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Photovoltaic Power Generation Forecasting Utilizing Long Short Term Memory

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Abstract

The modernization of the world has considerably reduced the prime sources of energy, such as coal, diesel and gas. Thus, alternative energy sources based on renewable energy have been the main concentration nowadays to address the world's energy demand and at the same time to restrict global warming. Among these renewable energies, solar energy is the main source used to generate electricity through photovoltaic (PV) systems. However, the output of PV power is highly intermittent. Thus accurately forecasting the output of PV systems is an important requirement to ensure the stability and reliability of the grid. This study develops and validates a short-term PV power forecasting model by using the combination of a genetic algorithm (GA) and Long Short Term Memory (LSTM). The performance of the proposed model is compared with LSTM baseline model by three errors (Root mean square error(RMSE), Mean absolute error (MAE), and Mean absolute percentage error (MAPE)) in two case studies.

Keywords: *PV power forecasting; Genetic algorithm; Long Short Term Memory; RMSE; MAPE*

Abbreviations

PV	Photovoltaic
LSTM	Long Short-Term Memory
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
GA	Genetic Algorithm

Tóm tắt

Sự hiện đại hóa của thế giới đã và đang giảm thiểu đáng kể các nguồn năng lượng sơ cấp như than đá, dầu diesel và khí ga. Do đó, các nguồn năng lượng thay thế như năng lượng tái tạo đang dần trở thành mối quan tâm chính hiện nay để giải quyết nhu cầu toàn thế giới và đồng thời hạn chế sự nóng lên của trái đất. Trong các nguồn năng lượng tái tạo, năng lượng mặt trời là một trong những nguồn năng lượng chính được sử dụng để phát điện thông qua hệ thống pin quang điện (PV). Tuy nhiên, công suất đầu ra của PV phần lớn gián đoạn. Từ đó việc dự báo chính xác công suất đầu ra PV là một yêu cầu quan trọng để đảm bảo độ tin cậy và ổn định của lưới điện. Nghiên cứu này phát triển và kiểm nghiệm mô hình dự báo ngắn hạn công suất phát của PV bằng việc sử dụng sự kết hợp của giải thuật di truyền (GA) và mạng Long Short-Term Memory (LSTM). Hiệu suất của mô hình đề xuất được so sánh với mô hình LSTM cơ sở bằng ba sai số (Sai số trung bình bình phương (RMSE), sai số tuyệt đối trung bình (MAE) và sai số tuyệt đối phần trăm trung bình (MAPE)) trong hai trường hợp nghiên cứu.

1. Introduction

The increase of the fossil fuel price and the decrease of the PV panel production cost have developed the penetration of renewable energy sources in the last decades. Renewable energy sources have many advantages in comparison with the primary energy sources, including being environment-friendly and sustainable. Among different types of renewable energies, solar photovoltaic (PV) energy is one of the main renewable energy sources. The PV output is largely intermittent, depending on the solar irradiance, the temperature, and different weather conditions. The abrupt change in solar power output affects significantly the reliability, stability, and planning of the power system. To cope with these circumstances, an accurate solar power output forecasting is necessary to ensure the reliability, stability, and high quality of the power system. It might avoid the power uncertainty impact on the grid and help power administrations and companies personnel adjust and optimize power generation plans promptly, improving utilization and economic efficiency of new energies [1], [2]. In addition, the PV power forecasting helps energy management in the smart grid become more efficient [3].

In general, many previous studies about the PV forecasting primarily concentrate on forecasting the PV power or forecasting the solar irradiance on PV panels. The PV power forecasting is achieved by constructing a forecasting model that maps historical data to the PV output power through a deep analysis of a large amount of historical data and mining the potential

