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Solar Irradiance Forecasting Using Deep Neural Networks

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Abstract

Predicting solar irradiance has been an important topic in renewable energy generation. Prediction improves the planning and operation of photovoltaic systems and yields many economic advantages for electric utilities. The irradiance can be predicted using statistical methods such as artificial neural networks (ANN), support vector machines (SVM), or autoregressive moving average (ARMA). However, they either lack accuracy because they cannot capture long-term dependency or cannot be used with big data because of the scalability. This paper presents a method to predict the solar irradiance using deep neural networks. Deep recurrent neural networks (DRNNs) add complexity to the model without specifying what form the variation should take and allow the extraction of high-level features. The DRNN is used to predict the irradiance. The data utilized in this study is real data obtained from natural resources in Canada. The simulation of this method will be compared to several common methods such as support vector regression and feedforward neural networks (FNN). The results show that deep learning neural networks can outperform all other methods, as the performance tests indicate.

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Keywords: Neural Networks; Solar; Irradiance; Power; DNN; DRNN; PV

1. Introduction

The increase in fossil fuel prices and the decrease of PV panel production cost have spurred the integration of renewable energy sources. Renewable energy sources have many advantages, including being environment-friendly

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and sustainable. However, these sources are highly intermittent. That is, the output power of renewable sources is variable and can be considered as a varying non-stationary time series. Solar photovoltaic (PV) systems are one of the main renewable energy sources and are simply panels that convert sunlight into electricity. The output of PV is highly dependent on solar irradiance, temperature, and different weather parameters. Predicting solar irradiance means that the output of PV is predicted one or more steps ahead of time. Prediction helps us improve various applications of power systems [1-2]. Figure 1 shows applications that use prediction to improve operation and planning of the power grid with the corresponding required time-resolution of the forecast [3-4]. Stability and regulation require information about the next seconds' solar irradiation. Reserve management and load following necessitate information about the next minutes or next hours, of solar irradiance. Scheduling and unit commitment need information about the next days of solar irradiance to operate optimally.

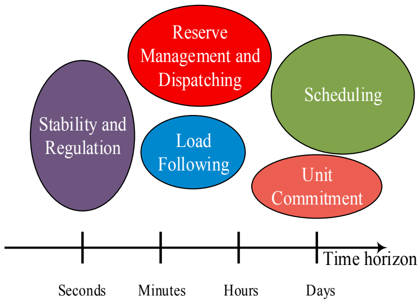

Fig. 1. Required time resolution of prediction.

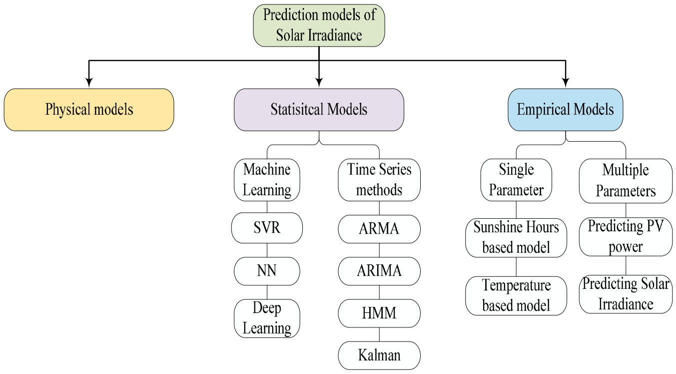

Fig. 2. Solar irradiance prediction methods

Quantitative forecasting methods can represent solar irradiance time series. That is, past data can be used to predict future samples [5]. The average of solar irradiance can be assumed to be repeatable. For example, the monthly average of solar irradiance of summer is always the highest among other seasons in any given year. However, the time series itself is stochastic and highly affected by the cloud motion. Volatility of fossil fuel price, public health, and global warming awareness spurs the renewable energy growth and necessitates the upgrade of the current electric grid. Renewable energy sources can bring many economic and social benefits. However, integrating these sources to the electric power grid is usually accompanied with challenges such as intermittency. Therefore, forecasting methods can mitigate the intermittency as it gives information about future trends and allows users make decisions beforehand. Figure 2 shows some of the most common methods used in predicting and forecasting solar irradiance. Modeling solar irradiance can be divided into three categories: physical, statistical, and empirical models.

