energies

MDPI

Article

Comparison of Power Output Forecasting on the Photovoltaic System Using Adaptive Neuro-Fuzzy Inference Systems and Particle Swarm Optimization-Artificial Neural Network Model

Promphak Dawan [1], Kobsak Sriprapha [2], Songkiate Kittisontirak [2], Terapong Boonraksa [3], Nitikorn Junhuathon [4], Wisut Titiroongruang [1] and Surasak Niemcharoen [1,*]

1 Department of Electrical Engineering, Faculty of Engineering, King Mongkut's Institute of Technology Ladkrabang, Bangkok 10520, Thailand; promphak.dawan@gmail.com (P.D.); ktwisut@kmitl.ac.th (W.T.)

2 Solar energy technology laboratory, National Electronics, and Computer Technology Center, National Science and Technology Development Agency (NSTDA), Pathum Thani 12120, Thailand; kobsak.sriprapha@nectec.or.th (K.S.); songkiate.kittisontirak@nectec.or.th (S.K.)

3 School of Electrical Engineering, Faculty of Engineering, Rajamangala University of Technology Rattanakosin, Nakhon Pathom 73170, Thailand; terapong.boo@rmutr.ac.th

4 School of Electrical Engineering, Faculty of Engineering, Bangkok Thonburi University, Bankok 10170, Thailand; Nitikorn.ju@gmail.com

* Correspondence: surasak.ni@kmitl.ac.th

Received: 15 November 2019; Accepted: 27 December 2019; Published: 10 January 2020

Abstract: The power output forecasting of the photovoltaic (PV) system is essential before deciding to install a photovoltaic system in Nakhon Ratchasima, Thailand, due to the uneven power production and unstable data. This research simulates the power output forecasting of PV systems by using adaptive neuro-fuzzy inference systems (ANFIS), comparing accuracy with particle swarm optimization combined with artificial neural network methods (PSO-ANN). The simulation results show that the forecasting with the ANFIS method is more accurate than the PSO-ANN method. The performance of the ANFIS and PSO-ANN models were verified with mean square error (MSE), root mean square error (RMSE), mean absolute error (MAP) and mean absolute percent error (MAPE). The accuracy of the ANFIS model is 99.8532%, and the PSO-ANN method is 98.9157%. The power output forecast results of the model were evaluated and show that the proposed ANFIS forecasting method is more beneficial compared to the existing method for the computation of power output and investment decision making. Therefore, the analysis of the production of power output from PV systems is essential to be used for the most benefit and analysis of the investment cost.

Keywords: PVs power output forecasting; adaptive neuro-fuzzy inference systems; particle swarm optimization-artificial neural networks; solar irradiation

1. Introduction

At present, the world population has become more alert to the use of renewable energy due to the impact of the use of energy from coal, petroleum, and natural gas, emitting large amounts of carbon dioxide gas, which causes global warming [1]. There are many interesting renewable energy sources such as solar energy, wind energy, water energy, ocean tidal energy, geothermal energy, and biofuels. These renewable energy sources are non-polluting and do not negatively affect the environment [2].

Nowadays, many scientists and researchers have studied and developed the ability to use renewable energy, such as solar energy, wind energy, and water energy, and it is expected that by 2030, 100% of energy will come from such renewable resources. Therefore, there is a clear trend that these renewable energies will play an important role in Thailand as well [3,4]. The most popular renewable energy in Thailand is solar energy. Since Thailand is located near the equator, it receives high amounts of solar energy. The average energy that can be obtained nationwide is about 4 to 4.5 kilowatt-hours per square meter per day. It consists of approximately 50% of direct radiation and the rest is diffused radiation, which is caused by water droplets in the atmosphere (clouds), which are higher than the area away from the equator to the north-south [5]. According to energy consumption estimates by the International Energy Agency in the year 2011, the use of solar thermal energy may be the main energy for electricity generation in the world in the next 50 years, which can reduce greenhouse gas emissions that affect the environment [6]. Solar radiation is measured to evaluate the energy potential, with hourly measurements that are 295–2800 nm and 695–2800 nm and ultraviolet (UV) 295–385 nm at the National Observatory of Athens (NOA) [7]. The intensity of the solar radiation will vary according to the area, day, time, and season, it will be of very high intensity in the afternoon and the sky conditions and wind speed will also affect the intensity and distribution of solar radiation [8]. However, the PV power output has a significant limitation in terms of instability of the power system as its output varies over a wide range throughout the day according to the available solar radiation. The energy storage can improve the stability of the PV system until low solar irradiance. Now, it is well known that the storage is still expensive, so we should get the most out of it [9]. Today, the industrial internet of things (IIoT) plays an essential role in creating tools to help entrepreneurs or investment decision-makers know the benefits of investing in IIoT applications of machine learning and deep learning to provide a new way to develop complex system models, instead of using system physics models to describe the behavior of that system. Some algorithms can infer the operation of the model from the sample input data, in which these models are used to forecast the state of the system, and it is often called forecasting analysis [10].

The power forecasting of PV systems has a variety of methods depending on the data that is used, such as the PV power forecasting with the 1D5P method. This uses the parameters of the solar panel and the solar radiation intensity to calculate the PV power of the solar system and can also improve the accuracy of power output with a weight function that is appropriate for each area [11]. Later, the predictive method with the HIstorical SImilar MIning (HISIMI) method was used to predict the short-term power of the solar system, and it was adjusted by using genetic algorithms and using historical forecasting data [12]. There are discrepancies in the power output forecasting for renewable energy due to fluctuations in renewable energy. The learning methods of machine learning models are more accurate than traditional predictive models. Precise forecasting helps stakeholders decide to plan investment and install solar farms connected to grid systems [13,14]. The auto-regressive moving average (ARMA) model is used, including the exponentially weighted moving average (EWMA) improvements by Piorno et al. [15]. Biological systems and natural phenomena exhibit chaotic behaviors that have been applied for PV power output forecasting. Such as least-squares support vector machines (SVM) methods, it can predict experimental chaotic time series [16] The power forecasting methods with artificial neural networks (ANN) is one method that is providing precise values, using actual measurement data learning to predict future power [17]. The hybrid method forecasting using artificial neural networks has been the basis of fuzzy inference systems (ANFIS) [18] and predictions using particle swarm optimization methods combined with artificial neural networks (PSO-ANN) [19]. The PV power forecasting with these hybrid methods is more accurate than other methods, which are interesting for many researchers to improve the power efficiency of the PV system as well as to develop different forecast models. In this research, we wanted to focus on the ANFIS model because it is an interesting method of forecasting at present, and it is the forecasting method with deep learning techniques that have not been widely used forecasting on solar power generation systems. It is a forecasting technique that can be applied to other complex systems that provide accurate and quick predictions. Then the ANFIS model is applied and compared with the ANN-PSO method, which has similar forecasting techniques. PSO-ANN is one of the forecasting techniques that is more accurate.

As the number of iterations and the number of particle swarms increases, the accuracy becomes more and more accurate. Therefore, the researcher focused on these two forecasting techniques.

So, this work was to study the power output forecasting of the PV systems by the hybrid model and the fast-operating process model. Therefore, the forecasting model using the ANFIS was applied in the study. The simulation results were compared with the PSO-ANN model forecasting. This article is divided into the following six sections. The first section is the introduction. The second section is an explanation of energy efficiency analysis in Thailand. The third section explains the PV power output forecasting model. The fourth section will discuss the case studies of this research and PV power data analysis, and in this study, we will use case study data as a solar system in Thailand. The fifth section will mention simulation results and analysis, and the last section is conclusions.

2. Energy Efficiency Analysis in Thailand

2.1. Energy Sources in Thailand

Natural gas is the primary fuel for electricity generation in the country. If considering the installed production capacity, the power plants that use natural gas as a fuel are approximately 67 percent. Natural gas is a hydrocarbon compound consisting of hydrogen and carbon, which is caused by the accumulation of fossilized micro-organisms that are hundreds of millions of years old. It is also able to separate components into methane, ethane, propane, butane, pentane, petroleum with gasification, etc.

Natural gas is clean energy, and the cost of electricity with natural gas is lower than fuel oil. However, it is slightly higher than coal because the electricity generating system in Thailand has a high proportion of natural gas, so we want to diversify to use other forms of fuel. The advantage of natural gas fuel is that it is a petroleum fuel that can be used with high efficiency. It has complete combustion and highly secure usability because it is lighter than the air, therefore, it floats up when a natural gas leak occurs. Most of it used in Thailand is produced by itself from domestic sources, thus helping to reduce the import of other fuels and saving a lot of foreign currency.

Lignite coal is a natural fuel used in electricity generation, which is a combustible fuel mineral. It consists of four essential elements, which are carbon, hydrogen, nitrogen, and oxygen. It is the second most used fuel from natural gas. The advantage of lignite is that electricity production costs are lower than other fuels, whether natural gas and renewable energy. Coal has a large number of reserves, especially lignite and sub-bituminous coal, which are found mainly in Mae Moh District and Li District, Lampang Province, Mueang District, and Krabi Province. Currently, clean coal technology can be used, which can eliminate more than 99% of coal pollution.

