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A Systematic Review of Neural Network Autoregressive Model with Exogenous Input for Solar Radiation Prediction Modelling Development

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Neural Network is one of the Machine Learning methods that has been applied in various Artificial Intelligence system development including solar radiation prediction modelling. Since there are multiple approaches had been developed using the Neural Network method, the study has been focusing on the development of a Multi-layer Neural Network model that can handle non-linearities and highly dynamic data. The integration of the Multi-layer Neural Network and the Non-linear Autoregressive Model with Exogenous Input (NARX) developed a compromising non-linear Neural Network model which can be applied in the modelling of solar radiation. This paper develops a systematic review of the Neural Network Autoregressive Model with Exogenous Input (NNARX) for solar radiation prediction modelling starts from the architecture and the comparative selection for the Training Function. The model is developed and analysed using MATLAB R2019a software. Results showed that the Levenberg-Marquardt Training Function performed better with the R^2 value of 0.94 for training and 0.91 for testing, making it the most suitable for the NNARX in the development of solar radiation prediction modelling.

Keywords: Neural Network; NNARX; Solar Radiation Prediction; Levenberg-Marquardt

I. INTRODUCTION

Solar radiation is defined as an electromagnetic energy source from the Sun. It is received by the Earth in terms of heat and energy. The heat is directly related to the Earth's climate, while the energy is harnessed by specific living organisms on Earth for life continuity. Throughout history, humans have found ways to utilise the heat and energy from the Sun in their daily routines, and eventually, it was discovered as an alternative energy source for electricity generation. The path to the discovery of solar energy in 1839 was led by Alexandre Edmond Becquerel, who observed an increase in electricity charge creation when the electrolytic cell with metal electrodes was exposed to light during an experiment using an electricity-conducting solution (Zalpouri & Sain, 2020). This phenomenon was later called the Photovoltaic Effect. Since then, various attempts and studies had been conducted, and in 1954, Daryl Chapin, Calvin Fuller, and Gerald Pearson from Bell Labs invented photovoltaic technology (Yudha *et al.*, 2018). The trio had managed to develop the world's first Silicon Photovoltaic cell, capable of generating electricity from the Sun's light.

During the discovery, the Silicon solar cell had only 4% efficiency and later increased to up to 11%. Since then, efficiency has always been the priority in developing solar cells using nanotechnology approaches. The idea is to develop high efficiency with low-cost materials to harness the maximum solar energy and generate more electricity. Solar radiation energy has been recognised as an environmentally-friendly energy source that is renewable, clean to produce, and safe to be utilised (Ummah *et al.,* 2021).

Solar radiation energy is not totally received by the Earth's surface at its maximum value as it is reflected, absorbed, and dispersed in the atmospheric layer of the Earth (Apeh *et al.,* 2021), as shown in Figure 1. Solar radiation energy is

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quantified in Watts per surface area by its intensity value, which is described as solar irradiance value (Wm^{-2}). The irradiance value was measured in Global Horizontal Irradiance (GHI). There is a three-parameter to calculate the GHI as Direct Normal Irradiance (DNI), Ground-reflected Irradiance (GI), and Diffuse Horizontal Irradiance (DHI).

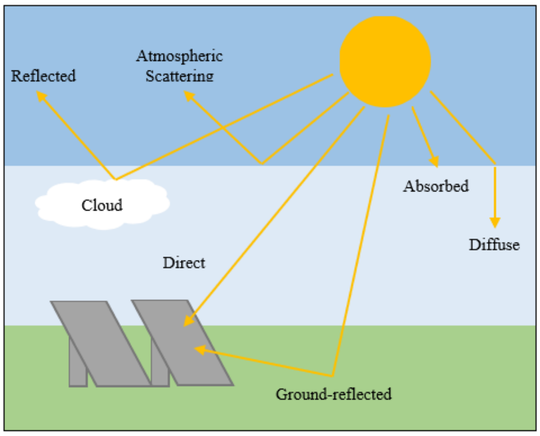


Figure 1. Solar irradiance visualisation

Since the development of a solar farm is costly and requires a preliminary test for stability and potential electricity generation, research has been conducted in developing a prediction model for solar radiation value, including the application of various Machine Learning methods such as Neural Network. Neural Network is a mathematical function developed to produce a functional relationship between input and output data for prediction modelling, data recognition, and instruction execution. McCulloch was the first to illustrate the concept of the decision-making process in the biological human brain based on neuron activity in 1943 (Penconek, 2020). Frank Rosenblatt presented the first Artificial Neural Network called perceptron in 1958 (Babatunde *et al.*, 2020) as shown in Figure 2.

