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Online Performance Monitoring of Grid-Connected Photovoltaic System using Hybrid Improved Fast Evolutionary Programming and Artificial Neural Network

Puteri Nor Ashikin Megat Yunus[1], Shahril Irwan Sulaiman[2], Ahmad Maliki Omar[3]
Faculty of Electrical Engineering
Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia.
*Corresponding author, e-mail: pu3kibi@yahoo.com[1], shahril_irwan2004@yahoo.com[2], ambomaliki@gmail.com[3]

Abstract

This paper presents the development of online performance monitoring methods for grid-connected photovoltaic (GCPV) system based on hybrid Improved Fast Evolutionary Programming and Artificial Neural Network (IFEP-ANN). The approach has been developed and validated using previous predicted data measurement. Solar radiation (SR), module temperature (MT) and ambient temperature (AT) has been employed as the inputs, and AC output power (PAC) as the sole output to the neural network model. The actual data from the server has been called and uploaded every five minute interval into Matlab by using FTP (File Transfer Protocol) and the predicted AC output power has been produced based on the prediction developed in the training stages. It is then compared with the actual AC output power by using Average Test Ratio, AR. Any predicted AC output power less than the threshold set up, indicates an error has been occurred in the system. The obtained results show that the hybrid IFEP-ANN gives good performance by producing a sufficiently high correlation coefficient, R value of 0.9885. Besides, the proposed technique can analyse and monitor the system in online mode.

***Keywords**: PV (photovoltaic); ANN (Artificial Neural Network); RMSE (Root Mean Square Error); AR (Average Test Ratio); FTP (File transfer protocol)*

1. Introduction

Grid connected photovoltaic (PV) system becomes an important part of the electrical system around the world, especially in more developed countries. The substantial growth of the global PV market is still expected due to strong PV technology prices and the increase in electricity prices generated by conventional resources along with the clear advantages of green energy and renewable as PV on delivering safe and clean energy. However, the number of monitored PV system is not aligned with the growing trend, as more PV plants, especially the smaller ones, which operating without proper monitoring system [1].

Most of the PV systems operating without any supervisory mechanism, especially PV systems for output power below than 25 kWp. Perhaps the reason is that monitoring systems are only implemented in large PV generators, where it represents a very small increase in the overall price of the system, but without the help of a minimum monitoring system, it is impossible to develop any effective supervision, diagnostic or control of the PV systems [2].

Nowadays, many techniques are developed to monitor PV systems. The conventional wired monitoring system provides reliable solutions in data transmission but have some limitations [3]. Besides, the physical constraints when placing data cables and the use of these cables also increases the cost of installation and maintenance. Hardware implementation also have been proposed in monitoring system [4-7]. However, all these proposed methods need additional device and also tend to increase the cost.

Some researcher used cable Ethernet in their proposed system. Dhimish in [8] proposed six monitoring subsystem which composed of Arduino Ethernet to send the data from the maximum power point tracker to the server/PC. This method utilizes IoT technology to integrate PV and environmental data monitoring. The same method also proposed in [9] which

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FPGA also used to interface the program of LabVIEW. The proposed method is based on sensors, NI CompactRIO platform, SIEMENS power meters, meteorological data collection system. However wired systems have their limitations, and are considered less favourable than the wireless option for the monitoring of a solar energy conversion system.

Thus, some researcher goes to the wireless implementation such as Zigbee-based wireless [3]. Followed by Martin in [10] which utilizes a full duplex digital system using the ZigBee protocol, based on the IEEE 802.15.4 standard for Wireless Personal Area Network (WPAN). Other studies proposed remote PV-system via satellite [11]. The satellite data transfer from the receiving ground station to the internet. Satellite observation is required to generate data necessary for the desired climate location [12].

Others approach used software implementation [13], GSM [14], wavelet transform [15], statistical approach based on the ANOVA and Kruskal-Wallis tests [16] and a comparison between the performances of a faulty photovoltaic module and Simulink model [17]. Based on the above literature review, it can be concluded that there are a variety of solutions using both wired and wireless technology and other different software platform.

In this paper, the online monitoring system that can notify the user of under progress systems without the need of additional tools and operating costs has been implemented. The development of an online monitoring system by using neural network and optimization have been proposed. The main objective of this approach is to give the signal to the person who responsible for the PV performance system immediately as fast as five minutes and can be operated in online mode.

