Forecasting Generation of 50MW Gambang Large Scale Solar Photovoltaic Plant Using Artificial Neural Network-Particle Swarm Optimization

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Abstract- Malaysia has been strongly dependent on non-renewable energy such as coal and natural gas to power up the country. As the country's natural resources are now depleting, solar energy is seen as the most suitable future energy specifically due to Malaysia's strategic location at the equator of the Earth. In Malaysia, many Large-Scale Solar Photovoltaic (LSSPV) plants have been developed as a result of effective policy by the government. However, one of the challenges faced by the independent power producers is the uncertainty of the output power from the LSSPVs due to fluctuation of weather conditions. This paper presents a forecasting power generation model of LSSPV farm using Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) technique. The UiTM 50MW LSSPV in Gambang, Pahang has been used as a case study. The PSO technique is utilized to optimize the weight of ANN for determining the best Mean Square Error (MSE) and regression performance. The forecasting model uses total global horizontal irradiance, global irradiation on the module plan and PV module temperature as input variables while Alternating Current (AC) output power as output variable. The input variables were chosen from a filtration process of the historical data. The historical data used in the training and testing process are from the month of May 2019 until August 2019. The data is forecasted at every 30 minutes' basis and compared with the actual AC output power. The result shows that the ANN-PSO method outperforms the traditional ANN with a better MSE and regression performance.

Keywords Large Scale Solar Photovoltaic (LSSPV), Generation Forecasting, Artificial Neural Network (ANN), Particle Swarm Optimization (PSO), regression analysis, meteorological.

1. Introduction

After independence in 1957, Malaysia has undergone rapid urban development and modernization to achieve its objective of becoming a first world country. To achieve this objective, the country's industry has developed from a small production plant to a large -scale production plant. As the country's population and economic experience rapid growth every year, the demand for electricity intensifies to keep with the growing trend. Statistic in 2016 from the Energy Commission of Malaysia reported that the mix source of fuel energy in Malaysia were primarily from coal at 42.5%, natural gas at 43.5% and hydropower energy at 14% [1].

The problem of using coal and natural gas is the resources are non-renewable, thus is depleting over time. Besides, the price of the raw materials fluctuate depending on the stability of the world's market [2]. This will lead to energy insecurity in the future as the sources started to drain and is worsen by the emission of greenhouse gas to the atmosphere. In solving this problem, the government is now shifted its efforts towards solar energy as an alternative resource over long time [3,4]. Gambang Large-Scale Solar Photovoltaic (LSSPV) farm which is owned by UiTM Power Sdn. Bhd. is one of the efforts taken by the public university i.e., Universiti Teknologi MARA (UiTM) to support the government's initiatives to reduce dependency on non-renewable energy. The Gambang LSSPV farm with the capacity of 50MW spanning 290 acres of land is capable to provide electricity up to 22,000 homes. The 220,000 solar panel is expected to generate a total of 80,000 MWh of clean energy yearly. The sight of Gambang LSSPV farm is shown in Fig. 1 below.

Fig 1. Sight of Gambang LSS farm

Although solar energy has the capability to replace coal and natural gas as the future main source of energy, it has one major weakness, where its output power is uncertain. The output power from the LSSPV plant has the characteristic of being non-linear, where it depends heavily on meteorological conditions such as solar irradiance and efficiency of electronic devices used in the system [5]. In contrast with energy generated by coal, the output power from the coal can be easily predicted based on the quantity of coal used during the generation process. The fluctuations of output power from LSSPV may affect power dispatch in the country and threatening the electricity grid. In Malaysia, the LSSPV owners are required to submit its forecasting output power to grid system operator for every specific period. The dynamic changes in meteorological variables have caused challenges in power forecasting using linear forecasting techniques. As consequence, various forecasting techniques have been proposed in literature using techniques such as Artificial Neural Network (ANN) [6,7], Support Vector Machine (SVM) [8,9], probabilistic model [10], Naïve Bayes [11], hybrid grey wolf, ant lion and whale optimization algorithms with multilayer perceptron [12], Firefly Algorithm [13], Fuzzy Logic Control (FLC) [14], Deep Recurrent Neural Network (DRNN) [15], and Adaptive Neuro-Fuzzy Interference System (ANFIS) [16]. However, limited application can be found for large scale solar PV applications. In short, the solar forecasting can be broken into four-time frames which are very short-term (up to 15 minutes), short-term (15 minutes-1 hour), medium-term (1 hour to 1 day) and long-term (beyond 1 day) [19].

