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Levenberg-Marquardt Algorithm Based Neural Network Model for Predicting Licensure Examination Performance of Civil Engineering Students

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Abstract

In the onset of the 4th Industrial revolution, wherein the use of artificial intelligence is mushrooming in research, the Artificial Neural Network (ANN) algorithm has become an advanced tool when it comes to building of performance models. This study utilizes ANN using MATLAB to create a model that can predict the performance of civil engineering students in the Licensure Examination.

Employing educational data mining techniques, the ANN model output could identify the student's performance in the Licensure Examination for Civil Engineering. The ANN models utilized Feed – Forward Back Propagation and Levenberg-Marquardt algorithm due to its simplicity and wide array of use. The utilization of the samples was distributed into three phases: training, validation and testing phase. Three (3) licensure examination periods were used for the creation of the prediction models from 2011, 2015 and 2018. The basis for the selection of the chosen periods was based on the change in the number of items in the licensure examination from 30 to 100 to 50 items. The input parameters were the student's academic performance in the different subjects divided into three categories patterned from the licensure examination criteria. The output used in modelling is the respondents' board examination score. From the data gathered, three (3) models were created for the three (3) civil engineering board exam subject areas..

Higher Education Institutions (HEIs) will be guided in determining the student's predicted performance and to carry out measures to give priority to the low performers. The identified civil engineering students should be given higher priority during the conduct of major and correlation courses in their terminal year. The early prediction data can help institutions to implement solution to improve the actual performance during licensure examinations. Using the output models and equations, the students can easily identify their predicted licensure examination performance integrating their academic records from the school and likely will give them proper motivation to improve.

Index Terms: *Civil Engineering, Licensure Examination, Neural Network Model, Prediction Model.*

I. INTRODUCTION

The performance models in the academe has become an advanced tool in analysing students predicted behaviour. This study focuses to build a model using Artificial Neural Network (ANN) using Matrix Laboratory (MATLAB) to predict the likelihood of civil engineering students to pass the Civil Engineering Licensure Examination administered by the Philippine Regulation Commission (PRC). The ANN model output could identify the student's performance in the Licensure Examination for Civil Engineering employing educational data mining techniques through the academic performance of students. Three (3) licensure examination periods were used for the models from 2011, 2015 and 2018.

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The variations in the number of items in the licensure examination from 30, 100 and 50 items were the basis for the selection of the periods. The input parameters were the student's academic performance in the different subjects divided into three (3) categories patterned from the licensure examination criteria such as the Mathematics, Surveying and Transportation engineering, Hydraulics and Geotechnical engineering and Design and Construction engineering. The subjects included in the licensure examination are based on Resolution No. 2 issued by the PRC (1995) promulgating the syllabi for the subjects in the civil engineering licensure examination [1]. The output used in modelling is the respondents' board examination rating. A total of 3 models were created from the three periods and three subject areas.

Determining the student's predicted performance will help Higher Education Institutions (HEI) to carry out measures that will give priority to those who will be predicted as low performers. The identified civil engineering students should be given higher priority during the conduct of major and correlation courses in their terminal year. Due to the early prediction, institutions can implement solutions and expect better results during licensure examinations. Using the output models, the students can easily view their predicted licensure examination performance integrating their academic performance in the academe. The HEI can utilize the model to identify measures in which the teaching and learning environment can be enhanced to improve the students' academic performance.

The academic achievement of students in their tertiary education in the Philippines is a key factor in their life. Taberdo and Taberdo [2] state that the student's academic performance may help as a tool to evaluate the quality of education that the HEI can offer. Far Eastern University Institute of Technology (FEU Tech) civil engineering department acts as a medium to bridge the students towards their attainment of being licensed civil engineers. Aside from the major subjects that the university offers, additional subjects on correlations courses were introduced to cater the needs of refreshing and reviewing the past subjects that were taken since their first year until their terminal year. Predicting the students' performance at high accuracy level during the period of their academic years becomes significant for which the institution can easily identify the strong and weak performers, as early as possible. In this case, the institution can lend additional support and mitigate measures that would enhance further the academic performance of the students during their terminal year or at the moment that their performance has been predicted. For the faculty handling major subjects relevant to passing the licensure examination, early prediction of level of performance could be considered cognizant in terms of improving the level of teaching and learning factors. The study of Taberdo (2018) concluded that teaching and learning process is a two-way communication and emphasizing the importance of the role of teachers [3].