1.1. Physical models

Several physical predictive models of solar irradiance can be found in the literature. One of the most widely used physical models is the irradiance model introduced by [6-8]. The total irradiance is the sum of direct and diffused irradiance, and ground reflected irradiance, as given in the following equation:

$$G_{TOT} = G_{DNI}.\cos(\theta) + G_{DIFF}\left(\frac{1+\cos(\beta)}{2}\right) + G_{REFL}\left(\frac{1-\cos(\beta)}{2}\right) \tag{1}$$

where β is the tilt angle of the PV panel and θ is the solar angle, which can be calculated by.

$$\cos(\theta) = \cos(z)\cos(\beta) + \sin(z)\sin(\beta)\sin(\phi_s - \gamma) \tag{2}$$

where z is the zenith angle (the angle between the vertical line and the beam radiation), and φ_s is the solar azimuth angle (the angle between the south of the projection of the beam and the PV surface). The angle α is the solar altitude angle, and γ is the surface azimuth angle, as shown in the Fig. 3.

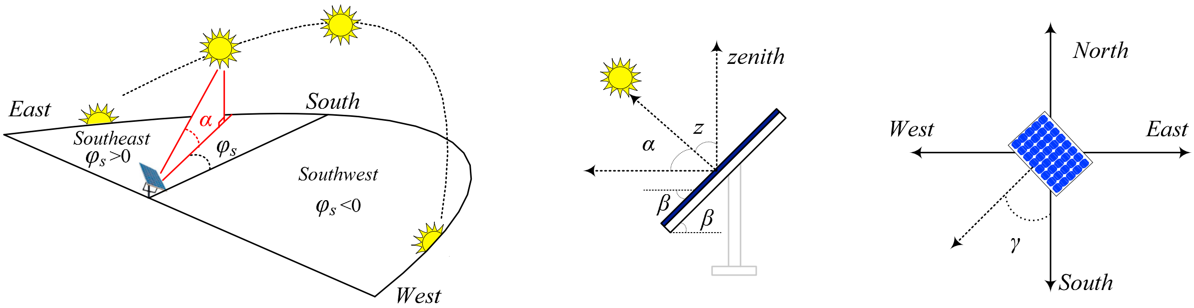

Fig. 3. Solar characteristics angles

1.2. Statistical models

Many statistical models for solar irradiance can be found in the literature. The most common methods are shown in Fig. 2. There are two types of statistical models: time series methods and machine learning algorithms. In time series methods, solar irradiance can be considered a time series that contains three components: long-term trend, periodical components, and the mean. The most common time series prediction method is the autoregressive moving average ARMA(p,q) [9-11], which can be given by

$$y_t = c + \underbrace{\phi_1 y_{t-1} + \ldots + \phi_p y_{t-b} + \varepsilon_t}_{Autoregressive} + \underbrace{\theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t}_{Moving\ Average} \tag{3}$$

where the first part of (3) is autoregressive AR and the second part of (3) is the moving average MA. The variables can be identified using Yule-Walker method. The time series should be tested for stationarity before applying this approach, and this might be a drawback of time series prediction methods. The machine learning methods are also prevalent. The most widely used method is support vector machine SVM. The SVM is a supervised learning machine algorithm. SVM is a suitable tool for prediction and classification. The idea of SVMs is to define the decision boundaries by the concept of decision planes [12]. It has been used in forecasting, but SVM might not be capable of extracting the long-term correlation of the time series or the very short-term components.

1.3 Empirical models

Several models can be found in the literature. The most common method is a sunshine-based model, which is given by (4), where a and b are empirical values, and GHI is global horizontal irradiance (monthly average). The monthly average of sunshine is given by S. The day length is given by S_o [13-15]:

$$\frac{GHI_{avg}}{H_o} = a + b\frac{S}{S_o} \tag{4}$$

2. Neural Networks

2.1. Feedforward neural networks (FNN)

Neural networks are a computational method that uses an enormous group of artificial neurons. These neurons are inexactly equivalent to axon in a biological brain. Neural networks are used in various fields such as machine learning, image processing, signal processing, and computer science, controlling power electronics converters that interface the PV systems [16-18] and modeling energy sources [2]. They consist of three parts: neurons, activation functions, and bias. The neurons can be either input neurons, output neurons, or hidden neurons. Fig. 4a shows a simple feed-forward neural network with one hidden layer. Fig. 4b shows the FNN with input from a sliding window [19-20].