2. Methodology

Historical data were collected from a grid-connected PV system mounted on the roof of Green Energy Research Centre (GERC) building, in UiTM Shah Alam, Malaysia. Module type used is a poly-crystalline. It has an AC nominal capacity of 5.405 kW, generated by 2 strings comprised with 12 and 11 modules respectively as in Figure 1. Both strings connected to their own MPPT before connecting to the AC/DC inverter. WebBox/server connected to the inverter as a data logger that records, logs and makes available data for the PV system. Thus, the client can linked and interact to the logger through internet or intranet. The user can get the data from the server, which recorded every five-minute interval in a day. The climate data have been used and selected for developing the new monitoring algorithm for this study. The monitoring is based on a comparison between the measured and predicted value of the model training process based on the AC output power. Besides, this system can operate in online mode since it can call data from the server into Matlab through internet/intranet.

There are two stages in this study. The first stages called as offline stages. In this stage, the prediction model of AC output power will be developed first in the neural network implementation. The process will go through the training and testing process in the neural network algorithm. Besides, the evolutionary programming has been applied in order to produce the best prediction of AC output power of the PV system. Hybrid of Fast Improved Evolutionary Programming- ANN (IFEP-ANN) has been chosen in the optimization for better result [18].

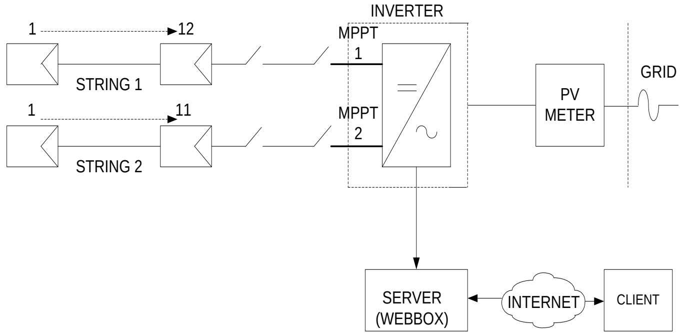

Figure 1. Schematic diagram of the PV site system

After that, the process will be continued with the online stages with new algorithm as Matlab will be called data directly from the server. FTP protocol coding has been used in the Matlab programming by using the IP address of the data logger. Data which consists of an overall data PV system has been updated every five minute interval to the server. However, only value of solar radiation, module temperature, ambient temperature and AC output power will be imported from the server and then compared with the predicted data which has been done in the offline stage. Therefore, users can monitor any problems based on markers plotted in the graph.

2.1. Offline Stage (Training and Testing)

The historical data are separated into training and testing set before proceed to the neural network algorithm. The training data set is used to develop the model, while the testing data set is used to verify the performance of the model. The data patterns are obtained based on a 5 minute interval. In this study, data for 10 days have been allocated for training process which consists of 2882 patterns while 5 days allocated for testing process corresponding to 1441 patterns. At this stage, the effectiveness of the model has been verified based on the highest correlation coefficient, *R* and the lowest root mean square error, *RMSE* computes as below:

$$RMSE = \sqrt{\frac{(a-t)^2}{n}} \quad (1)$$

Where *a* is the actual output of the training data and *t* is the target output of the training data. In addition, *n* is the number of data patterns for training. Higher *R* would imply a higher accuracy of the prediction model [19][20].

2.2. Hybrid IFEP-ANN

ANN is a process of generalization for mathematical model based on the biology of the nervous system. The neuron is a fundamental processing element of ANN. For the basic computational model, the neuron collect input signals from other neurons or sources and merge them. It will then perform necessary computation before mapping them to an output. Generally, the ANN model consists of one input layer, one hidden layer and an output layer. However, it can be employed with more than one hidden layer.

The ANN evolution can be achieved by developing the connection height, architecture or ANN learning algorithm. In general, there are many types of evolutionary methods to develop ANNs. One of the most popular methods is Evolutionary Programming (EP). Evolutionary Programming (EP) was originally proposed by Lawrence J. Fogel in the United States in 1960 when he studied artificial intelligence. The EP is a stochastic optimization technique based on search algorithms and quite similar to Genetic Algorithm (GA) in terms of the principle of natural evolution where this method is capable of solving constrained and unconstrained optimization problems.