Artificial Neural Network (ANN) is a statistical learning algorithm that is utilized to generate and create prediction models. ANN mimics the function of human brain therefore, it needs to learn or to be trained based on the training set that contains associated neurons in the form of weights and biases which calculate a predicted output values from the input parameters [4]. The study of Livieris, Drakopoulou and Pintelas (2017), has concluded that "MSP-trained neural networks exhibit more consistent behaviour and illustrate better classification results than the other classifiers", to which is tested in predicting the performance of the first year students in Mathematics [5]. The present study utilizes the Artificial Neural Networks (ANN) with the aid of MATLAB in the prediction modelling process. The Levenberg-Marquardt algorithm was used and is considered fitting to the purpose of the study since the algorithm is specifically intended to loss functions in terms of sum of squared errors.

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A. Objective of the Study

The foremost objective of the study is to create a prediction model for student's performance in civil engineering licensure examination using Artificial Neural Network.

II. MATERIALS AND METHODS

A. Data Gathering

Table 1 presents the summary of the number of data gathered. Based on the records on the licensure examination rating retrieved from the PRC, there is a total of 165 data sets for the tree (3) year periods of 2011, 2015 and 2018. The three periods considered in this study have different variations regarding the number of items per subject area of the Civil Engineering Licensure Examination. In the year 2011, 30 question items were given per subject criteria, in the year 2015, a total of 100 question items were given while in 2018, 50 questions were given during the licensure examination. All the 317 FEU Institute of Technology graduates, their corresponding academic performance records were gathered from the system records of FEU Institute of Technology.

The students' academic performance based on their grades were categorized into three (3), these are the Mathematics, Surveying and Transportation Engineering (MSTE), Hydraulics and Geotechnical Engineering (HGE) and Structural Design and Construction (SDC).

Table 1. Summary of Data Sets

Year	Number of Examination Items (MSTE/HGE/SDE)	Total Number of Data
2011	30/30/30	
2015	100/100/100	165
2018	75/50/75	

Table 2 presents the number of topics considered in each subject area in this study. These topics were also the input parameters utilized to generate a model to predic the student's performance in the licensure examination.

Table 2. Number of Topics/Clusters in each Subject Areas

Subject Area/Year	Number of Topics
MSTE	4
HGE	4
SDC	3

For Mathematics, Surveying and Transportation Engineering (MSTE), the topics/clusters include the following topics: Pre – Calculus (PC), Calculus (C), Allied Courses (A) and Surveying and Transportation Engineering (ST). Moreover, Hydraulics and Geotechnical Engineering (HGE) consists of the following topics/clusters: Fluid Mechanics (F), Hydraulics (H), Professional Courses (Water Resources Engineering Track) (PC) and Soil Mechanics (SM). For the third subject area which is the Structural Design and Construction (SDC), it comprises of the following topics: Pre – Design Courses (PD), Building Design and Construction (BDC) and Structural Engineering and Design (SED).

Table 3 shows the range of the input parameters used in each of the subjects considered in the study and its equivalent.

Table 3. Range of Input Parameter and its Equivalent

Rating	Equivalent
4.0	97 – 100 %
3.5	93 – 96 %
3.0	89 – 92 %
2.5	85 – 88 %
2.0	81 – 84 %
1.5	78 – 80 %
1.0	75 – 77 %
0.5	Failed
0.0	No Attendance

B. Artificial Neural Network

The ANN models utilized Feed – Forward Back Propagation Algorithm due to its simplicity and wide array of use. The topology of ANN models typically comprises of input layer, hidden layer containing hidden neurons and an output layer. The

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design criteria of the ANN are based on the following parameters: the training algorithm, adaptation learning function, performance function, hidden layers and hidden neurons, weights and biases and transfer function. The summary of the design criteria of the ANN models in this study is shown in Table 4.

Table 4. The Design Criteria of ANN Models

Parameter	Value
Training Algorithm	Levenberg – Marquardt Algorithm
Adaptation Learning Function	Gradient Descent with Momentum Weight and Bias Learning Function
Performance Function	Mean Squared Error (MSE), Pearson Correlation Coefficient (R)
Number of Hidden Layers	1
Number of Hidden Neurons per Hidden Layer	3 to 10
Transfer Function	Hyperbolic Tangent Sigmoid (Tansig); Logistic Sigmoid (Logsig)

*n = number of input parameters

The study utilized Matrix Laboratory (MATLAB) R2018a neural network toolbox for modelling and simulation of the data. The researchers used the Levenberg-Marquardt algorithm. The utilization of the samples was distributed into three phases: training, validation and testing phase. The distribution of samples to generate the model is 70% for the training phase, 15% for the validation phase and 15% for the testing phase. The models that were derived to predict the performance of the students in the civil engineering licensure examination based on their academic performance in school.