Normally, two types of fuel, namely furnace oil and diesel oil, are used for electricity generation in Thailand. Due to price hike in the international market, such fuels are becoming more and more expensive, resulting in an increase in electricity prices. Additionally, fuel oil causes more pollution than diesel and natural gas. Therefore, fuel oil was used as a secondary fuel rather than a primary fuel.

Diesel is used as fuel for electricity generation of diesel power plants. In Thailand, there are only three locations. Nowadays, the price of diesel has dramatically increased, resulting in a high cost. It also causes more pollution than natural gas. The use of diesel fuel, therefore, is used as a secondary fuel rather than a primary fuel.

Solar energy is a natural energy that is clean and free from pollution. At this time, it is used widely around the world. It is renewable energy with high potential and can be used endlessly. Especially, the use of solar energy to produce electricity, which will help strengthen the electrical system of Thailand and also help reduce global warming. The advantage of solar energy is that it is the largest natural energy source. It is an energy that will never run out, and there is no fuel cost. Solar energy can be used in energy sources that do not have electricity and are far away from power transmission and distribution systems. It is clean energy that does not cause pollution from the electricity production process. There is also renewable energy from water power, wind power, biomass energy, biogas, and waste energy. Figure 1 shows the proportion of electricity production from fuel and renewable energy sources in Thailand. In Thailand, the production of electricity from biomass is the highest, followed by water and solar energy [20].

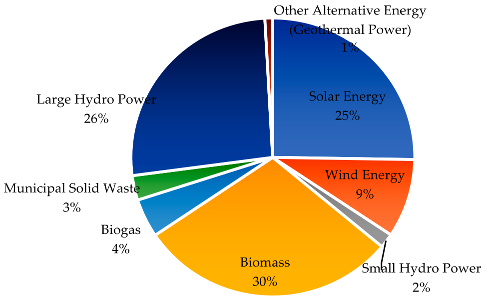

Figure 1. The proportion of electricity production from fuel and renewable energy sources in Thailand.

2.2. Solar Radiation

Solar radiation is the energy released from the sun, which hits the edge of the atmosphere called extraterrestrial solar radiation. In Thailand, ten provinces have the highest potential for the production of electricity from solar energy. Nakhon Ratchasima Province has the highest potential for solar electricity production in Thailand. However, the availability of high-intensity solar radiation will not guarantee the most efficient site for the installation of generation facilities, there are many other factors to be considered [21,22].

The solar potential in Thailand found that most areas receive the highest solar radiation between April and May in the range of 5.56–6.67 kWh/m^2/day. Moreover, the area that has the highest average annual solar radiation is in the Northeast. It covers parts of Nakhon Ratchasima, Buriram, Surin, Sisaket, Roi Et, Yasothon, Ubon Ratchathani, and Udon Thani and parts of the central region with an average annual solar radiation of 5.28–5.56 kWh/m^2/day. The area accounts for 14.3% of the country's total area. Additionally, 50.2% of the total area receives the average annual solar radiation during 5–5.28 kWh/m^2/day, and only 0.5% of the total area exposed to solar radiation is less than 4.45 kWh/m^2/day [23]. Figure 2 shows the average daily solar radiation intensity in Thailand.

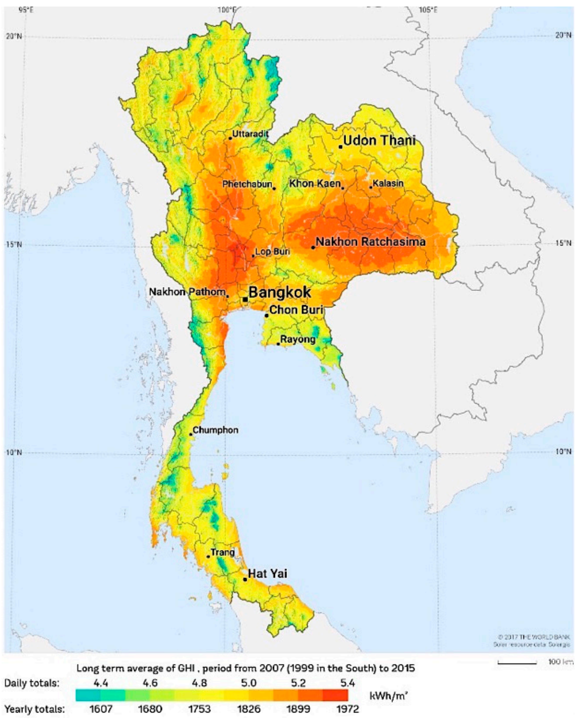

Figure 2. The average daily solar radiation intensity in Thailand [23].

3. PV Power Output Forecasting Model

The accurate forecasting of the PV power generation is essential for the estimation of cost and breakeven. Currently, there are many researchers, including this research, interested in studying the forecasting of power output produced by solar cell systems. In this section, we will explain the principles of the ANFIS and PSO-ANN forecasting models. The PSO-ANN model was used to compare the forecasting result, which has higher accuracy than other methods and can be applied to other areas of research [18]. The models of both methods are shown in the following topics.

3.1. ANFIS Model

Adaptive network-fuzzy inference systems (ANFIS) is a type of network adaptation based on the fuzzy inference systems (FIS), which is a theory adapted from the fuzzy logic theory. The fuzzy rules from the input and output data groups are created using the basis constructing of the neural network system. Artificial neural network (ANN) is a calculation model where its functions and methods are based on the structure of the human brain cells. The neural network follows graph topology in which neurons are nodes of the graph and weights are edges of the graph. It consists of such multilayers that should be a limit in order to the time of problem-solving. The weights changing in the connections between network layers are the training process of the network to achieve the expected output. Another model is neuro-fuzzy, which is a combination of fuzzy logic and neural networks to solve a variety of problems efficiently.

This theory is used in the analysis of problems consisting of information that is widely characterized by uncertainty. The structure of ANFIS will be a fuzzy inference system, which under consideration has two inputs (x and y), and one output is f for the first Sugeno fuzzy model [24,25]. This study uses the hybrid learning algorithm with the following principles. Figure 3 shows the fuzzy inference system [26].

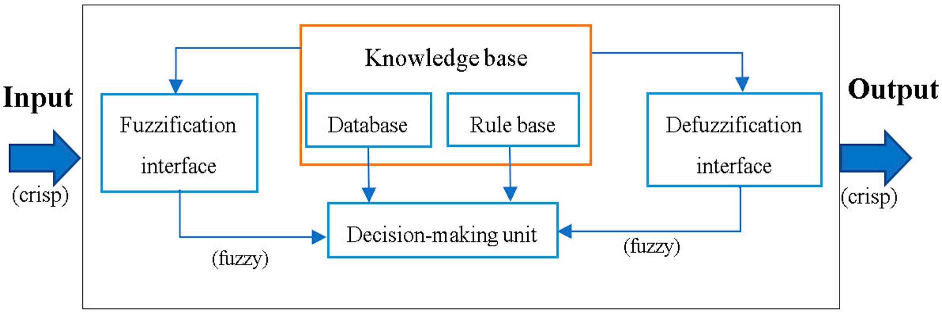

Figure 3. The fuzzy inference system [26].

Layer 1 consists of a member function of each input variable, which can be adjusted. The variables in this layer are also known as premise parameters and can be shown in Equation (1).

$$o_{1,i} = \mu_{Ai}(x) \tag{1}$$

Layer 2 is the calculation of all possible equations of the input vector relationships, which can be expressed in Equation (2). It has 4 (2^2 = 4) fuzzy rules.

$$o_{2,i} = wi(x, y) = \mu_{Ai}(x)\mu_{Bi}(y) \tag{2}$$

Layer 3 is normalized to find the input vector obtained from Layer 2, as shown in Equation (3).

$$o_{3,i} = \overline{w} = \frac{w_i}{w_1 + w_2} \tag{3}$$

Layer 4 is called standard perceptron, which can be written according to Equation (4), where (p, q, r) is called the consequent parameter.

$$o_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{4}$$

Layer 5 is the calculation to find the output value in real numbers, and the result can be written in Equation (5).

$$o_{5,i} = \sum_i \overline{w}_i f_i \tag{5}$$

In this study, the determination of consequent parameters using the least-square estimator method and the reverse pattern study to modify the premise parameters using the gradient descent method. The structure of the ANFIS is shown in Figure 4. Using the ANFIS model to predict the PV power output in this article, it will use 2 inputs, panel temperature, and solar radiation. The model training with one output using the measured power output from the PV system. The structure of a 5-layer model identifies a fixed node, while a square refers to a modified node in which parameters are changed during adjustment or training.