EP is one such discipline that has been used to improve the progress of finding optimum solutions in complex issues. For the last decade, EP techniques have been used and applied in several applications and solved many difficult optimization problems [21][22] . In the field of evolutionary computation, it is common to compare different algorithms using large test sets, especially when it involves optimization function tests. The mix of Gaussian-Cauchy during the mutation process has been developed for a single objective optimization[18] . The author finds that FEP is very good in having the lowest computational time. However the research is not concentrating on the fitness of the model based on RMSE and regression, R.

Thus, the improvement of hybrid with Gaussian and Cauchy are proposed in this work. The combination of these EP called Improved Fast EP (IFEP). In the ANN model, several parameters have been selected before perform the training stage. Firstly, Levenberg-Marquardt algorithm has been chosen as the learning rules for the ANN, since it has been widely used in solving many engineering problems due to its good capability and simplicity [23]. Besides, it has shown the best output compared to trainbfg, trainscg and trainrp [24].

According to the same author, there is no strict procedure on how to determine the value of ANN parameters, hence the transfer function configuration is set to be 'logsig, pureline'

Besides, the number of epochs is set to be 1000 in order to allow accurate convergence of the ANN.

In this study, model with three inputs and one solely output have been developed. The model utilizes SR, MT and AT as its input and total AC output power as its output. This model is comprised of all three factors that could affect the performance of the PV array. The model as illustrated in Figure 2.

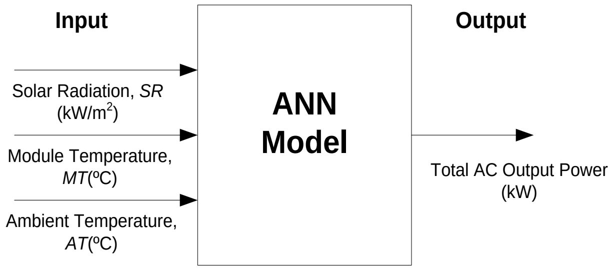

Figure 2. ANN Model – SR, MT and AT as inputs

The general mathematical expression for Gaussian operator is as in equation (2). A single offspring (x'_i) is made from each parent (x_i) by adding a random number with zero mean and standard deviation to each vector of the parent.

$$x'_i = x_i + G(0,\sigma^2{}_i) \quad \textit{for } i = 1,2\ldots\ldots\ldots n \tag{2}$$

Where $G(0,\sigma^2{}_i)$, represent a Gaussian random variable with mean 0 and standard deviation, σ_i.

For Cauchy operator, an offspring is created by the equation (3) below. Where $C_i(0,1)$ is a Cauchy random variable with scale parameter $k = 1$ centred at 0 that is generated anew for each value of *i*.

$$x'_i = x_i + \sigma_i.C_i(0,1) \qquad \textit{for } i=1,2\ldots\ldots n \tag{3}$$

Then, by using combination of Gaussian and Cauchy mutation known as Improved-Fast EP, an offspring $(x1'_i + x2'_i)$ is generated from the parent (x_i).

$$x1'_i = x_i + \sigma_i.G_i(0,1) \tag{4}$$

$$x2'_i = x_i + \sigma_i.C_i(0,1) \tag{5}$$

where, the standard deviation, σ_i is given as the Equation 6.

$$\sigma_i = \beta.\frac{f_i}{f_{\max}}(x_{i\max} - x_{i\min}) \tag{6}$$

Hence,

f_i = fitness value of *i*th individual

$f_{\max}$ = maximum fitness among the parents

The performance of the hybrid model evaluate by the lowest value of the root mean square error *(RMSE*) and the highest correlation coefficient, *R*. The whole process of the proposed algorithm is illustrated in Figure 3.

