Parallel ANN–PSO Algorithm for Hourly Solar PV Estimation

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**Abstract**

The solar power output of solar photovoltaic (PV) systems is associated with PV cell temperature, system conversion efficiency, solar PV reception area, solar irradiance, humidity, and seasonal meteorological variations. It is impossible to control the environmental impacts for remaining the best efficiency of PV systems. Thus, using the artificial neural network (ANN) to predicate PV outputs and facilitate power balance become an approach to improving the system reliability and power quality. In this exploratory research, we attempted to use a parallel ANN and particle swarm optimization (PSO) algorithm to develop an hourly solar PV power estimation model based on the data of solar power generation, PV system conversion efficiency, and cell temperature. Weight matrices related to various seasons and geographical areas for the estimation of power generation were trained by operation data. The parallel PSO–heuristic global optimization technique facilitates the generation of near-optimal solutions in the ANN training process. The accuracy of the model was verified by the root-mean-square error (RMSE) and mean absolute percentage error (MAPE). The estimation model may help electricity dispatchers to monitor solar power generation trends across areas and traditional power plants to accurately fulfil load demands. In a word, the proposed model can be used for improving large-scale power dispatch in an efficient way due to intermittent electricity generation.

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Keywords: Artificial Neural Network (ANN), particle swarm, Particle Swarm Optimization (PSO), Parallel PSO–ANN, optimization, solar electricity estimation

?Subject classification codes: include these here if the journal requires them?

# 1.Introduction

Solar photovoltaic (PV) systems, sources of renewable energy, are increasing rapidly. A shortcoming of such systems is that variation in sunlight makes PV power output nondispatchable and intermittent. System reliability can be improved through accurate estimation of solar irradiance and generated power, which in turn can prevent power imbalance. Therefore, for planners or coordinators of power systems, predicting or estimating power outputs is essential. Factors crucial to the generation of solar power include the PV cell temperature, system conversion efficiency, solar PV reception area, and solar irradiance. Predicting solar irradiance is challenging because this variable encompasses both diffuse and direct radiation, which are both associated with uncertainty. Scientific and technological advances have spurred improvements in the efficiency of inverter and converter sets and of solar PV conversion. Moreover, temperature characteristics, electronic circuit loss, and dust content are now more easily accounted for or optimized.

Research on solar power has centered on techniques for forecasting or estimating its generation. Such approaches can be classified as follows. Various artificial neural network (ANN) techniques have been leveraged in pattern recognition, prediction, and classification, among other applications [1-4]. Training ANN models with suitable data can enable trend prediction when immediate data are missing or otherwise unavailable. Solar power output can be affected by system efficiency, humidity, temperature, seasonal meteorological variations, and solar irradiance. In a study on the short-term forecasting of solar power output, an algorithm integrating an ANN with gradient descent was developed [1]. In another study, on the basis of meteorological data and fuzzy theory, power output data were used to train an ANN. The rationale was that the PV system output can be affected by meteorological conditions [2]. By combining a backpropagation neural network (BPNN) with particle swarm optimization (PSO), Zhong et al. (2014) designed a prediction model. The forecast accuracy met power grid firms’ requirements regardless of factors such as day type transitions [3]. To predict PV power output in the short term, a deep convolutional neural network was employed by Zang et al. [4]. Using data with two dimensions and correlations at hourly and daily timescales took meteorological elements into account, facilitated model training, and reduced the total data volume. For extreme weather, conventional models are insufficient for generating accurate day-ahead forecasts of PV power output. In one study, PV power output over the subsequent 24 hours was predicted through a BPNN, with an additional input parameter being aerosol index data [5]. Khwaja et al. (2017) developed an approach for forecasting power loads in the short term. Relative to other techniques, their approach had a shorter computational time and superior prediction accuracy [6]. Li et al. (2014) also sought to predict power loads in the short term, presenting a hybrid quantized Elman neural network that considered historical loads on an hourly scale, forecasted target temperatures, and used a minimal number of quantized inputs. The prediction accuracy was acceptable [7].

