Multi Variation Reactive Power Management Using Artificial Neural Network for Loss Prediction in Power System

Nur Asyikin Abd Jamel[1,a], Ismail Musirin[*2,a], Norziana Aminuddin[3,a], Siti Rafidah Abdul Rahim[4,b], Nor Azwan Mohamed Kamari[5,c], Muhammad Murtadha Othman[6,a], A. V. Senthil Kumar[7,d]

[a]School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, 40450, Shah Alam, Selangor, Malaysia

[b]Faculty of Electrical Engineering Technology,Universiti Malaysia Perlis,Kampus Pauh Putra, 02600, Arau, Perlis, Malaysia

[c]Department of Electrical, Electronic and Systems, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, Malaysia

[d]Hindusthan College of Arts and Science, Coimbatore, India

e-mail: [1]nurasyikinn01@gmail.com, [2]*ismailbm@uitm.edu.my, [3]norziana@uitm.edu.my, [4]rafidah@unimap.edu.my, [5]azwank@ukm.edu.my, [6]mamat505my@yahoo.com.my, [7]m_murtadha@uitm.edu.my

*Corresponding author: ismailbm@uitm.edu.my

Article Info
Page Number: 123 - 138
Publication Issue:
Vol 71 No. 3 (2022)

Abstract

Reactive power management plays vital roles in power transmission system as it affects the power system status. Variations in load in a power system network can possibly lead to voltage instability condition or voltage collapse phenomena. This can become worse, especially when the relevant power system operators do not know early information on the system status. Thus, a reliable technique should be utilized or implemented so that the current or forecasted status of the system can be known before any undesired event is experienced. This paper presents, "Multi Variation Reactive Power Management Using Artificial Neural Network for Loss Prediction in Power System". In this study, the various models of load bus were designed in order to analyze and compare how the different number of input features, can affect the regression results of ANN. The comparison of the performance results of regression is conducted in terms of Mean-Squared Error (MSE) for all the models designed.

Article History
***Article Received**: 12 January 2022*
***Revised**: 25 February 2022*
***Accepted**: 20 April 2022*
***Publication**: 30 May 2022*

Keywords: -Reactive power management; Artificial Intelligence; Artificial Neural Network.

Introduction

Voltage stability often becomes a dominant constraint for the determination of maximum transmitting power in power systems. It is necessary to ensure the proper operation of electrical equipment to prevent damage like overheating generators and engines, minimize transmission losses, and preserve the system's capacity to resist the collapse of voltage. There have been significant outages in several countries worldwide due to voltage instabilities [1], [2]. It is typically triggered by significant disturbances, such as lack of distribution, transmission lines, or transformers. A low variability characterizes it in the grid's operating point since the network is unable to meet growing reactive power demand in a manner that steadily decreases the voltage level before a sudden rapid transition. Reactive power may, in general, be either inductive or capacitive. A condenser can produce an inductive reactive power demand locally, while an inductor can absorb reactive power exceeds locally if needed. To sustain the voltage, reactive power (VAR) is required in order to deliver active power (watts) across transmission lines. As the reactive power supplied lower voltage, as voltage drops, the current must be increased to sustain power supply, allowing more reactive power to be absorbed by the system, and the voltage drops more. Lack of reactive power leading to voltage collapse was a causal factor in major blackouts around the world. Under article [3], voltage loss happened in the West Coast blackout in the United States back in 1996. Although blackout in the U.S. and Canada on August 14, 2003, the Task Force's final report reported that the outage was due to inadequate reactive power and the overestimation of dynamic reactive performance of the system generated as a common factor among significant outages in the United States.

Voltage failure is a process in which the voltage level can drop drastically following contingency conditions along with power system instability [10]. In order to effectively avoid blackouts, it is necessary to understand the mechanisms of voltage collapse. Voltage collapse is an imbalance of a system involving several elements of the power system such as increase in loading, generator outages, line tripping and more. In fact, due to reactive power deficiency, voltage instability commonly occurs. In order to increase the efficiency and the operation of power systems, reactive power is reduced, and voltage stability is improved. A simple relationship exists between reactive power and voltage may lead to a voltage collapse and growing effects in power systems.

Early researchers suggested a variety of methods for solving the voltage instability problem. The load compensation and voltage support are two components of the reactive control (VAR). The main aim of load compensation is to increase the system power factor, balance the system's real power, and compensate for the voltage regulation. The voltage support is designed to minimize the voltage variance of a particular transmission line terminal. Thus, VAR compensation increases the reliability of the AC system by increasing the transmittable maximum active power. A Static Var Generator (SVG) can be installed to ensure the AC system's stability caused by reactive power consumption. The SVG, also known as STATCOM, is a device commonly used to solve the problem of reactive power consumption. Installing SVGs at various locations and adjusting the reactive power output of different SVGs affects the voltage stability and the time required to restore stability. The adequate reactive power control allows the quantity of distributed energy to be increased, and the operational cycle's reliability to increase [11].

Moreover, earlier researchers implement various methods of algorithms of Artificial Intelligence (AI) for load flow analysis in the power system. Artificial Intelligence is referred to as simulating human intelligence in computers built to think like humans and emulate their actions. AI has the ability to solve and execute the simplest tasks to more complex tasks. Artificial intelligence objectives include learning, understanding, and perception. Generally, there are multiple types of AI, such as supervised learning, unsupervised learning, semi-supervised learning, and reinforced learning. Recently, researchers have concentrated on Artificial Neural Networks (ANNs) as an online voltage stability measurement tool [4]-[5]. Because of the voltage stability assessment problem's nonlinear nature, the neural network is best used compared to the traditional voltage stability monitoring analytical methods. Many ANN combinations and various networks have been used to solve the problem [6]-[8].