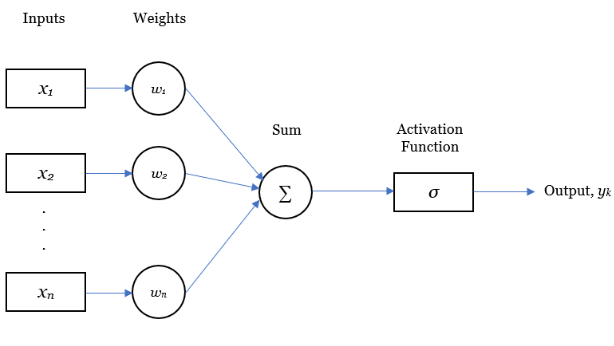


Figure 2. Perceptron

The process of perceptron works in one direction path as the input is passed to the output by the weight's mechanism. The entire input will progress to the activation function with their respective weights. The activation function produces the output in the range of [0, 1]. It is based on the type of data being handled, such as discrete or non-linear data.

There are two structures of Neural Network; single-layer feedforward and multi-layer feedforward (Ananthu *et al.*, 2021). The single-layer consists of a direct connection of the neurons between the input nodes and the output nodes. The multi-layer consists of more than one hidden layer in between the input and the output layers. Basically, Neural Network functions in three main processes consisting of training, testing, and validation. Training is the process of calibration between weight and bias in the network. The training of Neural Networks can be divided into supervised and unsupervised training (Chang *et al.*, 2020). Supervised training is when the input and output data are present in the network while unsupervised training is when only input data is present in the network.

The weight update in Neural Network is based on the backpropagation method (Perera *et al.*, 2020). This method calculates the error between the predicted output and the actual output. The process is repeated using a computing gradient until the error is minimised at the saturated value. As for time-series prediction in solar radiation prediction modelling development, the value of both input and output will be in the time-series function. There are three future value predictions consisting of:

a) Prediction of the future value based on past value:

$$y'(t) = F\{y(t)|y(t-1), y(t-2), \ldots\} \tag{1}$$

b) Prediction of the future value based on present value:

$$y'(t) = F\{y(t)|x(t), x(t-1), x(t-2), \ldots\} \tag{2}$$

c) Prediction of the future value based on both past and present value:

$$y'(t) = F\{y(t)|x(t), x(t-1), x(t-2), \ldots y(t-1), y(t-2), \ldots\} \tag{3}$$

Perceptron had evolved from a single feedforward network to a more complex multi-feedforward network, including the hybrid Neural Network. Hybrid Neural Network is defined as the combination of the Neural Network with another Neural Network and the combination of the Neural Network and other data processing methods (Altan *et al.,* 2021). Radial Basis Function Neural Network (RBFNN), Generalised Regression Neural Network (GRNN), and Neural Network Autoregressive Model with Exogenous Input (NNARX) are examples of a hybrid Neural Network. These multiple versions of Neural Network are developed to solve a specific problem and to perform various functions. For example, Convolutional Neural Network (CNN) had been applied in image processing, including image and pattern recognition (Patel, 2020). Prediction modelling using Neural Networks must be critically reviewed to produce a precise prediction result. Therefore, in this paper, the comparative review of the solar radiation prediction modelling development using NNARX is presented in a systematic way. This is done to prepare the proper framework design of the application of NNARX and other additional elements that could enhance the results for better prediction results with better architecture.

II. LITERATURE REVIEW

A. Solar Radiation Prediction Modelling

The solar radiation prediction was developed by previous studies focusing on the modelling method with multiple input parameters (Guermoui *et al.,* 2020). Irradiance data is among the input parameters that have been used in modelling the solar radiation prediction (Pang *et al.*, 2020), along with sunshine duration (Mensour *et al.,* 2017), temperature (Kisi *et al.*, 2019), and rainfall data (Blal *et al.*, 2020). The development of solar radiation prediction must consider entire related parameters (Sultan Mohd *et al.,* 2021). This study will conduct research in developing a solar radiation prediction model using selected correlative input parameters from the geographical and meteorological database that will be considered to contribute towards the sum of solar radiation value received on the surface of the earth.

The total solar radiation values are predicted using the climatological data as input parameters, such as temperature data, locality of the places, environment-related data, and the climate of the region. This prediction is based on the solar irradiance value captured on a horizontal surface, as it is the best way to collect DNI which is the major contribution to GHI values (Blal *et al.,* 2020; Fan *et al.*, 2020).

