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Multiple-Input Deep Convolutional Neural Network Model for Short-Term Photovoltaic Power Forecasting

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ABSTRACT With the fast expansion of renewable energy system installed capacity in recent years, the availability, stability, and quality of smart grids have become increasingly important. The renewable energy output forecasting applications have also been developing rapidly in recent years, and such techniques have particularly been applied in the fields of wind and solar photovoltaic (PV). In the case of solar PV output forecasting, many applications have been performed with machine learning and hybrid techniques. In this paper, we propose a high-precision deep neural network model named PVPNet to forecast PV system output power. The methodology behind the proposed model is based on deep neural networks, and the model is able to generate a 24-h probabilistic and deterministic forecasting of PV power output based on meteorological information, such as temperature, solar radiation, and historical PV system output data. The forecasting accuracy of PVPNet is determined by the mean absolute error (MAE) and root mean square error (RMSE) values. The results from the experiments show that the MAE and RMSE of the proposed algorithm are 109.4845 and 163.1513, respectively. The results prove that the prediction accuracy of the PVPNet outperforms other benchmark models, and the algorithm also effectively predicts complex time series with a high degree of volatility and irregularity.

INDEX TERMS Deep neural network, photovoltaic output power forecasting, photovoltaic system, renewable energy sources.

I. INTRODUCTION

The rapid development of the global economy constantly raises the demand for energy. Nowadays, the principal energy resources are oil, coal and natural gas, which apart from being non-renewable also cause serious environmental pollution, which further leads to effects such as a greenhouse, acid rain and ozone depletion, and the combustion of fossil fuels which is the most serious problem. To confront the shortage of energy and reduce fossil fuel pollution, scientists have begun to study renewable and green energy sources, such as sunlight, wind, water, and geothermal heat. According to an authoritative technical report of the International Renewable Energy Agency (IRENA), there has been major developments in global solar PV installations in the past 10 years [1]. Over 100 GW solar PV was installed globally in 2017, the fastest growth in solar PV installations can be observed in Asia, where newly installed PV systems exceeded 52 GW in China alone while total installed capacity exceeded 132GW globally [2], [3]. The photovoltaic energy plants have the major influence on the power increase in the world energy system. Currently, the biggest investment in renewable and green energy resources is a solar farm in Tengger Desert Solar Park in China. At present, the plant generates up to 1500 MW, and the largest solar array system has been installed in Zhongwei, Ningxia [4]. According to IEA's (International Energy Agency) most optimistic estimate, global solar PV installed capacity could exceed 1700 GW by 2030 [5].

PV power output depends mainly on the intensity of solar radiance. Other meteorological conditions such as the atmospheric temperature, wind speed and direction, and humidity, are also considered as potential parameters for forecasting

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of PV power output. Regarding the time scale, the forecastings can be divided into: ultra-short-term forecastings (a few minutes to 1 hour ahead), short-term forecastings (1 hour to several hours ahead), medium-term forecastings (several hours to 1 week ahead), and long-term forecastings (1week to 1 year or more ahead) [6]. In terms of the size of a spatial range, forecasting can be obtained for a single area or a regional area [7]. In the literature, several forecasting methods for prediction of a PV output power have been introduced. The direct forecasting models represent the regression models based on the usage of instantaneous power information which is established from the associated data [8] such as solar radiance, module temperature, humidity, wind speed, and so on. These data are supplied by the PV power plants or from numerical weather prediction (NWP) data [7], [9]. Modeling methods include the artificial neural networks (ANNs) [10]–[12], support vector machine (SVM) [13], multivariate regression [14] methods, and other methods [9]. The hourly solar and PV forecasts for horizons that cover the period between 0 and 48 hours were developed using a numerical weather prediction model [15].

In [16], an artificial neural network model for photovoltaic plant energy forecasting was proposed and analyzed. The proposed model provides a 24-hour weather forecast on the hourly level for all the daylight hours of the next day. In [13], Shi et al. employed the support vector machine to forecast the PV system output power based on the weather conditions. They used four types of weather conditions: clear sky, cloudy day, foggy day, and rainy day. A one-day-ahead PV output power forecasting model was established based on the SVM algorithm using the weather forecasting information and data on the previous PV output power. On the other hand, Bouzerdoum *et al.* [17] presented a short-term power forecasting of a grid-connected photovoltaic plant using a new hybrid model. Their model combined the seasonal auto-regressive integrated moving average (SARIMA) method and the SVM method. Also, it was shown that the performance of the hybrid model was better than the performance of both SARIMA and SVM models. Cervone *et al.* [18] proposed an algorithm based on the artificial neural networks and introduced an analog ensemble to generate 72-hour PV power forecasting of PV power plants using the input consisted of a numerical weather prediction model and computed astronomical variables. Dumitru *et al.* [19] employed the ANN algorithms for PV power forecasting because many ANN types such as feed-forward and Elman neural networks are suitable for PV power forecasting. The key reason the ANNs are used in PV power forecasting is that ANNs can correct the behavior of PV system while learning the changes that occur as a result of PV system external and internal factors evolution. Gensler *et al.* [20] employed the combinations of deep learning method and autoencoder, and long short term memory algorithms to compare the output power forecasting of 21 PV power plants using a standard multilayer perceptron and a physical forecasting model. Abdel-Nasser and Mahmoud [21] proposed a new deep long short term memory recurrent neural network algorithm for forecasting the PV power output. Also, the authors compared their algorithm with three different methods based on multiple linear regression, bagged regression trees, and neural networks algorithms for PV power forecasting. Raza *et al.* [22] proposed a multivariate neural network combined with the Bayesian averaging method for PV output power forecasting. The short-term forecasting (24 hours ahead) in different seasons was employed at the University of Queensland's for PV power plant from 2014 to 2015.

In [23], the optimized input data was fed to the traditional ANN and subjected to the short-term prediction process. Besides, the prediction results of the ANN, ANN-Particle Swarm Optimization, and ANN-Firefly Algorithm were compared in detail. The performance analysis showed that the ANN algorithm could not predict short-term output power by using only a small amount of input data. Since the local minimum value was continuously inserted in the Particle Swarm Optimization (PSO) method, the required performance could not be achieved. To solve the problem of falling into a local minimum [23], the Firefly Algorithm (FA) was proposed as a new optimization method that was proven to be the most efficient algorithm for short-term solar prediction. In [24], the authors proposed a detailed method for predicting PV energy production using a local sky-imager and neural network. The proposed method reduced the propagation errors by removing the usual chain of models from irradiation forecast to energy yield prediction. In [25], a review of the solar PV forecasting big data models including the motivation of project proposals, and characteristics and quality of the used data, was provided with the aim to assess the most appropriate and accurate state-of-the-art technologies to address the forecasting problems. To consider both physical (NWP meteorological variables) data and statistical (PV power SCADA records) data inputs, Eseye *et al.* [26] proposed a new hybrid method for short-term PV power forecasting based on the combination of SVM, PSO, and Wavelet transform (WT). This method for short-term solar power forecasting was proven as effective. The daily MAPE and NMAE values were 4.22% and 0.4% on average respectively, which was a better result than those of the other seven forecasting methods; also, the average calculation time was shortened for 15 seconds.

