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RADIAL BASIS FUNCTION AND THREE-LAYERED FEED-FORWARD NETWORK FOR THE OPTIMAL OUTPUT POWER OF PHOTOVOLTAIC MODULES

Syafaruddin*, Gassing and Faizal Arya Samman

Department of Electrical Engineering
Universitas Hasanuddin
Jalan Poros Malino Km. 6, Gowa 92171, Indonesia
{ gassing; faizalas }@unhas.ac.id
*Corresponding author: syafaruddin@unhas.ac.id

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Abstract. *Artificial neural networks are proven to be efficient and effective methods for the purpose of modeling, estimating, optimizing, predicting and controlling in engineering applications. Especially for applications in photovoltaic (PV) systems, artificial neural network models have been used to estimate the optimal output power of the PV modules. Artificial neural network methods are characterized by fairly computational process, good pattern recognition potentials in terms of solving the non-linear characteristic and variability output problems of PV system. Nevertheless, there are still possible weaknesses and shortcomings of this method during the computational process. Therefore, the research aims to develop and investigate the training process and validation of types of artificial neural networks in connection with the process of estimating the output power of PV modules based on crystalline Silicon technology. The types of artificial neural network method are radial basis function (RBF) and three-layered feed-forward network (TFFN). Meanwhile, the investigated PV modules are the crystalline Silicon solar panel technologies.*
Keywords: Computational intelligence, RBF, TFFN, Crystalline Silicon cells technology, PV modules

1. **Introduction.** One of the computational intelligence methods is artificial neural networks. Artificial neural networks have become an attractive choice in solving the estimation and optimization problems in the field of engineering. The advantages of this method compared to conventional computing methods are fairly computational process and have good pattern recognition potentials [1, 2]. Artificial neural network methods are also characterized with unnecessary knowledge of internal system parameters, fairly simple computing process and capable solving of multi-optimization problems [3]. In some cases, only data for training process is needed to obtain the optimum solution without giving solution of any non-linear mathematical formulas or performing statistical data as in the conventional optimization methods [4]. Therefore, artificial neural networks are proven to be suitable for system modelling, diagnostic process, optimum values, estimation, forecasting and controlling of a complex system.

The artificial neural networks can certainly be used for the process of optimization in PV systems. It is due to the natural characteristics possessed by non-linear output of systems. The search for the optimum point of a PV system with non-linear characteristics using conventional approach or other numerical methods would yield difficult computational process, the search process requires much computational time and it is difficult to reach convergence solutions in difficult situations. In addition, the output characteristics of the PV system are variable because they are influenced by environmental variables.

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The output power is greatly influenced by the level of sunlight intensity and ambient temperature where these two factors follow the natural photocurrent characteristics of solar cells [5]. Therefore, finding the optimum output power and energy is important to achieve a PV system conversion efficiency rating [6].

The optimum output power is often used as a target controller so that this becomes interested point to be investigated. However, the operating voltage of a crystalline Silicon solar module is strongly influenced by temperature. If the temperature rises, the operating voltage will drop, and vice versa. This condition is even worse when the sky is cloudy so that the intensity of sunlight becomes uneven, so that the optimum voltage might shift down very far from the global optimum point [7]. Therefore, the maximum output power cannot be linearized as a function of the intensity of sunlight and cell temperature. To overcome such problems, the artificial neural network methods are an attractive solution in identifying optimum points in all system operating scenarios.

The purpose of this research is to compare the performance of artificial neural networks namely radial basis function (RBF) and three-layered feed-forward network (TFFN) in order to estimate the maximum power of different solar panels based on Silicon crystalline technology. In other researches, the RBF and TFFN are still popular and fundamental methods either as a single method or a hybrid method amongst the artificial neural network methods in solving the uncertainty factors in predicting the engineering parameters. The radial basis function has been used to avoid the uncertainty factors regarding the scheduling operation in predicting the output power of PV generation systems [8]. Similarly, the RBF network has been utilized to determine the most influencing factor of climate inputs, such as the solar intensity on module surface and rising temperature on backside surface in order to predict the daily energy generation of photovoltaic systems [9]. Also, the RBF neural network has been effectively applied to tracking the optimal power point for the efficient energy production and improved efficiency performance of solar panels [10]. Meanwhile, the combination of particle swarm optimization and feed-forward neural network has been implemented to determine the optimal amount of bioenergy for the improved performance of microgrid systems [11]. Likewise, the scheme of training process in feed-forward neural network is improved with particle swarm optimization method in order to achieve high accuracy performance, optimal model topology and computational effort reduction in PV system application [12].