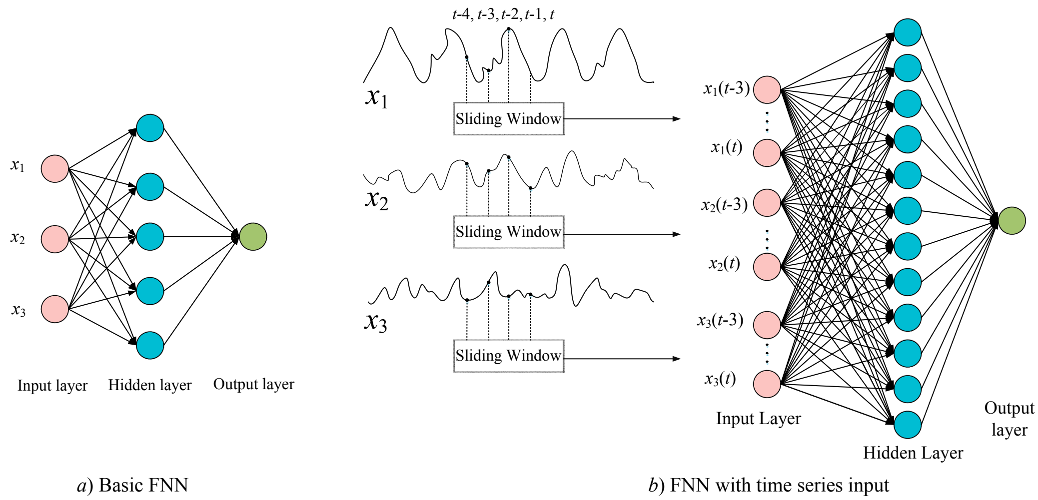

Fig. 4. Different architecture of FNN

2.2. Recurrent Neural Network (RNN)

A recurrent neural network is a type of neural network used in modeling and prediction of sequential data where the output is dependent on the input. It has been used in applications such as image processing, sentiment analysis, language translation, and speech recognition. The RNN is capable of predicting a random sequence of inputs thanks to its internal memory. The internal memory can store information about previous calculation. Fig. 5 shows the basic RNN, where the hidden neuron h has feedback from other neurons in an earlier time step multiplied by a weight W. When basic RNN is spread out into a full network, it can be seen that the input of a hidden neuron takes an input from neurons at the previous time step [21].

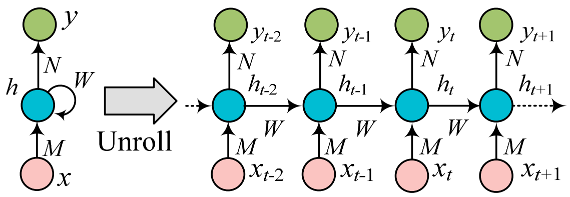

Fig. 5. RNN unfolded (left), and RNN folded (right)

The input x_t at instant time t is multiplied by the input weight vector to obtain the input of the first hidden neuron. Then, the next hidden neuron, h_{t+1}, will have the input of both x_{t+1} and the previous hidden neuron h_t multiplied by the weight W of the hidden neuron. The output neurons take the input only from the hidden neurons multiplied by the output weight N. The dynamic of the system is captured by

$$h_t = f_h(M \times x_t + W \times h_{t-1}) \tag{5}$$

$$y_t = f_y(N \times h_t) \tag{6}$$

where f is the activation function such as sigmoid, tanh, or ReLU. The training of RNN is comparable to the training of an artificial neural network that uses a similar method to the backpropagation (BP) which is called backpropagation through time (BPTT). The BP depends only on the current state values, while BPTT depends on current and previous state values.

2.3. Deep Recurrent Neural Networks (DRNN)

Deep neural networks consist of more than a hidden layer of neurons. Several studies [22-23] suggest that with more hidden layers, the neural network is capable of representing complex function more efficiently than RNN with less hidden layers. Fig. 6 shows the possible architecture of RNN as reported in [23]. Fig. 6a shows the conventional RNN already explained in the previous section. Fig. 6b shows the DRNN with a deep transition. The deep transition raises the number of nonlinear steps, which might increase the complexity of training such a network. One possible way to overcome such a challenge is to introduce a shortcut connection as in Fig. 6d. The shortcut connection offers a shorter path and bypasses the middle layers. Stacked RNN contains a stacked hidden layer u_t, as shown in Fig. 6c. The hidden layers u_t, and h_t can be used with different time scales. Working with various time scales can be very useful for reading from sensors that have different sampling rates. Figure 6e shows DRNN with another deep transition between the hidden layer and the output [23]. The gradient of RNNs can be difficult to tract in long-term memorization when they use their connection for short-term memory. Therefore, the gradient might either vanish or explode [23]. The long-term short term memory (LSTM) method was introduced to overcome vanishing or exploding gradient.