The overview of the architecture of the ANN model derived from the MATLAB neural network toolbox is shown in Fig. 1 to 3. It shows the number of input parameters used to create the network, the number of hidden neurons in the hidden layer and the output layer of the generated model.

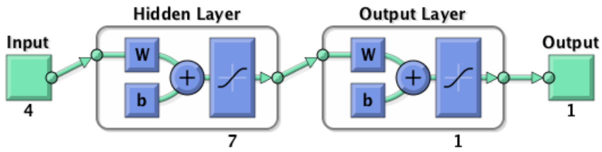

Figure 1. Overview of the Architecture of the Governing MSTE Model

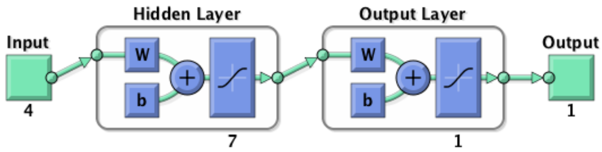

Figure 2. Overview of the Architecture of the Governing HGE Model

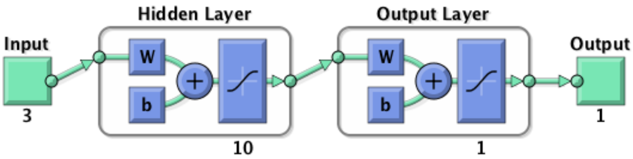

Figure 3. Overview of the Architecture of the Governing SDC Model

The model has input parameters on the students' final grades retrieved from the Registrar's records which are categorized into three (3) such as Mathematics, Surveying and Transportation engineering, Hydraulics and Geotechnical Engineering and Design and Construction engineering. For the selection of the best model, the researchers used the highest R validation value and lowest MSE as the primary criteria for the selection of the model [6]. Furthermore, as an additional criterion for the selection of the model, the percent error (% error) between the actual and predicted grades were used to select the best model. Figure 4 presents the detailed architecture of the ANN model generated in this study which was obtained from the training, validation and testing data.

After the simulation, the individual values of the lines shown in Fig. 4 that connects the input parameters to the hidden neurons in the hidden layer and consequently, to the output layer were obtained.

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These values are the weights and biases of the network.

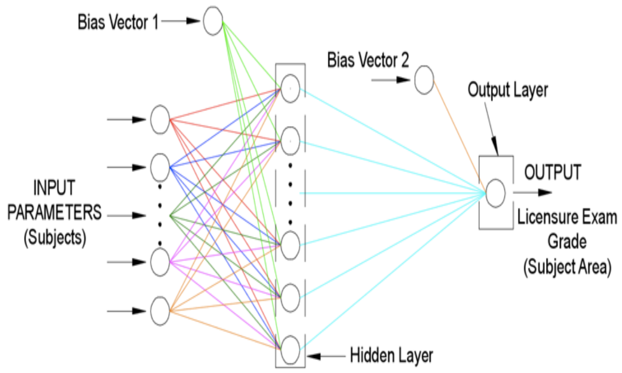

Figure 4. Detailed Architecture of the ANN Model

III. RESULTS AND DISCUSSION

A. Simulation Results

Table 5 presents the simulation results of the MSTE model. Different transfer functions were simulated (tansig, logsig and purelin) ranging from 3 to 10 hidden neurons. For the MSTE Model, the best model was attained from simulation using tansig function, 7 Hidden Neurons with Pearson's Correlation Coefficient (R_{all}) value of 0.91413, Mean Squared Error (MSE) of 18.73910 and Mean Absolute Percentage Error (MAPE) of 6.54003%.

Table 5. Simulation Results for the MSTE Model

Transfer Function	HN	Training	Validation	Testing
tansig	3	0.90328	0.96649	0.90843
	4	0.90064	0.95944	0.90125
	5	0.90935	0.94623	0.91699
	6	0.90718	0.95363	0.92379
	7	0.90668	0.95386	0.92665
	8	0.91270	0.91724	0.92055
	9	0.91165	0.92702	0.90977
	10	0.90788	0.93970	0.93343
Transfer Function	**HN**	**All**	**MSE**	**MAPE**
tansig	3	0.90948	19.94480	6.56177
	4	0.91017	19.44290	6.72284
	5	0.91360	19.09290	6.55828
	6	0.91295	20.01680	6.63860
	7	0.91413	18.73910	6.54003
	8	0.91129	22.72770	6.99694
	9	0.91271	21.52710	6.61506
	10	0.91398	18.88120	6.54189

The MSTE Model demonstrated significantly high correlation results and low mean squared error as shown in Figures 5 and 6.

