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SOLAR LOCATION ESTIMATION USING LOGSIG BASED ACTIVATION FUNCTION USING ARTIFICIAL NEURAL NETWORK APPROACH

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ABSTRACT

Solar panel is one of the renewable energy that can reduce the environmental pollution and have a wide potential of application. The exact solar prediction module will give a big impact on the management of solar power plants and the design of solar energy systems. This paper attempts to find the best Artificial Neural Network (ANN) based logsig transfer function and various training algorithm that can be used to calculate the temperature module (Tm) in Malaysia. This can be done by simulating the collected data of four weather variables which are the ambient temperature (Ta), local wind speed (Vw), solar radiation flux (Gt) and the relative humidity (Rh) into the Neural Network Tool in MATLAB. Three different ANN transfer function and 14 types of training were compared to choose the best method. Finally, an equation for the ANN model will be generated in order to calculate the temperature module based on ambient temperature, local wind speed, solar radiation and relative humidity variables.

Introduction

Due to the reduction of the conservative energy resources, the demand for renewable alternatives has increased. Among all the renewable energy, the solar energy which is well known as the pollution-free energy has gained worldwide attention. Accurate prediction of the solar generation is significant for the design of solar power plants and other systems. Besides that, it has been applied to our daily lives, such as the design for agriculture, water resources and passive heating of the building. The solar prediction has a high relationship with the surroundings conditions. Thus, it is necessary to make the solar prediction with several climate parameters including ambient temperature, total cloud cover, average temperature, evaporation, soil temperature, average cloudiness, average wind velocity, atmospheric pressure, and the relative humidity, etc [1-4]. The information of geographic position, for example altitude, longitude and latitude also can be use as the prediction model. As for this paper, the parameters used are ambient temperature, local wind speed, solar radiation flux and relative humidity.

As a prediction technique, the ANN Method has been widely applied in the solar power field, such as the estimation of photovoltaic energy generation and the global solar radiation prediction [5-6]. The collected data of the ambient factors of Ta, Vw, Gt and Rh were trained and tested by using all the trainings and transfer functions stated in order to find the best method to get an equation that can be used to calculate the temperature module in Malaysia which can help in designing the solar power plant system. This is because by calculating the Tm, we can predict the value of voltage and current that can be collected by using the photovoltaic. The structures of this paper are as follows. The explanation about solar prediction and ANN are explained in Section 2. The discussions about the methodology by the proposed systems applications, Artificial Neural Network (ANN) using MATLAB design flow presented. Experimental results, comparison and analysis for the module temperature, Tm with the predicted outputs and the equation obtained are explained in results and discussion section and finally, concluding remarks and future work are given in conclusion section.

Literature Review

Introduction to Artificial Intelligence (AI)

Artificial Intelligence (AI) is the computer science study about making a machine or developing software that has the ability like human intelligent [7-9]. It is an integration of the computer science study and physiology. AI is mainly about making computers behave like humans. AI tries to solve the complex problems in more human like fashion and in minimum time compared what a human takes. That is why it is called as Artificial Intelligence. Intelligence can be defined as the ability to think and imagine, creating, memorizing and understanding, recognizing patterns, making choices adapting to change and learn from experience. The major objective for this field of study is creating intelligence, either in trying to act like human-intelligent or not. AI is also known as "the study and design of intelligent agents", where an intelligent agent is a system that observe the environment and act to achieve the maximum rate of success.

Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is one of the studies of Artificial Intelligence and is a new computing technology in the field of computer science study. ANN also considers the integration of neural networks with another computing method such as fuzzy logic to maximize the interpretation ability of data. Neural networks mostly used for problem solving in pattern recognition, data analysis, control and clustering [10]. ANN has various features including high processing speeds and the ability to learn the solution to a problem from a set of data or examples. Multilayer Perceptron (MLP) and Radial Basis Function (RBF) networks are the most suitable and referred neural networks in the pattern recognition detection. The MLP network consists of different kind of Multilayer Feed Forward neural network. This network can be trained to form various decision surfaces in the input space. However, MLP training processes usually consume large computation time and local minima problem often occur [11].