Agbulut *et al.* (2021) developed the solar radiation prediction modelling using Artificial Neural Network (ANN) with a combination of input parameters, consisting of daily minimum and maximum ambient temperature, cloud cover, daily extra-terrestrial solar radiation, the sunshine duration based on the daily measurements, and the solar radiation. Predictive modelling is developed by using a 2-year range of data. Based on the results, it is shown that ANN delivers the best predictive results compared with other machine learning algorithms such as Support Vector Machine (SVM), kernel and Nearest-neighbour (k-NN), and Deep Learning (DL). However, the solar prediction using ANN can only manage to obtain regression results of 0.855.

Mohamed *et al.* (2019) also used an ANN for solar radiation prediction modelling with the input parameters of global solar radiation measurement, maximum and minimum air temperature, average air temperature, relative humidity, and atmospheric pressure. There are two algorithms for feedforward backpropagation ANN had been analysed in this study which are basic backpropagation (BB) and backpropagation with momentum and learning rate coefficients (BMLC). Based on the results, the BMLC manage to deliver better results than the BB thus suggesting that the support mechanism towards the BB had given better results for predictive modelling using ANN. Alluhaidah *et al.* (2019) take the same ANN with a hybrid approach of using Wavelet Neural Network (WNN) for solar radiation prediction modelling with only three input parameters of cloud cover, relative humidity, and air temperature.

Solar radiation prediction modelling also employs hybrid approach, which utilises various data processing techniques. In the study by Tao *et al.* (2021), they applied a hybrid combination of the Adaptive Neuro-Fuzzy Interference System (ANFIS), Slap Swarm Algorithm (SSA), and Grasshopper Optimisation Algorithm (GOA) for solar radiation prediction modelling. The inputs for this hybrid ANFIS model include the maximum, mean, and minimum air temperature. They compared this proposed hybrid ANFIS model with several other ANFIS models, such as classical ANFIS, as well as various hybrid ANFIS models like ANFIS-GOA, ANFIS-SSA, ANFIS-GWO, ANFIS-PSO, ANFIS-GA, and ANFIS-DA. The results showed that the proposed hybrid ANFIS outperformed all benchmarked models. This approach not only provides better accuracy in solar radiation prediction but also allows for presenting predictive results using air temperature data alone.

Yang *et al.* (2020) presents the combination of Radial Basis Function Neural Network (RBFNN) and Competitive Swarm Optimisation (CSO) to predict solar radiation using historical solar power data and weather conditions. The proposed of the study is to present the short-term solar power generation prediction using the RBFNN with several meta-heuristic algorithms such as CSO, GWO, Biogeography-based Optimisation (BBO), Monarch Butterfly Optimisation (MBO), Whale Optimisation Algorithm (WOA), Glow-worm Swarm Optimisation (GSO). Based on the results, the proposed RBFNN-CSO manage to deliver better results compared with other benchmarked method. The RBFNN which is a better version of ANN also needed support from the meta-heuristic algorithm to remove the error related to the black-box processing of the Neural Network.

Several authors have presented the work of hybrid combination of other types of Multi-layer Neural Networks. Zang *et al.* (2020) introduced the Deep Belief Network (FDBN) with an embedded clustering technique for solar radiation prediction, using global solar radiation data as its sole input parameter. The proposed method aims to reduce the need for having multiple input parameters to reduce the need of multiple input parameters, thus simplifying data analysis while achieving high-performance predictive analysis. Ghazvinian *et al.* (2019) employed Support Vector Regression with an Improved Particle Swarm Optimisation Algorithm to develop a solar radiation prediction model, incorporating historical solar radiation value, sunshine duration, wind speed, maximum and minimum air temperature, and relative humidity as input factors. The proposed hybrid combination yielded better predictive results, but required a substantial number of input data points.

Sozen *et al.* (2005) developed the MLPNN model for solar radiation prediction, utilising with the Logistic Sigmoid Transfer Function of Polak-Ribiere Conjugate Gradient and Levenberg Marquardt Training Function. They incorporated various climatological data for the modelling. In this paper, the Training Function has a critical impact on predictive modelling. Therefore, further analysis must be conducted on the listed Training Functions in conjunction with the dedicated Multi-layer Neural Network to determine the most suitable approach for predictive modelling of solar radiation.

NNARX, RBFNN, and MLPNN are advanced Multi-layer Neural Networks used in solar radiation prediction modelling. Mohammed *et al.* (2013) developed solar radiation prediction using NNARX, employing meteorological data from the year 2004 to 2007 for training and data from 2008 for the testing. The NNARX model achieved good prediction results, and its architecture showed resilience to the complexity introduced by the amount of the data loaded into the network. Unlike many other Multi-layer Neural Networks, NNARX demonstrated minor impacts from misfit and over-looping issues, making it well-suited for solar radiation prediction modelling. Additionally, Ojo and Adeyemi (2020) also utilised NNARX for solar radiation prediction. In this study, NNARX employed relative humidity, wind speed, and air temperature as input parameters. The results showed that NNARX outperformed MLPNN and Multivariate Linear Regression (MLR) intelligent predictors, achieving higher regression results with a lower root-mean-square error.