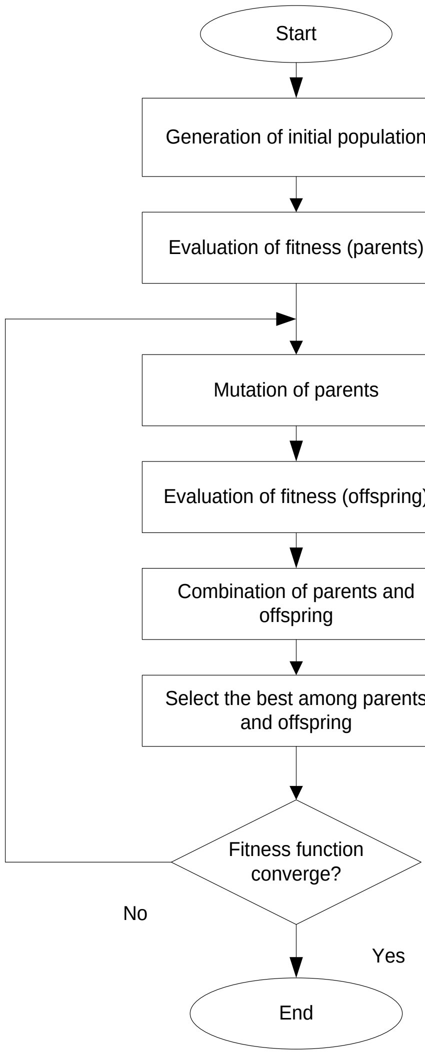

Figure 3. Flowchart for the hybrid Improved Fast Evolutionary Programming IFEP-ANN techniques

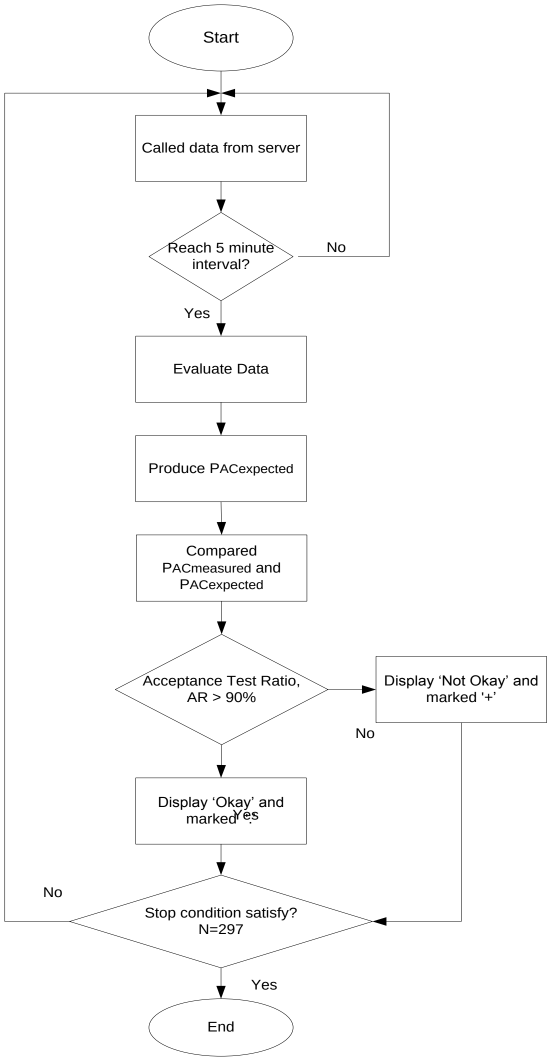

Figure 4. Flowchart for the online monitoring processes

2.3. Online Monitoring Algorithm

To make this new algorithm work successful, internet connection is essential for importing data from the server as fast as 5 minutes while at the same time monitor the system in online mode. Prior to that, the IP address of data logger / server should be known by the user / client as it will be used to call the required data from the logger / server using a specific FTP coding in Matlab. With the specific coding, the required data can be imported and updated every 5 minutes into the Matlab, so users can monitor under-performance systems as online modes. The process in online testing starts with running programs that have been developed first in Matlab.

This program will call the data from the logger / data server and automatically update the system from 00:00 hours until the current program runs and it will continue until 23:55 hours.

Data will be updated on the server for every five minutes. That means there are 297 pattern number in a day.

The process of online monitoring is illustrated in Fig. 4. The process starts with the data were called from the server by using FTP coding for every 5 minute interval and loaded into the system in the Matlab. Subsequently, the data were evaluated through neural network algorithms with optimized processes and produced expected AC output power, $P_{ACexpected.}$ It is then compared to the actual AC output power, $P_{ACmeasured}$. The comparison is based on an acceptance test ratio, AR. The system was displayed 'Okay' and marked with '.' if the ratio is greater than or equal to 90%. However, 'Not Okay' was displayed and marked with '+' if the output power value is less than the acceptance test ratio. This process was continue for every five minutes until the pattern number is reached at 297 which corresponds to 23:55 hours.