Numerous studies have endeavored to find optimal estimation solutions by executing PSO algorithms. PSO is employed for increasing simple physical dynamic models’ accuracy [8]. Using an experimental data set, the proposed PSO-based method for estimating parameters of an RC circuit model was determined to be effective. The proposed model significantly outperformed three other models in estimating a PV module’s thermal inertia. With a single-diode model introduced by Hamid et al. [9], solar cell parameters were extracted using a PSO algorithm. By employing data recorded by a commercial Si solar cell, the proposed algorithm was tested. Overall, the results indicated that the present method outperformed other approaches in solving solar cell optimization problems. Furthermore, PSO enabled the extraction of solar PV cells’ equivalent circuit parameters, yielding high parameter precision under variations in temperature and sunlight [10]. To properly manage solar farms, quantifying uncertainties in predictions of PV power output is pivotal. The proposed hybrid PSO model was employed in such forecasts, demonstrating favorable efficiency across seasons and meteorological conditions, including rainy, cloudy, and sunny days [11]. A parallel PSO method was used to extract and estimate a PV model’s parameters in terms of I–V characteristics. Simulations revealed that the proposed method was comparably accurate to PSO in increasing the computational speed [12].

Various studies have focused on estimating and predicting solar irradiance or solar PV output [13-25]. Case studies have demonstrated that ANN-based algorithms manage uncertainty and forecasting-related tasks well. Predicting solar PV output is typically essential when planning supply versus demand on an electrical grid. Aside from ANN-based algorithms, other algorithms or models can be used to search for solutions to problems in predicting PV output or solar irradiance. Support vector regression can enhance the accuracy with which the solar irradiance, temperature, and precipitation probability are forecast. This is accomplished through training input–output data sets of classified historical data on PV power output [26]. Using prediction data on temperature and cloud cover, one study constructed a daily forecast model that was installed in a system for monitoring PV output [27]. In another investigation, a daily model for PV output prediction was presented [28]. Sophisticated models for such forecasts can be developed by referring to data on humidity, dew point, and wind speed and direction; however, atmospheric conditions are typically associated with some uncertainty[29]. Making forecasts with relatively unpredictable data is both impractical and challenging. More favorable generalization and convergence can be realized through the application of an Elman neural network (ENN) to smaller networks and discrete-time sequence forecasts [30] [31].

The evidence on executing PSO algorithms to estimate PV output by using data on system conversion efficiency and solar irradiance is relatively scant. This paper first estimates PV output by employing a parallel ANN–PSO (PANN–PSO) algorithm. Characterized by volatility, randomness, and sporadicity, solar PV output is strongly linked to meteorological conditions. Herein, model accuracy is verified using the root-mean-square error (RMSE) and mean absolute percentage error (MAPE). In Section 2.1 of this paper, the PANN–PSO algorithm is reviewed. Section 2.2 introduces the model of solar PV output estimation. Numerical results and conclusions are presented in Sections 3 and 4, respectively.

### **2.Materials and Methods**

***2.1 PANN-PSO Algorithm***

Numerous interconnected nodes (nonlinear arithmetic units) constitute ANNs. Also simply called neural networks, ANNs are so termed because they function similarly to neural structures in humans—that is, in a decentralized yet coordinated fashion. Neural networks can manage large data volumes and generate outputs in accordance with the information inputs provide. ANNs make predictions by analyzing input parameters and determining the optimal input parameter–output parameter connections. In various fields—including computer science, signal processing, machine learning, and image processing—ANNs are used to find solutions.

Figure 1 displays the architecture of a basic neural network. It comprises three layers (input, hidden, and output). A matrix **W** represents the interlayer connection strengths. With a neural network, the principal objective is to generate an acceptable output by updating weight matrices on the basis of input information. Equation (1) represents the input–hidden layer relationship, and (3) presents that between the hidden and output layers. Equations (2) and (4) express sigmoid activation functions that make the response to the signal in nature. As shown in (5)–(7), the gradient descent approach brings outputs closer to targeted values. The main objective of optimization is to continually execute measures to minimize the deviation between outputs and targets. Optimization is an excellent means of determining the minimum of a function. However, algebra is often insufficient for solving complex functions. To avoid ending up in an incorrect valley of the solution space, training neural networks several times is necessary, as is commencing training from different initial points. In the context of neural networks, choosing various points corresponds to the selection of distinct parameters. Adopting various initial link weights can yield inappropriate solutions. Moreover, the trial-and-error involved is time consuming. Therefore, using artificial intelligence–based methods to update the weighted sums of inputs to output signals is an integral aspect of optimization in neural networks.

(1)

(2)

(3)

(4)

(5)

(6)

(7)

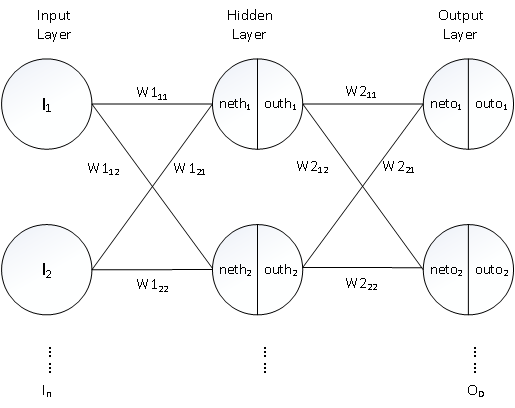


Figure 1: Neural network architecture.

