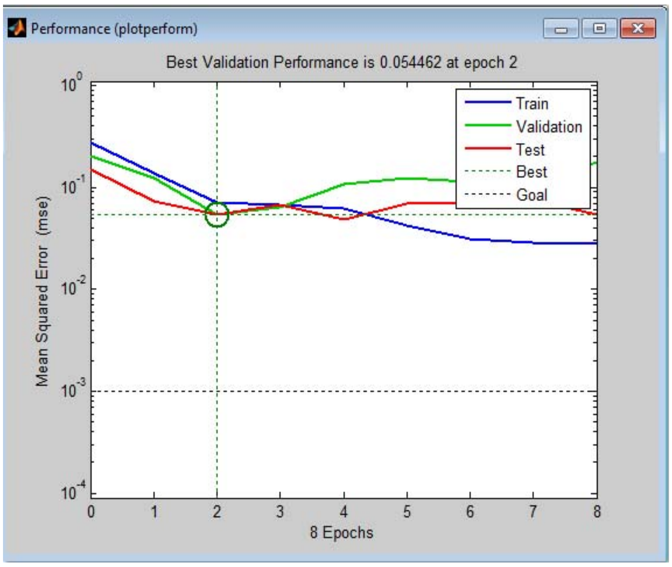

Fig. 1. Best Validation for DataMatrixSem1 with MSE=0.05544 [5]

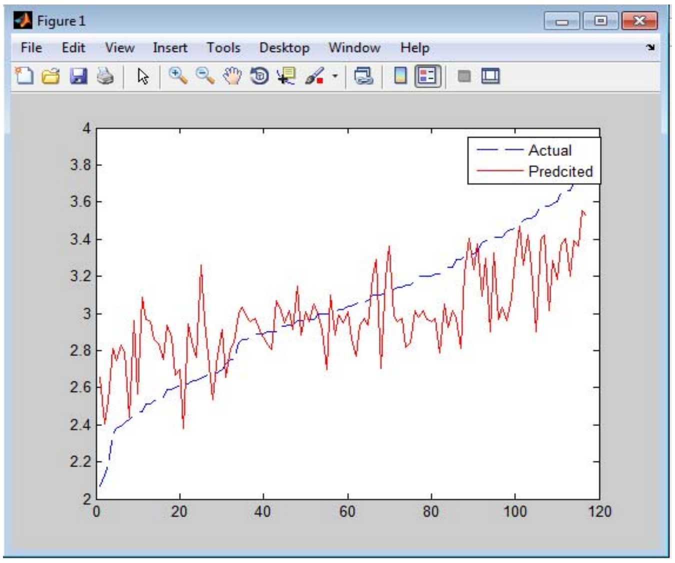

Fig. 2. Comparison Between Targeted and Predicted for Tested DataMaxSem1 (6 inputs) [5]

Fig. 2 shows the comparison between Targeted and Predicted performance for the Matriculation students based on six subjects as input variables at semester one. From the chart, we observed that there is a slight variation between Predicted and targeted 'CGPA at Semester 8' (called CGPA8 from this point onwards). It is also observed that at lower CGPA8, the predicted is higher than targeted while those with higher CGPA8, the predicted is lower than targeted.

The following figures show the output simulation for the Matriculation and Diploma students at semester three. Fig. 3 and 4 show results for Matriculation students at semester three. From Fig. 3 **MSE= 0.0409** for Matriculation students semester three and from Fig.5 **MSE= 0.0488** for the Diploma students.