This paper presents “Multi Variation Reactive Power Management Using Artificial Neural Network for Loss Prediction in Power System”. In this study, multi-model of ANNs were developed to address the variations of load for the management of reactive power for the purpose of power losses in power system. Validation process was conducted in the IEEE 30- Bus RTS. Results are convincing and should be feasible for power system operators' consumptions for their future planning and operation.

Artificial Neural Network

A neural network is known as a universal approximator and acts like a human brain. Artificial neural network (ANN) was successfully applied to a wide variety of real-world problems due to the ability to manage extraordinarily nonlinear and complex issues. Many researchers have used the concept of ANN in various types of fields, especially in the engineering field. Security assessment [18], voltage prediction problem [19], and load forecasting [20] are a few examples of ANN power-system applications.

The article [12] presents the voltage stability enhancement using ANN for the online operation of prediction transmission and consumption for the Voltage Collapse Proximity Index (VCPI) at load bus, which can be used to switch the Static VAR Compensator (SVC). Consequently, VCPIs obtained by the proposed tool could be useful in predicting emerging voltage instability situations and could help develop appropriate control behavior. ANN method has been proposed in [21] to allocate reactive power to compare the accuracy with the conventional Y-Bus matrix method. The findings indicate that the reactive power parallel to the characteristics of the traditional Y-Bus matrix system has a reasonable precision with simplicity in the determination using ANN. A study on ANN for optimal reactive power dispatch problem has been proposed in [15]. Multilayer feedforward with error propagation is used and tested on the sample system to compare the result with the classical optimization technique. The number of hidden neurons is optimized, which utilized Shannon's entropy, and the results obtained for accuracy and computation time are satisfactory. By these, the previous researchers have proven that ANN is suitable for the application of any complex system, mostly related to the power system field.

Methodology

Data Generation

In order to carry out the power system analysis on reactive power management, the data bus generation process is a primary step before executing the other process. Data generation can be defined as the process, creating or collecting data from the sampled source to use for theory, statistical, and methods of literature. Fig.1 shows the flowchart of this project, data generation. Generally, there are various types of IEEE data bus systems in the power system. The selection of the type of data bus system, depending on the researcher's aim. In this project, the data is generated from the data bus of the IEEE 30-Bus system. For this research aims of reactive power management, the data used in the bus system are reactive power, Qd at chosen load buses. The selection on the certain load bus is to model multi-variation of reactive power management and minimum voltage of IEEE 30-Bus system.

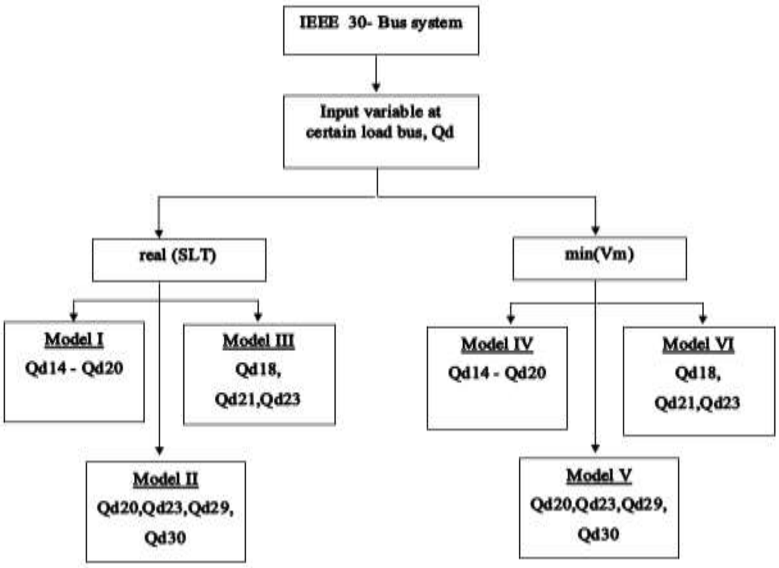


Fig. 1. The flowchart of data generation

Implementation of ANN

An Artificial Neural Network (ANN) can act as a computer framework for simulating how the human brain analyses and processes information. It is the basis of artificial intelligence (AI) and resolves impossible or difficult problems to overcome by human or statistical standards. ANN uses various layers of mathematical analysis to provide significance to the information they fed. It has self-learning capabilities to achieve better outcomes as more data become available. The main layers of ANN can be divided into three, which are the input layer, hidden layer, and output layer. The input layer will be the initial data for the network to be sent to the hidden layer. The hidden layer is an intermediate layer placed between the input and output layer where all the computation is done within this layer. Then the computed data sent to the output layer to produce the result for given inputs.