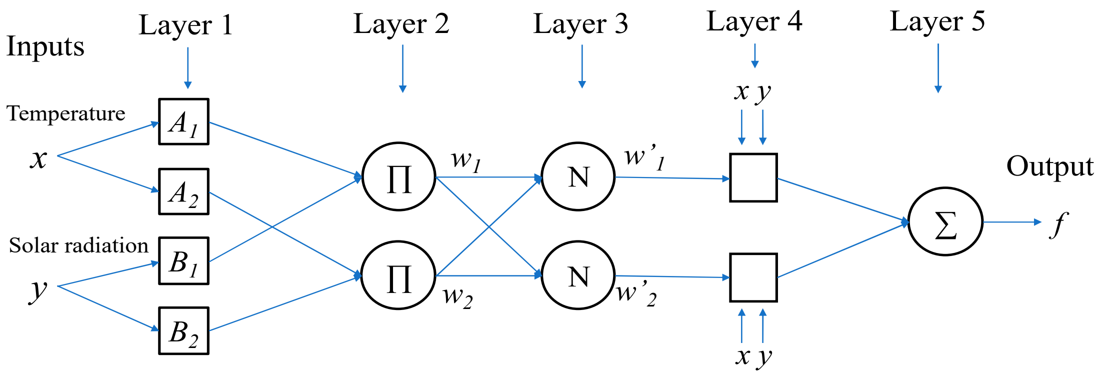

Figure 4. The structure of the adaptive neuro-fuzzy inference systems (ANFIS) model.

3.2. PSO-ANN Model

Particle swarm optimization (PSO) is a natural-inspired algorithm, especially the movement of fish and bird swarms. The change of both types is the movement of the small elements that move together in synchronous time. Fish or birds can move in a swarm, separate from the swarm, and then reunite into the swarm again. The movement of this particle swarm can be considered social behavior. Details of the PSO process were presented in 1995 by James Kennedy and Russell Eberhart [27].

A bird, which is comparable to one particle, and each particle remembers its current position, along with the direction and speed of its movement. Figure 5 shows the position and direction of particle movement. When each particle moves, each particle collects its best data (P_{best}) and compares it to find the best position of every particle (G_{best}). Every cycle at t time, the speed of movement is changed by using data of the best position of each particle and the best position of all particles [28,29].

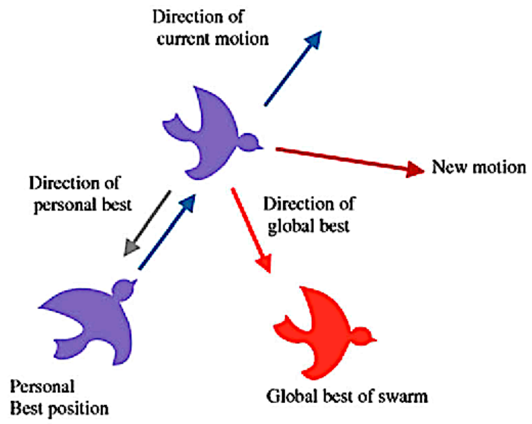

Figure 5. The position and direction of particle movement [28].

PSO has many features that are similar to evolutionary calculations, such as the genetic algorithm (GA). The initial population is randomly generated and used to find the best answer by adjusting that population in every calculation cycle. The solution of the system is represented by particles moving in the search space in the direction of the particles that are closest to the answer that is most appropriate at that time. PSO has been successful in many applications such as optimization of functions, training of artificial neural networks, and the fuzzy control system, including finding the power output or forecasting the suitable power of the photovoltaic power generation systems [30].

Artificial neural networks (ANN) is a simulation of the human nervous system with repeated learning. When learning from something that is repeated many times, it will be able to find a relationship from past learning [31,32]. Figure 6 shows the structure of an artificial neural network that is simulated from the human nervous system. This article will be a supervised learning network to help define the output target for the artificial neural network that uses the multilayer feedforward neural network. It is a back-propagation type which is rather complicated and non-linear. Each neural consists of weight and bias, which begin at random. There is also an activation function or transfer function, which helps to calculate the suitable values such as tan sigmoid, log-sigmoid, and linear. ANN consists of neurons, also called nodes in a circle (Node); the line connecting the nodes is called the weight (Weight) indicates the connection between nerve cells. The artificial neural network has three layers, the input layer, hidden layer, and the output layer.

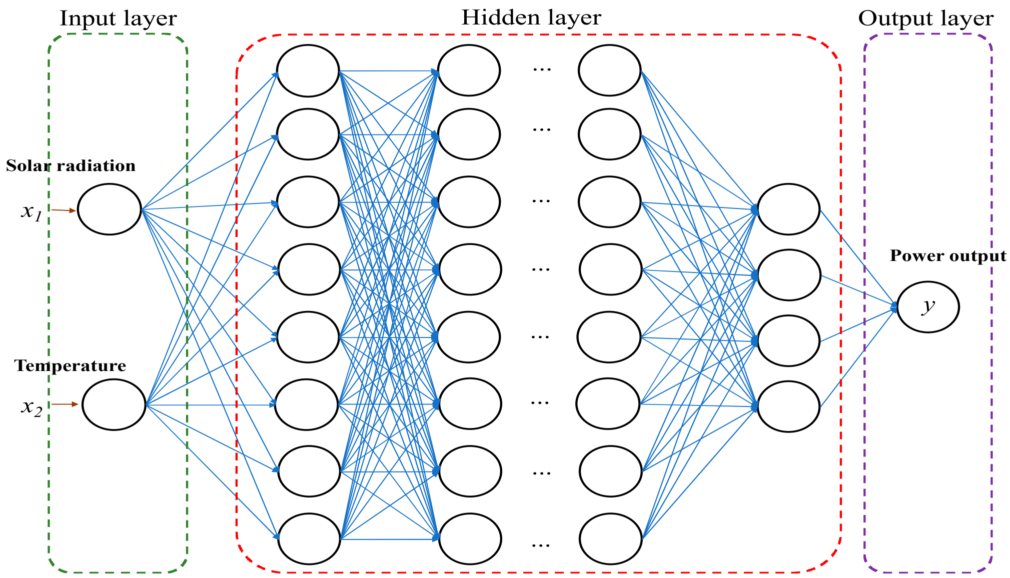

Figure 6. Forecast model based on artificial neural networks (ANN).

The procedure of the hybrid PSO-ANN forecast model is a combination of particle swarm optimization algorithm and BP_ANN algorithm using MATLAB® programs [33,34]. The first step is to determine the number of particles in the ANN structure, beginning with the sampling of particles showing weights, determining the position and speed of the particles. Next, simulate an artificial neural network and evaluate the suitability of initial particles. Find the best of G_{best} and P_{best}, calculate the fitness of each particle in the ANN structure. Find the best fitness in the group or calculation cycle, improve particle velocity and position. Then collect the best particle of the current particle and repeat it until you reach the maximum number of iterations you set [30,35]. Figure 7 shows a diagram of the operation of the hybrid PSO-ANN forecast model.

The parameters of the PSO algorithm are set before the optimization of the ANN model, which has two inputs: panel temperature and solar radiation. The training output is PV power output form the PV systems. Therefore, the structure of the ANN model is 2 8 8 8 4 1. For this article, use the number of particle swarm 100, the maximum number of iterations 100, lower and upper bound of variables −5 to 5, inertia weight 1, inertia weight damping ratio 0.99, personal learning coefficient 1.5, global learning coefficient 2.0, and 4 the number of neurons as shown in Table 1.

Table 1. PSO-ANN parameters.

Particle Swarm	Iterations	Lower-Upper Bound	Inertia Weight	Damping Ratio	Personal Learning Coefficient	Global Learning Coefficient	Number of Neurons
100	100	−5 to 5	1	0.99	1.5	2.0	4

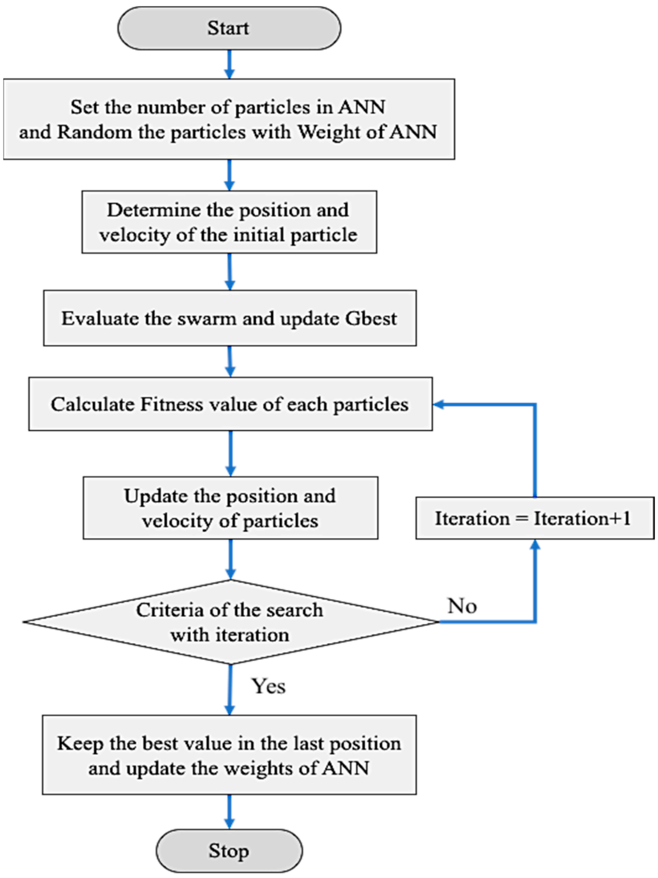

Figure 7. Diagram of the operation of the hybrid PSO-ANN forecast model.