ANN is one of the branches in machine learning technique where it is broadly used in forecasting and prediction in multiple engineering and non-related engineering fields. The architecture of ANN resembles the human biological neural system in which it consists of dendrite to receive input signal, axon to transmit output signal and synapse which link these components together. Despite the fact ANN is a good forecasting technique, it is often considered as heuristic. This happens as there is no guarantee that global minima which is problem with the best solution can be found since sometimes the solution stuck at local minima. The disadvantages of ANN algorithm is commonly relate to precision issues, time consuming and tedious try and error process in tuning the ANN parameters [17].

To overcome the ANN issues mentioned above, evolutionary computation is useful to optimize the ANN parameters [17]. Optimization techniques such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Grey Wolf Optimizer have been widely used as in [17], [18], [19] respectively. In this paper, PSO technique is used to optimize the weight of the ANN. PSO is first introduced in 1995 by Russell Eberhart and James Kennedy through inspiration after watching the social behavior of birds sharing information [20]. It uses a pack of swarm or candidate to find the optimal solution in a search space area. For each iteration, a personal best and global best is attained, and the position and velocity of the swarm is updated. The advantages of PSO over other optimization techniques are in its simplicity having less constraint and variable to tune, robustness to control parameters, and higher computational efficiency when compared with mathematical algorithm. Tuning the PSO parameters greatly affects the optimization performance through try and error process.

The novelty of this study is in development of LSSPV power generation forecasting model by integrating ANN and PSO techniques considering significant meteorological parameters. An LSSPV located in Gambang, Pahang with the size of 50MW was used as a case study. In achieving the objective, a single hidden layer of ANN model is used to forecast the AC output power for every 30 minutes' interval while PSO is integrated in the ANN model to optimize the synaptic weight of the ANN. The MSE was chosen as the fitness equation in the PSO algorithm to minimize the forecasting error. The optimized ANN-PSO model then underwent a testing process to observe the regression performances.

This research will benefit the power producers to determine and forecast the energy and revenue gained by the LSSPV plant. By accurately forecasting the power generation would help the developer to strategize and plan to improve the production such as reducing the power loss and integrating the solar system with battery storage. Furthermore, accurate forecasting of solar generation will assist grid system operator to determine accurate power dispatch and reserve for stability of the grid.

2. Methodology

2.1 Historical Data Acquisition and Filtration

To forecast the AC output power from the solar farm, a set of historical data is required which includes the input and output variables. The historical data acquired from Gambang LSS farm were obtained from five different weather stations that closely monitored by the meteorological department. The weather stations equip with pyranometers to measure solar irradiance, temperature sensors to measure ambient temperature, anemometers to measure windspeed and tipping bucket rain gauge to measure rainfall as shown in Fig. 2. The collected raw data consist of 3,136 sets of 30 minutes' interval ranging from the month of May until August 2019.

Fig. 2. Weather station located at Gambang LSS Farm (left) and tipping bucket rain gauge (right)

The input data variables include the meteorological parameters i.e., ambient temperature, wind speed, PV module temperature, total slope irradiation, global irradiance on module plane, total horizontal irradiation, and total global horizontal irradiance, while AC output power as output variable. Nevertheless, these variables were filtered out to determine significant variables for obtaining accurate forecasting model. Thus, each input variable regression was analyzed to investigate the relationship with the output, and the observed outlier data were filtered. The graph of output variable against each input variable for June 2019 before the filtration was performed are shown in Fig. 3, Fig. 4, Fig. 5, and Fig. 6 together with their regression values in Table 1.