Various approaches have been made explored using the parallel and series-parallel architecture of NNARX to divide its input into two components; deterministic and statistical (Salami *et al.,* 2013). Deterministic components, also known as endogenous components, are the parameter described using mathematical terms. On the other hand, statistical components, or exogenous components, have values influenced by other related parameters. The inclusion of both components enhances NNARX's performance in modelling non-linear predictions.

B. Neural Network Methodology

The concept of a Neural Network is based on the transfer of information between nodes, mimicking the movement of real neurons in human brain (Thakur & Konde, 2021). The are two main configurations of Neural Networks which are the Single-layer Neural Network and Multi-layer Neural Networks. An example of the configuration for a Single-layer Neural Network is shown in Figure 3.

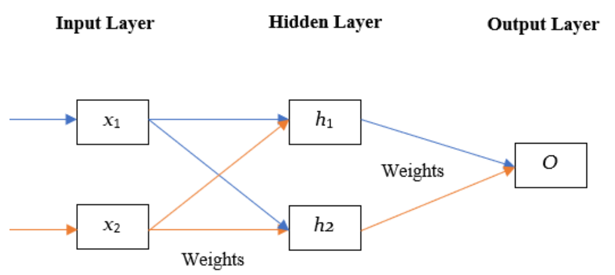


Figure 3. Single-layer Neural Network

Referring to Figure 3, the data in the input layer progresses to the hidden layer before proceeding to the output layer. Single-layer Neural Networks contain only one hidden layer. In contrast, Figure 4 illustrates the Multi-layer Neural Network, which comprises more than one hidden layer, resulting in a more complex architecture.

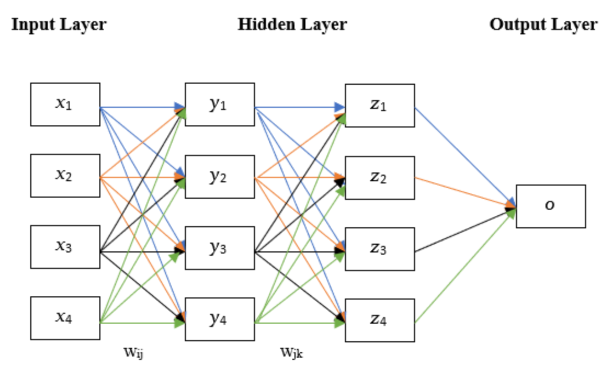


Figure 4. Multi-layer Neural Network

The comparison between Single-layer and Multi-layer Neural Networks is based on the number of hidden layers. This influences the computational calculation, taking into account the weight of interconnected neurons within each layer (Tirdad *et al.,* 2021). The weight is updated using the backpropagation technique, which involves employing a gradient descent or an optimisation algorithm to train the model using dedicated learning rates. The overall methodology flowchart of the Neural Network follows the steps as shown in Figure 5.

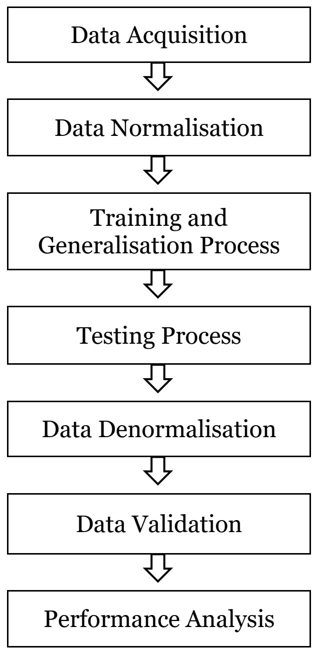
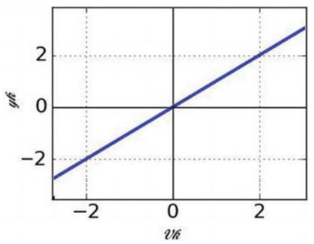
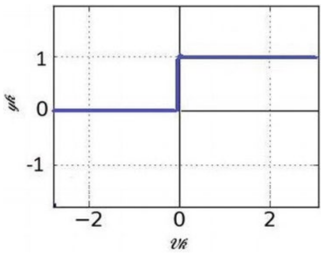
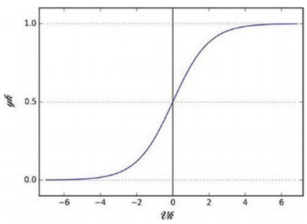
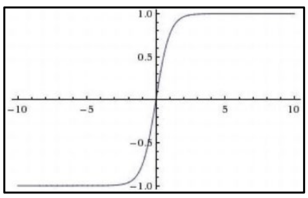