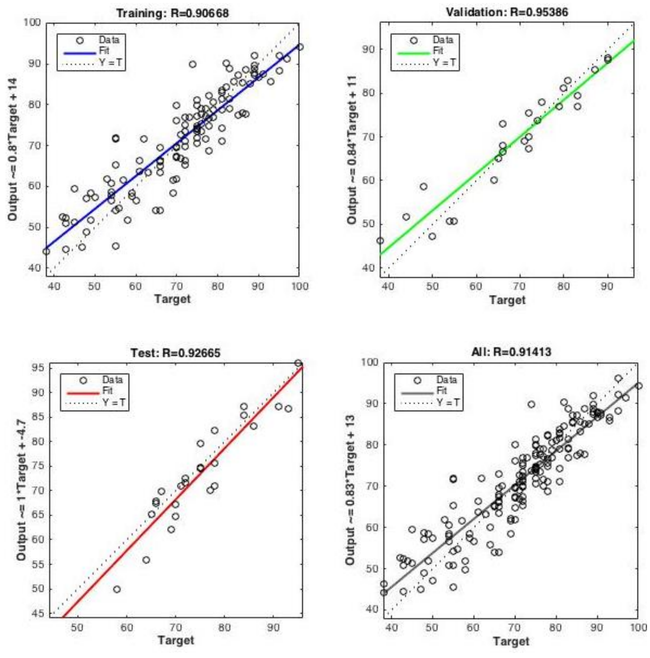

Figure 5. Correlation Plots for each Phases of Model Development for the MSTE Model

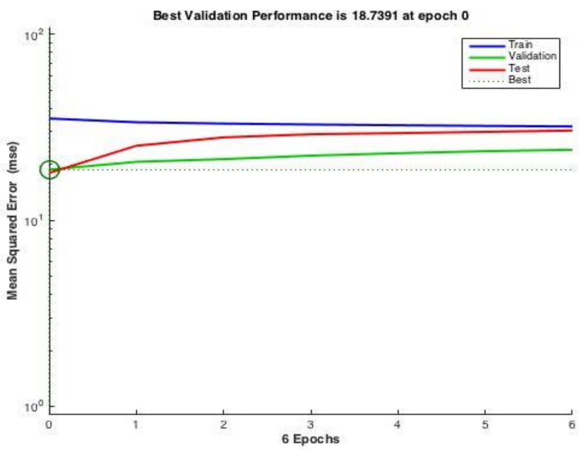

Figure 6. Performance and Mean Squared Error for the MSTE Model

Table 6 displays the simulation results of the HGE model. For the HGE Model, the best model was attained from simulation using using hyperbolic tangent sigmoid (tansig) function, 10 Hidden Neurons with Pearson's Correlation Coefficient (Rall) value of 0.92552, Mean Squared Error (MSE)

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of 14.45330 and Mean Absolute Percentage Error (MAPE) of 5.03277%.

Table 6. Simulation Results for the HGE Model

Transfer Function	HN	Training	Validation	Testing
tansig	3	0.84586	0.93298	0.88004
	4	0.84717	0.92448	0.92187
	5	0.90973	0.92637	0.92386
	6	0.91603	0.91339	0.91059
	7	0.86605	0.90469	0.88633
	8	0.87761	0.89629	0.91345
	9	0.87593	0.92606	0.94781
	10	0.91432	0.96939	0.94459
Transfer Function	**HN**	**All**	**MSE**	**MAPE**
tansig	3	0.86445	36.45950	6.61951
	4	0.87245	32.98120	6.51320
	5	0.91424	18.82750	5.31203
	6	0.91486	16.94740	5.29178
	7	0.87638	20.80940	6.51793
	8	0.88566	25.56750	6.36836
	9	0.89388	18.90840	5.67301
	10	0.92552	14.45330	5.03277

The HGE Model exhibited significantly high correlation results and low mean squared error as shown in figure 7 and 8.

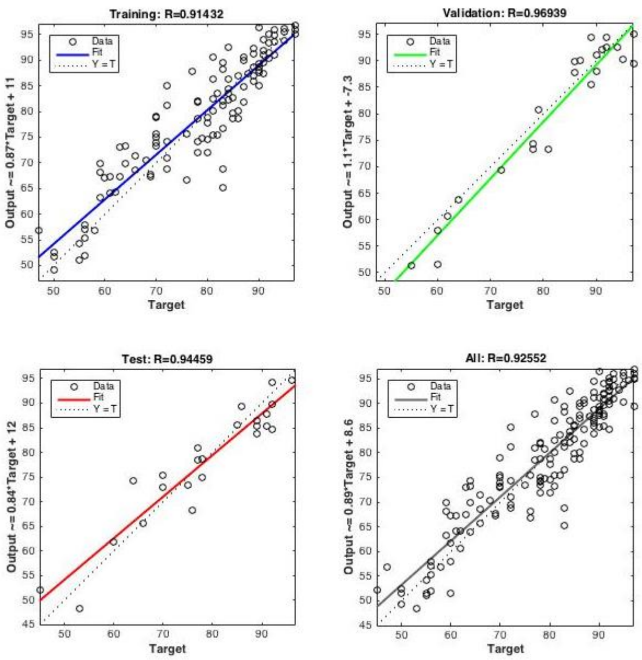

Figure 7. Correlation Plots for each Phases of Model Development for the HGE Model