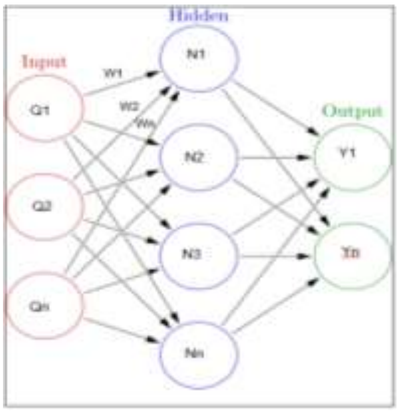


Fig. 2. ANN architecture

A single hidden layer as in Fig.2 is used, which consists of a number of neurons in it. The number of neurons in the hidden layer must be carefully considered. Using too few neurons can result in something called underfitting. Underfitting happens where the hidden layers have too few neurons to accurately detect the signals in a complex data set. Moreover, if using too many neurons in the hidden layers can result in several problems such as overfitting and increase the training time. By considering the number of the input features of all the models and output layer size, the number of neurons in the hidden layer is set to consist of 10 neurons as to avoid the network from underfitting or overfitting. All computational information is done in this layer and transform the input into something the output layer can be used for loss prediction.

Determination of Control Variable

Control variables are the variables that influence the outcome of a research. In order to accurately calculate the relationship of a dependent variable to an independent variable, other variables, known as confounding variables, need to be regulated. Although control variables are not a researcher's core concern, they are paramount to better understand the relationship between independent and dependent variables. If the confounding variables between the independent and dependent variable are not regulated in a research project, the results of a study could be skewed. Confounding can be regulated by use of randomization, restriction or matching. When correctly used, control variables can help the researcher to accurately understand the relationship between dependent and independent variables.

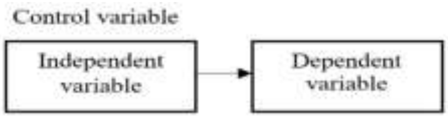


Fig. 3. Flow of control variable

In this research, a control variable may be kept constant or controlled for each test model. If a variable is potentially confusing, which the results do not reflect the actual relationship, it is the best to use it as a control variable in the analysis. Fig. 3 shown the flow of control variable of the study. The independent variable of the load bus's reactive power, Qd, in the system is controlled. The control of the independent variable will result to a dependent variable, which is a real power loss and minimum voltage. Potential control variables may be defined from the researcher's experience, a literature review, a conceptual model that directs the study, or the researcher's hypothesis.

Validation

In neural network, validation is one of the most important aspects that need to be considered before developing the necessary model of a network. Environmental modelling studies usually seek to extract the 'information' incorporated in a trained ANN to calculate the strength of correlations between the individual inputs and output or understanding the relationships that the hidden nodes represent. For this Artificial Neural Network models, the process of developing a validation dataset's neural network is similar to the training process, except that no weight matrices are created from the validation process. Predictive validation is used to check if the model can generalize the data used to improve the performance of the neural network model on a holdout dataset. The validation process will evaluate the model’s performance by comparing the training output prediction with the target value. If the accuracy of the validation process models is higher, the prediction model performs well. Otherwise, it is appropriate to run the model with different ANN architectures such as increase the number of neurons, or the hidden layer, until the training and validation datasets have minimum error values.

The validation process is referred to as the dataset that is used to test the performance of an ANN model once it has been developed and not to change the model structure or avoid overfitting during the model development process.

Effects of Correlation Coefficient, R

The correlation coefficient can be defined as a statistical measure of the relationship intensity between two variables' relative movements. The values range between -1.0 and 1.0. When the measured number greater than 1.0 or less than -1.0, it indicates there was a correlation measurement error. A correlation of 0.0 indicates, there is no linear relationship between the two variables. There are three types of correlation shown in Fig.4, which is the perfect positive correlation, perfect negative correlation, and no correlation.

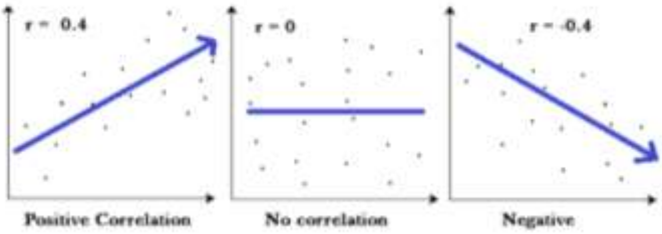


Fig. 4. Types of correlations

A correlation coefficient of 1 means a positive increase of a fixed proportion in the other for every positive increase in the variable. A correlation coefficient of -1 means that a negative decrease of the fixed proportion in the other is observed in any positive increase in one variable. No correlation means that there is no positive or negative increase with every increase. Both are not linked. The most commonly used linear regression is Pearson's correlation coefficient. It is used to measure the strength of the linear relationship. The formula to calculate the Pearson's correlation coefficient as in (1):

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{1}$$

Where r is the correlation coefficient, x_i is the value of input variable in the sample, $\bar{x}$ is the mean value of input variable, y_i is the value of output variable in the sample and $\bar{y}$ is the mean value of output variable.

Mean-Squared Error (MSE)

The primary objective of Machine Learning is to minimize the error described by the loss function. There are different ways of measuring the error for each type of Algorithm. In this project, Mean Square Error is the loss function used in the Regression Algorithms (MSE). Mean Square Error can be defined as a predictor using the average square difference between the expected value and actual value. The MSE can be calculated using formula (2):

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

Where n is the number of data, y_i is the actual value and $\bar{y}$ is the expected or predicted value.

In fact, MSE is always a positive value, but not a zero value, as it has randomness characteristics. The system is more accurate when the MSE is minimized, which presents the minimum error, as the expected values are close to the actual values. The mathematical advantages of mean square error are especially evident in its use in evaluating linear regression results, as it enables the variance in a dataset to be partitioned into variation explained by the model and variation explained by randomness.