PSO—which originates from social psychology, computer science, engineering, and the concept of swarm intelligence—differs from evolutional computation in that it employs candidate solutions (i.e., particles). Upon their initialization, the particles are assigned random values and given velocities in a stochastic manner. With each iteration, the velocity of individual particles is accelerated toward its former optimal position and a neighboring optimal position. These positions may correspond to a cost function with high or low fitness.

Optimization is ubiquitous, from the field of decision-making to finance and engineering. In almost all industrial and engineering applications, researchers strive to optimize efficiency, cost, or benefit. Optimization algorithms can be run through various methods. A typical approach for focusing on the nature of an algorithm is to divide it into deterministic and stochastic areas. Regarding the deterministic area, algorithms are implemented in a specified manner, involve specific variable designs, and have repeatable functions. Consider hill climbing: for a given starting point, the algorithm follows the same route across iterations.

By contrast, a certain degree of randomness exists in stochastic algorithms. Unlike the gradient descent algorithm, which requires a differentiable activation function for the calculation of derivatives, stochastic algorithms do not require a differentiable or continuous function. Moreover, they converge favorably without becoming stuck in local minima. Therefore, final solutions tend to differ occasionally. In general, optimization algorithms can be classified as bio-inspired, nature-inspired, or meta-heuristic. Within the search space, species seek to fulfill their needs, exhibiting various forms of social (e.g., cooperative) behavior. This is the inspiration for PSO. Personal experience (*Lbest*) and overall experience (*Gbest*) govern optimization algorithms, as does the current movement of particles determining their subsequent positions within the search space.

A swarm population of size N and dimension D has an initial position **X** = [*X1*, *X2*, ..., *XN*]*T*, where **X** also represents the networks’ weight matrix and *T* refers to the transpose operator. **X***j* = [*Xj,1*,*Xj,2*, ..., *Xj,D*] denotes each particle **X***j*(*j* = 1, 2, ..., *N*). Each solution vector or randomly generated particle is located between the lower and upper bounds of its corresponding components. This is expressed as, for the *j*th particle, *LBj <* **X***j,i < UBj* (*i* = 1, 2, ..., *D*), where *LBj*is the lower bound and *UBj*is the upper bound of the solution vector’s *j*th component. **XV** = [*XV1*, *XV2*, ..., *XVN*]*T* denotes the initial population velocity. Thus, the velocity of particle **X**i (*i* = 1, 2, ..., *D*) can be expressed as **XV***j* *=* [*XVj,1*, *XVj,2*, *...*, *XVj,D*]. Indexes *j* and *i* range from 1 to *N* and from 1 to *D*, respectively. Factors *c*1 and *c*2, as well as *r*1 and *r*2 (randomly generated numbers in the range 0–1), accelerate the experiences. The current motion, multiplied by an inertia factor *Ir*, is in the range *Ir,max* to *Ir,min*. In a PSO algorithm, each particle’s updated positions are expressed as follows:

(8)

(9)

In (8), represents the personal or local best *i*th component of the *j*th individual and denotes the *b*th component, up to iteration *k*, of the best overall individual. I*r* in (8) represents the inertia weight of the population’s velocity, defined in (10). The inertial factor *Ir* is used to reduce *Ir,max* linearly to *Ir,min* as progressive iterations draw nearer to obtaining the maximum value set. This can be expressed as

(10)

where *Ir,max* and *Ir,min* are the inertia weight’s lower and upper limits, respectively; *k* indicates the current iteration; and *itemax* is the maximum iteration count set.

The new particle positions must be within specified boundaries. Boundary condition violation by any particle component results in that component being set as

(11)

(12)

where in the PSO iteration process is a joint of the weight matrix of the neural network for the hidden layer and output layer , shown in (12).

Each particle’s initial **Lbest** refers to its initial weight. As for the initial **Gbest**, it refers to the initial weight of the best particle in a randomly initialized population. The rules by which **Lbest** and **Gbest** are updated are as follows:

At iteration *k*,

If Etotal(**Wk+1**) < Etotal (**Lbestk)**, **Lbest*k* + 1** = **W*k* + 1**; otherwise, **Lbest*k* + 1** = **Lbest*k***.