Figure 5. Flowchart of the generic Neural Network

Based on Figure 5, the process of Neural Networks begins with data acquisition. During this stage, the input data is stored in database format, organised with dedicated rows and columns. The program will read each dedicated data in the lines and virtually stores it in matrix order. Next, the data is normalised into a specific range using an Activation Function. The key differences in Neural Network architecture lie in the training and generalisation process, which then leads to the testing process. These steps also vary based on the type of Training Function used in the Neural Network. Once the training and testing are completed, the data is converted back to its original form through the data denormalisation process. This conversion allows the prediction results to be analysed for their efficiency and accuracy.

The complexity of the architecture is determined by the type of data handled in the system (Lin *et al.,* 2020). There are two common types of data which are linear and non-linear data. Linear data can be directly interpreted and can be solved using a single-layer network, while the non-linear data is subjected to the multiple constraints and may vary within certain limits. Regardless of the data types, the data loaded into the Neural Network must be normalised using an Activation Function. The purpose of this Activation Function is to compress the data to a smaller scale, preventing the model from getting stuck in large mathematical calculations that could lead to more errors. Table 1 displays the types of Activation Function used in Neural Networks.

Table 1. Type of Activation Function

Name	Formula	Graph
Linear function	$y_k = v_k$	
Step function	$y_k = \begin{cases} 1 \ if \ v_k \geq 0 \\ 0 \ if \ v_k < 0 \end{cases}$	
Sigmoid function	$y_k = \frac{1}{1+e^{v_k}}$	
Tanh function	$y_k = \frac{2}{1+e^{-2v_k}} - 1$	

The linear function establishes a direct relationship between input and output, while the step function sets a specific limit between input and output. The sigmoid function accommodates non-linear relationships between input and output within a discrete range of 0 to 1, and the Tanh function resolves non-linear relationships between input and output with the designated range of -1 to 1. The normalisation process is crucial throughout the training process of the Neural Network.

The Neural Network follows a process of predicting the output in relation to the input fed into the network. Prior to training, generalisation is required (Ghiassian *et al.*, 2020). The data is processed using weight calculation. Initially, the weighs are pre-calculated based on the number of inputs, hidden layers, and output layers. The weight calculation relies on gradient measurements, as shown in Figure 6.

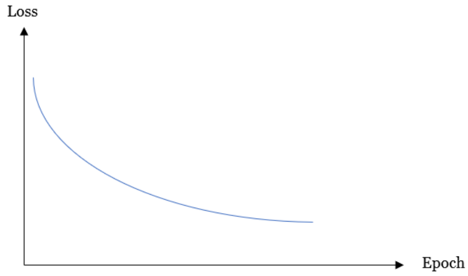


Figure 6. Loss VS Epoch graph

The loss is determined by calculating the difference between the actual value and the measured value, using the Mean Square Error (MSE) as shown in the equation below.

$$MSE = \left(\frac{\sum_1^N (y_{actual} - y_{measured})^2}{N} \right) \tag{4}$$

The MSE will gradually decrease until it reaches a minimum point where further reduction is not possible. This behaviour is controlled by a sliding window that has been set up with certain limits. The number of iterations until the MSE reaches this minimum value is referred to as an epoch.

In Neural Networks, this gradient measurement technique is defined as the Training Function. There are multiple options for Training Functions available for Multi-layer Neural Networks as shown in Table 2.

Table 2. Type of Training Function

Name	Acronyms
Levenberg-Marquardt	trainlm
BFGS Quasi-Newton	trainbfg
One-Step Secant	trainoss
Resilient Backpropagation	trainrp
Scaled-Conjugate Gradient	trainscg
Conjugate-Gradient of Fletcher-Reeves	traincgf
Conjugate-Gradient of Polak-Ribiére	traincgp
Conjugate-Gradient with Powell/Beale-Restarts	traincgb

The selection of Training Functions is based on how fast it can converge and how low is the error calculation results. The training of the Neural Networks had been set by certain epoch numbers. A small epoch number indicates that the network converges faster. That is why, for the prediction model development using a Multi-layer Neural Network, the selection of a Training Function is crucial in determining the accuracy and efficiency of the prediction results.