Data Management

Supervised learning uses a training set to teach a model on how to perform a task or make a prediction. It is also important to note that this training data must be labelled with the expected results or correct response for every single example in the dataset. In order to develop a robust machine learning algorithm for this project, some effort is initially needed to create a data set container of labelled examples using supervised learning. In practice, it will need to extract three subsets of the original labelled data, which is the training, validations, and testing sets. This is an important step in the evaluation of the efficiency and effects of hyperparameter tuning of various models.

The first step in making accurate predictions is to train a model. Therefore, dividing data is required to establish a solid foundation for the training data. A training set is the data used to train the model. This is fed into a model-generating algorithm. During each epoch, the model will be continuously trained on the same data in the training set and will continue to learn this data's features. With this ability of data train, it be able to map the model inputs to outputs by making predictions based on what is learned about the training data. Next is a validation set. This set used a smaller set of data compared to the training set. It is used to evaluate models' performance with different hyperparameter values and used to detect overfitting during the training stages. Besides, the validation set also tends to visualize how well the model is generalizing during the training.

Moreover, the test set is used to get an indication of the final output of the hyperparameter tuning model. Hyperparameter tuning is the process of deciding the right hyperparameter combination to optimize model efficiency. It is set before training (optimizing the weight and bias). Hyperparameter can be relate with the network structure and training algorithm such as setting the number of hidden layers, activation function, learning rate, number of epochs and more. Setting the right hyperparameter combination is the only way to achieve optimum efficiency from models. It is also helpful to get an understanding of how various models of neural networks operate against each other. Fig.5 illustrated the split of the original labelled data.

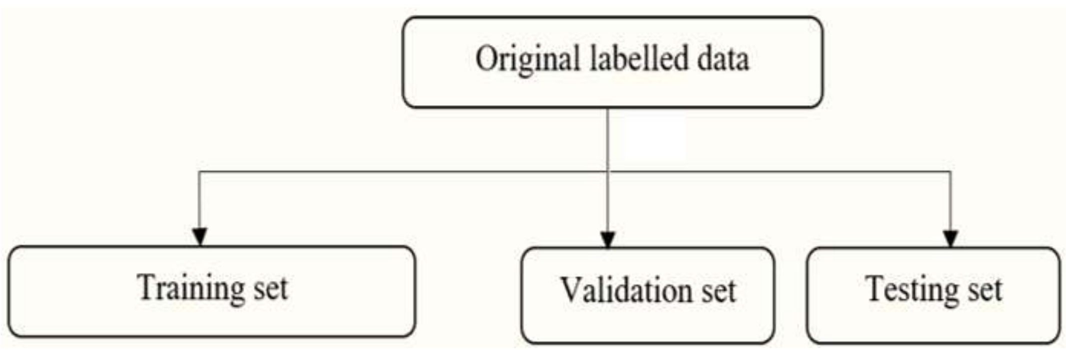
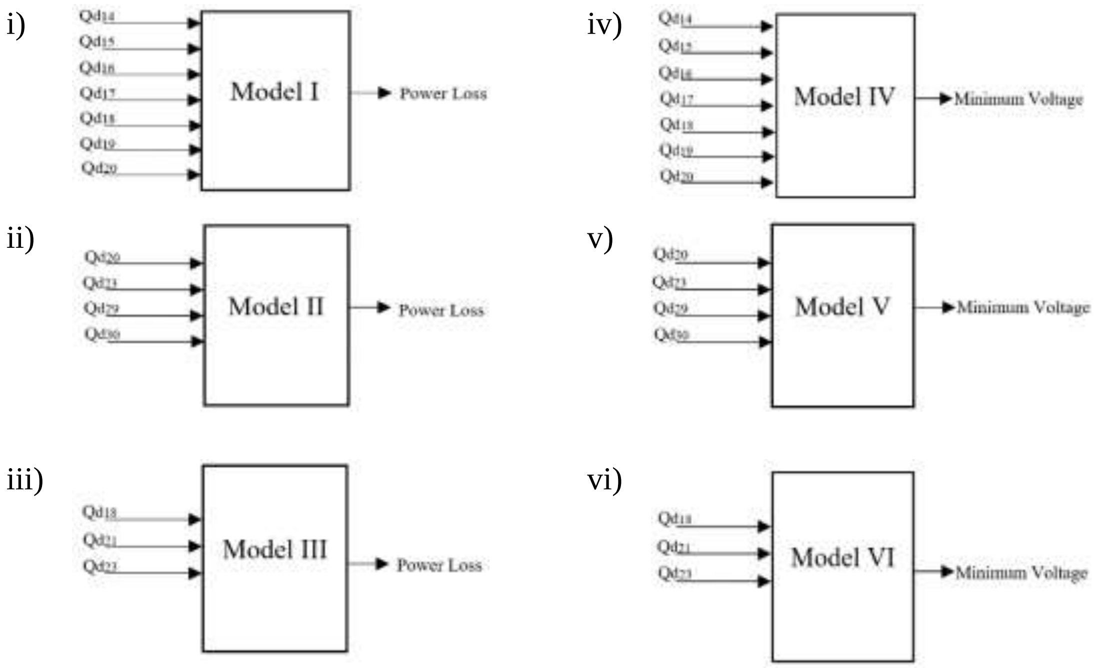


Fig. 5. The split of the original label data.