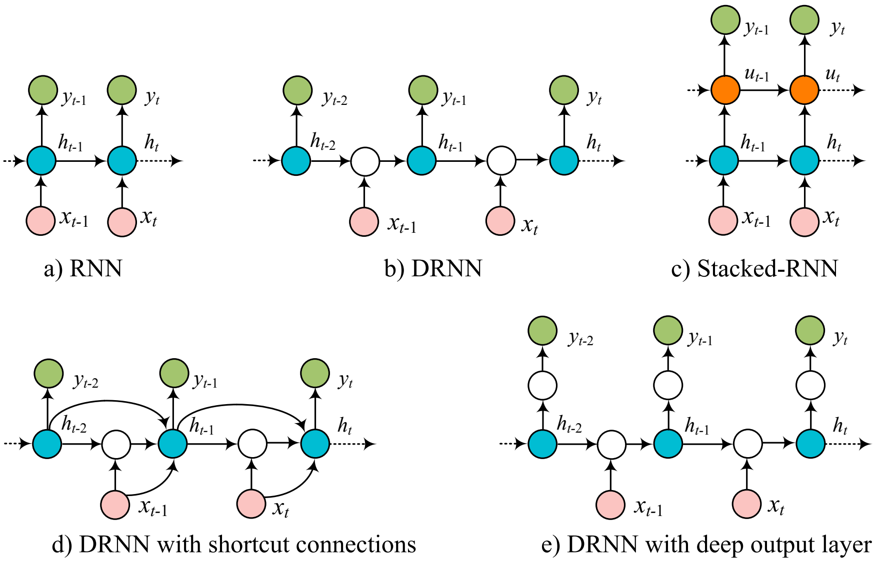

Fig. 6. Different types of DRNN

3. Data preprocessing

The prediction process has many steps, as shown in Fig. 7. Before the pre-processing, a dataset of solar irradiance must be obtained. The data was downloaded from [24] and the location and sample data are shown in Fig. 8 and Fig. 9. The data is a high-resolution time series recorded at 100 Hz frequency. The benefit of having high-resolution data is the ability to capture dynamic behavior such as ramp rates and fast fluctuations. Such information can help predict abnormal events and take action such as pre-emptive control [25]. The solar irradiance was recorded using LI-200S pyranometer every millisecond and then average over a period of 10 milliseconds [24]. The dataset contains global horizontal irradiance and global tilted irradiance with their corresponding time. The data was recorded for four days, March 24, February 8, October 8, and August 12, for clear-sky, overcast, variable, and very variable solar irradiance, respectively. Although data contains only four days, it is enough for training and predictions. The dataset from [24] needs pre-processing to clean and normalize data, as there are some misreading such as negative GHI readings. Several techniques in literature can clean data [26]. The simplest method is to remove misreadings and replace them with an interpolation of preceding and succeeding points.

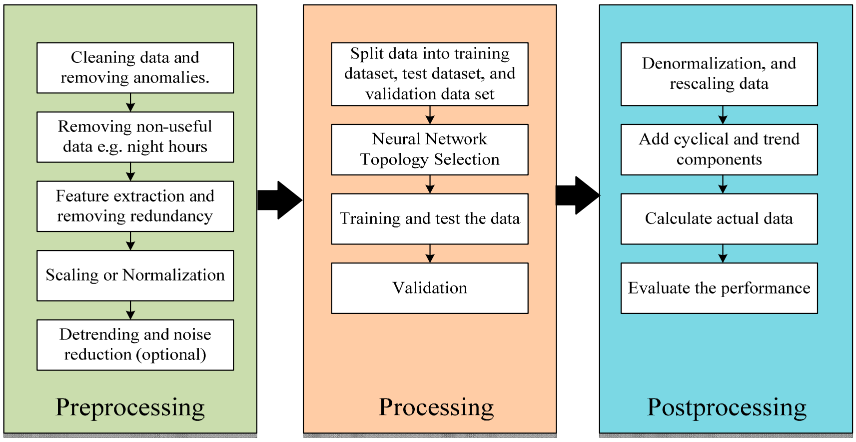

Fig. 7. Time series prediction process

3.1. Extracting cyclical behavior

Any function of time can be decomposed into a combination of sinusoidal and sinusoidal functions with different frequencies using Fourier transform. The goal of using Fourier transform with time series data is to extract cyclical behavior. Figure 10 shows a periodogram, a time series plotted in the frequency domain, and all components were extracted. At frequency 55 Hz, the magnitude is high, which means there is some cyclical behavior.