Following the previous literature, the performance investigation of these two artificial neural networks is important to enrich diversification methods based on artificial intelligence and to recommend any types of artificial neural network structures for a specific application based on the consideration of simple structure, flexibility of training process and the level of accuracy during training and validation process. In our study, the electrical characteristics of solar module based on crystalline Silicon technologies are basically the same where they have a negative voltage-temperature coefficient. This behaviour tends to produce the output power of PV module drops significantly. Therefore, the comparison performance of artificial neural network method can be useful in another part of the integrated research applications based on engineering measurements of estimation, prediction and control.

The development solar cells technology is very fast with the target of high-capacity system installation and increase in operating efficiency of solar energy. In line with the abundant availability of Silicon materials on the earth's surface, crystalline Silicon-based technology is dominantly compared to other non-crystalline Silicon solar cell technologies. In addition, as the reason for the high efficiency of energy conversion and the consideration of relatively low-cost of manufacturing, the solar modules with Silicon technology are getting mature in the implementation and easily found on the PV market. In this respect, the objective of the study is focused on the Silicon based PV modules technology, for instance, ASE-50 (EFG mc-Si), KC-80 (wafer mc-Si), BP-585 (c-Si) and AP-8225 (thin-film Si).

The article is organized as follows. The importance of comparison performance of RBF and TFFN has been shown in this Section 1. In Section 2, the technical specification of PV modules is presented. Section 3 provides the information of RBF and TFFN neural network modelling. Following in Section 4, the simulation results and discussion are presented. Finally, Section 5 shows the conclusion of this study.

2. **Technical Specification of PV Modules.** The modeling of solar modules is based on electrical model developed by Sandia National Laboratory (SNL), USA [13, 14]. It is a very effective model at characterizing solar panels performance in a variety of operating conditions and different environmental inputs. This model requires detailed input parameters for the solar module response in terms of intensity of sunlight, cell temperature, the arrival angle of sunlight intensity on panel surface and air masses condition. In addition, the model can be used to determine important points of the I-V curve parameters, such as short-circuit current, open-circuit voltage and maximum operating points [15, 16]. Also, the model was developed based on empirical functions of several solar modules performance that have been widely commercialized. In this research, the electrical characteristics of PV modules being investigated under standard test condition (STC: global irradiance of 1000 W/m^2 and cell temperature of 25°C) are provided in Table 1.

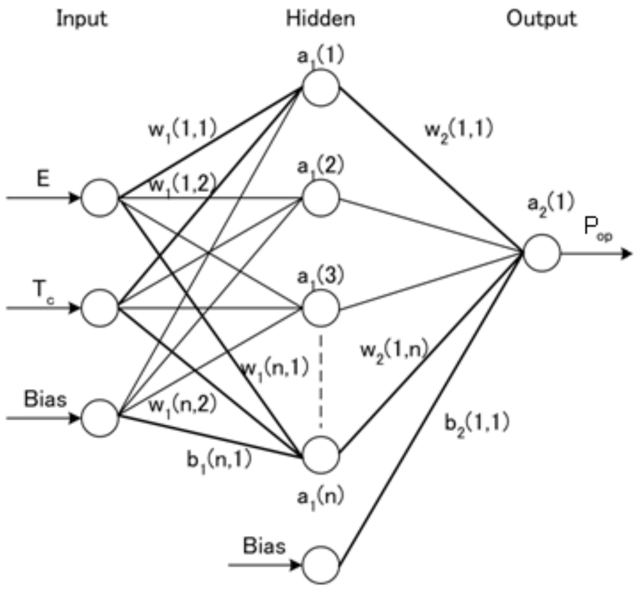
Table 1. Technical information of PV panels under STC conditions

Photovoltaic modules	Solar cell technologies	I_{SC} (A)	V_{OC} (V)	I_{MPP} (A)	V_{MPP} (V)	P_{MPP} (W)
ASE-50	EFG mc-Si	3.2	21.1	2.9	17.2	50
KC-80	Wafer mc-Si	4.97	21.5	4.73	16.9	80
BP-585	c-Si	5.0	22.0	4.7	18.0	85
AP-8225	thin-film Si	5.737	19.87	5.18	15.34	79.5