Gigoni *et al.* [27] evaluated the difference in the accuracy between a simple method (GB method) and more complex methods (the quantile random forest (QRF) and an ensemble of methods.) Although the authors noted that there was a little difference in the accuracy (the overall improvement in nMAE was only about 5%), the improvements were consistent for all the PV plants over the year, which made them statistically relevant. The most suitable forecasting method for particular weather conditions depends on the methodology characteristics; for instance, the GB performs best on cloudy weather, the QRF is best for intermediate values of the clear sky index (CSI), and the *k*NN is most suitable on sunny weather. On the other hand, the ensemble methods have the advantage of performing well under all weather conditions. Also, a more accurate weather forecast of solar irradiance could improve prediction accuracy by about 2∼3%. As presented in [28], a forecasting model used in Luxembourg was able to predict the expected PV power generation of the region up to 72 hours ahead. This model employed the solar irradiance based on hourly numerical weather predictions for PV power forecasting. The algorithm was able to forecast the expected hourly power production of Luxembourg PV systems by using a set of physical equations; 23 PV systems were selected to be reference systems. By comparing the forecasts for the reference systems with their actual, measured powers during a 2-year period, it was found that the forecast accuracy of the model was relatively high. However, to achieve the most accurate forecast of a PV module power it is necessary to measure the solar irradiation of the plane of array (POA) and the surrounding air temperature, but in practice, the POA irradiation may not be available, and this value can be only estimated from horizontal solar irradiation.

Moslehi *et al.* [29] studied different methods for forecasting solar PV output power in order to determine the most accurate models and provide insight into common forecasting errors. It was analyzed whether the final forecasting performance when different PV forecasting models were applied in different months was better or worse than when the same model was applied for a whole year. Namely, a simple annual model was compared with 12 different successively-applied monthly models. It was concluded that using a simple annual model is more efficient than using 12 different monthly models due to the convenience and simplicity of practical implementation. Therefore, a simple annual model is sufficient compared to 12 separate monthly models because it provides the convenience and simplicity of practical implementation. Yao *et al.* [30] proposed a new PV forecasting model based on the multiple reservoirs echo state network (MR-ESN). To ensure that the MR-ESN was sustainably applied to the PV power forecasting, sufficient conditions for transient stability of PV forecasting model were arranged. Then, a PV power forecasting example was used to demonstrate that the proposed model could significantly improve prediction performance. Authors in literature [31] expressed that the core problem in establishing weather classification models is the lack of training datasets (especially data from extreme weather conditions) and the choice of applied classifiers. Considering the aforementioned issues, Wang *et al.* [32] proposed a forecasting model using weather classifications based on the convolutional neural networks (CNN) and generative adversarial networks. Firstly, 33 single weather types were combined and reclassified into 10 new weather types. Next, training datasets were enhanced using a data-driven generation model called the generative adversarial network for each weather type. The CNN were trained by the enhanced dataset consisting of original and generated solar radiance data. The quality of the generative adversarial networks using the generated data is evaluated, and the authors compared the forecasting performance of CNN models with that of the traditional machine learning models such as the support vector machine, multilayer perceptron, and k-nearest neighbors algorithm. The authors also examined the forecast accuracy improvement achieved by the generative adversarial networks and applied a weather classification to the solar radiance prediction. The experiment results demonstrated that the generative adversarial networks could produce high-quality samples that capture the unique features of the original data instead of simply memorizing the training data.

Das *et al.* [33] reviewed the efficiency of PV power generation direct forecasting through comprehensive and methodical measures, the paper discussed the correlation importance of preprocessing model input data and input-output data. This review included the performance analysis of different PV power forecasting methods. Recent studies such as machine-learning methods based on historical statistics were also included in the review. The potential benefits of forecasting model optimization were also considered. In addition, the strengths and weaknesses of various forecasting methods such as simple and hybrid forecasting models were also discussed. A mathematical forecasting model was proposed in [35] in which the model was optimized by the Differential Evolution and Particle Swarm Optimization (DEPSO) method and was used for short-term PV power forecasting of a PV system installed at Deakin University at Victoria Australia. The performance of the proposed DEPSO was compared with the Differential Evolution (DE) and the standard Particle Swarm Optimization (PSO) across three different time horizons (1-h, 2-h, 4-h), comparison results proved that the proposed DEPSO method was more accurate and efficient than the DE and PSO approaches.

The advantages of machine learning are fast, low cost and high accuracy. On the other hand, deep learning uses neural network that is more layered than machine learning to analyze data and find patterns. Deep learning can tolerate high noise data and integrate seemingly unrelated data sources, and also explain non-linear relationships in data. Furthermore, deep learning has the ability for automatic feature extraction, which is also known as feature learning. Han *et al.* [34] proposed an alternative multi-model PV power interval forecasting model which accounts for seasonal distribution characteristics in power fluctuation. Seasonal distribution characteristics of PV power generation output can be observed over time by first analyzing PV output power, absolute power deviation, and relative variation rates, next, PV power deterministic forecasting multi-models based on each season are built on extreme learning machines. Bae *et al.* [35] applied ANN and SVM mechanisms to predict seasonal PV output power using different weather data sources. Nespoli *et al.* [36] compared the performances of two 24-hour ahead forecasting models both based on ANN. The two methods are trained with the same dataset, and so enables homogenous comparison which is very rare and valuable in current research literature. To understand relationships between weather information and actual PV power output, Three prediction models based on the ANN, deep neural network (DNN) and long term memory (LSTM) mechanisms are proposed in [37]. The proposed model is based on LTSM and is particularly intended to find hourly patterns in a day, and seasonal patterns across a longer period. Experiments were conducted with real-world datasets and the experiment results demonstrated that the proposed LSTM-based model yielded better results than the ANN-based model. In terms of mean absolute error, the LSTM-based model also performed 50% better than conventional statistical models.

Accurate forecasting of PV power may be a complex task due to the weather fluctuating nature. In recent years, artificial intelligence has been highly valued and applied to many engineering fields. Here, a deep convolutional neural network is employed for PV power forecasting in Taiwan. The major contributions of this paper are as follows: 1) development of a high-precision PV power forecasting algorithm; 2) performance comparison of several popular algorithms in the photovoltaic power forecasting; 3) validation of practicality and feasibility of the proposed ANN algorithm in the PV power forecasting.

This paper is organized as follows. The hardware electronic circuit of a photovoltaic system is presented in Section 2. The architecture of the proposed PVPNet is introduced in Section 3. The experimental results and results comparison are provided in Section 4. Finally, the conclusions are given in Section 5.