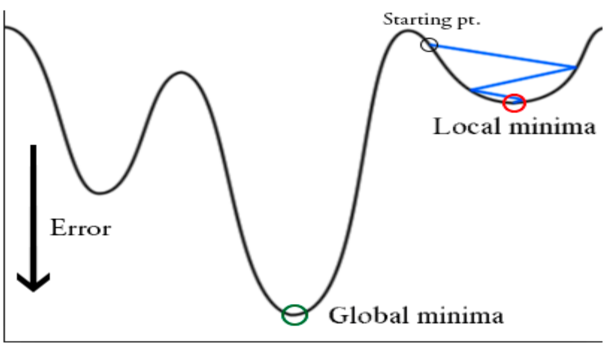

Figure 1: Local minima [11]

Multilayer Perceptron (MLP)

The Multilayer Perceptron (MLP) neural network is built up of simple components. A single-input neuron is shown in Figure 2(a). The scalar input p is multiplied by the scalar weight w to form wp, one of the terms that is sent to the summer. The other input, 1, is multiplied by a bias b and then passed to the summer. The summer output n, often referred to as the net input, goes into a transfer function f, which produces the scalar neuron output a. Typically, a neuron has more than one input. A neuron with R inputs is shown in Figure 2(b). The individual inputs p1, p2... and pR are each weighted by corresponding elements w1,1, w1,2, ... and w1,R of the weight matrix W. The transfer function f may be a linear or a nonlinear function of n. A transfer function which also known as the system function or network function, is a mathematical representation, in terms of spatial or temporal frequency, of the relation between the input and output. The transfer functions usually have a sigmoid shape, but they may also take the form of other non-linear functions, piecewise linear functions, or step functions [7-8].

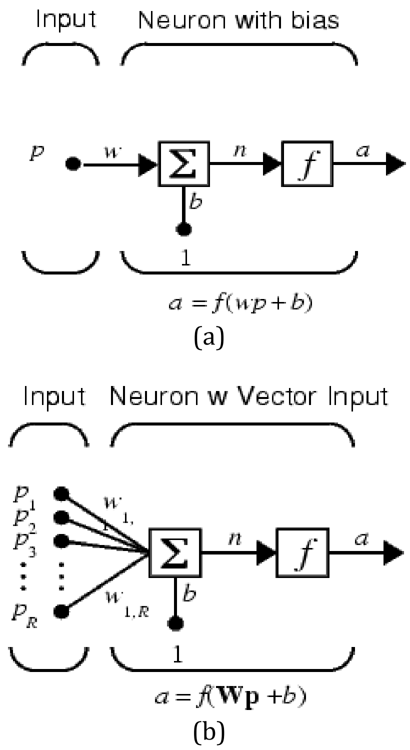

Figure 2: a) Single input neuron, b) multiple input neuron

Transfer Functions

One of the most commonly used functions is the Log-sigmoid transfer function (LOGSIG), which is shown in Figure 3. This transfer function takes the input (which may have any value between plus and minus infinity) and squashes the output into the range 0 to 1. The log-sigmoid transfer function is commonly used in multilayer networks that are trained using the back propagation algorithm, in part because this function is differentiable.

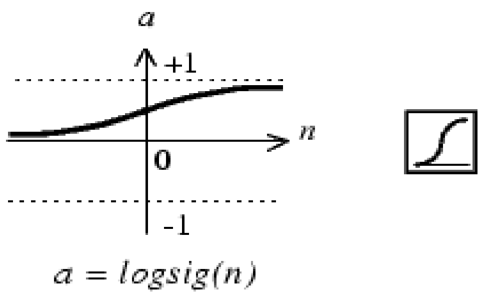

Figure 3: Log-sigmoid transfer function (LOGSIG)