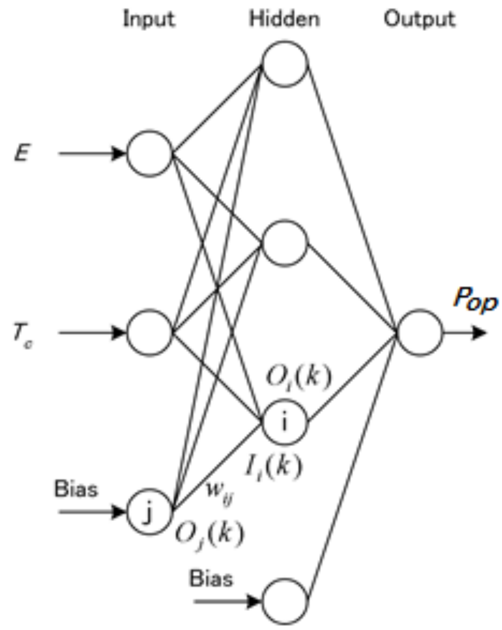
Remarks: I_{SC} = Short circuit current; V_{OC} = Open circuit voltage; I_{MPP} = Current at maximum power point; V_{MPP} = Voltage at maximum power point; P_{MPP} = Power at maximum power point.

The electrical characteristics as in Table 1 are the function of sunlight intensity cell temperature and the developed model is in accordance with the characteristics of a number of solar modules that have been commercialized nowadays. The characterization of PV module technology based on crystalline Silicon is explained as follows. The short-circuit currents depend linearly, while the open-circuit voltage depends logarithmically with the sunlight intensity. Regarding variations in environmental temperature, the short-circuit currents increased slightly due to particle mobility in semiconductor materials which was triggered by the large number of photons absorbed by the material. On the other hand, the open-circuit voltage decreases significantly due to negative voltage-temperature coefficient factors that follows the diode factor value. As results, the increase in temperature causes that the output power of PV modules is drastically reduced. Because of the unique characteristics of one solar module to other modules, a special design of artificial neural network is needed for the maximum power point tracking system. The assessments in determining the appropriate artificial neural network model are the level of accuracy, flexibility of process training and the simplicity of network structure.

3. **Modelling of Artificial Neural Network.** Radial basis function (RBF) as in Figure 1(a) and three-layered feed-forward network (TFFN) as shown in Figure 1(b) basically have the same structure which is a multi-layer perceptron group (MLP). The differences could be in the pattern of data mapping and algorithm, where RBF uses local mapping



(a) RBF



(b) TFFN

FIGURE 1. Structure of artificial neural network

while TFFN uses global mapping. It means that in the RBF method, only input that is close to the receptive field is processed through the activation function. The hidden layer obtained is a neuron at the center of the receptive field, while the receptive field itself is in the input space where the input vector is located. If the input vector is close to the receptive field, then the hidden layer will be obtained. The process of data training using the RBF network is fairly simple. Once the minimum error is reached, the training process stops and the number of hidden nodes will be achieved.

Meanwhile, the three-layered feed-forward network (TFFN) implements the back propagation algorithm and the descent gradient method to regulate weight in an effort to reduce learning error. The TFFN algorithm propagates the error between the actual output and the estimated output. For the forward flow, all input vectors, actual output and errors are calculated; while for the reverse flow, the gradient error of the weight is calculated by propagating the error back through the entire structure. Every time the gradient error is calculated, then the weight is adjusted. The consequence of this approach yields the variability of obtained weight values during the training process. Therefore, the possibility of choosing a simple structure is very high. The selection of the best structure requires intuitive thinking from the network designer. In general, the TFFN structure utilizes the sigmoid transfer function because of the unique differentiation features of the sigmoid function.

3.1. **Radial basis function (RBF).** The RBF network structure applies the transfer function between input and hidden layers. In this case, the input signals of $[E, T_c]$ are processed first with the distance Euclidean function, 'dist', including weights w_1 and bias b_1 which then become the input of the radial basis transfer function, 'radbas'. It yields output of a_1 in the hidden nodes. Mathematically, the RBF neural network algorithm is stated in (1) as follows:

$$a_1(n) = radbas[(dist(w_1(n,1)E + w_1(n.2)T_c))b_1(n,1)] \quad (1)$$

where n = number of hidden nodes.

The output of the second layer a_2 results which is the estimated output power of RBF neural network is simply obtained through the transfer function "purelin" between the output layer a_1 and weights w_2, including the bias b_2 of the second layer. The weights of this layer are normally obtained using the least square algorithm method compared to using the back-propagation techniques. The mathematical equation for the above conditions is stated in (2) as follows:

$$a_2(m) = purelin\left[\sum_{n=1}^{n}(w_2(m,n)a_1(n)) + b_2(1,1)\right] \tag{2}$$

where m = number of nodes in the output layer.