II. HARDWARE ELECTRONIC CIRCUIT

A solar cell basically denotes a semiconductor P-N junction based photodiode whose main function is to convert sunlight directly into electrical energy. This phenomenon is called the photovoltaic effect. The operation of a solar cell denotes the basic principle of the photoelectric effect. When sunlight strikes solar cell surface, a part of the solar energy is absorbed by the semiconductor material which will excite the electrons (negative) and holes (positive). Since the P-N junction generates a built-in electric field, the P-type semiconductor electrons move to the upper levels, and N-type semiconductor holes move to the lower levels. The junction area forms the positive and negative offset areas. The area that lacks electrons or holes is generally called the depletion region. When a depletion region is exposed to the sunlight, it absorbs the photon energy of appropriate wavelength and becomes excited producing many electrons and holes. Due to the built-in electric field, excited electrons freely move to the N-type semiconductor and excited holes freely move to the P-type semiconductor. Based on the electrical characteristics the equivalent circuit model can be established. The solar cell, PV module, and array model are discussed in the following. If raw data from solar PV, such as temperature, solar radiation, and output power, are not analyzed through a model before the monitoring system collects them into the database, then such data has no practical value for our power prediction study. Therefore, the mathematical model of the solar PV system mentioned in this second section is proposed for this analysis process, to further explain, the math model can assist in determining the rationality of the data collected by the monitoring system. We can use this math model to verify the data collected by the monitoring station, if the collected datum is not in a reasonable range, we can filter it out as an error, which can greatly increase the accuracy of the PVPNet during the training process, and enhance its practicability in future applications at solar PV power stations.

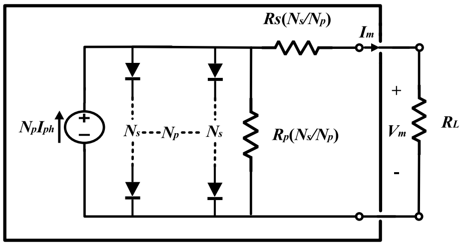

FIGURE 1. The equivalent circuit of a PV module.

A. PV MODULE AND ARRAY MODEL

In a wide range of applications, a low-level output power produced by a single solar cell is insufficient. Therefore, solar cells have to be arranged in a series-parallel configuration so as to produce enough current, voltage, and power. Another common problem related to solar cells is that the output power of only one PV module is unable to provide sufficient power for many loads. The PV array represents a group of PV modules connected in series-parallel configuration, and it is used to generate the required current and voltage. A simplified model of a typical PV module is presented in Fig. 1, where N_s cells are connected in series and N_p cells are connected in parallel [38], [39]; the corresponding current is defined by:

$$I_m = N_p I_{ph} - N_p I_{sat} \left[\exp\left(\frac{qV_m}{N_s A K_b T} \right) - 1 \right] \tag{1}$$

Obviously, the PV module power P_m can be calculated by:

$$P_m = I_m V_m = N_p I_{ph} V_m - N_p I_{sat} V_m \left[\exp\left(\frac{qV_m}{N_s A K_b T} \right) - 1 \right] \tag{2}$$

The PV array consists of N PV modules connected in series and M PV modules connected in parallel as shown in Fig. 2. The current and voltage of the PV array are respectively defined by:

$$I_A = \sum_{k=1}^{M} I_{sk} \tag{3}$$

$$V_A = \sum_{k=1}^{N} V_{mk} \tag{4}$$

where I_{sk} is the current of the k^{th} PV module, V_{mk} is the voltage of the k^{th} PV module. Additionally, the PV array power can be obtained by:

$$P_A = I_A V_A \tag{5}$$

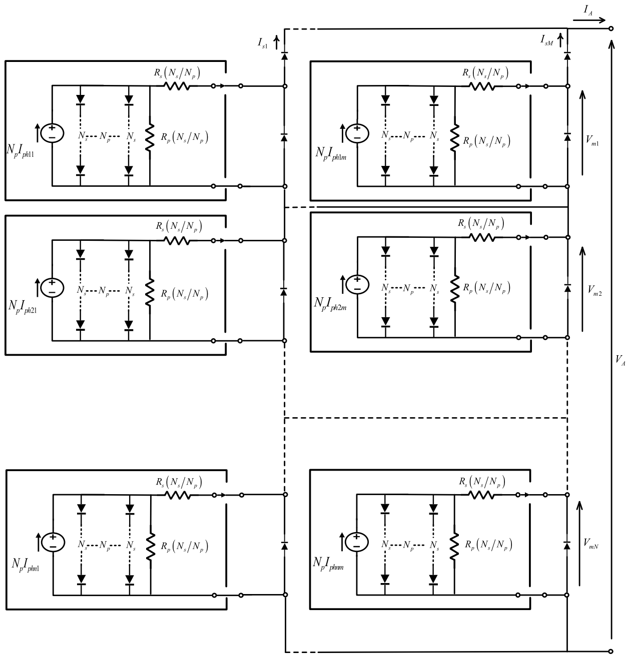

FIGURE 2. **The PV array configuration consisting of M columns and N rows [53].**

B. PV INVERTER MODEL

In a PV system, a PV array is connected to the inverter whose function is to convert DC power to AC power. This conversion is associated with losses which depend on the inverter type, DC operating power, and AC and DC voltages. The PV array generates a DC output which is then converted by into a utility-frequency AC current through an inverter. The AC current power can then be fed to the commercial electrical grid or consumed by a local off-grid electrical network. It is evident that the conversion efficiency of a PV inverter greatly affects the power system's AC output power. The PV system output power can be expressed by:

$$P_{sys} = \eta_{Inv} \times P_A \tag{6}$$

$$\eta_{Inv} = \left(a_0 + a_1 \times p_{dc} + a_2 \times p_{dc}^2\right)/p_{dc} \tag{7}$$

where η_{Inv} represents the efficiency of a PV inverter, P_{Sys} is the output power of a PV system, P_{dc} is the DC input of a PV inverter, and a_0, a_1, a_2 are the coefficients related to the PV inverter efficiency.

C. PV SYSTEM

A PV system is a type of power generation system designed to electricity generated from solar energy by means of photovoltaic cells [40]. The major components of a PV system include: PV panels whose function is to convert sunlight into electricity, a PV inverter which is used to convert DC power to AC power, string isolating switch, cabling, piping, DC circuit breaker, AC circuit breaker, leakage circuit breaker, and other electrical components. Strictly defined, a PV array encompasses only the ensemble of PV panels, which is the visible part of the PV system, and does not include any other hardware usually referred to as BOS (Balance-of-System). The core function of a PV system converts sunlight directly into electricity. Different types of PV systems include rooftop-mounted systems, building-integrated systems, and large utility scale power systems, the scale of PV systems could range from several kilowatts to hundreds or even thousands of megawatts. The architecture of a monitoring system that can collect important electrical and meteorological information about on-grid PV systems is presented in Fig. 3.