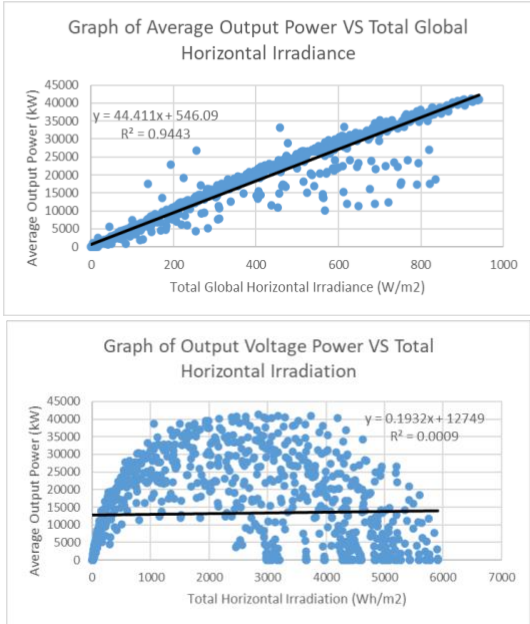

Fig. 3. Graph of Average Output Power vs Total Global Horizontal Irradiance and total horizontal irradiation before Filtration

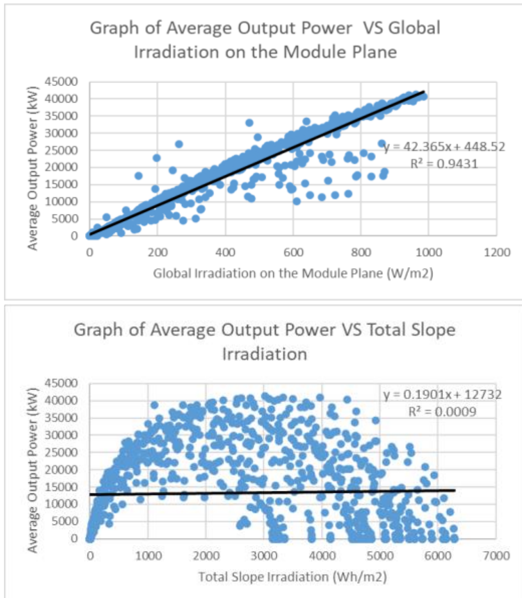

Fig. 4. Graph of Average Output Power vs Global Irradiance on The Module Plane and Total Slope Irradiation before Filtration

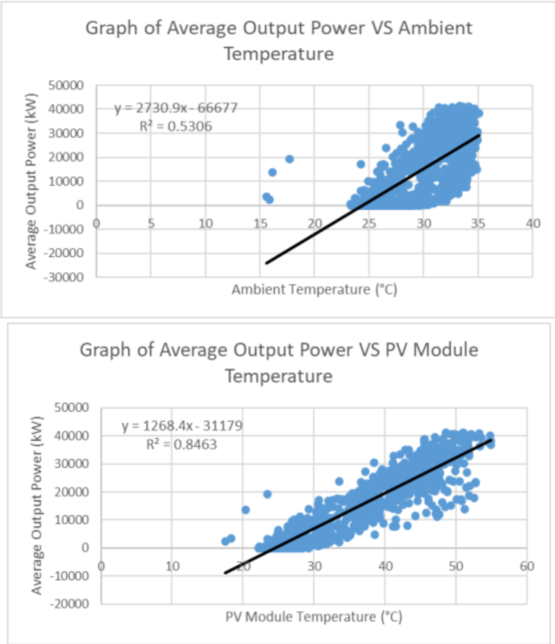

Fig. 5. Graph of Average Output Power vs Ambient Temperature before filtration and PV module temperature before Filtration