In this project, the generated data of various load bus models are used for the training data set. Some important aspects need to be considered before deciding the split ratio for each of the data sets. Usually, the validation and testing sets have a much smaller percentage ratio compared to the training set. Depending on the amount of the generated data, the data is set to be 70% for training purposes, while the rest is split equally to be 15% for validation and testing purposes. There are several factors that can affect the exact proportion of the split, but usually, the greatest part of the data is generally used for training. At the project launch, validation and test sets are set aside and are not used for training. This may seem obvious, but it is notable that the validation and test set are there to test the model's efficiency.

Lastly, it is important to have a test set of data for tuning the hyperparameters as some information from the validation process might leak into the models. The test set is not part of training and is not involved in model tuning. This set leaks no information into the models, so it can be used safely to get the idea of how well the model will perform loss prediction production. Proposed models are as follows:



Results and Discussion

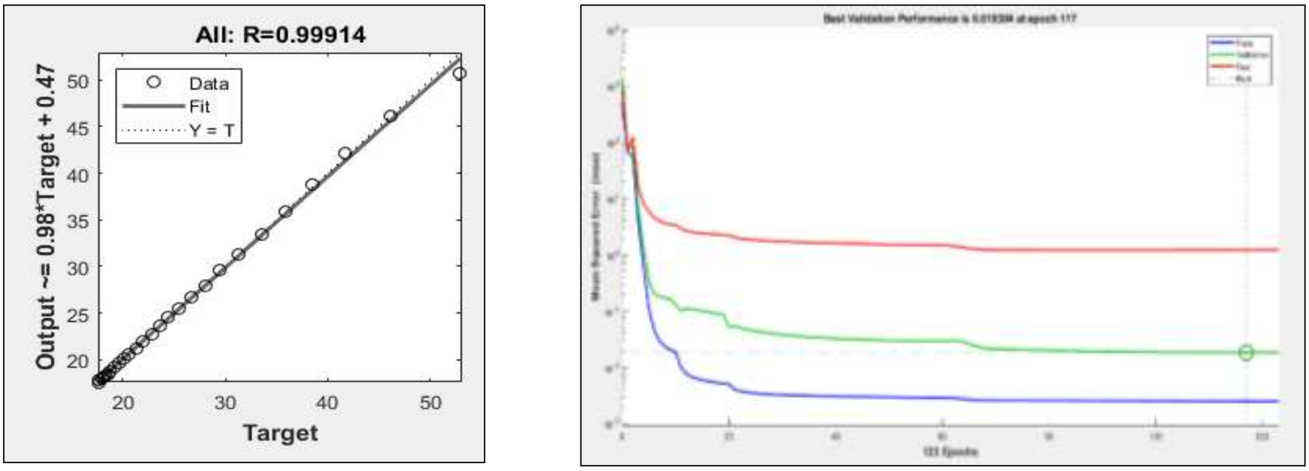
Comparison Data of the Models

This section presents the results and discussion for the study. Several models have been developed namely Model I, Model II, Model III, Model IV, Model V and Model VI.

Model I, Model II and Model III for Real Power Loss

I. Model I

This model is designed to address the variation of 7 input variables namely Qd14, Qd15, Qd16, Qd17, Qd18, Qd19, and Qd20 for power loss prediction. The first model utilized the data of load variations at buses 14 until 20. The results presented in Fig. 6(i) and Fig. 6(ii). From Fig. 6(i), it is observed that the regression for this model network is 0.99914. This overall regression is obtained by the combination of regression results of the training, validation and testing datasets. From Fig. 6(ii), the best validation performance is 0.018304 at epoch 117. The blue line indicates the training performance, green line indicates the validation performance, and red line indicates the testing performance. The training stopped when the validation error increased for 116 iterations, which occurred at the epoch 123. No significant overfitting has occurred by iteration 117 which it shows the best validation performance of the model.

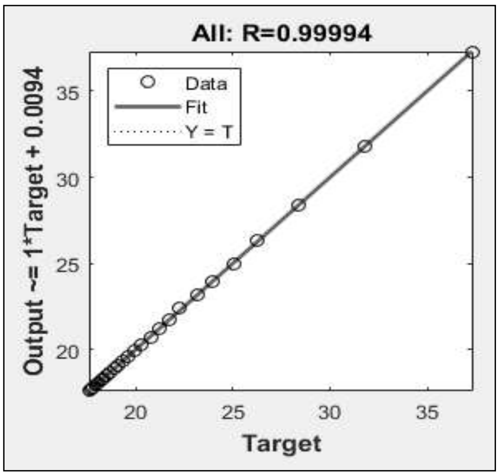


(i) (ii)