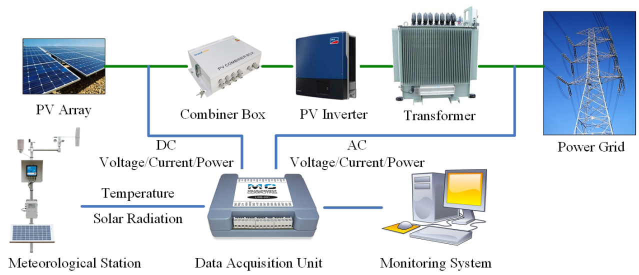

FIGURE 3. **The structure of an online monitoring system of the on-grid PV system [7].**

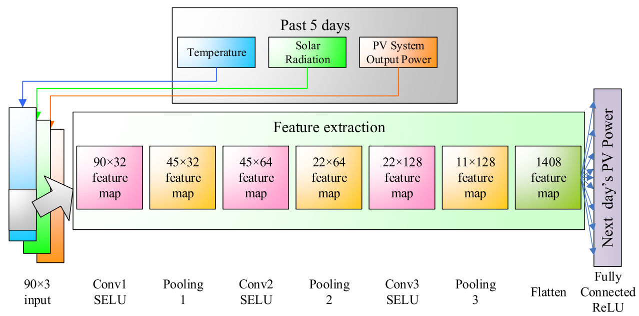

FIGURE 4. **The structure of the proposed PVPNet.**

III. PROPOSED PVPNET

The structure of the proposed PVPNet is shown in Fig. 4. The CNN structure is applied to the proposed PVPNet. The convolution in CNN is the method of feature extraction, this function must rely on continuously learning with large amounts of data and meet the established conditions as much as possible to achieve its goal. However, CNN relies on the optimizer to learn more effectively by using backpropagation. The CNN generally used for image recognition is a two-dimensional convolution operation. Since the data that PVPNet is applied to is one-dimensional data, here we mainly use one-dimensional convolution layers. The traditional neural network architecture is simple, and it is harder to grasp the correlation between adjacent data. Because CNN possess the concept of weight sharing and stride, the CNN architecture can more effectively grasp the relationship between adjacent data and extract its features. Because many of CNN's weights are shared, the amount of parameters are fewer than that of the traditional neural network and is easier to train. However, in general, many studies have used the architecture

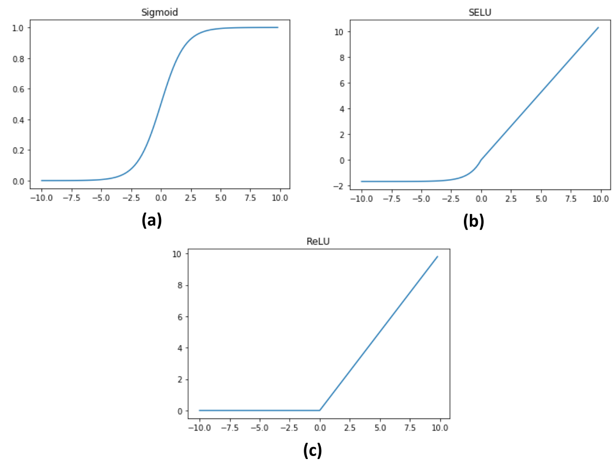

FIGURE 5. **The activation functions: (a) sigmoidal function, (b) SELU function, and (c) ReLU function.**

of the Recurrent Neural Network (RNN) for the prediction of time sequence. Although the PVPNet designed in this paper is based on CNN, it has higher performance than RNN. As for the PVPNet optimizer, the Stochastic Gradient Descent (SGD) is used for parameter optimization. The batch size of the training process is 32. Since the general Batch Gradient Descent (BGD) requires all training samples when updating each parameter, the training process becomes abnormally slow as the number of samples increases, so the SGD is proposed to solve the drawbacks of BGD. Therefore during the training process, the speed of SGD is much faster than BGD. The information on temperature, solar radiation, and PV system output power in the past 5 days is considered as a PVPNet input. There are 18 records of temperature, solar radiation, and PV system output power per day. Therefore, the input information related to the past 5 days has the size of 90×3. Here we include three different kinds of information into the input of PVPNet. It is worth noting that these three different kinds of information are not superimposed on one another in the same dimension, but are superimposed in the second dimension in the feature map. That is to say, the input shape is not (270, 1), but (90, 3). The reason is that the characteristics of different data are different, and temperature, solar radiation, and PV system output power are all time series data, so that superimposition of the data in the same dimension will cause the data to lose its time significance. The benefits of superimposition in the second dimension can not only preserve the significance of time, but also preserve the characteristics of various information, and extract feature independently in different convolutional filters. This is also one of the major considerations of PVPNet at the time of its design. Besides, there are 3 one-dimensional convolution layers in PVPNet, namely Conv1, Conv2, and Conv3, as presented in Fig. 4. The kernel sizes of Conv1, Conv2, and Conv3 are 9, 7, and 5, respectively, and the corresponding numbers of kernels are 32, 64, and 128, respectively. One kind of the activation functions is a sigmoidal function (*sigmoid*) defined by (8) and presented in Fig. 5(a). However, the sigmoidal function may cause the gradient vanishing problem. Therefore, in the PVPNet, the scaled exponential linear unit (SELU) function [41] is chosen as an activation function of the convolution layers. The SELU function is defined by (9) and presented in Fig. 5(b). The performance of SELU activation function was validated in [41], and the values of λ and α in [41] were $\lambda = 1.05$, $\alpha = 1.67$. Moreover, to save the most important information and reduce the feature size, there are three pooling layers in the PVPNet, namely Polling1, Polling2, and Polling3. The size of all polling layers is set to 2. After three convolution layers and three pooling layers, the feature map is flattened into one dimension. With the aim to avoid the overfitting problem, the dropout method [42] with a dropout rate of 0.15 is used in the flattening layer. The fully connected network is applied at the end of the PVPNet. To cut off the negative forecasting results, because the photovoltaic system cannot have the negative power values, the rectified linear unit (ReLU) function is chosen as an activation function of the output layer. The ReLU function is given by (10) and illustrated in Fig. 5(c). Finally, the PVPNet output represents the forecast result of the photovoltaic system power for the next day.

$$\mathrm{sigmoid}(x) = \frac{1}{1+e^{-x}} \tag{8}$$

$$\mathrm{SELU}(x) = \lambda \begin{cases} x & \text{if } x > 0 \\ \alpha e^{x} - \alpha & \text{otherwise} \end{cases} \tag{9}$$

$$\mathrm{ReLU}(x) = \max(0, x) \tag{10}$$

Algorithm 1 Deep Learning Algorithm of the Proposed PVPNet

```
Load the dataset
Transform all the values into [0, 1]
Split the training data and testing data
Reshape the input data to 90×3
Initialize the deep neural network
For each epoch
        Shuffle the order of the training data
        Partition the training data into batches
        For each batch
                Feed forward the batch data
                Calculate the loss value
                Use SGD to optimize the parameters
        End
End
Get the inference results by the testing data
Inverse transform the forecasting results to the
original data scale
Evaluate the performance of the proposed PVPNet
Terminate
```