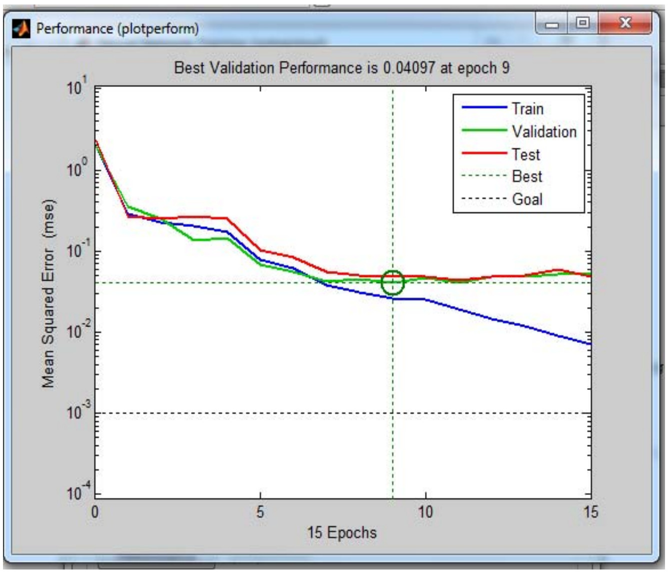

Fig. 3. Best Validation DataMaxSem3 MSE=0.0409

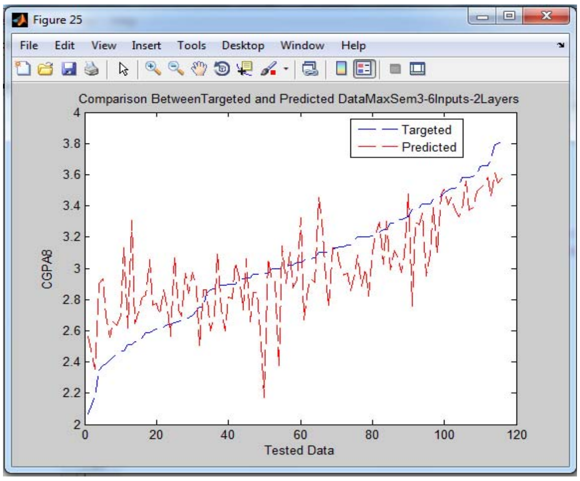

Fig. 4. Comparison Between Targeted and Predicted DataMaxSem3 (6 Inputs)

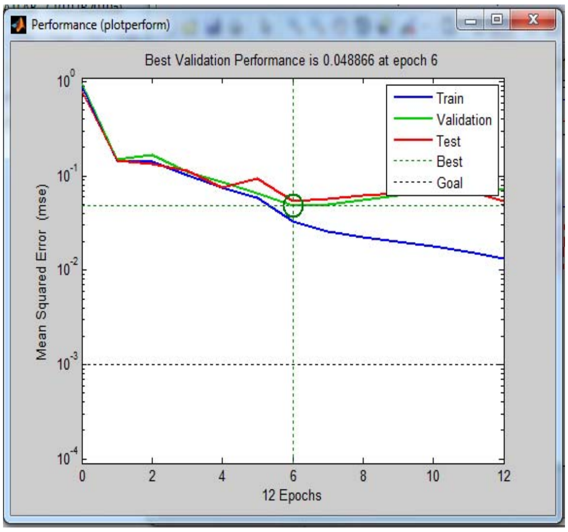

Fig. 5. Best Validation DataDipSem3 MSE=0.0488

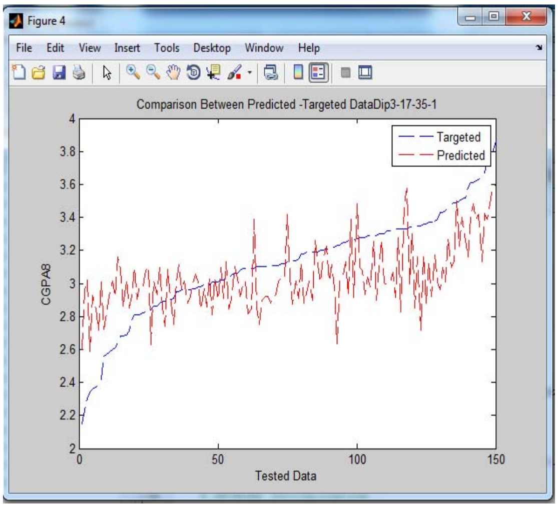

Fig. 6. Comparison Between Targeted and Predicted DataDipSem3 (6 Inputs)

Next, we discuss the results as depicted in Fig. 4 and 6. Referring to the two charts, it can be seen that the trends are similar. It is observed that at lower CGPA8, the predicted is higher in both Matriculation and Diploma students, while at higher CGPA8 the predicted is lower than the targeted or the actual value. The actual value has been shown to be better that the one predicted by the NN predictor model. There could be an explanation for this fact. One possible reason could be that UiTM Faculty of Electrical Engineering positive intervention (which have been implemented) was successful.