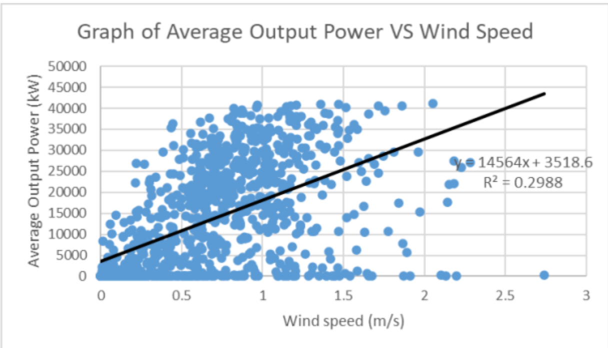

Fig. 6. Graph of Average Output Power vs Wind Speed before Filtration

Table 1. Regression between input variable and output variable before data filtration for June 2019

Input Variable	Regression, R^2
Total Global Horizontal Irradiance (W/m^2)	0.94430
Total Horizontal Irradiation (Wh/m^2)	0.00009
Global Irradiance on the Module Plane (W/m^2)	0.94310
Total Slope Irradiation (Wh/m^2)	0.00090
Ambient Temperature (°C)	0.53060
PV Module Temperature (°C)	0.84630
Wind Speed (m/s)	0.29880

Variable with a strong regression is regarded as variable which possess a value of R^2 greater than 0.75. Hence, input variables that have poor correlation with the output variable were omitted. The input variables that were omitted are wind speed, ambient temperature, total slope irradiation and total horizontal irradiation. Thus, PV module temperature, global irradiance on the module and total global horizontal irradiance were selected as the final input variables for the ANN model. In order to further improve the regression, outlier data that affect the performance of the ANN model were filtered out with confirmation from plant operator. These outlier data might presence due to maintenance process. Fig. 7 and 8 show the graph of output variable against the selected input variables. Meanwhile, Table 2 summarizes the regression value of each selected variable. The total input-output data used for the ANN model after the data filtration process was 2,104.

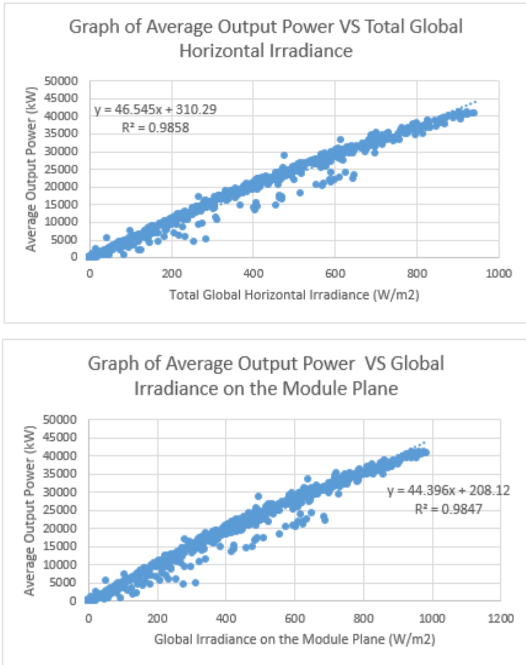

Fig.7. Graph of Average Output Power vs Total Global Horizontal Irradiance and Global Irradiance on the Module Plane after Filtration

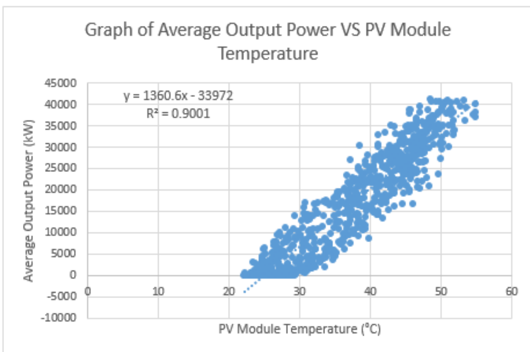

Fig. 8. Graph of Average Output Power vs PV Module Temperature after Filtration

Table 2. Regression between input variable and output variable after data filtration for June 2019