3.3. *Accuracy of the Simulation Results*

After the simulation, the simulation results will be checked for accuracy, so all measurement forms will always have inaccuracies or uncertainties. An effective experiment must begin with the smallest data error; the percentage of the error can determine the accuracy and reliability of the experiment. Therefore, there must be a realistic and accurate quantity for comparison. If S is defined as the standard quantitative physics and E is the same physical quantitative value as S but obtained from the experiment, then the percentage error can be determined by the Equation (6).

$$\text{The percentage error } = \frac{|E - S|}{S} \times 100\% \tag{6}$$

Statistical analysis can find the best numerical solution of all data sets and determine the statistical error of the answer. The best replacement number is the average value or mean value [36]. In order to assess the accuracy of the prediction methods, the mean absolute percent error (MAPE) and root mean squared error (RMSE) are used as criteria for consideration, [31] which can be found in the following equation.

Mean square error (MSE) is an indication of the variance of the forecasting error which can be obtained by Equation (7)

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{X_i - Y_i}{Y_i}\right)^2 \tag{7}$$

where Y_i is the measured power value, X_i is the predicted value, and n is the amount of data to be tested; it is the power in every period of measurement.

Root mean square error (RMSE) or standard error (SE) is shown by Equation (8).

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\frac{X_i - Y_i}{Y_i}\right)^2} \tag{8}$$

Mean absolute error (MAP) is shown by Equation (9).

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{X_i - Y_i}{Y_i}\right| \tag{9}$$

The mean absolute percent error (MAPE) is shown by Equation (10). It is also possible to calculate the forecast accuracy (Acc), which indicates how close the forecast the power value to the actual value, which can be obtained by Equation (11).

$$MAPE(\%) = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{X_i - Y_i}{Y_i}\right| \times 100 \tag{10}$$

$$Acc = 100 - \text{MAPE } (\%) \tag{11}$$

4. PV Power Output Data Analysis

This research uses a case study area in the northeastern region of Thailand with the installation of a 14 MW solar cell system using a 330 W polycrystalline solar panel, the maximum solar irradiation of 1.142 kW/m^2, the highest ambient temperature of 39.4 °C, and the highest panel temperature of 57.44 °C. This data is obtained from a PV plant in the Nakhon Ratchasima province. The results of the measurement are used for one year as forecasting data. Figures 8 and 9 shows the annual solar irradiation and solar panels temperature.

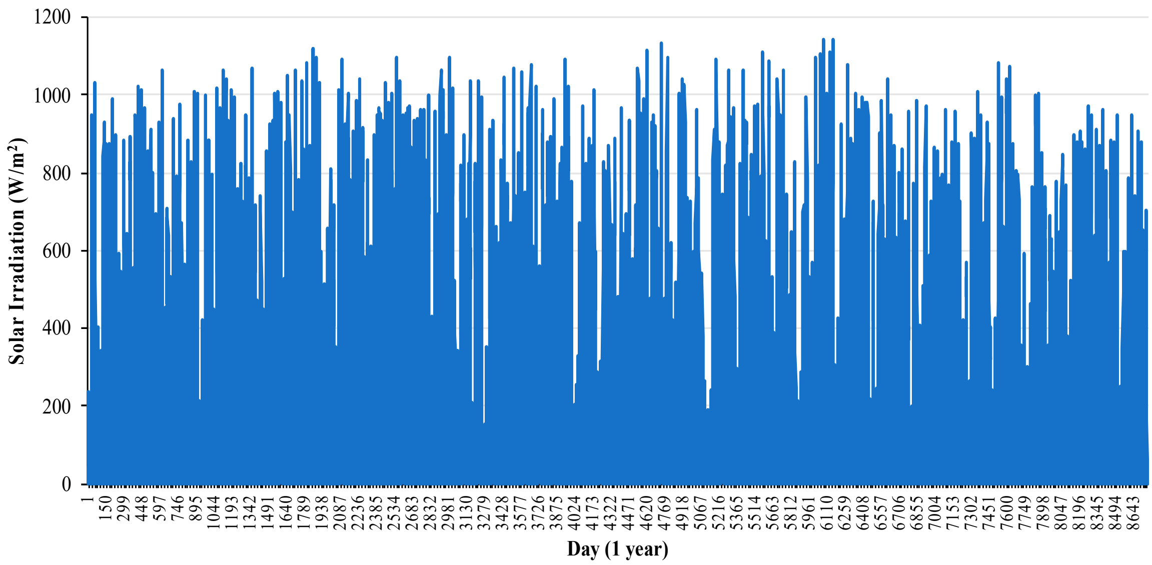

Figure 8. Annual solar irradiation of the case study area.

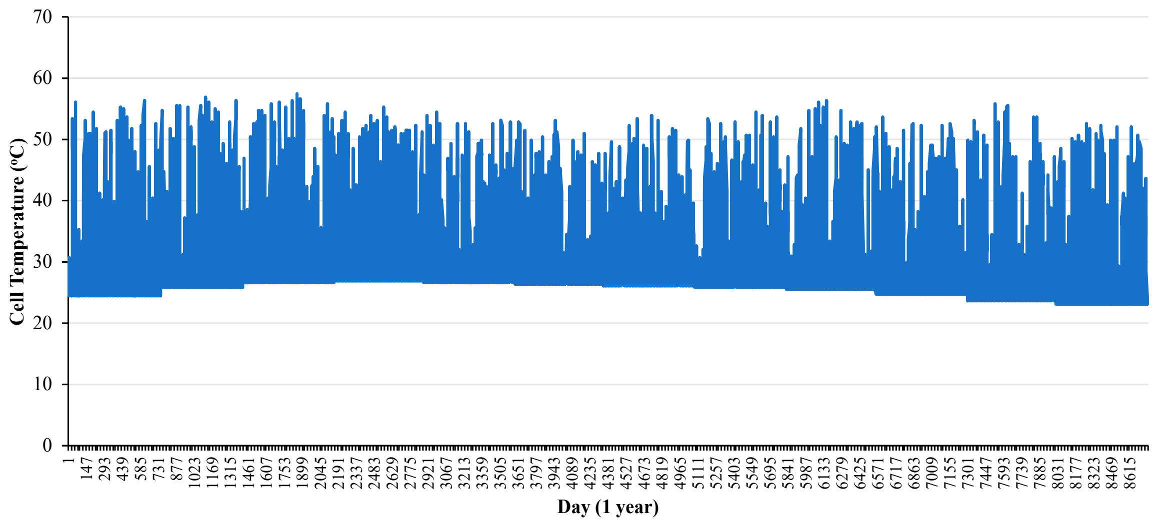

Figure 9. Annual solar panels temperature.

This PV power generation system will be connected to the grid system (Grid connected) and it will produce the electricity for the power distribution systems to be the source of the residential electricity load. In order to study the energy efficiency, we must also analyze the output power of this solar power generation system. Figure 10 shows the PV power output produced by the solar system case study and solar irradiance, for example 5-day data during April in 2018. The input data used for learning of the model is the temperature of the solar panel, ambient temperature, solar irradiance, and PV output power.

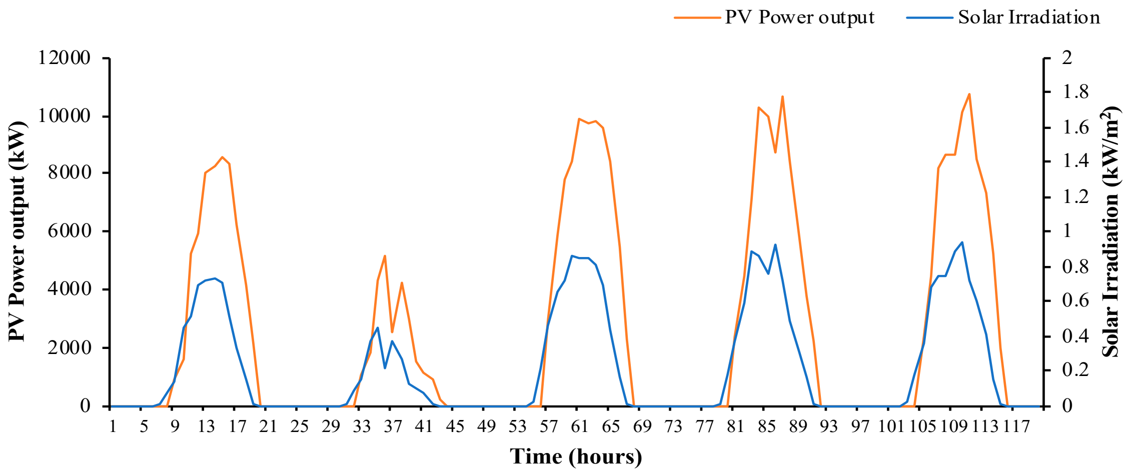

Figure 10. PV power output and solar irradiance.