The pseudo code of the proposed PVPNet is given in Algorithm 1. The first step is the dataset loading. To fit the suitable range, the data are normalized in the range [0, 1]. The data are divided into two parts, the training data and testing data. The training data are used for CNN model training, and testing data are used to evaluate the CNN model performance. Because the input data include information on three parameters, namely, the temperature, solar radiation, and AC energy, recorded during the past five days, the data should be grouped to obtain the input with the size of 90×3. After the data preprocessing is done, the proposed deep neural network is initialized. In every epoch, the training data are shuffled and then partitioned into batches. Here, the batch size is 32 which means that there are 32 records in one batch. All the training batches are fed to the CNN model as an input, and the loss value is obtained. The loss function of the PVPNet is the root mean squared logarithmic error (RMSLE). Besides, the SGD method is chosen for optimization of CNN model parameters. After the training process is completed, the final forecasting results are obtained by the testing data. The final forecasting results are denormalized, i.e., transformed to the original scale. Lastly, the performance of the proposed PVPNet is evaluated.

IV. EXPERIMENTAL RESULTS

This section includes two parts, the description of data and description of experimental results. To validate the performance of the proposed CNN model comprehensively, the performances of several popular machine learning methods, namely the support vector machine (SVM) [43]–[46], the random forest (RF) [47], [48], the decision tree (DT) [49], [50], the multilayer perceptron network (MLP) [51], and the long short term memory network (LSTM) [52] are compared with the performance of the proposed PVPNet.

A. DATA DESCRIPTION

The data consisted of samples containing the information on module temperature, solar radiance, and PV system output power. These samples were defined by the resolution of the thermometer, radiometer, and digital power meter, which determined the predictability of the dataset. The computer monitoring system of the PV power system collected data including module temperature, solar radiance, and PV system output. An ISO 9060 Class 2 radiometer was used to capture at least one data record per minute, and an A/D signal converter was applied to enable network storage to the Gateway. The data were transmitted to back-end servers daily via Internet connection through the Internet File Transfer Protocol (FTP) protocol from the network gateway. The used datasets of Taiwan that contain the module temperature, solar radiance, and PV system output power are presented in Fig. 6. As shown in Fig. 6, the weather characteristic of Taiwan, i.e., a high uncertainty of temperature and solar radiation, may influence the forecasting results.

B. EXPERIMENTAL RESULTS

Solar PV output power is closely related to temperature and solar radiation, in particular, the climate in Taiwan is distinctly divided into four seasons. There are often thunderstorms in the summer and typhoons in summer and autumn. This unique and diverse climatic condition has representative

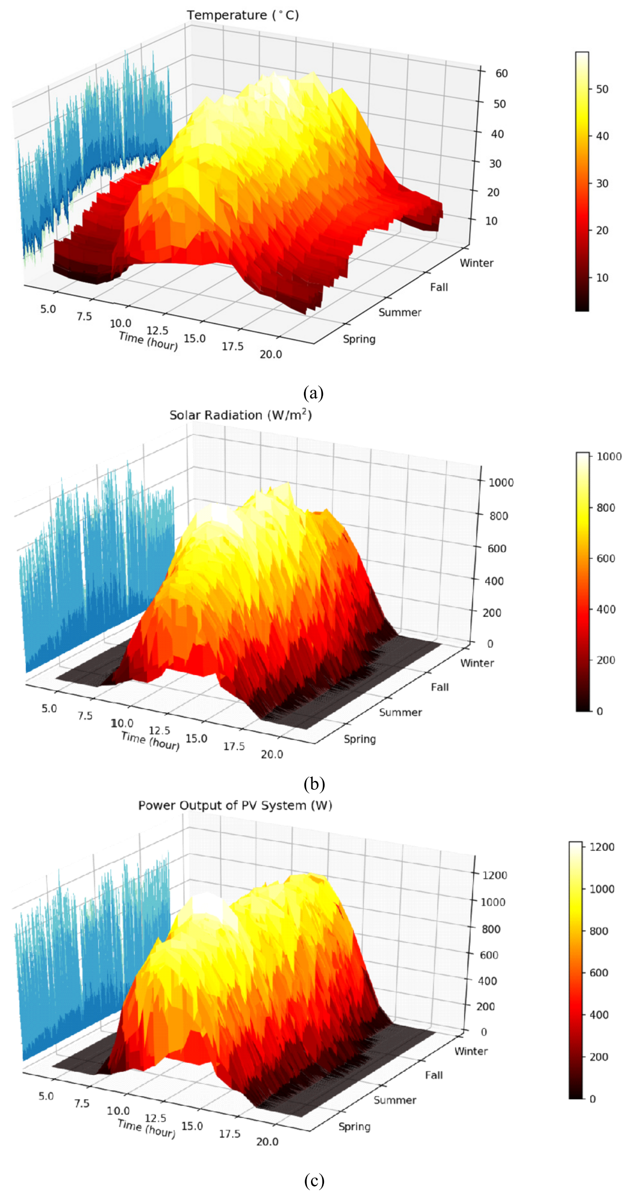

FIGURE 6. The solar energy dataset: (a) temperature, (b) solar radiation, and (c) PV system output power.

significance when analyzing the correlation between solar PV output data and meteorological data. When the seasons change, the temperature and solar radiation rate also show dramatic changes, which makes Taiwan a valuable field for solar PV research testing and verification. The relationship between temperature, solar radiation, solar PV output and seasonal variation of this monitoring station can be clearly seen in Figure 7. The forecasting results of the SVM, RF, DT, MLP, LSTM, and the proposed PVPNet are presented in Fig. 7, Fig. 8, Fig. 9, Fig. 10, Fig. 11, and Fig. 12, respectively, and the comparison of all obtained experimental results is presented in Fig. 13. In order to achieve short-term PV forecasting, the input of all the models consisted of information on temperature, solar radiation, and PV system output power in the past 5 days, and the output was the PV system output power for the next day. Since the frequency of data retrieval is per hour, deducting hours without daylight, the amount of input data is 90 pieces in the range of 5 days. In addition, PVPNet considers three kinds of information: temperature, solar radiation, and PV system output power, so the total amount of input data is as much as 90 x 3 pieces. The PVPNet prediction result is not only a single data, but the hourly prediction results of the PV system output power of the next day. The length of input and output is feasible and practical for PVPNet applications in short-term PV forecasting. As shown in Figs. 9-14, all the machine learning methods could handle the PV power forecasting problem. However, the forecasting error of the MLP, DT, and SVM was higher than of the other methods. On the other hand, the performance of the LSTM and RF was obviously better than of the MLP, DT, and SVM. The LSTM model was a recurrent neural network, which considered the time sequence relation of the input data. Therefore, the LSTM achieved good results in time series modeling. The RF was a model ensemble technique, and it could be treated as many combinations of the DTs. The experimental result demonstrated that the model ensemble technique was effective in the PV power forecasting. Even though all the machine learning methods had certain advantages, the proposed PVPNet achieved an excellent result in the PV output power forecasting.