Input Variable	Regression, R^2	Regression Improvement (%)
Total Global Horizontal Irradiance (W/m^2)	0.9858	4.15
Global Irradiance on the Module Plane (W/m^2)	0.9847	4.16
PV Module Temperature (°C)	0.9001	5.38

2.2 Design of ANN Model

A single layer of feed forward ANN network was chosen to forecast the AC output power from Gambang LSSPV farm. The proposed ANN black box for this research is depicted in Fig. 9. The ANN black box takes in PV module temperature, module plane global irradiance and total global horizontal irradiance as input variables while the AC output power as output variable. The total pattern data used for the ANN model was 2,104 and divided at a ratio of 60/40 [8]; where 1,263 data was used for the training process and the remainder 841 data was used for the testing process.

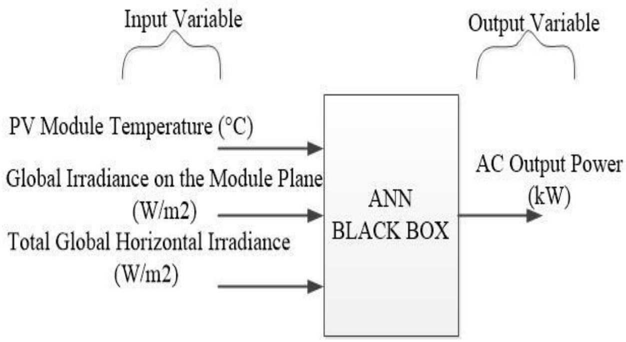

Fig. 9. ANN black box for Gambang LSS farm output power forecasting

The flowchart for the ANN training and testing process is shown in Fig. 10. At the start of ANN training process, the input and output training variables were defined and normalized to a value between -1 and 1. These data need to be normalized to a common scale to increase rate of convergence since these data have difference range of values. Once the data normalization completed, the type of backpropagation algorithm was set for the training process. Levenberg-Marquardt algorithm (trainlm) was chosen for the training process since it was proven to have a faster convergence rate and used widely in many forecasting studies. The 'trainlm' algorithm was used to update the ANN weight and bias at every epoch and its performance was evaluated based on the MSE value. Parameters such as number of epochs was fix at 500 to enable accurate convergence and MSE performance goal was set at 10^{-2}. To increase the ANN performance, the ANN black box was configured by adjusting the ANN learning rate, momentum rate and the number of neurons in hidden layer. The process of determining the correct values for these parameters to produce accurate forecasting model was time consuming, as it was performed using a trial-and-error method. Varying the ANN parameters through the trial-and-error method do not guarantee the optimum solution since the traditional ANN method is known to have its solution trap at the local minima. At the end of the training process, the trained ANN data was denormalized and saved.

In the testing process, the input and output test variables were first called out. These data then underwent the same process as the training, where it was normalized and de-normalize at the end of the process. During the testing, the data underwent a post-processing procedure in which the regression value was also obtained. The ANN model was evaluated and regarded as having a strong regression if the testing process has a regression value approaching 1.