5. Simulation Results and Discussion

A MATLAB program is used to simulate the PV power output forecasting by inputting one year of input data, which is the actual measured power output, solar irradiation, panel temperature, and ambient temperature. The PSO-ANN technique is used to simulate the calculation cycle of 100 cycles, the population of 100 population, and the number of neurons of 10 cells. The annual power output forecasts are shown in Figure 11, in which some of the predicted electrical power is less than zero because it is a random method. It has a maximum error of 1721 kW, as shown in Figure 12. In April it is the month in which the most energy was produced from solar energy and it is summer in Thailand, which has the most solar radiation intensity. Therefore, the forecasting results of April 1–7 were selected. Figure 13 shows a weekly PV power output forecasting with PSO-ANN. Figure 14 shows a weekly percentage error of PV forecasting using PSO-ANN. In a positive state, the predicted value is higher than the actual value, and in a negative state, the predicted value is less than the real value. It can be seen that the percentage error from the forecast is as high as 190.7% because the PV power forecasting value is much higher than the actual PV power of the system (actual PV power value of 238.5 kW and PV power forecasting value of 693.5 kW). The PSO-ANN is a technique for determining optimal values with sampling, so high errors may occur due to the input instability. The simulation results, when compared to the real power output, can be seen that at night without irradiation intensity, the PSO-ANN model has a rather high discrepancy. The calculation efficiency of the ANFIS method was 429.522 s.

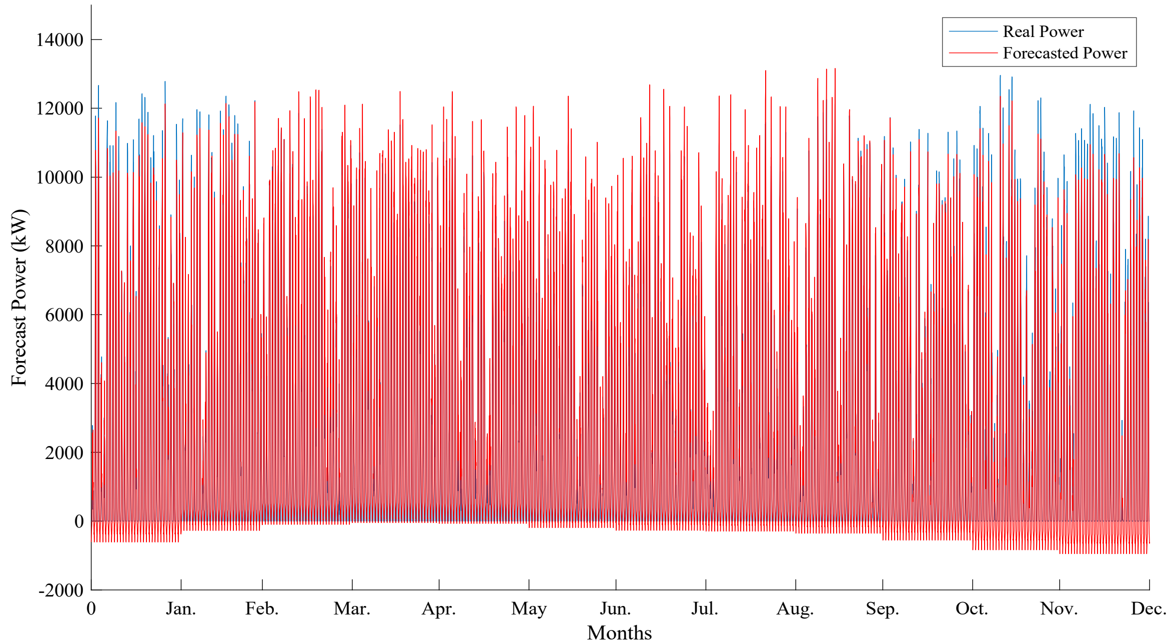

Figure 11. Annual PV power output with PSO-ANN forecasting.

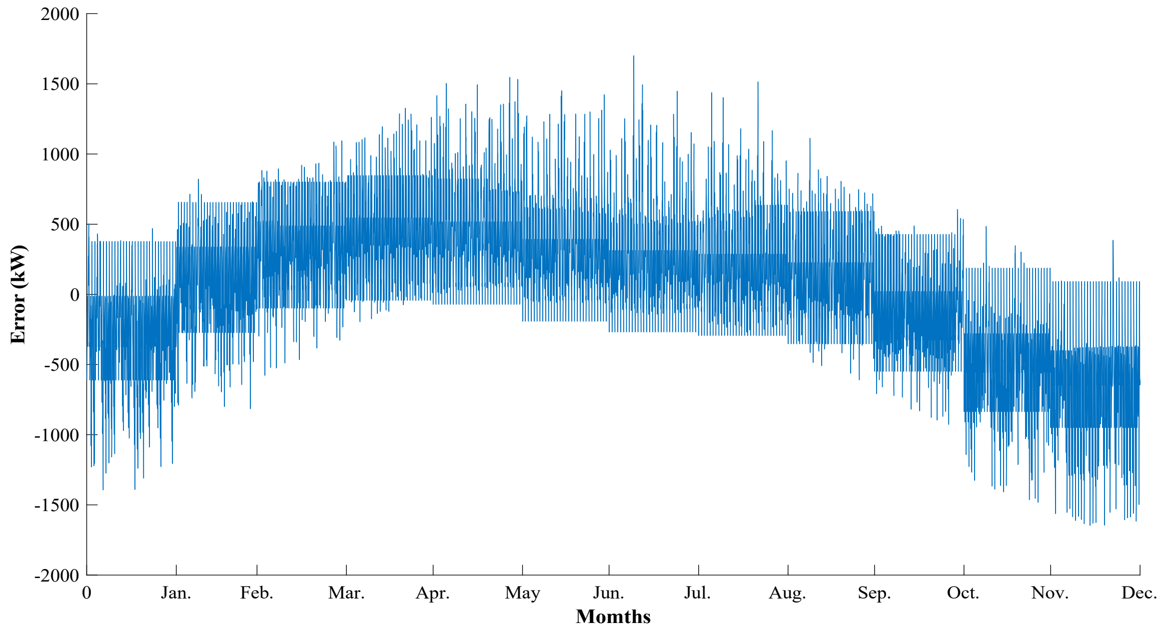

Figure 12. Annual PV power output error with PSO-ANN forecasting.

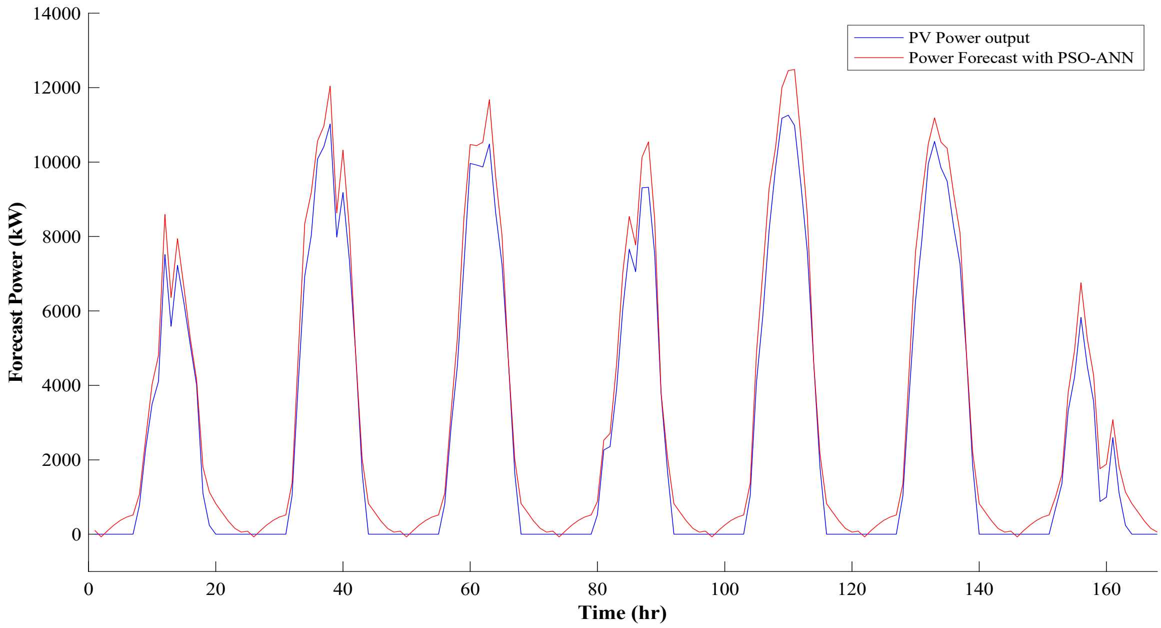

Figure 13. Weekly PV power output with PSO-ANN forecasting.