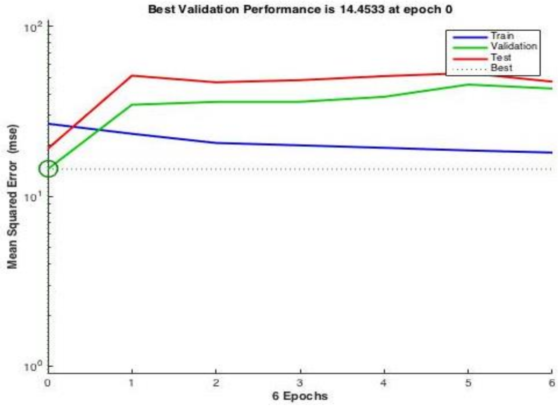

Figure 8. Performance and MSE for the HGE Model

Table 7 demonstrates the simulation results of the SDC model. For the SDC Model, the best model was achieved from simulation using using hyperbolic tangent sigmoid (tansig) function, 10 Hidden Neurons with Pearson's Correlation Coefficient (Rall) value of 0.92477, Mean Squared Error (MSE) of 8.38170 and Mean Absolute Percentage Error (MAPE) of 5.03010%.

Table 7. Simulation Results for the SDC Model

Transfer Function	HN	Training	Validation	Testing
tansig	3	0.88226	0.96771	0.93975
	4	0.90368	0.95629	0.95460
	5	0.90143	0.94269	0.94517
	6	0.88558	0.93351	0.95279
	7	0.90216	0.93703	0.92338
	8	0.90215	0.92650	0.95840
	9	0.88771	0.94423	0.97009
	10	0.90646	0.97240	0.95824
Transfer Function	**HN**	**All**	**MSE**	**MAPE**
tansig	3	0.90365	20.08480	6.12538
	4	0.91601	16.64520	5.11879
	5	0.91307	22.85870	5.13303
	6	0.90357	17.35130	6.02610
	7	0.91006	24.37680	5.54955
	8	0.91382	29.81920	5.63000
	9	0.90609	19.48580	5.59403
	10	0.92477	8.38170	5.03010

The SDC Model displayed high correlation results and low mean squared error as shown in Figures 9 and 10.

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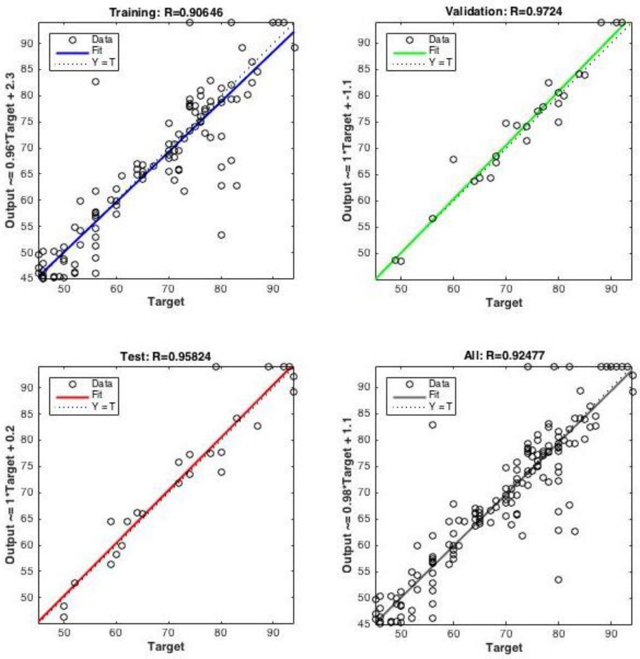

Figure 9. Correlation Plots for each Phases of Model Development for the SDC Model

The results show that the MATLAB Neural Network Toolbox is very efficient to be utilized in order to predict the performance of the students in the Licensure Examination. This is due to the capability of the ANN in deriving and analyzing complex non – linear relationships between input and output variables.