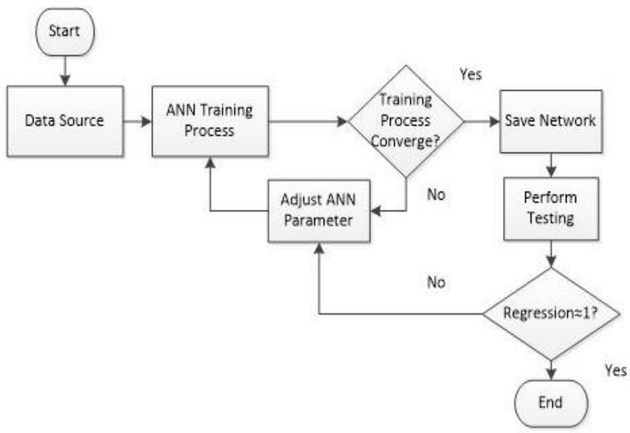

Fig. 10. Flowchart for ANN training and testing process

2.3 Design of ANN-PSO Model

A hybrid model which composes of an integration between ANN and PSO was proposed to increase the output power forecasting accuracy. Metaheuristic techniques such as PSO have been proven successful in many forecasting studies to solve the major problem of the traditional ANN training that tends stuck at local minima. The local minima are not the optimum solution of a problem where it usually stuck between two maxima neighbors, at the case the neural network think it has found the best solution. The local and global minima problem is illustrated in Fig. 11.

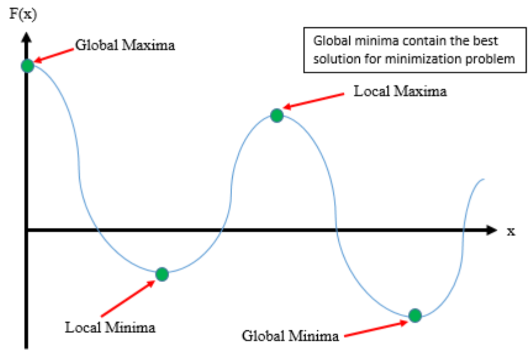

Fig. 11. Illustration of local minima and global minima problem

In the ANN-PSO model, the input and output training variables as in Fig. 9 was first initialized and normalized to a value between -1 and 1. A single layer feed forward neural network was then created with Lavenberg-Marquardt algorithm (trainlm) as the training algorithm. The weight and bias value of un-optimized ANN was passed to the PSO algorithm to find the best weight and bias to be used in the ANN model.

In the PSO algorithm, there are few parameters that need to be initialized at the beginning of the simulation. Firstly, the size of potential candidates or swarm size need to be set. These swarm will work together to find the optimal solution in a search space area. The acceleration constants C_1 and C_2 are defined as personal acceleration constant and global acceleration constant, respectively. A usual practice is to initialize the summation value of C_1 and C_2 equal or less than 4. The inertia weight, *w* determines the swarm ability to find the optimal solution in a search space area. A small value of *w* results in searching of solution in a local area due to lower flying velocity step, while a high value of *w* promotes the exploitation of particle in new space.

For each individual swarm in the PSO algorithm, a random velocity and position is assigned where each individual swarm has its own fitness value. At each iteration, the swarm personal best, *Pbest* and global best, *Gbest* are compare and updated. The swarm *Pbest* is interpreted as the best fitness value achieved by individual swarm at each iteration, while *Gbest* is the best fitness value experienced by the whole swarm. Once *Pbest* and *Gbest* are determined, the swarm velocity and position are updated at each iteration by the following formula (1) and (2):

$$\upsilon_{id}(k+1) = \omega\upsilon_{id}(k) + C_1r_1{=}(P_{best}(k) - \chi_{id}(k)) + C_2r_2(G_{best}(k) - \chi_{id}(k)) \quad (1)$$

$$\chi_{id}(k+1) = \chi_{id}(k) + \upsilon_{id}(k+1) \quad (2)$$

The MSE performance was evaluated for each iteration by using the updated weight searched by the PSO algorithm. The stopping criteria of the whole algorithm was set at 300 iterations to allow satisfying convergence rate. The trained data by the ANN-PSO algorithm was de-normalized at the end of the simulation to achieve a comparable reading performance as the actual data. Testing was performed to determine the regression performance of the optimized ANN-PSO model. The overall flowchart of the ANN-PSO algorithm is shown in Fig. 12.