If Etotal(**Wk+1**) < Etotal (**Gbestk)**, **Gbest*k* + 1** = **W*k* + 1**; otherwise, **Gbest*k* + 1** = **Gbest*k***.

Here, Etotal (·) is an objective function or fitness function influenced by the minimization error.

The following procedure describes the implementation of the PSO algorithm:

Step 1: Set the PSO parameters (i.e., *Ir*, *c1*, and *c2*)*.*

Step 2: Initialize the particles’ weights and velocities (**X** and **Xv**, respectively).

Step 3: Assess every particle’s Etotal (; i.e., fitness); next, determine the best particle index *b*.

Step 4: Select = , for all *j*, *i*, and = .

Step 5: Set *k*, the iteration count, to 1.

Step 6: Update the particles’ velocity and position.

Step 7: After this update, assess each particle’s fitness. For all *j* and *i*, Etotal () = Etotal (). Determine the best particle index *b*.

Step 8: Update the Lbest of each particle ∀ p. If Etotal () < Etotal (), =; otherwise, .

Step 9: Update the population’s Gbest. If Etotal () < Etotal (), =; otherwise, .

Step 10: If *k* < *itemax,* *k* = *k* + 1; return to Step 6. Otherwise, proceed to Step 11.

Step 11: The optimal solution is obtained.

***2.2 Proposed PV Output Estimation Model***

Solar irradiance and system efficiency contribute crucially to the generation of electricity through solar power. Cell temperature, frequently discussed in the literature, is another key factor. Higher operating temperature results in lower PV cell efficiency. In PANN–PSO training, solar irradiance data are actual measurement data recorded by solar power plants. The temperature of the solar cell and the frequency of its maintenance, as well as other factors such as the orientation angle and solar panel elevation, all affect a solar cell’s energy conversion efficiency. This variable is complex and challenging to quantify. Some data are impossible or laborious and difficult to obtain. Nevertheless, a model can apply records of PV panel operation to PV output prediction. To a certain extent, actual electricity generation can represent system efficiency. The quotient of the actual electricity and the system’s power capacity, as presented in (13), yields the efficiency of the system.

(13)

(14)

(15)

(16)

where,

: system conversion efficiency of i site in time t

: solar irradiance of i site in time t

: normalized solar irradiance of i site in time t

: actual electricity of site i in time t, unit kW

: solar irradiance in time t, unit W/m2

: system capacity in site, unit kW

: normalized actual electricity of site i in time t, unit kW

: PV cell temperature of i site in time t

: normalized PV cell temperature of i site in time t

In relation to solar irradiance and the learning process of ANNs, smaller solar power plants may affect the system minimally. Consequently, before training commences, the data must be normalized. As shown in (14), the actual solar power is denoted the power generated per kilowatt in each site. When the calculation sequences are complete, power generation is reverted to its original scale. Solar irradiance is uniformly presented in watts per square meter. For the training of weight matrices, energy conversion efficiency and cell temperature may require normalization. In (15), solar irradiance is divided by 1000 W/m2. The base cell temperature in (16) is 50°C; however, another reasonable number can be selected.

To maximize precision, the estimation model must collect the largest possible amount of relevant data. Although sunlight is typically available from 6:00 to 18:00, sunshine hours differ somewhat across seasons. Solar irradiance in summer and winter is plotted against sunshine hours at a specific site in Figure 2. In Figure 3, solar PV output at the same site is plotted against sunshine hours in summer and winter. Here, 6:00 to 18:00 constitutes the model’s prediction timescale. The scale divides each day into four periods: the growth, peak, recession, and no power generation periods (6:00–9:00; 10:00–14:00; 15:00–18:00; and 1:00–6:00 and 19:00–24:00, respectively). Only the growth, peak, and recession periods are considered in the prediction model.

A model employing a neural network and time cutting for the estimation of solar power generated hourly at specific sites was constructed. Because the training sets used contain multiseasonal data collected from various regions of Taiwan, specifically northern, central, and southern Taiwan, the model can be used for year-round estimation in regions unconnected to the test sites. For the all-day estimation of hourly PV output, the cell temperature, energy conversion efficiency, and solar irradiance can be employed as the inputs in each test case, such that the PANN–PSO model’s three timescales comprise a parallel architecture. Results on PV output over 1 week are shown in Figure 4. Figure 5 presents the training process of the PANN–PSO model. Displayed in Figure 6 is a schematic of the training process. The steps of model implementation are listed as follows.



Figure 2. Solar irradiance versus sunshine hours in summer and winter.



Figure 3. Solar PV output versus sunshine hours in summer and winter.