TABLE 1. The experimental results regarding the MAE.

Test	SVM	RF	DT	MLP	LSTM	PVPNet
#1	175.5593	126.7358	169.4133	186.0410	130.179	118.4290
#2	152.7000	129.3172	154.2179	185.6150	129.588	114.7140
#3	164.3828	116.5610	134.9049	198.4280	125.660	106.3480
#4	154.7138	109.6464	127.2846	196.8460	128.587	111.6810
#5	168.6545	119.2656	132.0736	214.8070	141.870	119.5680
#6	170.5644	124.8878	143.9455	218.6770	146.402	125.4840
#7	156.5199	112.7732	134.7301	212.8320	133.930	115.2420
#8	131.2716	113.3046	134.7244	193.1240	121.998	104.5310
#9	114.9829	105.5861	131.6038	187.7310	103.532	94.49460
#10	108.9916	110.8834	152.5708	182.5570	100.672	98.98370
#11	122.7981	107.1174	127.9044	186.8400	102.248	94.85370
Average	147.3763	116.0071	140.3067	196.6816	124.0605	109.4845

The performances of the methods were also evaluated regarding MAE and RMSE, which were calculated by (11) and (12), respectively. Table 1 gives the MAE performance, and Table 2 gives the RMSE performance. There were 11 tests involved in the experiment. The records of the previous four months were used as the training data, and the records of the two following months were used as the testing data. The training data was used only for model training, and the testing data was used only for model testing. The samples included in the training and testing data were all different in all the eleven conducted tests. The methods ranking regarding the MAE was as follows: PVPNet (109.4845), RF (116.0071), LSTM (124.0605), DT (140.3067), SVM (147.3763), and MLP (196.6816). On the other hand, the methods ranking regarding the RMSE was as follows: PVPNet (163.1513), LSTM (164.1908), RF (167.5256), SVM (185.2254), DT (206.6184), and MLP (224.9958). According to the experimental results, the LSTM and RF achieved a good result in terms of both MAE and RMSE. The forecasting ability of the SVM, DT, and MLP was slightly inferior. However, the proposed PVPNet achieved the best performance. The obtained results verified the practicality and feasibility of the PVPNet in the photovoltaic system power forecasting.

TABLE 2. The experimental results regarding the RMSE.

Test	SVM	RF	DT	MLP	LSTM	PVPNet
#1	212.3696	185.8760	245.5526	215.4228	181.5181	171.1124
#2	187.1405	185.8605	222.9139	216.4840	178.2209	175.4204
#3	198.8175	168.0830	197.3417	230.4934	172.0600	161.1667
#4	195.9707	163.0234	190.0232	226.9111	175.3983	167.4735
#5	206.6963	174.4145	197.7907	246.0399	187.1287	178.8056
#6	211.3427	181.6228	213.9825	248.4994	191.7689	183.8636
#7	201.3662	164.2345	199.7346	240.2002	172.3131	174.6402
#8	168.3494	163.5488	199.0364	222.2471	156.5239	156.1673
#9	152.9636	149.4897	193.6007	214.4414	133.2390	145.4986
#10	143.2027	155.3349	223.6194	205.0304	126.9121	140.9093
#11	159.2605	151.2940	189.2063	209.1842	131.0154	139.6068
Average	185.2254	167.5256	206.6184	224.9958	164.1908	163.1513

$$\mathrm{MAE} = \frac{1}{N}\sum_{n=1}^{N}\left|y_n - \hat{y}_n\right| \tag{11}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{n=1}^{N}\left(y_n - \hat{y}_n\right)^2}{N}} \tag{12}$$

As can be seen in Fig. 14, although the PVPNet prediction results were closest to the actual, measured values, the prediction results of all the machine learning methods followed the same trend. In summary, all the machine learning methods could solve the problem of short-term photovoltaic power forecasting. Among the SVM, RF, and DT which are ones of the most widely used machine learning algorithms, the RF had the best performance, but the SVM and the DT also had certain advantages and disadvantages.

The operation concept of the RF is evolved from the DT, and it is equivalent to the combination of multiple DT algorithms. Compared with the SVM, the operation of the RF is much simpler; however, in the short-term photovoltaic power forecasting, the RF has better predictive performance than the SVM. Moreover, the complexity of the operational concept does not necessarily affect the prediction performance. In the experiments, the MLP, the LSTM, and the PVPNet had completely different performances. As can be seen in Table 1 and Table 2, the RMSE of the MLP was much higher than that of the LSTM and the PVPNet. This means that the short-term photovoltaic power forecasting is a complex process requiring a more complex neural network architecture to achieve good results. The LSTM is generally good at dealing with the time sequence problems, so it was natural that it achieved better results than the MLP. However, the PVPNet based on CNN achieved the best results.

As well known, the application of the CNNs in image recognition is very common and well executed. Besides, a two-dimensional CNN is generally used in image recognition. On the other hand, in this work, we use a one-dimensional CNN and apply it to the time sequence problem.

TABLE 3. The comparison of recent works on PV power forecasting [33].

Authors and Ref.	Forecast horizon	Forecast error	Forecasting model
Leva et al. [15]	24 h ahead	Normalized RMSE (nRMSE) 12.5−36.9%	ANN
Liu et al. [54]	24 h ahead	Mean absolute percentage error (MAPE) 7.65%	Back- propagation (BP) based ANN model
Dolara et al. [55]	24 h ahead	Normalized MAE (NMAE) < 2.64%, and weighted MAE (WMAE) < 9.88%	Physical model
Kang et al. [56]	24 h ahead	Approximate MAPE 11%	*k*-means clustering method
Chen et al. [57]	24 h ahead	MAPE 8.29−10.80% (sunny day)	SOM and RBFNN
Ding et al. [58]	24 h ahead	MAPE 10.06% (sunny day) and 18.89% (rainy day)	ANN and similar day selection algorithm
Cococcioni et al. [59]	24 h ahead	MAPE < 5.0%	Time series analysis and feed-forward NN (FFNN) with tapped delay lines
Tao and Chen [60]	24 h ahead	Error 8.8%	GA-based NN
Mori and Takahashi [61]	24 h ahead	Maximum error 0.228 pu	Hybrid Method (GRBFN, DA, and evolutionary particle swarm optimization (EPSO))
Yang et al. [62]	24 h ahead	Minimum Relative average error 0.88%	Space fusion and Markov chain
Antonanzas et al. [63]	24 h ahead	nRMSE 22.54%	Support Vector Regression model trained by numerical weather predictions (NWP).
Larson et al. [64]	24 h ahead	Relative root mean square error in the range of 10.3% -14.0%	Least-squares optimization of NWP
Lu and Chang [65]	24 h ahead	MAPE 3.7128% and RMSPE 4.652%	Radial basis function neural network
El-Baz et al. [66]	24 h ahead	RMSE 15.3%, MAE 8.5%, and MBE 1.53%	Clear sky model, system efficiency calculation, partial shading detection, and regression trees
Our PVPNet	24 h ahead	Average MAE 109.4845 and Average RMSE 163.1513	Convolutional neural network (CNN)