C. NNARX

NNARX is the combination of a Multi-layer Neural Network and the Autoregressive model with Exogenous Input (ARX). The ARX is widely applied in time-series modelling (Sultan Mohd *et al.,* 2020). This combination enables the system able to perform non-linear prediction-based time-series modelling. The Tapped Delay Line (TDL), which combines past and present time-step data, is typically used to illustrate the structure of NNARX. The Feed Forward Network consists of hidden layers and a weight matrix used to calculate errors before the network's weight is updated backward. There are two architectures of NNARX; Series-Parallel Architecture (SPA-NNARX) as shown in Figure 7 and Parallel Architecture (PA-NNARX) as shown in Figure 8.

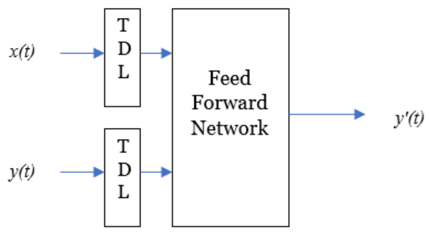


Figure 7. SPA-NNARX

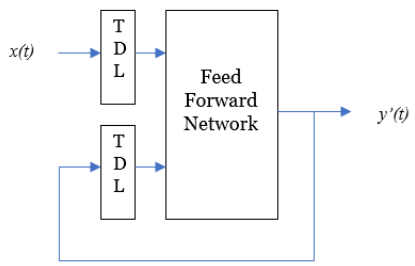


Figure 8. PA-NNARX

In SPA-NNARX, the input *x(t)* is fed into the Feed Forward Network along with the actual output of *y(t)* to develop a prediction output *y'(t)*. On the other hand, in PA-NNARX, the input *x(t)* is fed into the Feed Forward Network with the past predicted output to predict the future prediction output *y'(t)*. In other words, the PA-NNARX does not use the actual output to produce the prediction output. For this paper, SPA-NNARX will be used in the training process, while PA-NNARX will be used for the testing process.

III. METHODOLOGY

In this paper, the development of NNARX is carried out using MATLAB R2019a software, with the process illustrated in Figure 9. The NNARX modelling necessitates the use of a Neural Network toolbox.

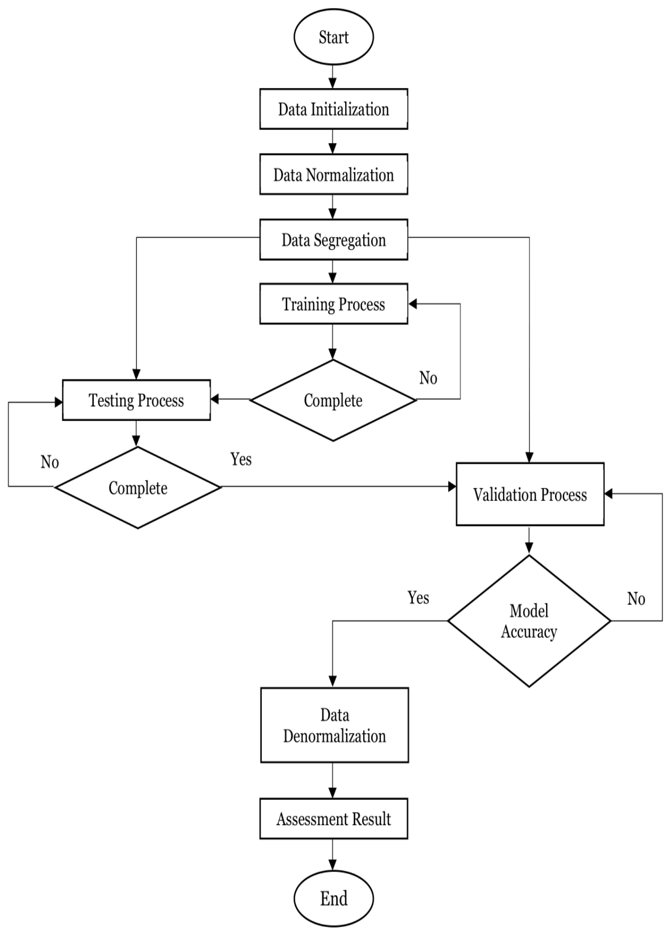


Figure 9. Methodology process of proposed NNARX

The Neural Network Toolbox in MATLAB is utilised to segregate the data into three groups, with 70% used for training, 15% for testing, and another 15% for validation. The training phase primarily utilises the input data for the generalisation process. Data are randomly sampled in sequence to maximise the possibilities of relationship behaviour between the input and output of the prediction model.

The input data for the solar radiation prediction is presented in Table 3. These parameters were obtained from the SOLCAST database, accessible at https://solcast.com. The selected parameters are specific to the capital city of Malaysia, Kuala Lumpur, and were gathered hourly from 2017 to 2019. Prior to being fed into the NNARX training, this data will be normalised using the Sigmoid Function.

