Forecasting Daily Power Generation of a PV Power Plant based on Deep Learning

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***Abstract*—The use of PV power plants has increased significantly in recent years. The use of PV power plants has issues in the power grid system, where the PV power plant cannot generate a stable output every day due to weather changes. To solve those issues, forecasting using deep learning models emerges as the solution. This study explains how to forecast the PV power output using historical weather data. The forecast period is 24-hours ahead and employs several deep learning models, such as RNN, LSTM, BiLSTM, ConvLSTM, and LSTM-BNN. The results show that forecasting the 24-hour PV power output using historical weather data as input for the deep learning model is possible and express promising results. Based on the implementation, the LSTM-BNN models outperform other models with a small MSE and MAE metrics value of 0.0082 and 0.0847, respectively.**

***Index Terms*—Deep Learning, Power Output Forecasting, PV Power Plant, Recurrent Neural Network**

I. Introduction

In our current society, electricity emerges as an important aspect of daily life. As society modernizes, the demand for electricity is expected to increase [1]. In the past, electricity was generated from a power plant fueled by fossil fuels. As a result, it emits a lot of pollution, like carbon dioxide and greenhouse gases, which cause a significant climate issue in the world. Therefore, renewable energy sources are seen as promising alternatives to generate electricity, replacing fossil fuels. According to [2], various types of renewable energy exist, such as solar energy, wind energy, geothermal energy, hydropower, ocean energy, and bioenergy. These renewable energies can be used to replace the use of fossil fuels, thus enabling the generation of electricity without emitting any pollution.

Among various types of renewable energies, solar power is the most preferred and utilized. By using a photovoltaic (PV) module, the solar energy can be directly converted into electricity. The process of generating electricity using solar power is simple; it does not require a stable water supply as in hydropower or expensive construction as in geothermal energy. In solar energy, the PV module can be installed almost anywhere, as long as it receives direct sunlight. Moreover, the PV module has a relatively low installation cost and is easier to construct compared to other renewable energies. By adding an energy management system, a battery, and an inverter, the electricity generated by the PV module can be easily integrated with the power grid. Due to the aforementioned advantages, the installation of solar power plants grows rapidly in the world, where it is forecast that the annual installed capacity will reach 222 GW [3].

However, despite having numerous advantages, solar energy-based power plants also have several issues. Every day, the amount of sunlight received by the PV module is changed due to various environmental factors, such as cloud cover that prevents the PV module from receiving sunlight directly. As a result, the amount of electricity generated by the PV module is highly stochastic [4], proportional to the rapid changes in the environment. Hence, constant electric power cannot be generated by the PV, which becomes a huge problem when using it as the primary power source. A constant electric power supply is important to ensure that the generated electricity is adequate to fulfill consumer energy demands. Uncertainty in power generation also affects power grid system planning and pricing, especially when numerous PV power plants from residential and commercial users are integrated into the main power grid system [5].

In order to solve the uncertainty problem in power generation, it is necessary to perform a forecast of the PV power plant's electricity output. The forecasting method utilizes the PV power plant's historical data to provide an estimation of the future output power of the PV. The forecasted output power can be utilized for better planning, decision-making, or power trading [5]. According to [5], we normally group the forecast period into four categories:

1) Very short-term: less than 1 minute.
2) Short-term: between 1 hour and several hours.
3) Medium-term: between 1 week and 1 month.
4) Long-term: between 1 month and 1 year.

Several works propose various forecasting methods for each forecast period. In [6], a 5-minute ahead power output forecast is performed, where artificial neural networks (ANN), random forests (RF), decision trees (DT), extreme gradient boosting (XGB), and long short-term memory (LSTM) are utilized to learn from historical weather data and solar power output. The results show that all algorithms can be used for forecasting PV power output, and ANN shows the best performance among other algorithms. The results of this very short-term forecast period are usually used for control purposes in the PV power plant.