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rules of data. The methods include linear regression [4], k-means clustering [5], ARIMA [6], grey theory, and artificial neural network (ANN) [7]. Besides, the combination of more than two methods such as physical – machine learning model, statistical – machine learning model, and machine learning - machine learning model creating metaheuristic (hybrid) models has become prevalent in forecasting problem, especially in the PV power forecasting. Ref. [8] shows that the combination of the LSTM – RNN forecasting model based on time correlation principles regarding different patterns of the PV is more accurate than the individual model. Motivated by recent advancements in deep learning methods and their satisfactory performance in the energy sector, a hybrid deep learning model combining wavelet packet decomposition (WPD) and long short-term memory (LSTM) networks is proposed in [9]. The study [10] represents short-term PV power forecasting by constructing a 3-stage approach which is formed by combining empirical mode decomposition (EMD) technique, sine cosine algorithm (SCA), and extreme learning machine (ELM) technique. Ref. [11] presents a radial basis function neural network with decoupling method for day-ahead PV power generation forecast. Results are compared with autoregressive integrated moving average (ARIMA), backpropagation neural network (BPNN), and radial basis function neural network (RBFNN), and the actual measured PV power outputs.

The purpose of this study is to produce daily forecasting model for PV power based on the historical PV power data collected from the National Renewable Energy Laboratory (NREL) utilizing genetic algorithm (GA) combining Long Short Term Memory (LSTM) model. The GA is used to find out the optimal parameters of the LSTM model before predictive capability assessment. Besides, the performance of the proposed model is tested by comparing with the LSTM benchmark model in root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) assessment. The rest of the study is following as below: Section 2 focuses on the proposed model, section 3 represents the results and discussions about the proposed model in two case studies whilst section 4 is dedicated to the conclusions of this study and future works.

2. Methodology

2.1. Long Short Term Memory (LSTM)

Long Short-term Memory Neural Network was proposed by Hochreiter and Schmidhuber in 1997 to avoid long-term dependencies through targeted design [12]. An advance of LSTM model in comparison with a single hidden layer RNN is that LSTM stores information in a control unit outside the normal flow of the RNN, hence introducing a new state unit c_t. The structure of an LSTM cell is shown in Fig. 1. In this figure, at each time t, i_t, f_t, o_t and c_t are input gate, forget gate, output gate and candidate value [13], which can be described as the following equations:

$$i_t = \sigma(W_{i,x}x_t + W_{i,h}h_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma(W_{f,x}x_t + W_{f,h}h_{t-1} + b_f) \tag{2}$$

$$o_t = \sigma(W_{o,x}x_t + W_{o,h}h_{t-1} + b_o) \tag{3}$$

$$c_t = \tanh(W_{c,x}x_t + W_{c,h}h_{t-1} + b_c) \tag{4}$$

where $W_{i,x}$, $W_{i,h}$, $W_{f,x}$, $W_{f,h}$, $W_{o,x}$, $W_{o,h}$, $W_{c,x}$ and $W_{c,h}$ are weight matrices, b_i, b_f, b_o and b_c are bias vectors, x_t is the current input, h_{t-1} is the output of the LSTM at the previous time $t-1$, and σ is the Sigmoid activation function. The forget gate determines how much of prior memory value should be removed from the cell state. Similarly, the input gate specifies new input to the cell state. Then, the cell state a_t is computed as:

$$a_t = f_t \circ a_{t-1} + i_t \circ c_t \tag{5}$$

where $\circ$ denotes the Hadamard product [14]. The output h_t of the LSTM at the time t is computed as below:

$$h_t = o_t \circ \tanh(a_t) \tag{6}$$

Hereafter, the predicted output $\widehat{z}_t$ is computed by using the output h_t:

$$\widehat{z}_t = M_y h_t \tag{7}$$

where M_y is a projection matrix to reduce the dimension of h_t [15]. Fig. 2 indicates a structure of the LSTM networks unfolded in time. In this structure, an input feature vector x_t is fed into the networks at the time t. The LSTM cell at current state receives a feedback h_{t-1} from the previous LSTM cell to capture the time dependencies. The network training aims at minimizing the usual squared error objection function f based on targets y_t by utilizing back-propagation with gradient descent:

$$f = \sum_t \|y_t - \widehat{z}_t\|^2 \tag{8}$$

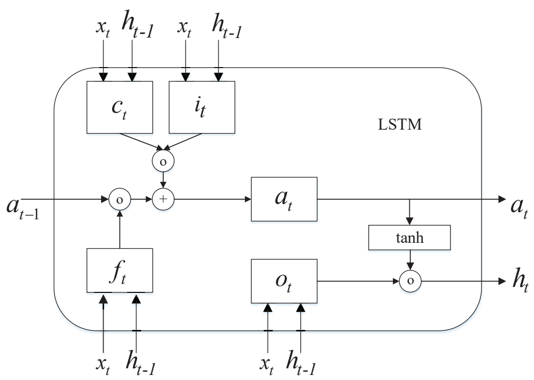


Figure 1: Structure of an LSTM cell

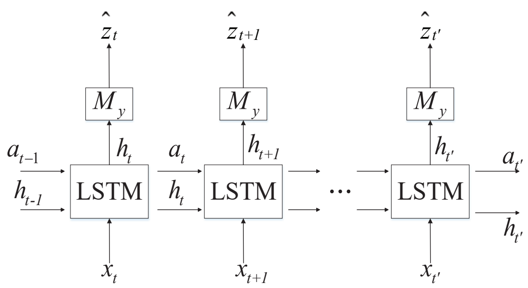


Figure 2: Structure of LSTM networks

Table 1: Configuration of the LSTM Benchmark Model

```
model = tf.keras.models.Sequential([
keras.layers.LSTM(100, activation='tanh',
input_shape=(shape), return_sequences= True),
keras.layers.LSTM(150, activation='tanh'),
keras.layers.Dropout(0.3),
keras.layers.Dense(1)
])
```

Table 2: Genetic Algorithm Search Parameters

Parameters	Value
Population size	10
Crossover rate	0.5
Mutation rate	0.05

2.2. Proposed Model

A genetic algorithm (GA) is a search heuristic that is inspired by Charles Darwin's theory of natural evolution. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring of the next generation. In this paper, GA is dedicated to exploring the optimal window size and the number of neurons in the hidden layer of Long Short-term Memory (LSTM) model in the training process. The moving window is normally called a sliding window method with the definition is the use of prior time steps to predict the next time step. The cost function used for GA in this study is Root Mean Square Error (RMSE) on validation set that measures the difference between the actual values and the predicted values. Table 2 indicates the parameters of GA algorithm using in this study. After the searching process is terminated, the model is implemented completely for testing with testing set. The model implementation is created using Python programming language with Tensorflow and Keras library. The proposed model is represented in Fig. 3. Table 1 indicates the configuration of the LSTM benchmark model.

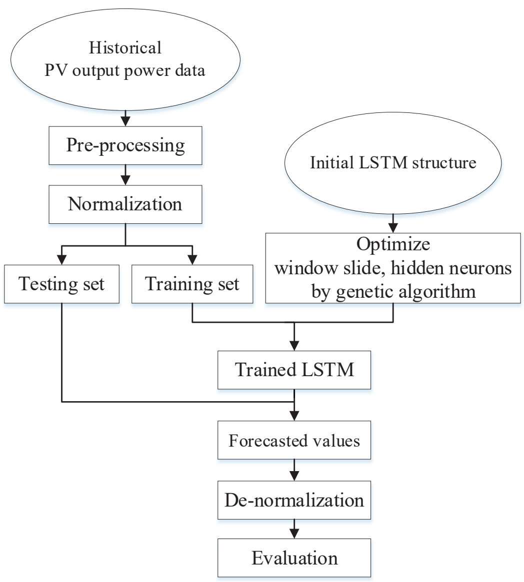


Figure 3: Proposed Model

3. Results and Discussions

3.1. Data

The dataset consists of the historical PV power values in 2006 from a solar photovoltaic (PV) power plant at Kentucky, United States. The unit for the PV power is Mega Watts (MW). The data points are available at an interval of one hour provided by the National Renewable Energy Laboratory (NREL) [16]. In this study, the proposed model is assessed in two case studies in comparison with the benchmark model. The collected dataset is divided into three parts: Training set, Validation set, and Testing set. The training set is adopted to adjust weights and biases of the predictive model. The validation set is dedicated to evaluate the training process of the proposed model whereas the testing set is used to assess the performance of the proposed model. In case study 1, the testing set is considered only from 8.00 AM to 4.00 PM on each day of September, 2006 for forecasting one day in advance or two days in advance, respectively. In case study 2, the data analysis is conducted similar to case study 1, but the dataset in December is utilized instead of September. Fig .4 depicts the time plot graph of PV power data values in 2006. In addition, the PV power values are normalized to range from zero to one as following equation:

$$x_{nom} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

3.2. Performance Metrics

Three errors were proposed to evaluate the performance of the forecasting model:

- Root mean square error (RMSE) measures the difference between the actual values to the predicted values. The RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(G_i - \widetilde{GP}_i\right)^2} \tag{10}$$

  where G_i is the actual output, $\widetilde{GP}_i$ is the predicted output, and n is the number of samples.
- Mean Absolute Error (MAE) is the average of absolute errors:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|G_i - \widetilde{GP}_i\right| \tag{11}$$

- Mean Absolute Percentage Error (MAPE) reflects the ratio of error to the true value in percentage.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{G_i - \widetilde{GP}_i}{G_i}\right| \times 100\% \tag{12}$$

3.3. Prediction Evaluation

- In case study 1, the historical PV power values in September, 2006 are conducted for forecasting in two instances: one day in advance and two days in advance. Table 3 and Table 4 indicate the RMSE, MAE, MAPE comparison between the proposed model and the referenced model in two cases. As can be observed from Table 3, the RMSE, MAE, and MAPE of the proposed model are lower than the benchmark model (RMSE: 4.9 versus 6.74, MAE: 3.98 versus 5.56, and MAPE: 10.3 versus 13.12). This results

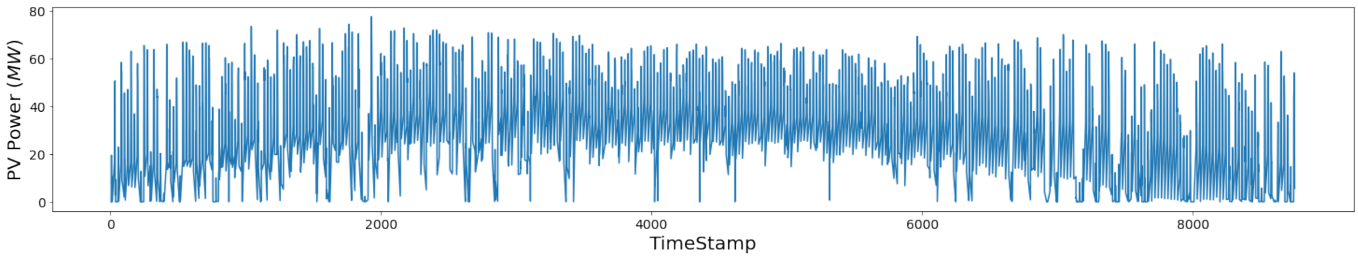
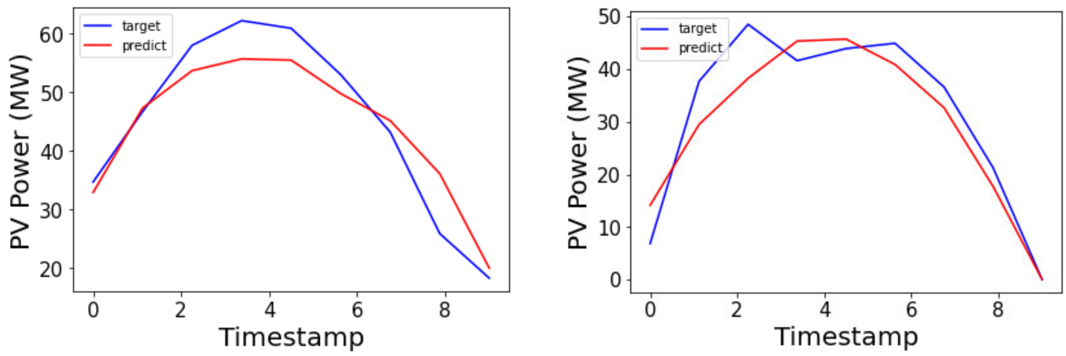
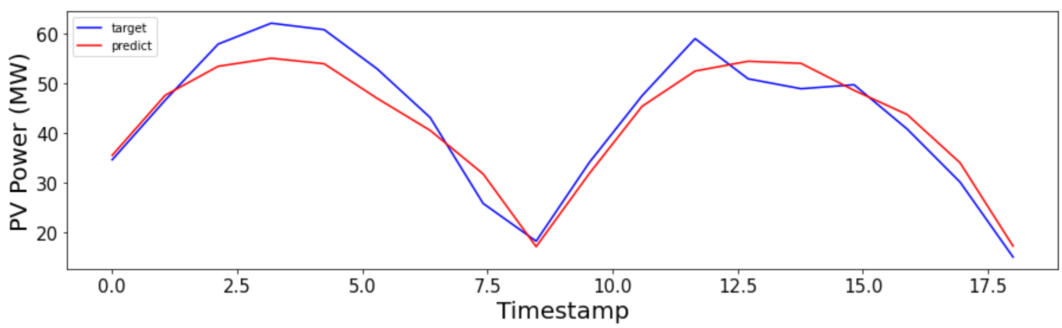