ANN Techniques for Solar Prediction

ANN design primarily involves input layer, hidden layer, output layer, connection weight and biases, activation function and summation node. Its action is divided into two stages: learning (training) and generalization (recalling). In training network weights and biases are used to generate the target output by reducing the error function. The networks are progressed through learning algorithm and trained by epochs which are entire cycle of all training data existing in the network. The learning techniques are divided into supervised, unsupervised, reinforcement and evolutionary learning. The supervised learning is based on totaling of variance between the real network output and preferred output. The weights and biases are modified by organizing training pattern set and resultant errors between the preferred output and the subsequent network output. Thus supervised learning proceeds as closed loop feedback system where error is the feedback signal. The error degree is characterized through mean squared error (MSE) [12-13]. The MSE is determined after each epochs and the learning process is finished when MSE is minimized. ANN techniques have become alternative methods to conventional techniques and are used in a number of solar energy applications. Kaouther et. al. [6] has reviewed ANN for sizing of photovoltaic systems and Wu & Wang [5] has reviewed ANN for photovoltaic applications. ANN has many applications for modeling, prediction and forecasting of monthly, daily and hourly solar radiation.

Methodology

The method of Artificial Neural Networks was used to simulate the data collected. The objective of the analysis was to obtain a relationship between module temperature and the ambient conditions (ambient temperature, relative humidity, wind speed, and global irradiance). The ANN was selected due to its computational and generalization capability. Besides that, it has more prediction accuracy than the Linear, Nonlinear and Fuzzy Logic [13-14]. In this chapter, the planning on designing the artificial neural network by using MATLAB and neural network programming will be described. The input data and target data were imported into the MATLAB Neural Networks Toolbox. Both data were in Excel format. After that, new network was designed. There are total 14 networks designed to find the best method with the least MSE and Regressions near to value one. All the networks use the same network type which is Feed Forward Back Propagation (FFBP).

There are 14 types of trainings that can be done in FFBP. The trainings included in FFBP are BFGS Quasi-Newton (BFG), Bayesian Regulation (BR), Conjugate Gradient with Beale-Powell Restarts (CGB), Conjugate Gradient Back Propagation with Fletcher-Reeves Restarts (CGF), Conjugate Gradient with Polak-Ribiere Restarts (CGP), Gradient Descent (GD), Gradient Descent with Momentum (GDM), Gradient Descent with Adaptive Learning Rate (GDA), Gradient Descent with Momentum And Adaptive Learning Rate (GDX), Levenberg Marquardt (LM), One Step Secant (OSS), Random Weight / Bias Rule (R), RProp (RP), and Scaled Conjugate Gradient (SCG). For each of these trainings, the Log-Sigmoid (Logsig) are used. As shown in Figure 3, the network model is created, whereas the x values refer to the input values, w is the weight, b is the bias and out is the output of the predicted results. In the current work, the target is the measured module temperature, the inputs are monitored ambient parameters, the neural network is a mathematical model/equation and the adjusted weights are the corresponding coefficients of the ambient parameters [15-17]. The amount of data to be trained and tested is set as 720 set of data. The predictions and the actual targets will be shown to show the comparison between them. From the prediction data and actual targets, the accuracy and precision of the neural network can be determined.