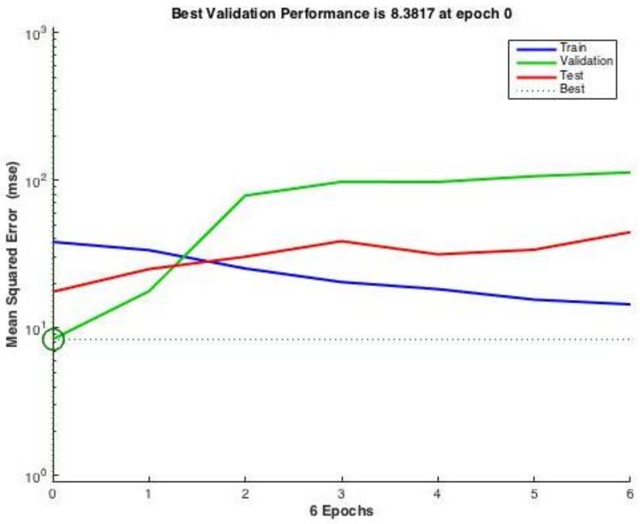

Figure 10. Performance and MSE for the SDC Model

B. Derivation of the Equation for the Governing Models

The derivation of the simulation results shown in Tables 5 to 7 includes the utilization of the weights and biases obtained from the MATLAB Neural Network Toolbox simulation and data normalization. For the MSTE model, the equations of the normalized values was presented in equations 1 to 4 (the subscript “N” indicates the normalized value). These equations are the input variables in the MSTE model.

$$P_N = 0.63158(P - 0.83333) - 1 \quad (1)$$

$$C_N = 0.63376(C - 0.70139) - 1 \quad (2)$$

$$A_N = \frac{2}{3}(A - 0.75000) - 1 \quad (3)$$

$$ST_N = 0.64574(ST - 0.90278) - 1 \quad (4)$$

for the hidden layer, the derived equations for the hidden neurons were presented in equations 5 to 11.

$$a_{11} = \tanh\begin{pmatrix} -0.14104P_N - 0.049873C_N - 1.7367A_N \\ +1.2283ST_N - 1.4039 \end{pmatrix} \quad (5)$$

$$a_{21} = \tanh\begin{pmatrix} -1.7475P_N + 0.020272C_N + 1.0541A_N \\ +0.78094ST_N + 0.58821 \end{pmatrix} \quad (6)$$

$$a_{31} = \tanh\begin{pmatrix} -1.1507P_N - 1.7245C_N + 0.1308A_N \\ +0.73014ST_N - 2.2506 \end{pmatrix} \quad (7)$$

$$a_{41} = \tanh\begin{pmatrix} 1.8524P_N - 0.10594C_N + 1.5227A_N \\ -1.0757ST_N - 0.15584 \end{pmatrix} \quad (8)$$

$$a_{51} = \tanh\begin{pmatrix} 1.0469P_N - 0.2124C_N + 1.3069A_N \\ -0.25303ST_N + 0.057055 \end{pmatrix} \quad (9)$$

$$a_{61} = \tanh\begin{pmatrix} 1.7735P_N + 0.067806C_N + 0.70706A_N \\ -3.1236ST_N + 0.66964 \end{pmatrix} \quad (10)$$

$$a_{71} = \tanh\begin{pmatrix} 0.6785P_N + 0.69575C_N - 3.0038A_N \\ -0.01546ST_N + 2.8786 \end{pmatrix} \quad (11)$$

from the hidden layer to the output layer the normalized predicted MSTE grade can be obtained using the equation:

$$MSTE_N = \tanh\begin{pmatrix} -0.88239a_{11} - 0.46253a_{21} - 1.0678a_{31} - 1.3177a_{41} \\ +1.6116a_{51} - 0.49336a_{61} - 0.75721a_{71} - 0.32361 \end{pmatrix} \quad (12)$$

the equation 12 was converted to determine the non – normalized MSTE model and presented in equation 13.

$$MSTE = \frac{67(MSTE_N + 1)}{2} + 23 \quad (13)$$

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The equations of the normalized values for the HGE model were displayed in equations 13 to 15 (the subscript “N” indicates the normalized value). These equations are the input variables in the HGE model.

$$F_N = \frac{4}{7}(F - 0.5) - 1 \tag{14}$$

$$H_N = 0.60006(H - 0.667) - 1 \tag{15}$$

$$PC_N = \frac{2}{3}(PC - 1) - 1 \tag{16}$$

$$SM_N = \frac{16}{27}(SM - 0.625) - 1 \tag{17}$$

for the hidden neurons in the hidden layer, the derived equations were presented in equations 18 to 27.