Figure 4: PV Power Data Values in 2006. X-axis: Timestamp.



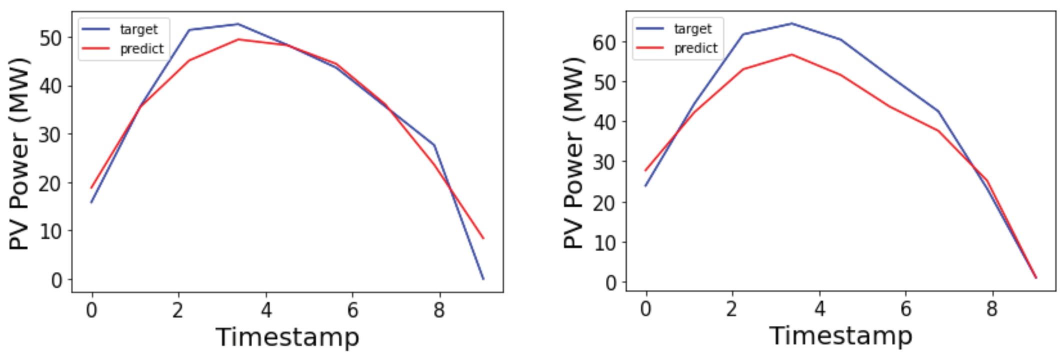
Sep 8th 2006 **Sep 12th 2006**

Figure 5: Predicted and Actual Value Graphs Using Proposed Model for One Day Ahead Forecasting in Case Study 1



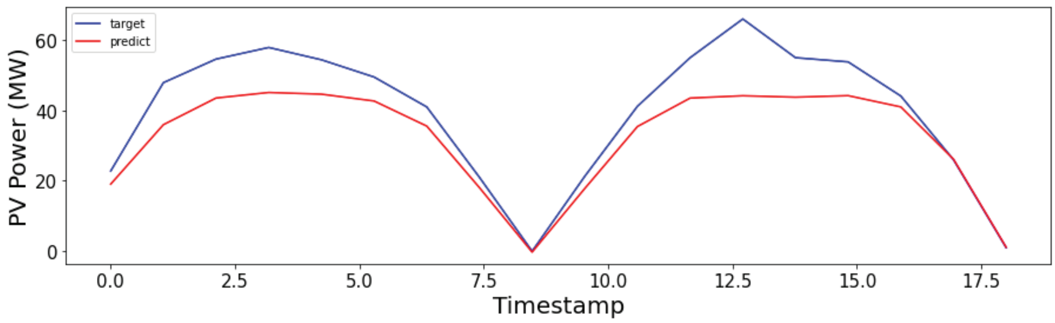
Sep 8th 2006 and Sep 9th 2006

Figure 6: Predicted and Actual Value Graph Using Proposed Model for Two Day Ahead Forecasting in Case Study 1