Step 1: Use as data on PV output at various sites the cell temperature, energy conversion efficiency, and solar irradiance as the training sets. The data collection period in this study was 6:00–18:00 daily from March 2017 to March 2018.

Step 2: Normalize the data to ensure consistency in units and thereby prevent the appearance of singular numbers during training. For example, for each test case, convert the PV output into kilowatts. The solar irradiance is normalized into the solar irradiance of site *i* in time *t*.

Step 3: Temporally categorize the data into the growth, peak, and recession periods to enhance training accuracy. In general, PV output is extremely low in mornings and evenings, the times of day corresponding to low solar irradiance. During these times, the energy conversion efficiency typically deviates from the linearity of the solar PV output curve.

Step 4: Establish PANN–PSO models corresponding to the three intervals (i.e., the growth, peak, and recession periods).

Step 5: Evaluate the prediction accuracy (through the MAPE and RMSE).

The MAPE refers to the error between the estimated and actual values; smaller values are more favorable than larger values. Equation (17) demonstrates how the MAPE is calculated. As presented in Table 1, MAPE values of <10% and ranging from 10% to 50% correspond to high and acceptable-to-favorable precision, respectively.

 (17)

Table 1: Mape Evaluation Criteria

|  |  |
| --- | --- |
| **MAPE** | **Prediction Ability** |
| <10% | High precision |
| 10%~20% | good |
| 20%~50% | acceptable |
| >50% | bad |

The smaller the RMSE, which represents the distribution of errors, the more accurate the estimation result. Equation (18) displays the RMSE calculation process.

 (18)

where ,

*y* : actual a power output,

*y*′:estimated power output,.

*n* : number of *y*′:estimated values.

Operation data from a 157.3-kW solar power plant were used, and the MAPE and RMSE of various ANN-based algorithms were calculated using one arbitrary initial weight matrix and the accompanying conditions (Table 2). With regard to the MAPE and RMSE, the proposed PANN–PSO algorithm considerably outperformed the BPNN and ENN.

Table 2: Application of various algorithms to data on a 157.3-kW solar power plant.

|  |  |  |
| --- | --- | --- |
| **Method** | **MAPE** | **RMSE** |
| BP-Neural Network | 25.71% | 1.59kW |
| ELMAN-Neural Network | 26.63% | 3.13kW |
| PANN-PSO | 6.10% | 1.53kW |

Results of an analysis of operation data from one specific week are displayed in Table 3. Analysis of data grouped for the same hourly period across different days revealed that, according to the MAPE and RMSE, the model was highly accurate for all hours except 6:00 and 18:00. At these times, the PV output was relatively small, as indicated by the larger MAPEs. As presented in Figure 4, particular certain meteorological conditions caused PV output to be unstable all week. Nevertheless, acceptable estimation solutions were obtained. Overall, the results revealed high model accuracy.

Figure 4: PV output over a 1-week period.

Table 3: MAPE and RMSE of 1 week of estimation data.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Hour** | **RMSE** | **MAPE** | **Hour** | **RMSE** | **MAPE** |
| 6 | 4.74 kW | 36.65 % | 13 | 1.56 kW | 2.12 % |
| 7 | 1.67 kW | 3.07 % | 14 | 1.1 kW | 16.23 % |
| 8 | 1.42 kW | 1.93 % | 15 | 0.45 kW | 2.43 % |
| 9 | 0.48 kW | 0.82 % | 16 | 5.23 kW | 1.19 % |
| 10 | 1.48 kW | 1.15 % | 17 | 1.54 kW | 22.49 % |
| 11 | 2.23 kW | 2.00 % | 18 | 1.56 kW | 53.65 % |
| 12 | 4.01 kW | 7.06 % |  |  |  |

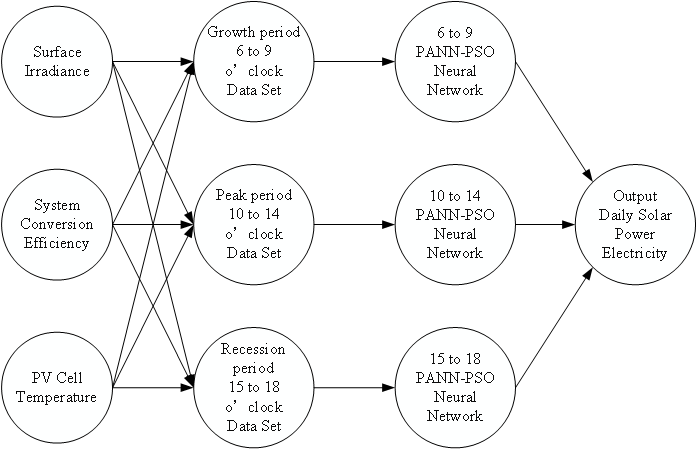


Figure 5: Training process of the PANN–PSO models.