Also, we use three types of information, namely temperature, solar radiation, and output power, as a CNN model input. A one-dimensional CNN only strides along the time direction but does not stride toward the "thickness" of the three data sequences. The application of 1D CNN method is relatively rare in the prediction of time series, but in this paper, it shows superior results over all the other tested methods, which is one of the main contributions of this paper. Compared with the MLP and LSTM, CNN has another advantage, that is, it requires fewer training parameters. Namely, since the LSTM requires more parameters, its training process is slow. On the other hand, an MLP does not have the weight sharing feature of a CNN, so it has more training parameters than CNN. Another benefit of CNN is that fewer parameters are needed to obtain a more accurate prediction performance.

In [33], a detailed comparison of different PV power forecasting methods was provided. In this work, we selected several common forecasting methods with the same forecast horizon and compared them with the proposed PVPNet. The comparison results are shown in Table 3. The forecast error was used as a performance indicator. As can be seen in Table 3, all the methods achieved good results.

The ANNs are widely used in PV power forecasting. Many studies used ANN architecture in the prediction models. Thus, an ANN has a great contribution to the PV power forecasting research field. However, although CNN is a type of ANNs [46], it is rarely used in PV power forecasting. On the other hand, we use a one-dimensional CNN for PV power forecasting, which is different from the general practice. Comparing the proposed method with the common machine learning algorithms, it is found that the proposed model has better performance than the other tested methods. In [33], it can be found that the 24-hour-ahead forecast horizon is very common in the field of PV power forecasting. Therefore, the importance of short-term photovoltaic power forecasting is evident. The proposed method has excellent performance, and accordingly the considerable contributions.

The experiment in this paper is divided into training data experiment and testing data experiment, there is no duplicate information between training data and testing data. In the process of training, training data is used to train the model and testing data is not included in the training process. A performance comparison is conducted after the model training is completed and the test is performed. It is fair to use testing data for performance testing, because in the real world the future information to be predicted is unknown. Therefore, there is no way in incorporate currently unknown information into the training material. We believe it is more reasonable to use testing data that has not been used in the

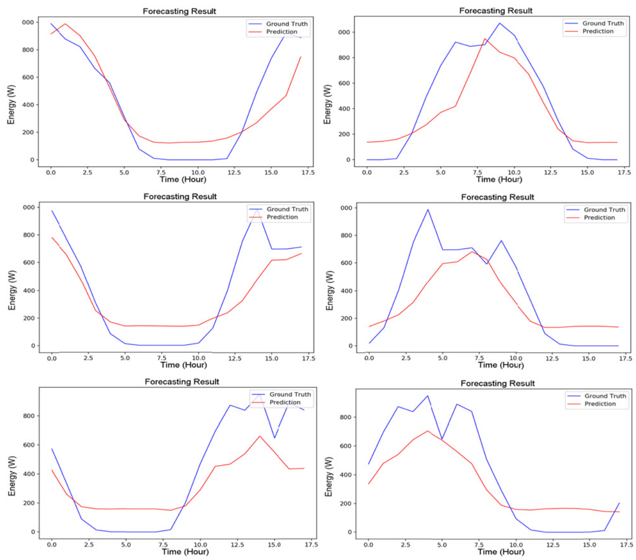

FIGURE 7. The forecasting results of the SVM.

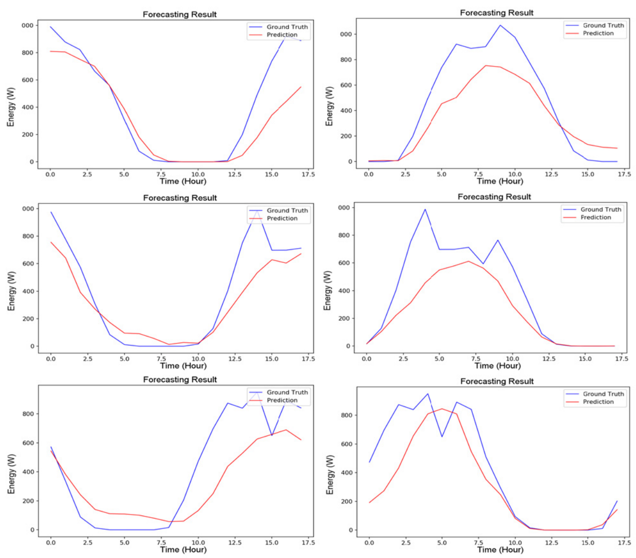

FIGURE 8. The forecasting results of the RF.

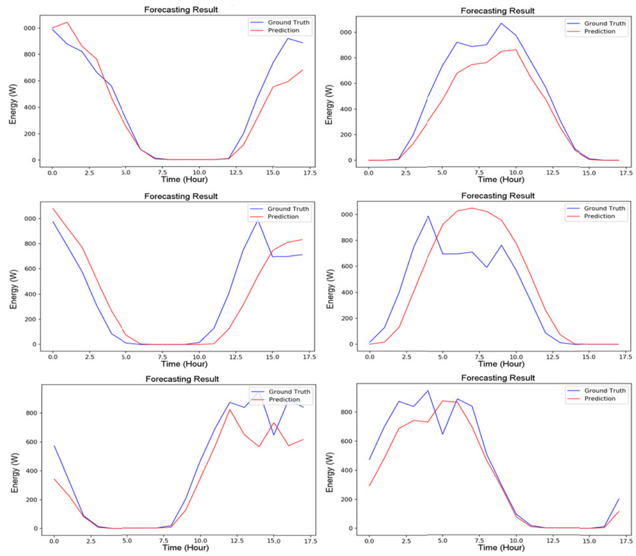

FIGURE 9. The forecasting results of the DT.