Fig. 8. Solar farm [google maps]

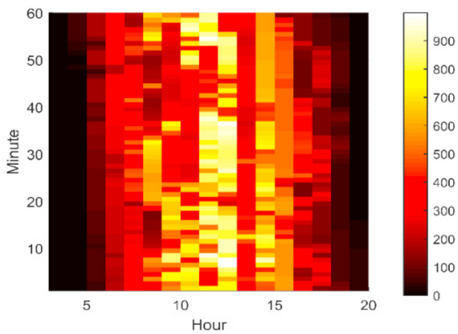

Fig. 9. Solar irradiance map

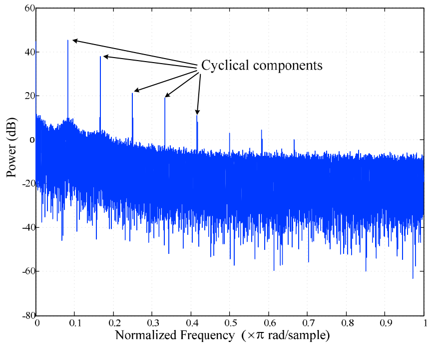

Fig. 10. Extracting cyclical behavior

3.2 Data cleaning

One of the most important steps in preprocessing is to clean the data from the abnormal data that comes from a missing sensor reading or incorrect readings from logging devices, such as negative data and radiation data that are bigger than the theoretical data limits. The missing data can be replaced using the linear interpolation method. The wrong readings can be replaced either with theoretical data or removed and then replaced with the maximum limit if it is beyond limit or interpolation results. In this paper, solar irradiance at night was eliminated using the primary elimination method. Depending on the season, the data time was taken from 5-6 a.m. to 7-8 p.m. Eliminating irradiance during night enhances the performance of the prediction process as only useful data feed the neural network. Another way to remove unuseful data or irradiance at night is to cluster the data using the fuzzy c-mean clustering algorithm. This is the best way to divide the time series data into seasons. Figure 11 shows the irradiance before removing irradiance and demonstrates the irradiance after removing unuseful irradiance data.

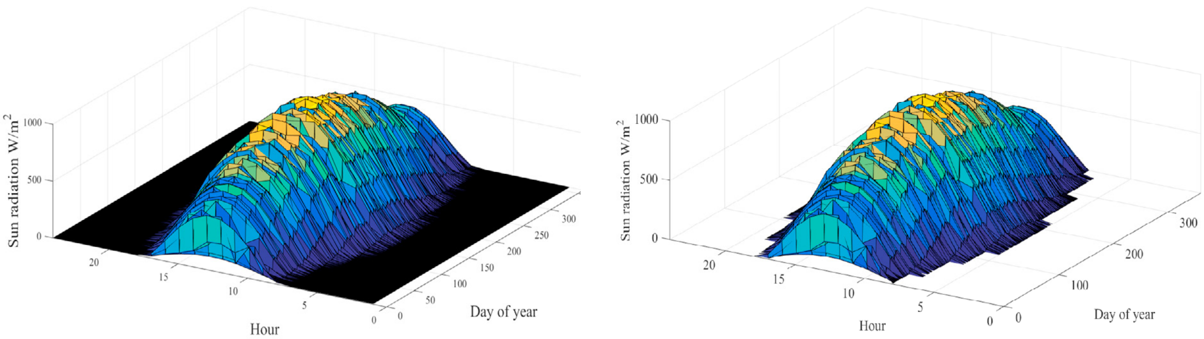

Fig. 11. Solar irradiance before removing night hours (left) and after removing night hours (right)

3.3 Normalization

Normalization is the next step of the pre-processing stage. In this step, all data are scaled between zero and one and align the entire probability distribution of the input values. Equation (7) is used to normalize the data:

$$y = \frac{(y_{max} - y_{min})(x - x_{min})}{(x_{max} - x_{min})} + y_{min} \tag{7}$$

where y is the normalized input, y_{max} is 1, and y_{min} is 0. In this method, x is assumed to have only real values. In this study, a built-in MATLAB function, *Mapminmax*, was used to normalize data between 0 and 1.