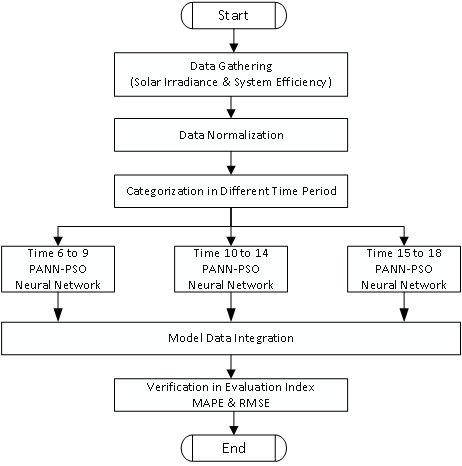


Figure 6: Flowchart of the model training process.

**3.Numerical Results**

***3.1Model Verification***

Model verification proceeded in the follow manner:

Step 1: Weighted matrices trained using PV output data from the selected sites from March 2017 to March 2018 were examined.

Step 2: Operation data (cell temperature, energy conversion efficiency, and solar irradiance), as model inputs, were classified in accordance with the timescales and examined areas.

Step 3: The input data were substituted into the trained weight matrices to estimate PV output.

Step 4: The estimated and actual PV output were compared. The error ranges were examined to determine whether the model estimated PV output in various test cases with favorable accuracy.

***3.2.Estimation Performance***

Model estimation performance was assessed. For a 157-kW solar power plant, the curves of estimated and actual PV output (denoted Est. and Act. Output in the tables, respectively) were examined. Moreover, the MAPE and RMSE obtained using various combinations of inputs were tabulated. In addition, the error in the estimated PV output of the northern, central, and southern plants across seasons was calculated and is discussed as follows.

Factors affecting solar PV output are complex. This paper centers on three key factors. First, the energy conversion efficiency represented all the factors influencing a solar power plant. Data on cell temperature and solar irradiance were measured and recorded. Tables 4 and 5 present the results of model application involving cell temperature, solar irradiance, and energy conversion efficiency over a 1-day period and a 1-week period, respectively. In Table 4, regarding the MAPE value, using the energy conversion efficiency as an input yielded more favorable estimation results than using the cell temperature as an input. More favorable RMSE results were obtained when all three factors were considered in the test case. Table 5 displays the predicted PV output of the 157.3-kW plant for one day under various inputs. With regard to the cell temperature and solar irradiance, Case3 yielded an MAPE and RMSE superior to those obtained in Case1 and Case2. Figure 7 presents the PV output of the 157.3-kW plant as estimated over 1 week, and Figure 8 shows the error in this estimation. Overall, the results demonstrated that all three test cases were acceptable model inputs and yielded acceptable estimations of PV output. Using the cell temperature as a learning input was problematic. Specifically, selecting a base temperature for input normalization was challenging. Moreover, although solar power is almost impossible to generate under extremely low irradiance, still have cell temperature. Because the energy conversion efficiency, cell temperature, and solar irradiance can affect the learning procedure, the model was verified by examining its performance under various combinations of input1, input2, and input3, and the conditions under which the optimal performance was realized were determined.

Table 4: Predicted 1-day PV output of the 157.3-kW plant with various inputs.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Case | Input1 | Input2 | Input3 | MAPE | RMSE |
| 1 | Solar Irradiance | System Conversion Eff. |  | 16.03% | 0.25kW |
| 2 | Solar Irradiance | Cell Temp. | System Conversion Eff. | 13.01% | 0.47kW |
| 3 | Solar Irradiance | Cell Temp. | - | 17.21% | 1.22kW |

Table 5: Predicted 1-week PV output of the 157.3-kW plant with various inputs.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Case | Input1 | Input2 | Input3 | MAPE | RMSE |
| 1 | Solar Irradiance | System Conversion Eff. |  | 9.11% | 1.51kW |
| 2 | Solar Irradiance | Cell Temp. | System Conversion Eff. | 10.98% | 2.57kW |
| 3 | Solar Irradiance | Cell Temp. | - | 7.77% | 1.46kW |

Figure 7: Daily estimation of the PV output of the 157.3-kW plant over 1 week.

Figure 8: Error in the estimated PV output of the 157.3-kW plant over 1 week.