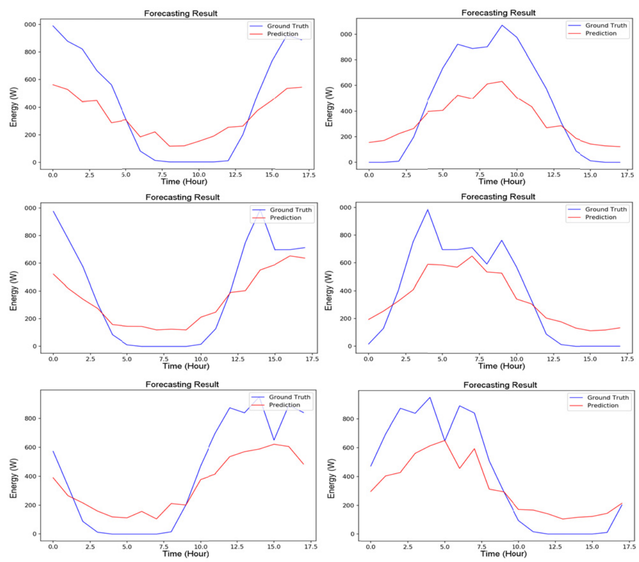

FIGURE 10. The forecasting results of the MLP.

training process for performance analysis. Since the training data has already made the model aware of all the answers during training, the model usually performs well with training data. Yet in many cases, the performance in training data can be misleading, if the model is over-trained and overfitting occurs, the model prediction may perform poorly in actually applications. This is also the main reason why this model verifies its accuracy with testing data.

There are clear seasonal differences in Taiwan's climate, when the seasons change, the temperature and solar radiation also show dramatic changes. PV forecasting at a time when the seasonal change is more severe will have more uncertainties. Each forecasting model has its own advantages and disadvantages, and random processes may occurs in the training processes of each model which will slightly affect the final performance. A few models performed better than the PVPNet at some points in time, the climate characteristics and random processes during training are among some of the factors that might have made an impact on the results. Therefore, 11 different tests were conducted in the experiment of this paper. Although PVPNet did not obtain the lowest MAE and RMSE in each test, the results of a single test cannot be used to judge the overall performance of the model. It is more reasonable to use the average performance as the scoring standard. Therefore the average MAE and RMSE are the most important indicators for judging the effectiveness of the model. On average, PVPNet performed better than the more common machine learning algorithms. Therefore, the

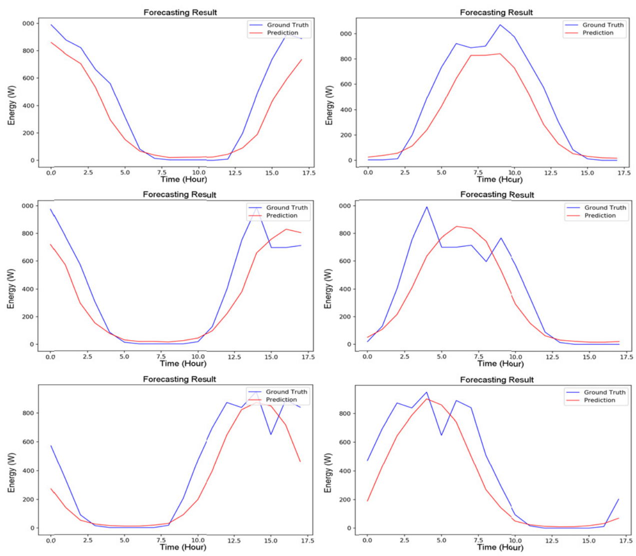

FIGURE 11. **The forecasting results of the LSTM.**

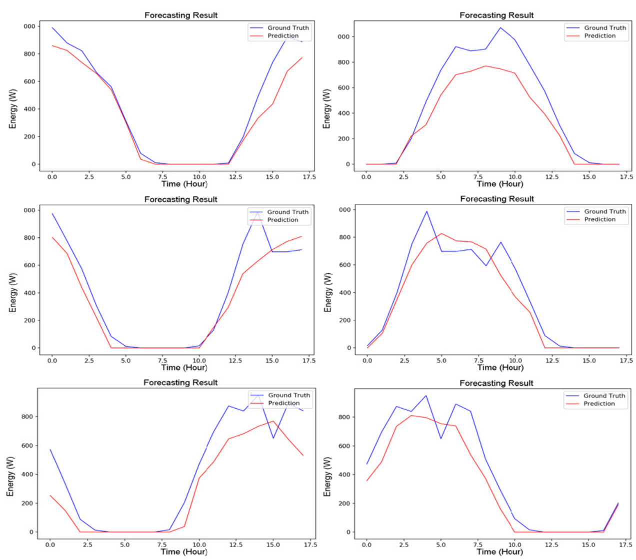

FIGURE 12. **The forecasting results of the proposed PVPNet.**

experiment proves the validity and feasibility of the PVPNet proposed in this paper.

V. CONCLUSIONS

This paper proposes a powerful deep convolutional neural network model (PVPNet) for short-term forecasting of a photovoltaic system output power. The proposed network is validated by experiments with the real collected data. The information on temperature, solar radiation, and PV system output power in the past five days is considered as an input of the proposed PVPNet, while its output is the PV system output power for the next 24 hours. In the experiment, 2015 solar energy dataset was used. The performance of the proposed network was evaluated by the comparison with the commonly used, popular machine learning methods

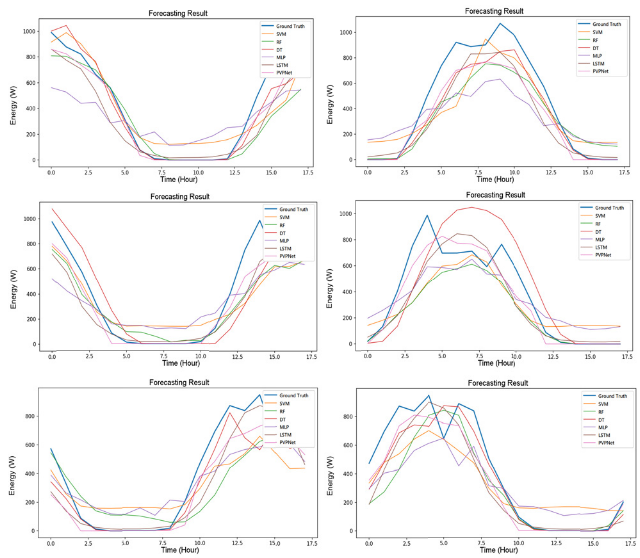

FIGURE 13. **The comparisons of all the obtained forecasting results.**

such as SVM, RF, DT, MLP, and LSTM. The comparison was conducted regarding the MAE and RMSE. According to the comparison results, the performance of the proposed PVPNet was better than of the other algorithms. In addition, the feasibility and practicality of the proposed algorithm were validated successfully.

According to the all obtained results, it can be concluded that the proposed PVPNet algorithm can reduce the monitoring expenses, the initial cost of hardware components, and the long-term maintenance costs of the future PV farms. Simultaneously, the results verify that the proposed PVPNet algorithm for short-term forecasting has strong generalization ability and robustness, and achieves a very good forecasting performance.

APPENDIX

See Figs. 7–13.

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