$$b_{11} = \tanh\begin{pmatrix} -2.2408F_N + 0.21497H_N + 2.927PC_N \\ +3.024SM_N + 0.74454 \end{pmatrix} \tag{18}$$

$$b_{21} = \tanh\begin{pmatrix} -1.7366F_N + 1.9415H_N - 0.22965PC_N \\ -2.3591SM_N + 1.1783 \end{pmatrix} \tag{19}$$

$$b_{31} = \tanh\begin{pmatrix} 4.4368F_N - 3.9575H_N + 3.2994PC_N \\ -3.2082SM_N - 1.5676 \end{pmatrix} \tag{20}$$

$$b_{41} = \tanh\begin{pmatrix} 1.2397F_N - 1.5923H_N + 0.79761PC_N \\ -1.7965SM_N + 0.21312 \end{pmatrix} \tag{21}$$

$$b_{51} = \tanh\begin{pmatrix} -4.9803F_N + 2.8679H_N - 1.2371PC_N \\ +2.3442SM_N + 0.46091 \end{pmatrix} \tag{22}$$

$$b_{61} = \tanh\begin{pmatrix} -0.16208F_N + 2.6944H_N + 1.3398PC_N \\ -1.9146SM_N + 0.68127 \end{pmatrix} \tag{23}$$

$$b_{71} = \tanh\begin{pmatrix} -2.153F_N - 1.2593H_N + 1.3486PC_N \\ -0.78572SM_N - 0.48306 \end{pmatrix} \tag{24}$$

$$b_{81} = \tanh\begin{pmatrix} 1.418F_N - 2.5633H_N + 1.8793PC_N \\ -2.2327SM_N + 0.73678 \end{pmatrix} \tag{25}$$

$$b_{91} = \tanh\begin{pmatrix} 2.3857F_N + 0.050972H_N + 4.774PC_N \\ -2.4701SM_N + 3.6693 \end{pmatrix} \tag{26}$$

$$b_{101} = \tanh\begin{pmatrix} -1.2169F_N - 0.23768H_N - 2.4776PC_N \\ +0.70096SM_N - 2.5318 \end{pmatrix} \tag{27}$$

from the hidden layer to the output layer the normalized predicted HGE grade can be obtained using the equation:

$$HGE_N = \tanh\begin{pmatrix} 0.36218b_{11} - 0.45484b_{21} - 1.3875b_{31} + 1.172b_{41} - 1.1067b_{51} + 0.29352b_{61} \\ +0.083547b_{71} - 0.86906b_{81} - 1.4089b_{91} - 2.7905b_{101} - 0.4662 \end{pmatrix} \tag{28}$$

the equation 28 was converted to determine the non – normalized HGE model and presented in equation 29.

$$HGE = 26(HGE_N + 1) + 45 \tag{29}$$

The equations of the normalized values for the HGE model were displayed in equations 30 to 32 (the subscript “N” indicates the normalized value). These equations are the input variables in the SDC model.

$$PD_N = 0.63158(PD - 0.73333) - 1 \tag{30}$$

$$BDC_N = \frac{20}{29}(BDC - 1) - 1 \tag{31}$$

$$SED_N = 0.62539(SED - 0.73056) - 1 \tag{32}$$

for the hidden neurons in the hidden layer, the derived equations were presented in equations 33 to 42.

$$c_{11} = \tanh\begin{pmatrix} -3.0207PD_N + 8.797BDC_N + 8.268SED_N \\ -8.5966 \end{pmatrix} \tag{33}$$

$$c_{21} = \tanh\begin{pmatrix} 12.4193PD_N + 5.5116BDC_N - 9.8564SED_N \\ -11.8626 \end{pmatrix} \tag{34}$$

$$c_{31} = \tanh\begin{pmatrix} -20.9181PD_N + 1.1589BDC_N + 5.023SED_N \\ -11.8565 \end{pmatrix} \tag{35}$$

$$c_{41} = \tanh\begin{pmatrix} -8.0485PD_N - 2.0749BDC_N - 3.3598SED_N \\ -10.4339 \end{pmatrix} \tag{36}$$

$$c_{51} = \tanh\begin{pmatrix} 1.1911PD_N + 1.8071BDC_N + 0.33763SED_N \\ +0.77933 \end{pmatrix} \tag{37}$$

$$c_{61} = \tanh\begin{pmatrix} 14.8279PD_N + 7.0107BDC_N + 4.5118SED_N \\ +19.0433 \end{pmatrix} \tag{38}$$

$$c_{71} = \tanh\begin{pmatrix} 18.2935PD_N - 1.0888BDC_N - 5.3218SED_N \\ -3.5305 \end{pmatrix} \tag{39}$$

$$c_{81} = \tanh\begin{pmatrix} 9.588PD_N - 21.5182BDC_N + 7.4484SED_N \\ +9.1711 \end{pmatrix} \tag{40}$$