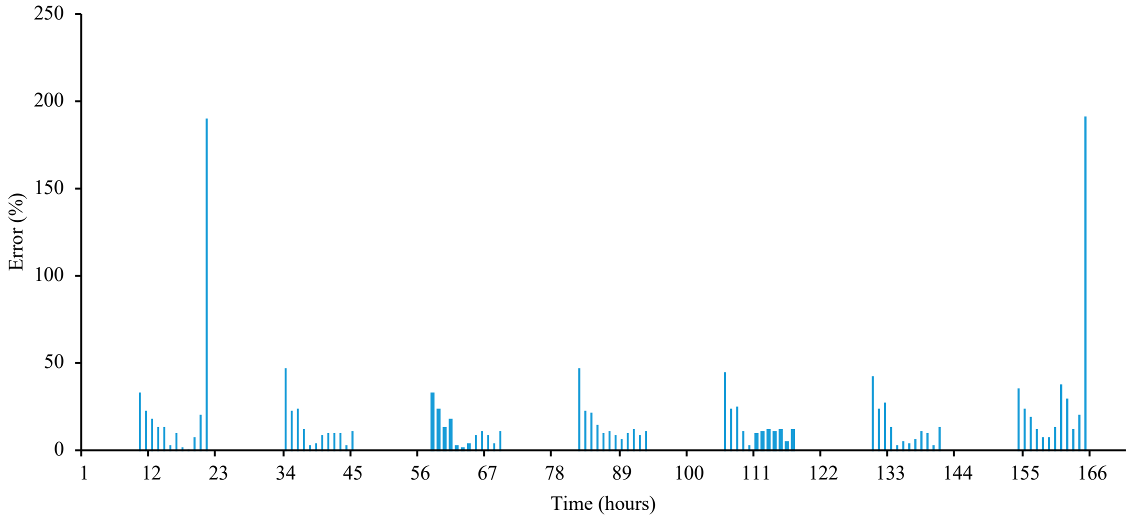

Figure 14. Weekly PV power output percentage error with PSO-ANN forecasting.

The simulation of PV power output forecasting with ANFIS is shown in Figure 15, which is a comparison between the actual PV power output and the PV power forecasting. Figure 16 shows the annual error of PV power output forecasting, which a maximum of 1742.2 kW. The maximum error occurs in the period from October to December. Figure 17 shows a weekly PV power output forecasting with ANFIS, and Figure 18 shows a weekly percentage error of PV power forecasting using ANFIS. It can be seen that the forecasted results at night have less error than the PSO-ANN method. Figure 19 shows the comparison of power output forecasting, which shows that the PV power forecasting using the ANFIS method provides more accurate forecasting results than the PSO-ANN method. The calculation efficiency of the ANFIS method was 3.5675 s.

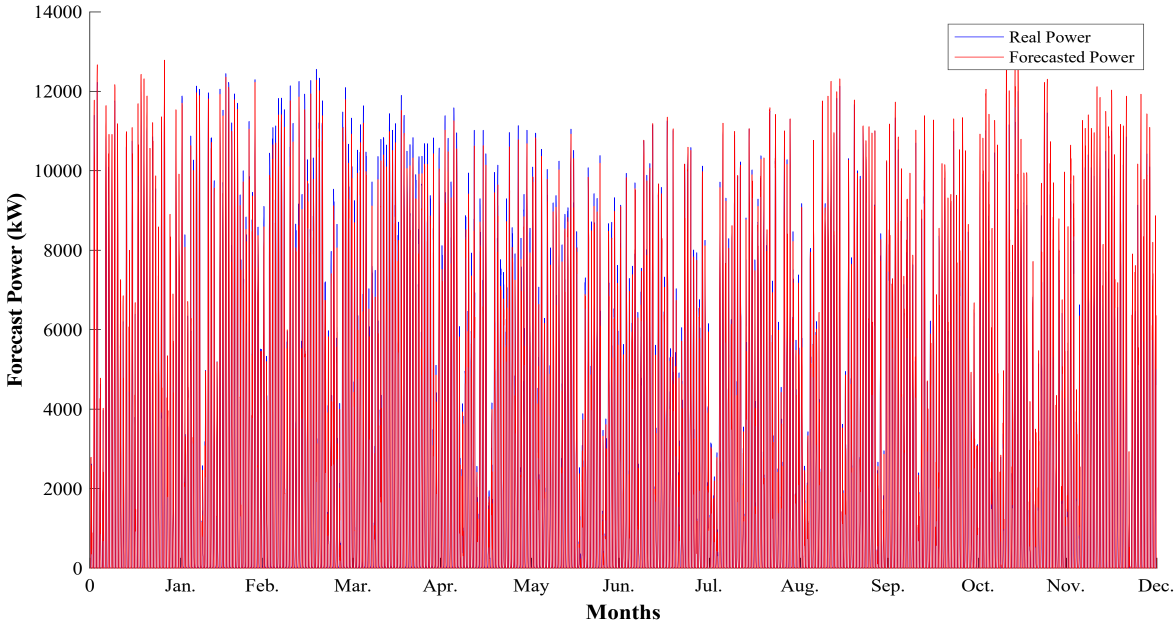

Figure 15. Annual PV power output with ANFIS forecasting.

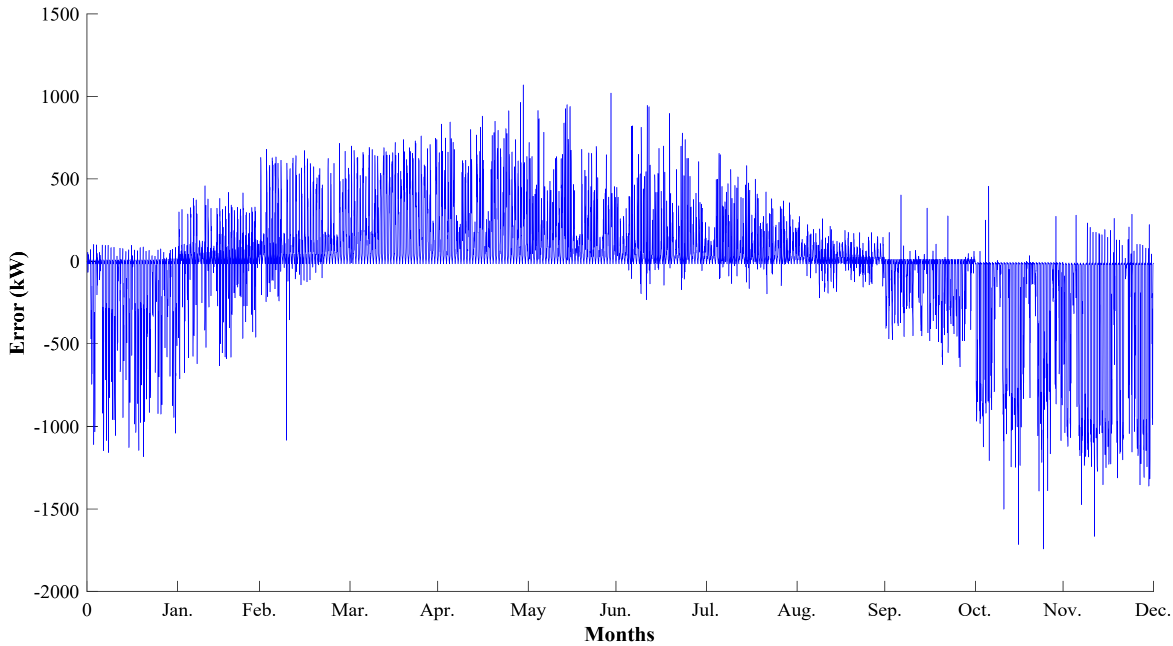

Figure 16. Annual power output error with ANFIS forecasting.