4. Data training and DRNN implementation

After normalization, the data was split into three parts: training data set, testing dataset, and validation dataset with 70%,15%, and 15%, respectively. The architecture used was DRNN with long-term short-term units (LSTM) with two hidden layers and 35 hidden neurons. Keras API and MATLAB was used to implement the model. Another model was implemented as a reference mode. The reference model uses an FNN. The FNN was trained using Backpropagation method. The hidden neurons and number of layers were chosen by trial and error to achieve the maximum performance out of FNN. After training, the data was renormalized using *mapminmax.*

5. Performance Evaluation

Several methods are used to evaluate the performance of a prediction method. The most common methods are main bias error (MBE), mean squared error (MSE), and root mean square error (RMSE), and they can be calculated using the following equations:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(G_i - \widehat{GP}_i)^2, \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(G_i - \widehat{GP}_i)^2} \tag{9}$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(G_i - \widehat{GP}_i), \tag{10}$$

where G is the actual output, $\widehat{GP}$ is the predicted output, and n is the number of samples. The MBE can point out the misjudgment in forecasting. If the MBE is negative, the forecast overestimates the observation, and if the MBE is positive, it means the forecast underestimated the observation. The MSE is used in the training process as an objective function that needs to be minimized. The RMSE is the square root of MSE and is used when only small errors are tolerated.

6. Results and Discussion

Figure 12 shows a sample of training data in four different weather conditions: few clouds, scattered, overcast, and clear-sky. The results of the predictive model are shown in Fig. 13. The actual data plotted with the standard deviation of the predictive model is plotted as well because the experiments had different random initializations. The average RMSE of the DRNN is 0.0513 in training and 0.068 in testing. On the other hand, the average RMSE of the DRNN is 0.0746 in training and 0.086 in testing. This method gives promising results, as the RMSE is the lowest. Table 1 shows a comparison of different prediction methods. The comparison was made on the test dataset. A feedforward neural network was implemented using one hidden layer with 21 neurons. It was trained using the Levenberg–Marquardt algorithm. The training was stopped early to avoid the overfitting issues. FNN has the poorest performance among the other methods. The support vector machine has better performance than FNN. However, the deep learning LSTM outperforms other methods.

Table 1: Performance test

Method	RMSE	MBE
FNN	0.16	0.005
SVR	0.11	0.0042
Deep Learning (LSTM)	0.086	0.004

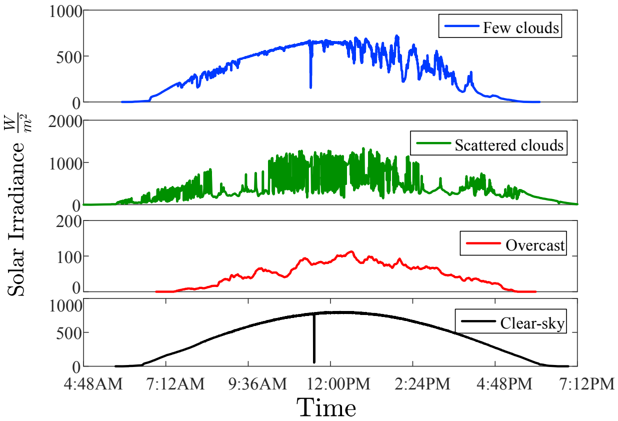

Fig. 12 Solar irradiance in different weather conditions

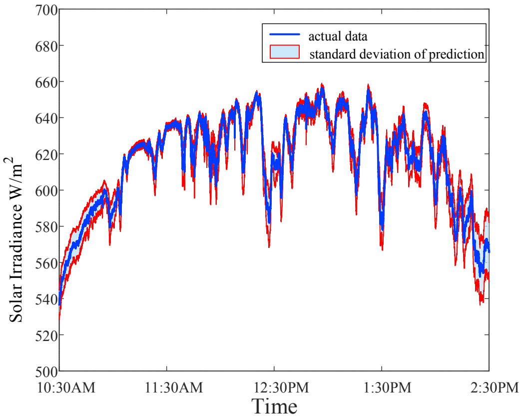

Fig. 13 Prediction results

7. Conclusion and future work

This paper presented a deep learning neural network algorithm and was implemented to predict short-term solar irradiance. This method was applied to real data obtained from a Canadian solar farm [24]. The data was cleaned, and anomalies such as wrong readings were removed and the data normalized to be ready for training. Then, the network was implemented to train the data and predict the future samples. The results were presented and were compared to other methods such as FNN. All other predictive models exhibited lower accuracies and more bias error than deep learning neural network. Deep recurrent neural networks have potential in big-data applications, renewable energy forecasting, and predictive modeling. Solar irradiance time series can be treated as big data if the sampling rate and volume are high.

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