The short-term forecast period is the common period for PV power forecasting. As shown in [7, 8, 9, 10, 11], numerous researchers try to forecast the PV power output from 1-hour ahead up to 72-hour ahead. Varieties of algorithms were also utilized and proposed, and most of them showed reliable forecast performance. The popularity of the short-term forecast period is caused by its important application, where it is usually used for scheduling or decision-making for the next day. Then, some researchers also perform a medium-term forecast, where an evolutionary seasonal decomposition least-square support vector regression (ESDLS-SVR) is proposed for forecasting monthly PV power output in Taiwan [12]. The medium-term forecast is usually used for easier power system planning and scheduling maintenance, according to [5].

In this work, the purpose is to develop a 24-hour power output forecast using several deep learning algorithms. The forecast utilized PV power output and weather data that was collected from real-world implementation. Several models, such as recurrent neural network (RNN), LSTM, bidirectional LSTM (BiLSTM), convolutional LSTM (ConvLSTM), and LSTM-bayesian neural network (LSTM-BNN), are utilized in this work to compare the performance of each model and output the best-performing models.

II. Dataset Collection

The dataset collection is important to develop proper data for the models to learn. The dataset collection in this work is divided into two parts: collecting the PV power output data and collecting the weather data around the PV power plant.

A. PV Power Output Data

The PV power output data is gathered from the power conditioning system (PCS) that is installed in the PV power plant. To get the data from PCS, an IoT platform is developed, as explained in [13]. The PV power output is sampled every hour and directly stored in the database. This data records how many kWh the PV power plant is generating every hour. Hence, the collected data from the PCS is increment data, where the PV power output is always increasing over time. The data collection was performed from January 1, 2021, to December 31, 2021, with a total of 8,760 data points collected.

B. Weather Data

At the time of the experiment, the observed PV power plant didn't have any weather stations. To provide the weather data, data from meteorological agencies is utilized. The weather data is collected from the meteorological agency's website, where only recorded weather data in the specific area of the PV power plant is utilized. The collected dataset has a sampling time of 1 hour and 8,760 data points. The collected weather data has 10 features, such as temperature, precipitation, wind speed, wind direction, humidity, daylight, solar radiation, snowfall, total cloud cover, and ground temperature.

III. Methodology

This section provides an explanation of the data preprocessing to make the data ready to be fed into the models for the learning process. Moreover, an explanation of each model's working mechanism is also provided in this section.

A. Data Preprocessing

To make the model easier to learn about the data, proper data preprocessing is implemented. There are two parts to the preprocessing: scaling and feature selection. First, the scaling ensures that all data are in the same value range. In this work, minmax scaling is utilized to rescale the data into values between -1 and 1. The formula for minmax scaling is as follows:

$$X_{scaled} = \frac{X_{data} - (-1)}{1 - (-1)} \tag{1}$$

Then, since the features of weather data are too many, we need to eliminate them to reduce the computational complexity. The feature elimination is based on the feature selection procedure, where only features that have a high correlation to the PV power output are utilized. In this work, Pearson's correlation coefficient is utilized to calculate the correlation between each weather feature and PV power output. The equation for Pearson's correlation is as follows:

$$r = \frac{\Sigma(x_i - \hat{x})(y_i - \hat{y})}{\sqrt{\Sigma(x_i - \hat{x})^2 \Sigma(y_i - \hat{y})^2}} \tag{2}$$

From the calculation, of the 10 weather data features, only 3 have a high correlation with the PV power output. The three features are solar radiation, ground temperature, and sunlight periods. Therefore, the other 7 features are eliminated, and only 3 features are utilized as input for the models to learn.

B. RNN Model

In this work, a simple RNN model is considered, where the architecture of the model follows the description in [14]. The RNN is using the simplest form, where it has a vanishing or exploding gradient problem.

C. LSTM Model

The LSTM is an improvement from the simple RNN model. The vanishing gradient problem is solved in the LSTM model due to some modifications in the network architecture. We develop the LSTM architecture in this work, following the explanation in [15].

D. BiLSTM Model

In [16], BiLSTM is proposed and aims to improve long-term dependency performance by utilizing forward and backward directions. The BiLSTM uses two LSTM models that are combined into one layer, where one LSTM model acts as the forward layer while the other LSTM acts as the backward layer.