Table 3. List of Input Parameters

Parameters	**Unit**	**Measuring Equipment**
Air Temperature	°C	Temperature + Humidity Sensor
Dew Point	°C	Temperature + Humidity Sensor
Precipitable Water	cm	Water level reading at the nearest water reservoir
Cloud Opacity	%	Observation on surface plate
Wind Speed	ms^{-1}	Anemometer
Surface Pressure	mbar	Barometric Pressure Sensor
Solar Irradiance	Wm^{-2}	Solar cell

As mentioned before, MATLAB R2019a software offers various Training Function that can be used. For analysis purposes, NNARX will be developed using each of these Training Functions. Figure 10 illustrates the network developed for solar radiation prediction modelling using SPA-NNARX for training, and Figure 11 displays the network developed for solar radiation prediction modelling using PA-NNARX for testing.

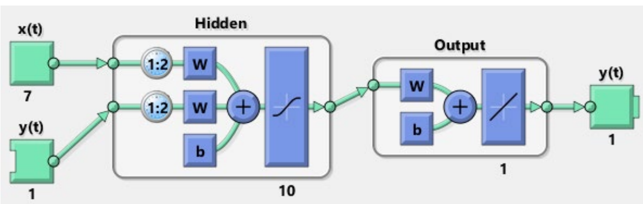


Figure 10. SPA-NNARX

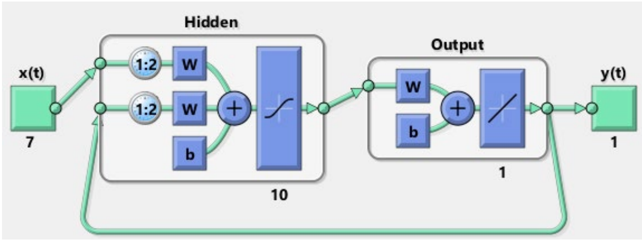


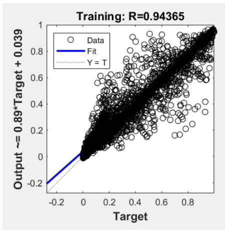
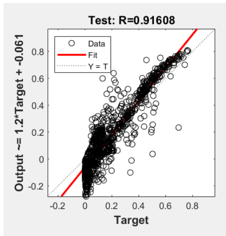
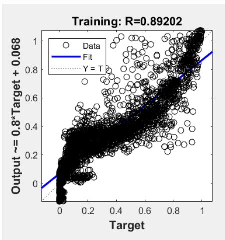
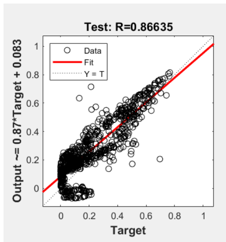
Figure 11. PA-NNARX

The input layer consists of 7 input parameters and 1 actual output, while the hidden layer is set to 10, and there is only 1 output layer. The delay is initially set to 2 as per MATLAB's default value. In the context of backpropagation calculation, the bias is always set to 1, and the weight is continually updated using gradient calculation.

IV. RESULTS AND DISCUSSIONS

The prediction results are presented in terms of Regression value, R2. MATLAB displays the results of Training, Testing, Validation, and overall values. There is a difference in regression results between the training and testing phases, as shown in Table 4.