To determine the error in the system, the acceptance test ratio, AR is used as appropriate to be implemented for immediate time consideration. As a requirement for the SEDA (Malaysian Sustainable Energy Development Board) regulatory, Acceptance Test Ratio, AR must be greater or equal to 0.9. The equation is given as in (7).

$$AR = \frac{P_{measured}}{P_{\mathrm{exp}ected}} \geq 90\% \tag{7}$$

3. Results and Analysis

There are two sections in this result. The first result describes the performance of the hybrid improved fast evolutionary programming and ANN (IFEP-ANN). The next section describes the performance of the system based on AR value. After successfully training the hybrid IFEP-ANN, the result for the prediction of the total AC power output of the PV system are illustrated in Table 1. In terms of fitness of the hybrid model, it can be shown from the value of correlation coefficient, *R* where it is higher in the testing process as 0.98857 compared to the value in the training process gives 0.96017. At this good performance, the optimization chooses the learning rate, *x1,* momentum rate, *x2* and number of nodes in hidden layer at 0.1269, 0.0975 and 20 respectively.

Table 1. Training Parameters and result of the best model chosen

Parameters	Value
Learning rate (*x1*)	0.1269
Momentum rate (*x2*)	0.0975
Number of nodes in hidden layer	20
Type of transfer function	Logsig, Purelin
RMSE training	277.6464 W
RMSE testing	425.7352 W
Correlation coefficient, *R* for training	0.96017
Correlation coefficient, *R* for testing	0.98857

In addition, Figure 5 shows the results for both output power expected and measured with the hybrid IFEP-ANN. It is clear to see that the result for IFEP-ANN are very precise as the predicted and targeted output value are very close. The next graph shows the AR performance results in the online process. The testing time has been simulated on 7th May 2017. From Figure 6, the graph shows the complete plot graph for a day, which consist of a pattern number of 297. From the graph, it can be seen that the value of expected power, $P_{ACexpected}$ having below than the average test ratio, AR occurred for two times. However, the rest are marked with '.' which give the signal to the user that the system is in good condition.

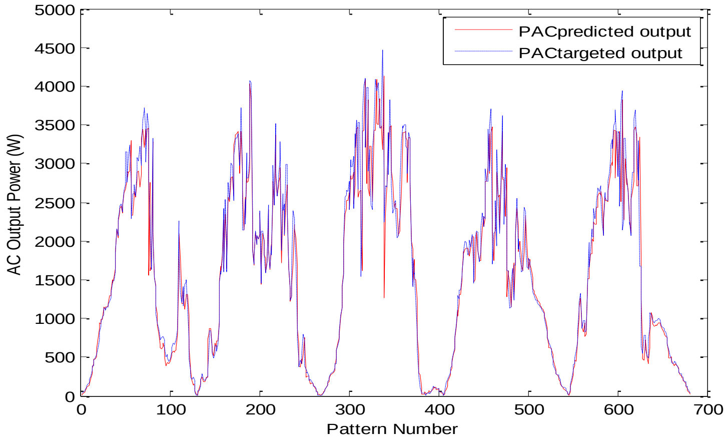

Figure 5. Graph for P_{AC}measured and P_{AC}expected with hybrid IFEP-ANN

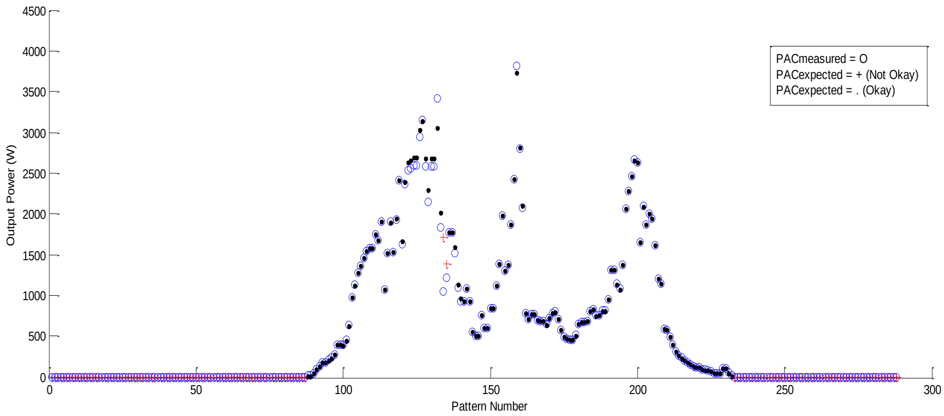

Figure 6. Graph for P_{AC}measured and P_{AC}expected for a day with total pattern number of 297

4. Conclusion

This approach found to be useful for the fault detection method. The online system monitoring shows the system operates faster as five minutes by using artificial intelligence method. It could be more reliable if the system can operate in online mode for both training and testing process in the neural network.

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