In general, solar power generation is more efficient at lower latitudes than at higher latitudes. However, Taiwan is relatively narrow, especially in the north–south direction. In view of the substantial differences in climatic characteristics across regions and seasons, the training sets were classified for four seasons and three test sites (power plants in northern, central, and southern Taiwan, respectively). Furthermore, because only combinations of three inputs were considered, the number of trained and acquired weight matrices in the test model was 36. Three test cases were considered for each plant. In Case1, Case2, and Case3, the inputs were solar irradiance and energy conversion efficiency; all three factors; and solar irradiance and cell temperature, respectively. The characteristics of the test cases are displayed in Table 6. The proposed approach was used to estimate the hourly PV output by referring to predictions of solar irradiance as well as other available information. MATLAB R2015b, run on a personal computer with a 64-bit Windows 7 operating system, was employed for the experiments.

Table 6: Characteristics of the North, Central, and Southern sites.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Place | Capacity | Location | | | Average Amb. Temp. (℃) | Average duration of sunshine (h) |
| Latitude | longitude | Level (m) |
| North Site Plant | 149.6kW | 24°52'22"N | 121°01'11"E | 82 | 17.7℃ | 1851 |
| Central Site Plant | 499.9kW | 24°10'23"N | 120°35'32"E | 206 | 23.3℃ | 2043 |
| South Site Plant | 327kW | 22°49'54"N | 120°30'36"E | 37 | 25.1℃ | 2212 |

The results obtained for the northern, central, and southern sites are discussed as follows. Figures 9–16 present the results of PV output estimation and the error in this estimation for the northern site over four seasons. The error in predictions of hourly PV output during summer was less than 5%. Larger deviation errors were noted for fall and winter because of the atmospheric changes occurring in those seasons. Moreover, according to the observation data of the Central Weather Bureau, sunshine duration is shorter in fall and winter than in spring and summer. Figures 17–24 illustrate the results of PV output estimation and the error in this estimation for the central site over four seasons. As illustrated in Figure 24, the estimation error approached 13% on certain days. Figures 25–32 display the results of PV output estimation and the error in this estimation for the southern site over four seasons. In all four seasons, the estimation error remained below 5%. Table 7 presents the results of 1-month PV output predictions for the three sites in various seasons and under differing inputs. Case1, Case2, and Case3 and the corresponding MAPE and RMSE values represent weight matrices trained using distinct input combinations and contributed to the high accuracy of the proposed PANN–PSO algorithm in PV output estimation. The mean MAPE and RMSE were 1.015 and 10.62, 1.16 and 12.00, and 0.97 and 10.02 in Case1, Case2, and Case3, respectively. Determining which case yields the optimal results is challenging. However, energy conversion efficiency and solar irradiance data are frequently available and easily estimated from historical data should measurement data for certain periods be missing or distorted.

Power generation from sunlight is unstable compared with power generation from fossil fuel combustion. Considerable meteorological changes, whether over the course of a day or between consecutive days (Figures 9–32), can complicate the estimation of solar PV output. Overall, the results indicated the favorable predictive accuracy of the PANN–PSO model as trained using 1 year of PV output data.

Figure 9: Daily estimation of the PV output of the 149.6-kW plant in spring over 1 month (northern site).

Figure 10: Error in the estimated PV output of the 149.6-kW plant in spring over 1 month (northern site).

Figure 11: Daily estimation of the PV output of the 149.6-kW plant in summer over 1 month (northern site).

Figure 12: Error in the estimated PV output of the 149.6-kW plant in summer over 1 month (northern site).

Figure 13: Daily estimation of the PV output of the149.6-kW plant in fall over 1 month (northern site).

Figure 14: Error in the estimated PV output of the 149.6-kW plant in fall over 1 month (northern site).

Figure 15: Daily estimation of the PV output of the 149.6-kW plant in winter over 1 month (northern site).

Figure 16: Error in the estimated PV output of the 149.6-kW plant in winter over 1 month (northern site).

Figure 17: Daily estimation of the PV output of the 499.9-kW plant in spring over 1 month (central site)

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Figure 18: Error in the estimated PV output of the 499.9-kW plant in spring over 1 month (central site).

Figure 19: Daily estimation of the PV output of the 499.9-kW plant in summer over 1 month (central site).

Figure 20: Error in the estimated PV output of the 499.9-kW plant in summer over 1 month (central site).

Figure 21: Daily estimation of the PV output of the 327-kW plant in fall over 1 month (central site).

Figure 22: Error in the estimated PV output of the 499.9-kW plant in fall over 1 month (central site).