Table 4. Regression Results

Training Function	**Training**	**Testing**
trainlm		
trainbfg		

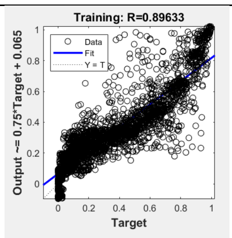
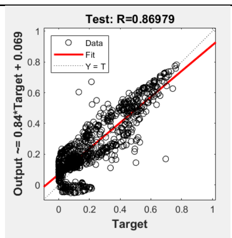
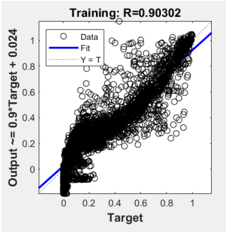
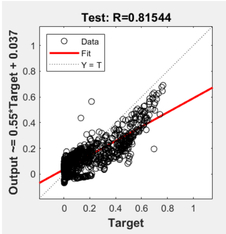
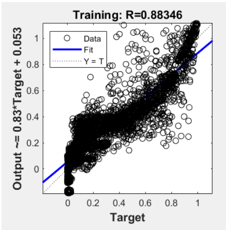
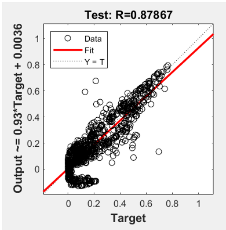
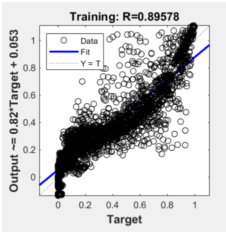
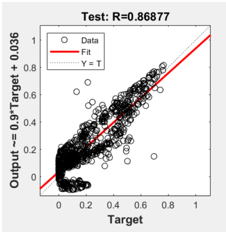
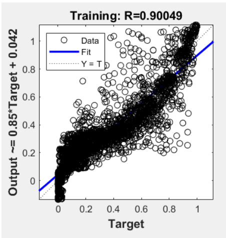
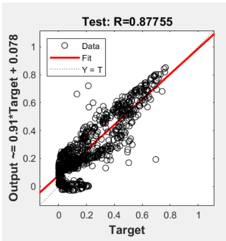
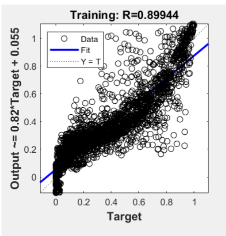
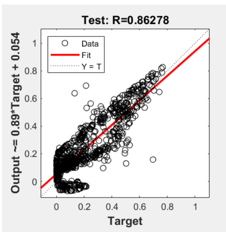
trainoss		
trainrp		
trainscg		
traincgf		
traincgp		
traincgb		

Table 5 presents the results of the analysis, with a focus on the regression value, R^2. The R^2 value is a crucial indicator of the accuracy and precision of the prediction model. It is obtained from both the Training and Testing phases. It is important to note that there may be a slight difference between the results obtained from training and testing. During training, the model is adjusting itself by iteratively calculating errors between actual and predicted results to minimise the value, while in testing phase, it solely relies on the predicted values.

Table 5. Regression Results

NN	Training Function	Epoch	R^2 for Training	R^2 for Testing
NNARX	trainlm	10	0.94365	0.91608
	trainbfg	8	0.89202	0.86635
	trainoss	9	0.89633	0.86979
	trainrp	9	0.90302	0.81544
	trainscg	8	0.88346	0.87867
	traincgf	10	0.89578	0.86877
	traincgp	10	0.90049	0.87755
	traincgb	10	0.89944	0.86278

The results presented in Table 5 demonstrate that Levenberg-Marquardt Training Function (LMTF) yielded favourable outcomes for both the training and testing of NNARX, with an acceptable number of epochs. In Neural Network training, the epoch plays a crucial role in determining the speed of convergence of training, testing, and validation, as shown in Figure 12.

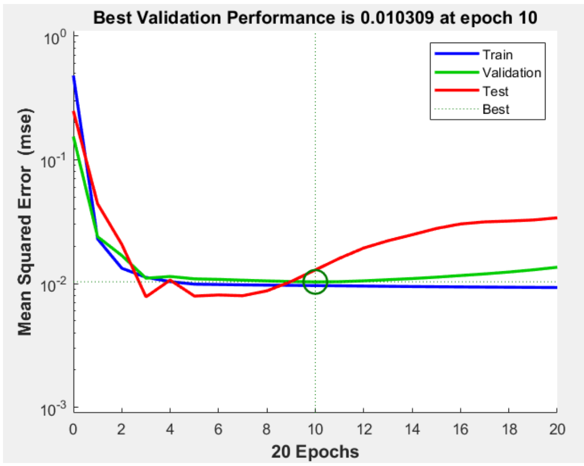


Figure 12. Best Validation Performance results for 'LMTF'

To enhance the learning rates and efficiency of the prediction results, it is recommended to apply optimisation techniques during the training of NNARX. The combination of optimisation method can help reduce the gradient calculation and lead to improved performance results for the prediction.

V. CONCLUSION

As for the conclusion, this paper has presented the process of developing NNARX for solar radiation prediction modelling using MATLAB R2019a software with the Neural Network toolbox. The study explored several Training Functions available for Multi-layer Neural Network model development, testing each of them for both the training and testing phase of the NNARX. Two types of architecture, SPA-NNARX for training and PA-NNARX for testing, were used in this paper. The evaluation of results was based on overall prediction output, with a comparison to the real output using regression value, R^2 to determine the precision of the predicted output. The findings revealed that the LMTF demonstrated the best performance results when compared to other Training Functions. For future research, it is recommended to use LMTF as the Training Function in improved NNARX models. Additionally, applying LMTF to the NNARX method for other non-linear dynamic predictive modelling applications is encouraged. This study provides valuable insights into the development of NNARX for solar radiation prediction and lays the foundation for further advancements in the field of solar energy forecasting.

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