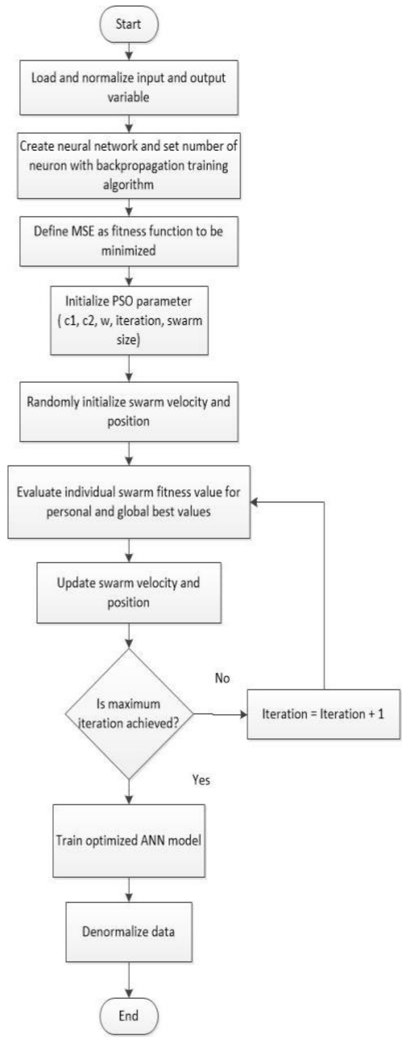

Fig. 12. Flowchart for ANN-PSO algorithm

2.4 Performance Evaluation

In order to evaluate the performance of ANN in this study, the predicted output was compared with the targeted output using several performance criteria such as the coefficient of determination (R^2) and mean square error (MSE) as presented in equations below.

(3)

(4)

3. Results

3.1 Traditional ANN Performance

The ANN model training process involved trial-and-error method, where the parameters of ANN were varied according to its forecasting performance. The performance was evaluated based on the MSE and regression values. A small MSE value indicates high forecasting accuracy, while a regression value near to 1 shows a strong correlation between the input and output variables. Potential parameters that can be adjusted include the ANN learning rate, momentum rate and number of neuron hidden layer. Table 3 shows the result of R^2 by varying the ANN learning and momentum rate as in [8]. The number of epochs was set constant at 500 while number of neurons in single hidden layer was set at 4.

Table 3. Results of varying learning and momentum rate

Learning rate	Momentum rate	Goals	Regression, R^2
0.9	0.8	10^{-2}	0.99183
0.9	0.7	10^{-2}	0.99606
0.8	0.9	10^{-2}	0.99499
0.8	0.7	10^{-2}	0.99398
0.7	0.8	10^{-2}	0.99598
0.7	0.9	10^{-2}	0.99623

It can be seen from the results at Table 3 that adjusting the learning rate and momentum rate of the ANN model did not give much impact on the model regression performance. Another parameter that can be adjusted in the ANN model is the number of neuron in the hidden layer. Table 4 shows the result of varying the ANN neuron number in a single hidden layer. The learning rate was kept constant at 0.3, the goal at 10^{-2}, while momentum rate at 0.8. It is depicted from the results that increasing the number of neuron in the hidden layer increases slightly the regression value.

Table 4. Results of varying number of neurons

Learning rate	Momentum rate	Neuron number	Regression, R^2
0.3	0.8	1	0.99601
0.3	0.8	2	0.99526
0.3	0.8	3	0.99556
0.3	0.8	4	0.99563
0.3	0.8	5	0.99615
0.3	0.8	6	0.99660

3.2 ANN-PSO Hybrid Model Performance

Hypothetically, the performance of ANN-PSO model is expected to have a better regression and MSE performance than the traditional ANN model. In the ANN-PSO model, the weight and bias of the ANN model were optimized to increase the accuracy of the output forecast. The parameters in the PSO algorithm were set constant, where the weight was set equals to 1 and the swarm size is set at 60 populations, meanwhile *C1* and *C2* were adjusted to a value between 1.5 and 2. The number of neurons in the single layer was adjusted through a trial-and-error method, where the value was chosen based on the MSE and regression performance. Table 5 shows the performance of the ANN-PSO model at different neuron number in the single hidden layer.