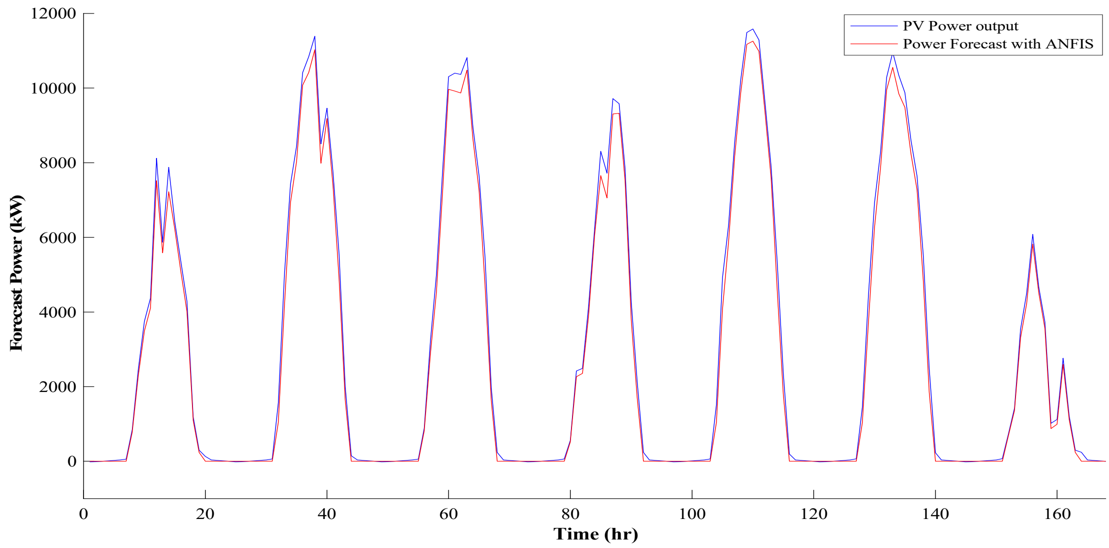

Figure 17. Weekly PV power output with ANFIS forecasting.

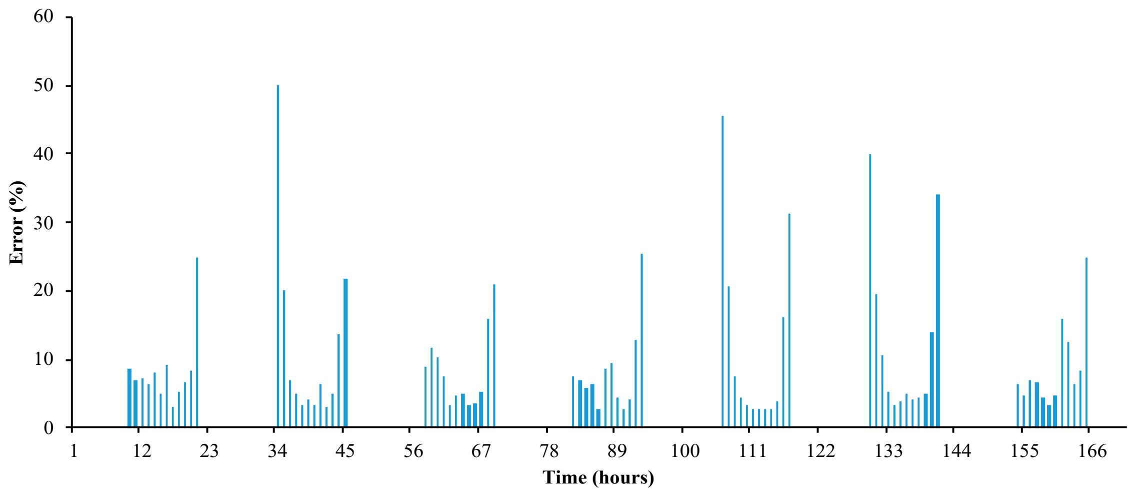

Figure 18. Weekly PV power output percentage error with ANFIS forecasting.

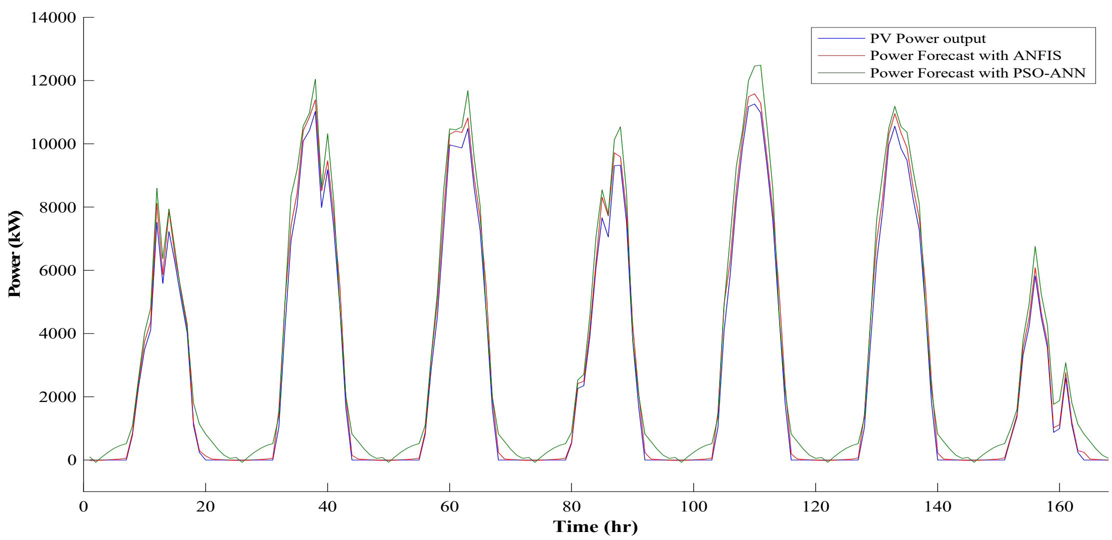

Figure 19. Comparison of PV power output forecasting.

Table 2 shows the calculation results to assess the accuracy of the simulation results of the PV power forecasting model using the PSO-ANN model and ANFIS model. The indicators such as MSE, RMSE, MAD, MAPE, and Accuracy are used for evaluating forecasting performance. The simulation results show that the ANFIS model has less error than the PSO-ANN model and has 99.8532% greater accuracy. RMSE is another indicator used to check the accuracy of the simulation results. Forecasting results with the ANFIS model provided an RMSE value of only 0.1184, which is less than the PSO-ANN model. When compared with the results of the PV power output forecasting of D. Lee and K. Kim [37], they predict the power output with long- and short-term memory (LSTM) -based models with an RMSE of 0.563 with summer, so it shows that the simulation results with the ANFIS model have greater accuracy. The calculation efficiency of the ANFIS model takes less time than the PSO-ANN model. Therefore, this article shows that the ANFIS model is more efficient for the PV power forecasting than the PSO-ANN model, and it also takes quick calculations.

Table 2. Performance and forecast accuracy of the model.

Models	MSE	RMSE	MAE	MAPE (%)	Accuracy (%)	Calculation Efficiency (s)
PSO-ANN	0.3234	0.5687	8.8233	1.0842	98.9157	429.522
ANFIS	0.0140	0.1184	1.1952	0.1468	99.8532	3.5675

6. Conclusions

In this article, the PV power output is forecast using one-year of electricity production data from a solar power plant in the northeast Thailand area. A comparison of the PV power output forecasting using the ANFIS and PSO-ANN method was undertaken. The performance of the ANFIS and PSO-ANN models were verified accurate with MSE, RMSE, MAP, and MAPE. The accuracy of the ANFIS model is 99.8532%, and the PSO-ANN method is 98.9157%. The calculation efficiency of the ANFIS model takes less time than the PSO-ANN model. The simulation results show that the ANFIS method has more accurate simulation results than the PSO-ANN method. For the most efficient use of PV power generation systems, it is necessary to analyze the energy consumption of the user load (household loads, industrial loads, department store loads). The forecasting results of the PSO-ANN model has more discrepancies than the ANFIS method at night. Therefore, nighttime inputs may be omitted before the simulation. The ANFIS model is an interesting method for forecasting at present, and it uses deep learning techniques to solve the problem. It is a forecasting technique that can compare to other complex systems which provide accurate and quickly predictions. The power output forecasting is essential for planning the installation of a PV power system. The PV power output forecasting using the ANFIS model is another method that can predict and analyze the energy, cost, and cost-effectiveness that will occur in the future. Future work will study the PV power output forecasting in a new method and a more efficient way and improve the input data with small deviations, which can make the simulation results more accurate. Additionally, to analyze the simulation results using reliable and widely used methods.

Author Contributions: P.D. and T.B. conducted the initial design, conceptualization, writing, editing, and developing the proposed forecasting method; N.J., K.S., and S.K. contributed the resources, data curation, and analysis; W.T. and S.N. conceived the theoretical approaches, review, and investigation. All authors have read and agreed to the published version of the manuscript.

Funding: The APC was funded by King Mongkut's Institute of Technology Ladkrabang (KMITL).