Figure 23: Daily estimation of the PV output of the 499.9-kW plant in winter over 1 month (central site).

Figure 24: Error in the estimated PV output of the 499.9-kW plant in winter over 1 month (central site).

Figure 25: Daily estimation of the PV output of the 327-kW plant in spring over 1 month (southern site).

Figure 26: Error in the estimated PV output of the 327-kW plant in spring over 1 month (southern site).

Figure 27: Daily estimation of the PV output of the 327-kW plant in summer over 1 month (southern site).

Figure 28: Error in the estimated PV output of the 327-kW plant in summer over 1 month (southern site).

Figure 29: Daily estimation of the PV output of the 327-kW plant in fall over 1 month (southern site).

Figure 30: Error in the estimated PV output of the 327-kW plant in fall over 1 month (southern site).

Figure 31: Daily estimation of the PV output of the 327-kW plant in winter over 1 month (southern site).

Figure 32: Error in the estimated PV output of the 327-kW plant in winter over 1 month (southern site).

Table 7: PV output, mape, and RMSE of the Northern, Central, and Southern plants in various test cases.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Place** | **Rated**  **(kW)** | **Season** | **A month**  **PV Output** | | **Different Test Cases** | | | | | |
| **Best Est. Gen (kWh)** | **Act. Gen (kWh)** | **Case1** | | **Case2** | | **Case3** | |
| **MAPE**  **(%)** | **RMSE**  **(kW)** | **MAPE**  **(%)** | **RMSE**  **(kW)** | **MAPE**  **(%)** | **RMSE**  **(kW)** |
| North Site Plant | 149.6 | Spring | 18408 | 18449 | 0.93 | 5.85 | 1.00 | 7.71 | 1.10 | 6.14 |
| Summer | 23798 | 23845 | 0.31 | 3.31 | 0.64 | 5.55 | 0.65 | 6.24 |
| Fall | 10280 | 10316 | 1.85 | 6.70 | 2.24 | 6.50 | 1.11 | 3.69 |
| Winter | 9129 | 9177 | 2.77 | 6.01 | 2.78 | 5.71 | 2.83 | 5.51 |
| Centr-al Site Plant | 499.9 | Spring | 59504 | 59648 | 0.56 | 15.75 | 0.95 | 24.62 | 0.58 | 15.21 |
| Summer | 65490 | 65622 | 0.77 | 21.90 | 0.60 | 16.95 | 0.74 | 21.77 |
| Fall | 43377 | 43443 | 0.94 | 11.15 | 0.83 | 12.88 | 0.79 | 8.99 |
| Winter | 40407 | 40512 | 0.89 | 13.54 | 1.46 | 21.06 | 1.21 | 16.96 |
| South Site Plant | 327 | Spring | 43377 | 43443 | 0.94 | 11.15 | 0.83 | 12.88 | 0.79 | 8.99 |
| Summer | 43483 | 43592 | 0.94 | 15.03 | 0.85 | 13.42 | 0.62 | 12.12 |
| Fall | 25868 | 25885 | 0.66 | 9.03 | 1.07 | 10.15 | 0.76 | 9.78 |
| Winter | 26973 | 27002 | 0.62 | 8.05 | 0.62 | 6.52 | 0.44 | 4.87 |

**4.Conclusion**

The solar energy–related policies and subsidies in Taiwan have increased solar power plant investments in various regions. Given that PV output is intermittent and nondispatchable, it is critical for coordinators or planners of power systems to accurately estimate PV output. In this study, we demonstrated a PANN–PSO algorithm to predict PV output on the basis of cell temperature, energy conversion efficiency, and solar irradiance. An arbitrary initial weight matrix associated with various seasons and geographical areas was used to train the model, and the operation data from a solar power plant verified the MAPE and RMSE of various ANN-based algorithms. The proposed PANN–PSO algorithm outperforms the BPNN and ENN with respect to the MAPE and RMSE. Employing trained weight matrices established from existing field operation data sets, the PV output of three test sites across seasons was estimated. As a result, the model accuracy was acceptable for predicting PV output under meteorological conditions with substantial fluctuations in one day or over a month.

The contributions of this paper is that an hourly solar PV power estimation model by a parallel artificial neural network, particle swarm optimization algorithm and long short-term memory model is presented. Weight matrices associated with different seasons and geographic areas for PV generation estimation have been trained by real measured operation data. The parallel PSO algorithm with heuristic global optimization technique assists the training process of artificial neural network and long short-term memory model to get near optimal solutions precisely.

## Data Availability：Data availability on request.

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