Table 5. Performance of ANN-PSO model at different neuron number

Neuron number	MSE before	MSE after	Regression, R^2
1	2.10350	0.00350	0.99702
2	3.48083	0.00334	0.99704
3	1.28115	0.00346	0.99663
4	2.52394	0.00338	0.99709
5	3.10094	0.00346	0.99698
6	1.20900	0.00331	0.99727

Based on Table 5, it can be observed that the ANN-PSO forecasting model at 6 neuron number in the single hidden layer has the best regression and MSE performance. Although the difference in regression between the models are very small, model with better regression value will have a better forecasting accuracy. Thus, the ANN-PSO model at 6 neuron number was chosen to forecast the AC output power for the Gambang LSSPV farm. The training performance of the chosen model at each iteration is shown in Fig. 12. Fig. 13 shows the comparison of the forecasted power generation as compared to the actual power generation of the LSSPV. The result shows the forecasted data and actual data are almost perfectly similar with each other.

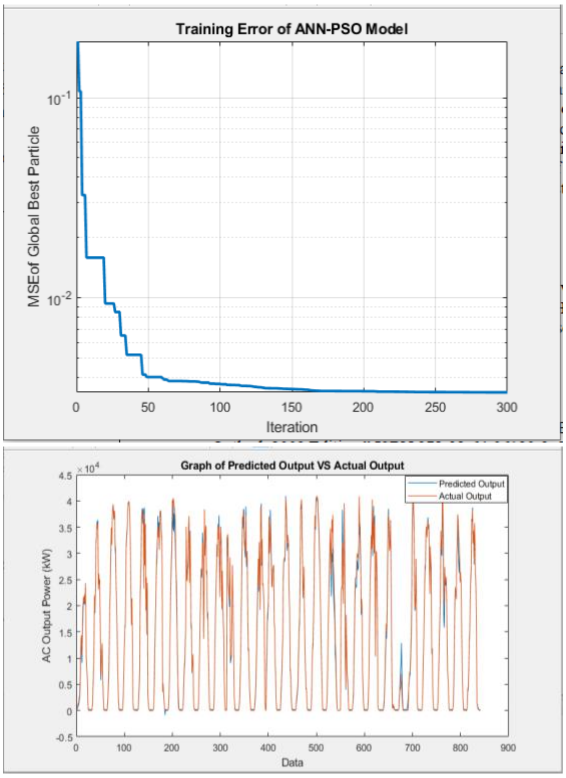

Fig. 13. Training Performance of ANN-PSO Model and Predicted Output Vs Actual Output of AC Output Power

3.3 Performance Comparison between Traditional ANN and ANN-PSO Hybrid Model

The forecasting performances of the traditional ANN and the ANN-PSO hybrid model are shown in Table 6. The models were chosen based on their best respective parameters' performance during the simulation.

Table 6: Performance comparison between ANN and ANN-PSO hybrid model

Performance criterion	Traditional ANN	ANN-PSO
Mean Square Error, MSE	0.010	0.00341
Regression, R^2	0.99668	0.99727

Based on Table 6, the ANN-PSO have the best MSE and regression value compared to the ANN technique. The performance of traditional ANN method is worse than the ANN-PSO hybrid method due to its characteristic of easily stuck in local minima solution.

4. Conclusion

In this paper, an optimization technique called PSO is proposed to be used with the traditional ANN to increase the forecasting accuracy of AC output power at Gambang LSSPV farm. A total of 2,104 filtered data at 30 minutes interval ranging from the month of May until July 2019 was used in the ANN testing and training process. The PSO technique was used to optimize the weight and bias of the ANN neural network. Results show that the proposed ANN-PSO hybrid model achieved better MSE and regression performance compared to the traditional ANN method and regression analysis.

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