Acknowledgments: The author's thanks to King Mongkut's Institute of Technology Ladkrabang for supporting this research. The authors would like to thank the solar energy technology laboratory, National Electronics and Computer Technology Center, National Science and Technology Development Agency (NSTDA) for supporting the data for this research.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Alternative Energy. Available online: https://en.wikipedia.org/wiki/Alternative_energy (accessed on 10 July 2019).
2. Zehner, O. *Green Illusions*; University of Nebraska Press: Lincoln, NE, USA; London, UK, 2012; pp. 1–169; 331–342.
3. Jacobson, M.Z.; Delucchi, M.A. A path to sustainable energy by 2030. *Sci. Am.* **2009**, *301*, 58–65. [CrossRef] [PubMed]
4. Jacobson, M.Z.; Delucchi, M.A. Providing all global energy with wind, water, and solar power, Part I: Technologies, energy resources, quantities and areas of infrastructure, and materials. *Energy Policy* **2011**, *39*, 1154–1169. [CrossRef]
5. Inthacha, S. The Climatology of Thailand and Future Climate Change Projections Using the Regional Climate Model Precis. Ph.D. Thesis, University of East Anglia, Norwich, UK, May 2011.
6. Prospect of Limiting the Global Increase in Temperature to 2·°C is Getting Bleaker. Available online: https://www.iea.org/newsroom/news/2011/may/2011-05-30-.html (accessed on 10 July 2019).
7. Papaioannou, G.; Nikolidakis, G.; Asimakopoulos, D.; Retalis, D. Photosynthetically active radiation in Athens. *Agric. For. Meteorol.* **1996**, *81*, 287–298. [CrossRef]
8. Codato, G.; Oliveira, A.P.; Soares, J.; Escobedo, J.F.; Gomes, E.N.; Pai, A.D. Global and diffuse solar irradiances in urban and rural areas in southeast Brazil. *Theor. Appl. Climatol.* **2017**, *93*, 57–73. [CrossRef]
9. Janjai, S. *Solar Radiation*; Department of Physics, Faculty of Science, Silpakorn University Campus: Nakhon Pathom, Thailand, 2014.
10. The Industrial Internet of Things Volume T3: Analytics Framework. Available online: https://www.iiconsortium.org/pdf/IIC_Industrial_Analytics_Framework_Oct_2017.pdf (accessed on 1 December 2019).
11. Kittisontirak, S.; Dawan, P.; Atiwongsangthong, N.; Titiroongruang, W.; Chinnavornrungsee, P.; Hongsingthong, A.; Manosukritkul, P. A novel power output model for photovoltaic system. In Proceedings of the International Electrical Engineering Congress (iEECON), Pattaya, Thailand, 8–10 March 2017; pp. 209–212.
12. Monteiro, C.; Santos, T.; Fernandez-Jimenez, L.; Ramirez-Rosado, I.; Terreros-Olarte, M. Short-term power forecasting model for photovoltaic plants based on historical similarity. *Energies* **2013**, *6*, 2624–2643. [CrossRef]
13. Mohammed, A.A.; Aung, Z. Ensemble learning approach for probabilistic forecasting of solar power generation. *Energies* **2016**, *9*, 1017. [CrossRef]
14. Agoua, X.G.; Girard, R.; Kariniotakis, G. Probabilistic models for spatio-temporal photovoltaic power forecasting. *IEEE Trans. Sustain. Energy* **2019**, *10*, 780–789. [CrossRef]
15. Piorno, J.R.; Bergonzini, C.; Atienza, D.; Rosing, T.S. Prediction and management in energy harvested wireless sensor nodes. In Proceedings of the 1st International Conference on Wireless Communication, Vehicular Technology, Information Theory and Aerospace & Electronic Systems Technology, Aalborg, Denmark, 17–20 May 2009.
16. Pano-Azucena, A.; Tlelo-Cuautle, E.; Tan, S.; Ovilla-Martinez, B.; Fraga, L.D.L. FPGA-based implementation of a multilayer perceptron suitable for chaotic time series prediction. *Technologies* **2018**, *6*, 90. [CrossRef]
17. Abuella, M.; Chowdhury, B. Solar power forecasting using artificial neural networks. In Proceedings of the North American Power Symposium (NAPS), Charlotte, NC, USA, 4–6 October 2015.
18. Omid, M.; Ramedani, Z.; Keyhani, A.R. Forecasting of daily solar radiation using neuro-fuzzy approach. In Proceedings of the 5th International Mechanical Engineering Forum, Prague, Czech Republic, 20–22 June 2012; pp. 728–742.
19. Hoballah, A.; Erlich, I. PSO-ANN approach for transient stability constrained economic power generation. In Proceedings of the IEEE Bucharest Power Tech Conference, Bucharest, Romania, 28 June–2 July 2009; pp. 1–6.
20. Department of Alternative Energy Development and Efficiency. Ministry of Energy in Thailand. Energy Situation. Available online: https://www.dede.go.th/download/stat62/sit_2_61_dec.pdf (accessed on 10 July 2019).
21. Solar Energy Distribution at the Top of the Atmosphere and at the Surface of the Earth. Available online: http://www.physics.usyd.edu.au/teach_res/hsp/sp/mod7/m7emrSpectra.pdf (accessed on 20 October 2019).
22. Ministry of Energy. Promotion of Using Hot Water from Solar Energy, Power Point Presentation. Available online: https://www.slideserve.com/pete/outline (accessed on 10 July 2019).

23. Solar Resource Maps of Thailand. Available online: https://solargis.com/maps-and-gis-data/download/Thailand (accessed on 10 July 2019).
24. Jang, J.-S.R. ANFIS: Adaptive network-based fuzzy inference system. *IEEE Trans. Syst. Cybern.* **1993**, *23*, 665–685. [CrossRef]
25. Aghbashlo, M.; Hosseinpour, S.; Mujumdar, A.S. Artificial neural network-based modeling and controlling of drying systems. *Intell. Control Dry.* **2018**, *1*, 155–172.
26. Brahim, K.; Zell, A. ANFIS-SNNS: Adaptive network fuzzy inference system in the stuttgart neural network simulator. *Fuzzy Syst. Comput. Sci.* **1994**, *1*, 117–127.
27. Kennedy, J.; Eberhart, R. Particle swarm optimization. In Proceedings of the IEEE International Conference on Neural Networks, Perth, Australia, 27 November–1 December 1995; pp. 1942–1948.
28. Jumpasri, N.; Pinsuntia, K.; Woranetsuttikul, K.; Nilsakorn, T.; Khan-Ngern, W. Improved particle swarm optimization algorithm using average model on MPPT for partial shading in PV array. In Proceedings of the International Electrical Engineering Congress (IEECON), Chonburi, Thailand, 19–21 March 2014.
29. Esmin, A.A.A.; Coelho, R.A.; Matwin, S. A review on particle swarm optimization algorithm and its variants to clustering high-dimensional data. *Artif. Intell. Rev.* **2013**, *44*, 23–45. [CrossRef]
30. Abdullah, A.G.; Suranegara, G.M.; Hakim, D.L. Hybrid PSO-ANN application for improved accuracy of short-term load forecasting. *IEEE Trans. Power Syst.* **2014**, *9*, 446–451.
31. Nespoli, A.; Ogliari, E.; Leva, S.; Pavan, A.M.; Mellit, A.; Lughi, V.; Dolara, A. Day-ahead photovoltaic forecasting: A comparison of the most effective techniques. *Energies* **2019**, *12*, 1621. [CrossRef]
32. Martins, R.P.; Ferreira, V.H.; Lopes, T.T. Artificial neural network for probabilistic forecasting of the output power of photovoltaic systems. In Proceedings of the Simposio Brasileiro De Sistemas Eletricos (SBSE), Niteroi, Brazil, 12–16 May 2018.
33. Le, L.T.; Nguyen, H.; Dou, J.; Zhou, J. A comparative study of PSO-ANN, GA-ANN, ICA-ANN, and ABC-ANN in estimating the heating load of buildings' energy efficiency for smart city planning. *Appl. Sci.* **2019**, *9*, 2630. [CrossRef]
34. Houria, B.; Mahdi, K.; Zohra, T.F. PSO-ANN's based suspended sediment concentration in Ksob basin, Algeria. *J. Eng. Technol. Res.* **2014**, *6*, 129–136.
35. Said, S.Z.; Thiaw, L. Performance of artificial neural network and particle swarm optimization technique based maximum power point tracking for photovoltaic systems under different environmental conditions. *J. Phys. Conf. Ser.* **2018**, *1049*, 012047. [CrossRef]
36. Yousif, J.H.; Kazem, H.A.; Alattar, N.N.; Elhassan, I.I. A comparison study based on artificial neural network for assessing PV/T solar energy production. *Case Stud. Therm. Eng.* **2019**, *13*, 100407. [CrossRef]
37. Lee, D.; Kim, K. Recurrent neural network-based hourly prediction of photovoltaic power output using meteorological information. *Energies* **2019**, *12*, 215. [CrossRef]