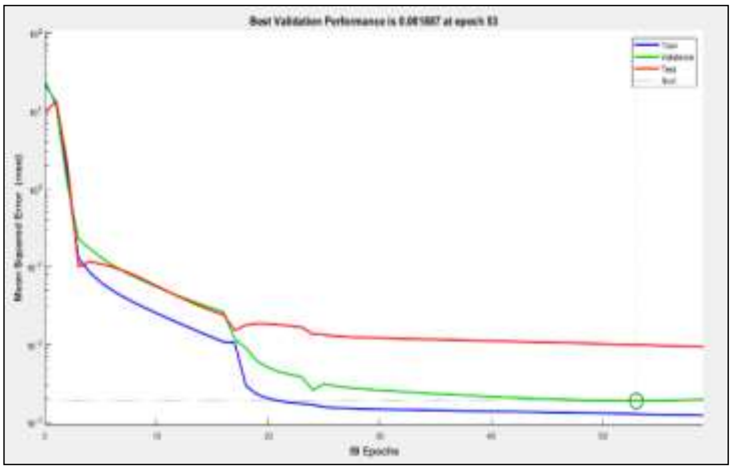
Fig. 6. Results of Model I

II. Model II

This model is designed to address the variation of 4 input variables namely Qd20, Qd23, Qd29, and Qd30 for power loss prediction. The second model utilized the data of load variations at buses 20, 23, 29 and 30. The results presented in Fig. 7(i) and Fig. 7(ii). From Fig. 7(i), it is observed that the regression for this model network is 0.99994. This overall regression is obtained by the combination of regression results of the training, validation and testing datasets. From Fig. 7(ii), the best validation performance is 0.001887 at epoch 53. The blue line indicates the training performance, green line indicates the validation performance, and red line indicates the testing performance. The training stopped when the validation error increased for 52 iterations, which occurred at the epoch 59. No significant overfitting has occurred by iteration 53 which it shows the best validation performance of the model.



(i)

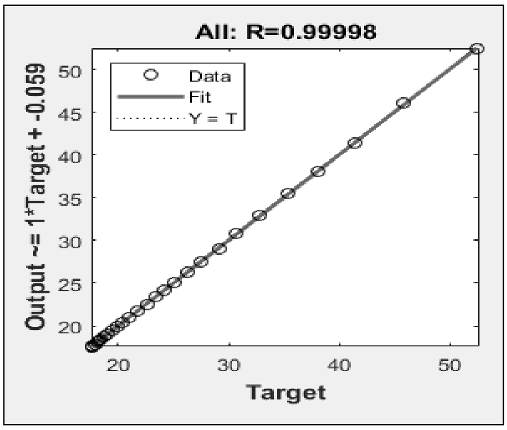


(ii)

Fig 7. Results of Model II

III. Model III

This model is designed to address the variation of 3 input variables namely Qd18, Qd21, and Qd23 for power loss prediction. The third model utilized the data of load variations at buses 18, 21 and 23. The results presented in Fig. 8(i) and Fig. 8(ii). From Fig. 8(i), it is observed that the regression for this model network is 0.99998. This overall regression is obtained by the combination of regression results of the training, validation and testing datasets. From Fig. 8(ii), the best validation performance is 0.00029833 at epoch 5. The blue line indicates the training performance, green line indicates the validation performance, and red line indicates the testing performance. The training stopped when the validation error increased for 4 iterations, which occurred at the epoch 11. No significant overfitting has occurred by iteration 5 which it shows the best validation performance of the model.



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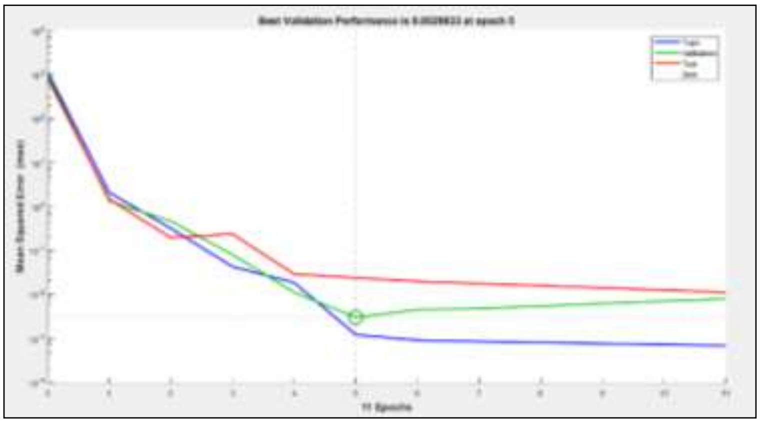


(ii)

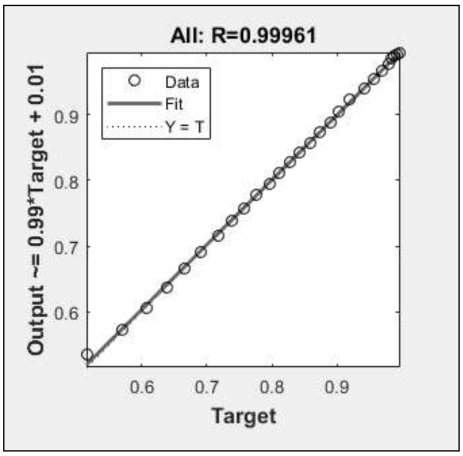
Fig 8. Results of Model III

The results obtained show that Model III gives the best regression performance of 0.99998 compared to Model I and Model II which is 0.99914 and 0.99994, respectively. The model considered as the best when the regression result is closest to 1. Model III consist of a smaller number of input features which can optimize the prediction compared to Model I and Model II. A simple formula of linear regression can be expressed as $y = mx + c$, where y is the dependent variable, m is the slope of line, x is the independent variable and c is the intercept. As the concept of this network will learns by adjusting the weight and biases associated with the input values are adjusted each time to do the prediction, using less number of input features will result in better accuracy as unnecessary information can be eliminated. It can be explained by the correlation coefficient effect in the models. Model I and Model II have more input features compared to Model III. Having a greater number of features may lead to decline in the accuracy if they contain any irrelevant features creating noise in the model. A high correlation between the dependent and independent variables is desired whereas the high correlation between 2 independent variables is undesired. Moreover, the analysis shows that MSE of Model III is 0.00029833, give the best performance of Mean Square Error compared to the other models. It shows the value is the closest to 0. It defined the Model III has the minimum error of average squared difference between the estimated values and the actual values. Besides, the less input features of Model III result in the least time to train the network.