In the computational training process, the input vector which causes a decrease in network errors is applied to updating the new hidden neurons. If an error which is obtained after a new neuron added is low enough or close to a goal error, the training process will stop.

3.2. **Three-layered feed-forward network (TFFN).** In this research, the connection of input-output data of TFFN network is explained. The sigmoid transfer function is applied on the data relationship of the input-output nodes. For each node i in the hidden and output layers, the output signal $O_i(k)$ is obtained as follows:

$$O_i(k) = \frac{1}{1+e^{-I_i(k)}} \tag{3}$$

Variable $I_i(k)$ in (3) is the input signals of sunlight intensity (E) and temperature of solar panel (T_c) of node i for every kth sampling. The input $I_i(k)$ is the submission of all weights with output node j, $O_j(k)$ in (4) as follows:

$$I_i(k) = \sum_j w_{ij}(k)O_j(k) \tag{4}$$

where w_{ij} = weight between nodes j and i.

In the training process, the weights w_{ij} are updated for several times so that the optimal input-output relationship is achieved following the lowest values of the sum of squared errors (SSE) as follows:

$$SSE = \sum_{k=1}^{N}[t(k) - O(k)]^2 \tag{5}$$

where N = total of training pattern, $t(k)$ = target of the kth of actual maximum power and $O(k)$ = estimated maximum power (P_{op}). For overall training data pattern, the minimum error function is continuously evaluated and weight connection w_{ij} is revised based on the minimum error values in (5).

3.3. **Training and validation process.** The process of collecting training data is performed by calculating the actual maximum power based on the mathematical model recommended by Sandia National Laboratory by considering input sunlight intensity (E) and cell temperature (T_c). The correlation between these parameters is in the range of values E = 100-1000 W/m^2 and T_c = 10-65°C for each type of crystalline Silicon PV modules technologies, namely ASE-50 (EFG mc-Si), KC-80 (wafer mc-Si), BP-585 (c-Si) and AP-8225 (thin-film Si). There are 150 data sets for the training process taken from half-day of measurement from 6:00 am to 12:00 pm in clear sky conditions which covers the entire domain problems.

After all training processes have been carried out for each module, the best structure will be selected for each type of solar module technologies and then validated with different types of weather conditions as in Figure 2. The first validation is to confirm the network structure that is considered the best with sunny weather conditions, referring to a half-day measurement from 12:00 noon to 6:00 pm. There are 138 data combinations of the intensity of sunlight with cell temperature. These half-day data are considered for

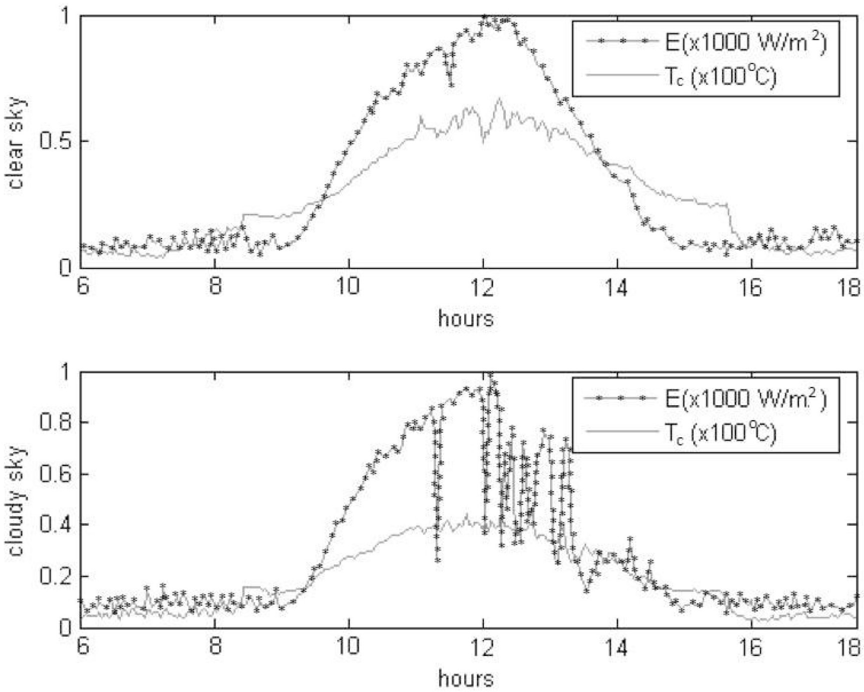


FIGURE 2. Profiles of irradiance (E) and cell temperature (T_c)

validation because data from 6:00 am to 12:00 noon has been used for the training process. Utilizing the training data pattern for validation process will make the subjectivity of network structure in pattern recognition. The second validation is to use measurement data from 6:00 am to 6:00 pm during cloudy weather conditions. For this condition there are 289 data combinations of sunlight intensity and cell temperature. After the validation process is finished with a small confirmation of validation error, the artificial neural network structure can be used for estimating the maximum power of solar modules with different inputs of weather conditions.