It was also noted that Matriculation students reached the higher CGPA8 at a slower rate (Fig 4) compared to those from Diploma students (Fig. 6.) by simple comparison of the area under the curves for both Fig. 4 and Fig. 6., which shows more area under the curve of Fig. 6. This could also imply that Diploma students are already at a better academic ability compared to their peers from Matriculation at the start of the degree program. However, as the semester progresses, the Matriculation students improved quickly (i.e. achieved CGPA higher later on). This could be due to their strong fundamentals in the core subjects as compared to the diploma holders which helped them to understand learn the new thus scoring more in harder core subjects at higher semesters. Finally all the students achieve the desired CGPA8 together upon graduation.

It can be seen that in all the three cases, those with lower CGPA8, the predicted performance could be planned to be higher than the targeted performance. Thus strategic positive intervention and actions can be suggested by the Academic advisors so as to improve the final CGPA upon graduation. It is noted that those Diploma students have another five more semesters before reaching the final semester for graduation. As for the Matriculation students, they have seven semesters before final semester and it is better to academically advise them as early as possible upon detection of poor performance or ability analysis namely at completion of semester one. The detection mechanism can be implemented using our proposed NN based predictor model. This can be followed by strategic steps to be applied taken to remedy the situation much earlier, for example, at the end of semester one instead of waiting for semester three results.

V. Discussion And Recommendation

In this section, we shall describe our suggestions for some practical steps and interventions that the university management can do to help improve the Electrical degree students' academic performance before graduation. For example, let us take the case of those students with low CGPA at early semester, namely semester one from Matriculation entry level and semester three coming from Diploma entry level, where low CGPA implies that they have poor ability in their fundamental subject courses. Such students may not be able to fully absorb with ease, the many engineering fundamentals and may not be able to solve many difficult problems at any one time. With this kind of ability, they are advised to take lesser credit hours in one semester so that they can focus and manage their study based on own ability at their own pace. Such students would need to extend another one or two semesters in order to complete degree program to fulfil the total credit hours required. They can plan to take up summer schools (or inter-session) during their long holidays so to reduce their burden during the normal semester. Due to their lower academic ability they only take incremental courses one at a time. However, our study could help increase the opportunity to alleviate this problem. By using our NN based predictor model, the lecturers and academic advisors can now play active roles by intervening with proper motivational advises to improve their ability to graduate earlier.

It is also important to note that, in electrical program, the courses tend to get harder and more complicated as they go up into higher semester of the study plan course structure. Furthermore the total credit hours keep on increasing as they go up in the higher semesters and students have to maintain the momentum of high achievers to ensure high CGPA towards graduation. Our suggestion is to encourage those with high CGPA at early semesters to share their understanding and better study skills with fellow colleagues with lower academic ability. This could be implemented in the form of mentor-mentee style between the better and the worse academic students.

VI. CONCLUSIONS

We have presented an NN prediction model to predict the academic performance of Electrical Degree students based on multi entry level, in particular, Matriculation and Diploma entry levels. We have developed the model for three different cases, namely, i) Matriculation entry level students at semester three and ii) Diploma entry level students at semester three. The trend and pattern of the outcomes of the prediction model holds true for all two different cases. This indicates that the NN model is acceptable and can be used to predict student academic performance.

For the students' performance prediction study, the input parameters of the NN model were taken from live data of Grade Points of courses scored by students, which include the fundamental subjects at semester one and three, respectively. We are able to do a prediction of the students' performance in the final semester upon graduation. For this study, the final CGPA at semester eight is, in fact, the output of our NN prediction model. During the whole prediction exercise, data collected were divided into either training or testing sets. We have also considered several other parameters including training algorithms technique, network architecture, learning rate, momentum rate and number of neurons in hidden layers before we managed to get the best of our NN based prediction model. However such model is limited to electrical Degree students at the Faculty and it can be extended to other department with suitable input variables. The designer must determine the input predictor variables for any particular students' program.

Finally, we can safely conclude that for this study, there is a direct correlation between students' strong academic ability on fundamental subjects at early semester and their overall academic performance upon graduation. This leads to a conclusion that indeed fundamental subjects must be fully understood and grasped because without them other subjects in the subsequent higher semester will be very difficult. We also suggest that strategic intervention can be done to help underachieving students as early as possible, by using our NN based predictor model so as to improve the students overall academic performance.

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