Model IV, Model V and Model VI for Minimum Voltage

I. Model IV

This model is designed to address the variation of 7 input variables namely Qd14, Qd15, Qd16, Qd17, Qd18, Qd19, and Qd20 for minimum voltage prediction. The fourth model utilized the data of load variations at buses 14 until 20. The results presented in Fig. 9(i) and Fig. 9(ii). From Fig. 9(i), it is observed that the regression for this model network is 0.99961. This overall regression is obtained by the combination of regression results of the training, validation and testing datasets. From Fig. 9(ii), the best validation performance is 3.8172e-06 at epoch 6. The blue line indicates the training performance, green line indicates the validation performance, and red line indicates the testing performance. The training stopped when the validation error increased for 5 iterations, which occurred at the epoch 12. No significant overfitting has occurred by iteration 6 which it shows the best validation performance of the model.



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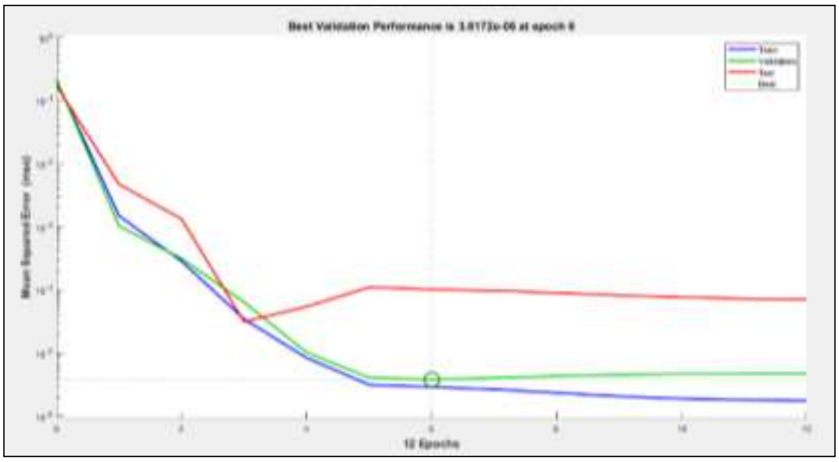
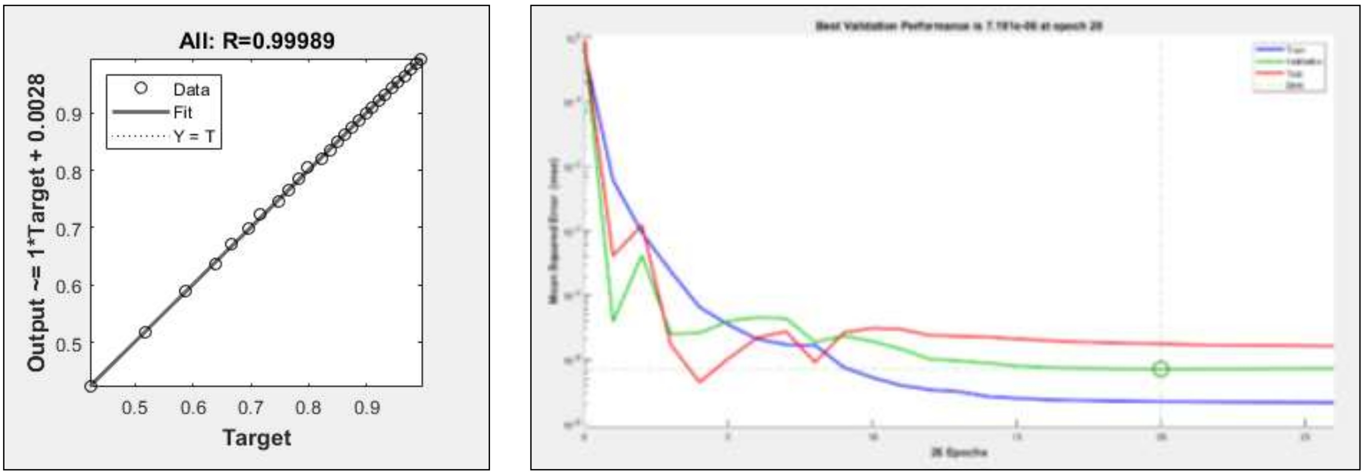


(ii)

Fig. 9. Results of Model IV

II. Model V

This model is designed to address the variation of 4 input variables namely Qd20, Qd23, Qd29, and Qd30 for minimum voltage prediction. The fifth model utilized the data of load variations at buses 20, 23, 29 and 30. The results presented in Fig. 10(i) and Fig. 10(ii). From Fig. 10(i), it is observed that the regression for this model network is 0.99989. This overall regression is obtained by the combination of regression results of the training, validation and testing datasets. From Fig. 10(ii), the best validation performance is 7.191e-06 at epoch 20. The blue line indicates the training performance, green line indicates the validation performance, and red line indicates the testing performance. The training stopped when the validation error increased for 19 iterations, which occurred at the epoch 26. No significant overfitting has occurred by iteration 20 which it shows the best validation performance of the model.