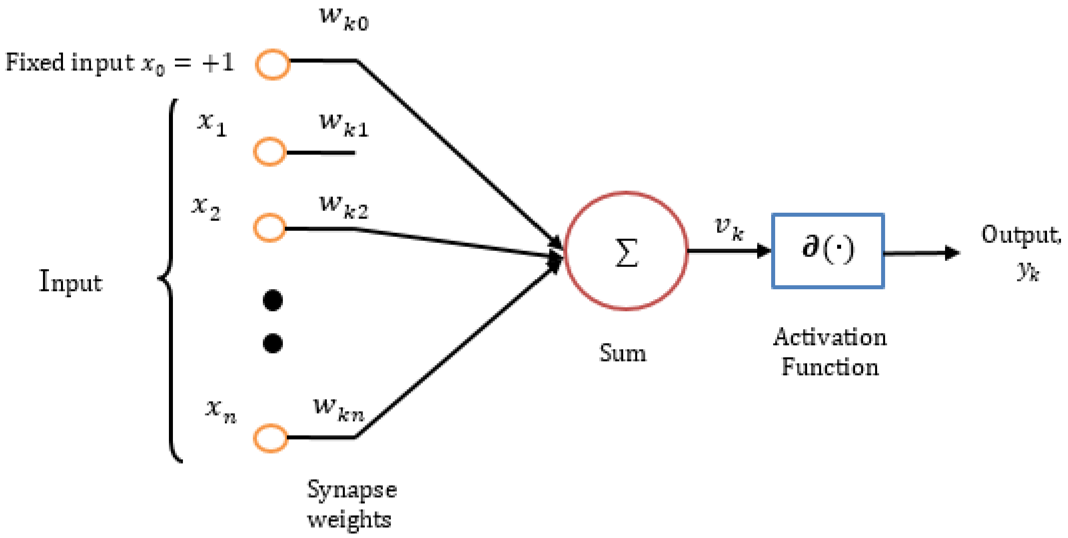

Figure 4: Block diagram of ANN

Result and Discussion

As stated before, Mean Squared Error (MSE) which indicates the degree of error to the network can be used to find the best method of training for the data. Besides that, the regression with the value nearest to one will also indicate a good performance of the trainings. From Table 1, the values of MSE are acceptable in order to estimate the solar best location very well. From the table, BR training algorithm capable to train the network with the lowest MSE performance with 2.4172. LM training algorithm shows the second best performance with 3.3284 MSE measurement. CGP training algorithm shows the third best performance with MSE measurement of 5.7528. Then training algorithm performance follows by GDM, RP, BFG, CBG, R GD, GDX, and GDA training algorithms. The third last of the training algorithm is given by SCG training algorithm with 10.6530 while OSS training algorithm shows 11.3230 of MSE as the second last performance, respectively. Last but not least, CGF training algorithm show the worst performance among fourteen of them with 14.7059.

Table 1: MSE for LOGSIG Training Algorithm

Training Algorithm	MSE
BR	2.4172
LM	3.3284
CGP	5.7528
GDM	5.8179
RP	5.9710
BFG	7.9428
CBG	6.9363
R	6.9548
GD	7.3885
GDX	7.5582
GDA	8.5016
SCG	10.6530
OSS	11.3230
CGF	14.7059

From Table 2, the performance on regression have been shown, respectively. The regression performance may range from 0 to 1, thus 1 is the best. From the table, BR training algorithm given the best performance among others with 0.8364 follows by LM training algorithm capable to give 0.7947 as the second. CGP come as the third with 0.7846 at regression performance. The performance then follows by

SCG, GDA, GD, OSS, R, CBG, RP and BFG. CGF training algorithm give the worst performance with 0.1315 regression performance. GDM training algorithm gave the second last performance with 0.1884 while GDX shows the third last performance with 0.4583.

Table 2: Regression for LOGSIG Training Algorithm

Training Algorithm	Regression
BR	0.8364
LM	0.7947
CGP	0.7846
SCG	0.7663
GDA	0.7498
GD	0.7449
OSS	0.7154
R	0.6790
CBG	0.6438
RP	0.6149
BFG	0.5674
GDX	0.4583
GDM	0.1884
CGF	0.1315

From both tables, clearly shows that the different between stochastic and deterministic based training algorithm models. The BR training algorithm families are designed based on the stochastic model while BP training algorithm families are derived from the deterministic model. A stochastic model can be defined as a random variables collection. Compare to deterministic model, its try to find familiar kind of algorithm itself. From the result, it shows that most of BR training algorithm is takes time to reach the peak of converge but enable to give high accuracy performance compared to others training algorithm. combination. Most of BP training algorithm capable to reach the optimum convergent point very fast but unable to perform well since they are trapped in local minima during the training process. However, the training algorithm capable to perform better since some modification have been made to release from local minima. LM training algorithm origin from BP training algorithm after some modification by adding Gauss-Newton. Its help along with gradient descent by BP training algorithm to search for global minima.

Conclusion

From the results, the research can be concluded that TANSIG is the most suitable transfer function to simulate the data of the ambient factor of temperature module due to small value of MSE and high value of regression. But it is deniable that the PURELIN transfer function shows a good performance for overall trainings in Feed Forward Back Propagation.

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