$$c_{91} = \tanh\begin{pmatrix} -13.3714PD_N - 8.5717BDC_N - 12.9271SED_N \\ +6.1365 \end{pmatrix} \tag{41}$$

$$c_{101} = \tanh\begin{pmatrix} -11.0084PD_N - 0.35401BDC_N - 5.5987SED_N \\ -14.1121 \end{pmatrix} \tag{42}$$

from the hidden layer to the output layer the normalized predicted SDC grade can be obtained using the equation:

$$SDC_N = \tanh\begin{pmatrix} -7.438c_{11} - 4.5157c_{21} + 0.13953c_{31} - 9.6944c_{41} + 0.75213c_{51} - 3.8204c_{61} \\ -0.13251c_{71} + 0.16245c_{81} - 7.7188c_{91} + 5.3056c_{101} - 4.9023 \end{pmatrix} \tag{43}$$

the equation 43 was converted to determine the non – normalized SDC model and presented in equation 44.

$$SDC = \frac{49}{2}(SDC_N + 1) + 45 \tag{44}$$

C. Effect of the Number of Hidden Neurons to Pearson’s Correlation Coefficient (R) and Mean Squared Error (MSE)

The effect of the number of hidden neurons to Pearson’s Correlation Coefficient (R), Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) for MSTE model was presented in Figures 10 to 12.

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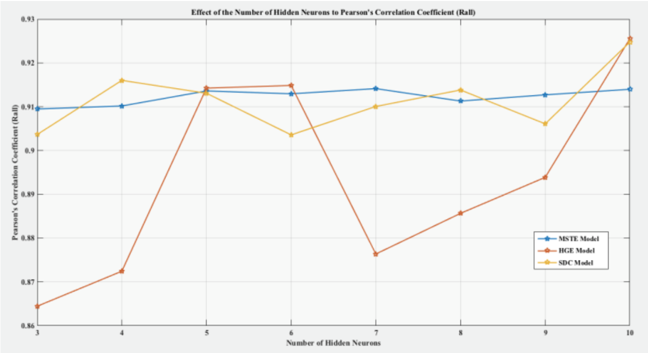

Figure 10. Effect of the Number of Hidden Neurons to the Pearson's Correlation Coefficient (R_{all})

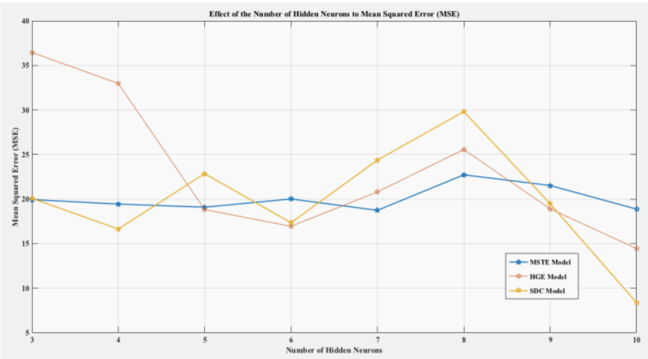

Figure 11. Effect of the Number of Hidden Neurons to the Mean Squared Error (MSE)

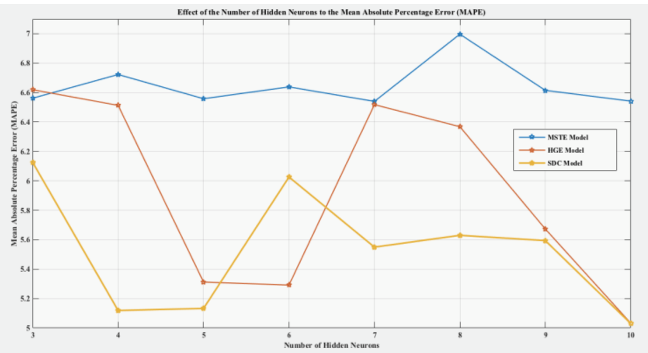

Figure 12. Effect of the Number of Hidden Neurons to the Mean Absolute Percentage Error (MAPE)

The results shows that the number of hidden neurons has no significant effect on the value of Pearson's Correlation Coeffcient, Mean Squared Error and Mean Absolute Percentage Error.

CONCLUSION

The researchers had developed prediction models to forecast the performance of the students in the Civil Engineering Licensure Examination based on their academic performance in different subjects. All the three (3) models have shown significant and high correlation results and minimal errors.

It can be concluded, that based on the output models, the MatLab Neural Network Toolbox is very efficient in the prediction modelling using ANN. Therefore, it is recommended that the output models can be used in predicting the student's licensure examination performance in civil engineering.

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