Dec 28th 2006 **Dec 3rd 2006**

Figure 7: Predicted and Actual Value Graphs Using Proposed Model for One Day Ahead Forecasting in Case Study 2



Dec 8th 2006 and Dec 9th 2006

Figure 8: Predicted and Actual Value Graph Using Proposed Model for Two Day Ahead Forecasting in Case Study 2

could be acceptable because the proposed model find out the optimal hyper-parameters of the LSTM model, thus the minimum RMSE is obtained. Fig .5 illustrates the predicted and actual values graphs from the proposed model in one day ahead forecasting for specific days. As can be seen from this figure, the considerable difference occurs during the 10^{th} to 14^{th} of the day since the PV power increases rapidly in this period. Hence, this might be difficult to predict accurately. In term of forecasting two days in advance, the obtained RMSE, MAE, and MAPE of the referenced model are greater than the proposed model. In other words, the proposed model outperforms the benchmark model in two cases. In addition, the MAPE of proposed model in two day-ahead forecasting is 8.78% while the MAPE achieved from one day-ahead forecasting is 10.3%. This might demonstrate the proposed model is relatively suitable for two-day ahead forecasting with the PV power values in September. Fig .6 represents the Predicted and Actual value graphs from proposed model for two day-ahead forecasting.

Table 3: One Day Ahead Forecasting Results in Case Study 1

	RMSE(W/m^2)	MAE(W/m^2)	MAPE(%)
Proposal	4.9	3.98	10.3
Ref.	6.74	5.56	13.12

Table 4: Two Day-Ahead Forecasting Results in Case Study 1

	RMSE(W/m^2)	MAE(W/m^2)	MAPE(%)
Proposal	4.48	3.75	8.78
Ref.	5.08	4.43	12.05

- In case study 2, the historical PV power values in December, 2006 are conducted for forecasting in two instances: one day in advance and two days in advance. Table 5 and Table 6 indicate the RMSE, MAE, and MAPE comparison between the proposed model and the referenced model in two cases. In both two instances, the errors of the proposed model are smaller than the benchmark model. In particular, the MAPE obtained from the proposed model is 6.92% whereas the benchmark model attained 10.51% for one-day-ahead forecasting. Fig .7 indicates the predicted and actual values graphs from the proposed model for one-day-ahead forecasting in some specific days of December. As can be seen from this figure, the predicted curve is relatively similar to the actual curve. The difference appears during hour 10^{th} to hour 13^{th} of the day when solar irradiance obtained on the PV cell is maximum. Due to the weather characteristics of assessed location, the solar irradiance in December ranges insignificantly. Besides, the PV power has large correlation to the solar irradiance. Hence, the PV power values in December are uncomplicated to predict in comparison with the others. In two-day-ahead forecasting, the MAPE comparison between two models has insignificant difference (12.91% versus 13.86%). The predicted results of two-day-ahead forecasting are greater than one-day-ahead forecasting due to the seasonal weather characteristics. Fig .8 presents the graphs showing the actual and predicted power of the proposed model in two-day-ahead forecasting.

Table 5: One Day-Ahead Forecasting Results in Case Study 2

	RMSE(W/m^2)	MAE(W/m^2)	MAPE(%)
Proposal	4.03	2.92	6.92
Ref.	4.52	3.53	10.51

Table 6: Two Day-Ahead Forecasting Results in Case Study 2

	RMSE(W/m^2)	MAE(W/m^2)	MAPE(%)
Proposal	9.14	7.03	12.91
Ref.	10.7	9.23	13.86

4. Conclusion

This study proposes a short-term forecasting model utilizing GA and LSTM based on historical PV power data from NREL. The results show that the proposed model has better performance in comparison with the LSTM baseline model. Since the data collected from NREL is relative inadequate and this study only assesses the performance of the predictive model in two months (September and December), the optimal hyper-parameters of the predictive model must be updated if the number of data points increase considerably. Thus, the accuracy of the proposed model could be higher in term of PV forecasting on cloudy days. In the future, the multivariate forecasting will be implemented by adding solar irradiance and meteorological data. This might yield higher accurate prediction due to the explicit dependence of the PV power output on climate conditions.

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