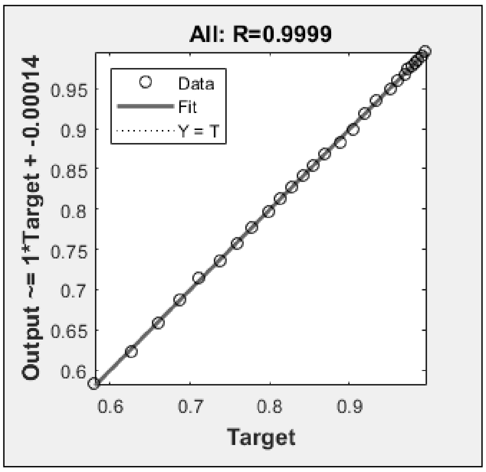


(i) (ii)

Fig. 10. Results of Model V

III. Model VI

This model is designed to address the variation of 3 input variables namely Qd18, Qd21, and Qd23 for minimum voltage prediction. The sixth model utilized the data of load variations at buses 18, 21 and 23. The results presented in Fig. 11(i) and Fig. 11(ii). From Fig. 11(i), it is observed that the regression for this model network is 0.9999. This overall regression is obtained by the combination of regression results of the training, validation and testing datasets. From Fig. 11(ii), the best validation performance is 2.6641e-07 at epoch 6. The blue line indicates the training performance, green line indicates the validation performance, and red line indicates the testing performance. The training stopped when the validation error increased for 5 iterations, which occurred at the epoch 11. No significant overfitting has occurred by iteration 12 which it shows the best validation performance of the model.



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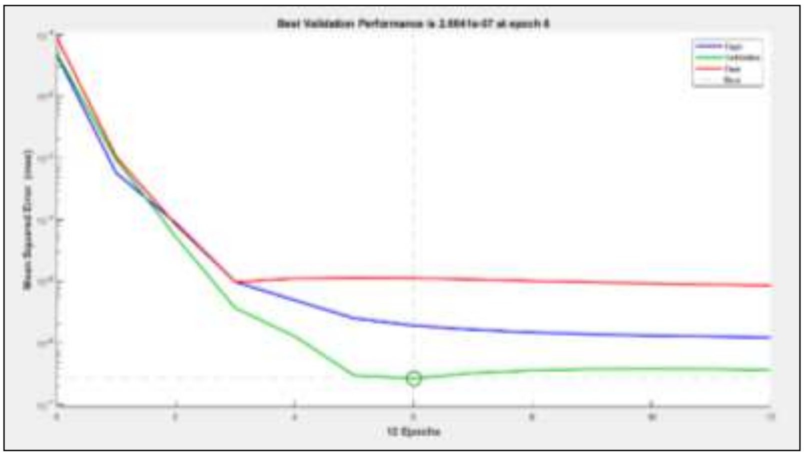

(ii)

Fig. 11. Results of Model VI

The results obtained show that Model VI gives the best regression performance of 0.9999 compared to the value of regression of Model IV and Model V, which is 0.9961 and 0.9989, respectively. The regression of ANNs will predict an output variable using the input features which is the independent variables of the network. The Model VI considered as the best when the regression result is closest to 1. Compared to Model IV and Model V, the Model VI has the less number of input features which can optimized the loss prediction. This can be explained by the correlation coefficient effect in the models. Until the most effective solution to a problem has been obtained, the ANN learning method is based on modifying weighted connections between nodes (independent variables). Having both input (independent variable) and output (dependent variable) in the network allows estimating an error based on its target output and present output. This can be used for network corrections by updating weights and achieving optimal results. As the network do correction by updating weight for every time prediction, it is better to have less input features for better accuracy as having more features will result in irrelevant features that can create noise in the model. High correlation of between the independent and dependent variable required for a better prediction.

Next, the comparison of MSE between the models show that Model VI has the best result compared to Model IV and V. The value of the MSE of Model IV is 0.26641e-07, which it has the error value closest to 0. It defined the Model VI has the minimum error of average squared difference between the estimated values and the actual values. Hence, the results obtained for the power loss prediction and minimum voltage prediction, proved that the models that have less input features such as Model III and Model VI will have a better accuracy of loss prediction.

Conclusion

This paper has presented “Multi Variation Reactive Power Management Using Artificial Neural Network for Loss Prediction in Power System”. In this study, six Artificial Neural Network models have been developed to address the variations of several loads in the IEEE-30 Bus RTS. The reactive power at certain load buses was taken to produce variation of reactive power management models for loss prediction. The data generated of the variation models of Model I, Model II, Model III, Model IV, Model V and Model VI were analyzed and presented in the results. As nowadays, Artificial

Intelligence is the most implementations method used for power system analysis, Artificial Neural Network (ANN) was modelled in this study. The same ANN architecture of single hidden layer is designed to predict loss for the variation models of reactive power management to see which model gives the best result for predictions. The same data size for training, validation and testing data sets were implemented for all the models. The comparative studies on the regression result of ANN of the variation models have been conducted and presented. The results obtained shows that Model III gives the best results for power loss prediction, while Model VI gives the best results for minimum voltage prediction. The value of regression, R for Model III is 0.99998 and Model VI is 0.9999. Compared to the other models, the results of regression value, R of the Model III and Model VI is closest to 1, which it shows the strong correlation between the input and target values with minimum Mean Square Error (MSE), defined the errors closest to zero. It is proved that the smaller number of input features used result in the better accuracy of predictions as unnecessary information can be eliminated.

Acknowledgement

The authors would like to acknowledge the Research Management (RMC) UiTM Shah Alam, Selangor, Malaysia and the Ministry of Higher Education, Malaysia (MOHE) for the financial support of this research. This research is supported by MOHE under Fundamental Research Grant Scheme (FRGS) with project code: FRGS/1/2018/TK07/UITM/03/1 and 600-IRMI/FRGS 5/3 (082/2019).

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