4. **Simulation Results and Discussion.** Several criteria must be analyzed to recommend the artificial neural network as successful method for the purpose of estimation, prediction and control in engineering parameters. These criteria are the training process, level of accuracy during the training and validation process including the confirmation of network structure. For the purpose of this analysis, the following rules are implemented.

Training process: (a) **Simplicity:** The simplicity can be seen based on the consistency error of training process obtained every time when the program runs without data input changes. The simplicity condition can be clearly obtained on RBF and ANFIS networks. (b) **Complexity:** The training process is said to be complex when structure and error training always change every time the program is run even though the input data does not change. There is advantage to this condition in terms of the opportunity to choose more network structures. Nevertheless, it is very dependent on the intuition users capability to ensure the best network structure.

Accuracy: The level of accuracy is measured during the training and validation process based on the SSE values. The threshold settings are needed to assume high or low order of SSE values. The sequence of criteria is as follows:
* Low order: less than 10^{-3}
* Medium order: 10^{-4}-10^{-5}
* High order: more than 10^{-5}

Network structure: The network structure is confirmed with the number of hidden nodes obtained from training results based on the type of transfer function used in the input-hidden layer and output connections. The research is expected to yield a recommendation for artificial neural networks that are suitable for the estimated maximum output power of various types of solar module technology. Optimal artificial neural networks are determined from the simplicity of structure and training process and the level of accuracy which are the important factors in the maximum point control and tracking of PV modules output power. From the training results, the information about the number of hidden nodes and training errors for each module is shown in Table 2. In addition, the level of accuracy in the validation process is stated in Table 3.

Table 2. Hidden nodes and training error

Photovoltaic modules	No. of hidden nodes		Training error	
	RBF	TFFN	RBF	TFFN
ASE-50 (EFG mc-Si)	5	2	3.43×10^{-5}	3.99×10^{-3}
KC-80 (wafer mc-Si)	5	6	1.66×10^{-4}	2.62×10^{-3}
BP-585 (c-Si)	5	2	1.71×10^{-4}	6.05×10^{-3}
AP-8225 (thin-film Si)	5	2	1.94×10^{-4}	1.87×10^{-3}

Table 3. Sum of squared error (SSE) during validation process

Photovoltaic modules	RBF		TFFN	
	Clear sky	Cloudy sky	Clear sky	Cloudy sky
ASE-50 (EFG mc-Si)	2.59×10^{-4}	5.31×10^{-4}	2.35×10^{-2}	3.88×10^{-2}
KC-80 (wafer mc-Si)	1.43×10^{-3}	3.72×10^{-3}	4.57×10^{-2}	5.82×10^{-2}
BP-585 (c-Si)	1.67×10^{-3}	4.43×10^{-3}	3.67×10^{-2}	4.38×10^{-2}
AP-8225 (thin-film Si)	2.15×10^{-3}	5.71×10^{-3}	2.16×10^{-2}	3.27×10^{-2}

The results of the training process are indicated by the number of hidden nodes for each type of modules. The fewer hidden nodes show the simplicity of the structure of TFFN compared to the method of RBF neural network. Of course, with a large number of hidden nodes, it will correspond to the accuracy of the obtained results. With the simplicity of the artificial neural network structure, the TFFN method is good enough to be used for mapping between the intensity of sunlight and temperature cells to estimate the output power of crystalline Silicon based solar modules. However, a lot of time is needed during the training process and the level of accuracy must always be validated by varying input criteria. The validation method is similarly conducted with the RBF network.

5. **Conclusions.** The paper has presented the comparison performance of artificial neural networks based on radial basis function (RBF) and three-layered feed-forward network (TFFN) in determining the estimated maximum output power. The RBF network can provide a high degree of training and validation accuracy in the order of 10^{-3}, as well as the number of hidden nodes to 5 for all types of PV modules. Meanwhile, the three-layered feed-forward network method can correlate the characteristics of module technology with network structure. In addition, the TFFN method might produce relatively low validation error compared to the results of the training process, whereas the RBF method is relatively better in terms of training and validation if no needs of the information regarding solar modules technology. In the next stage of this research, the performance of artificial neural networks is investigated for the other types of non-crystalline PV technologies.

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