E. ConvLSTM Model

ConvLSTM is an improvement of LSTM, as explained in [17]. In ConvLSTM, a convolutional layer is utilized to extract the spatial information contained in the input data. Moreover, the matrix multiplication that is contained in LSTM is replaced with a convolution operation.

F. LSTM-BNN Model

The LSTM-BNN model is a hybrid of the LSTM and BNN models, where the LSTM acts to extract the important features contained in the data while the BNN performs the value prediction [18]. The LSTM-BNN model consists of two models and can be expressed as the following equations: The LSTM part has the same equation as in the regular LSTM model, where the equation for the output LSTM part is as follows:

$$y_{LSTMout}(t) = \sigma(W_{y_{LSTMout},j} j(t) + b_{y_{LSTMout}}) \quad (3)$$

Then, the output from the LSTM model is used as input for the BNN part; the equation is as follows:

$$f(x) = \sigma(v_0 + \Sigma_{j=1}^{J} v_{jk} \times \sigma(w_0 + \Sigma_{i=1}^{I} w_{ij} y_{LSTMout})) \quad (4)$$

IV. Implementation

A. Training Settings

The model training process is performed using Python code with the help of the Tensorflow libraries. The computation processes in this work utilize a computer with the following configuration: an Intel Xeon Silver 4210R processor, 128 GB of memory, an RTX 3090 GPU, and the Windows 11 operating system. To evaluate the model's performance, five types of evaluation metrics are utilized, such as mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R^2). The input data is batched into 16 batches and converted into a sliding window format with an input window length of 24 and target data of 24, representing 24-hour forecasting. Then, the training dataset is split into 80% for training and 20% for validation.

Additionally, a learning rate of 1e-5 is applied when training with the ADAM solver selected as the optimization algorithm. The activation function is using Tanh because it outputs data with a value of -1 to 1, which fits with the preprocessing applied to the data. All models are trained with an epoch of 200.

B. Prediction Results

After training the models with the training data, we test them using separate testing data that differs from the training data. All models are tasked with predicting the 24-hour PV power output based on the previous day's weather data. Fig. 1 shows the prediction results from all models. It is clear that the prediction results from LSTM-BNN produce a closer value to the ground truth compared to other models. The LSTM-BNN clearly performs better than other models. However, the LSTM-BNN fails to predict correctly when the ground truth value is approaching zero. The other models, such as LSTM, RNN, BiLSTM, and ConvLSTM, are able to better predict when the ground truth is approaching zero. However, when the ground truth is more than zero, between hours 7 and 16, the LSTM, RNN, BiLSTM, and ConvLSTM cannot produce prediction values that close to the ground truth.

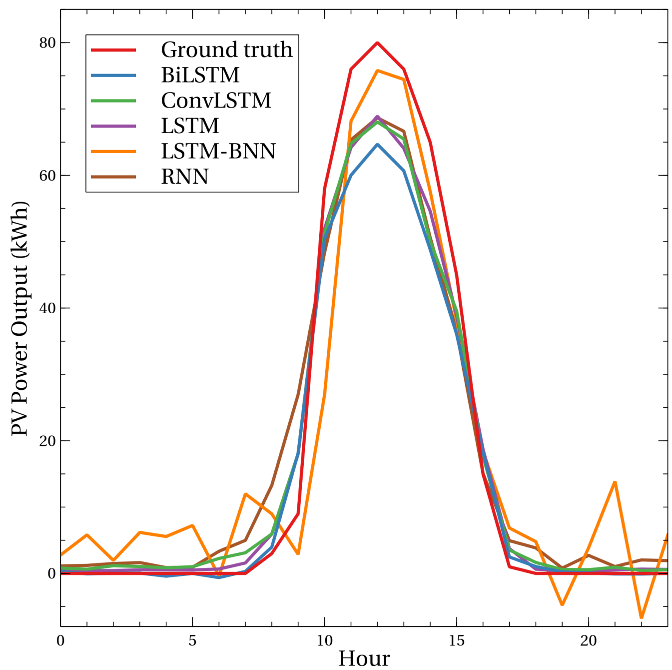

Fig. 1. Prediction results from all models.

The results shown in Fig. 1 are consistent with the evaluation metrics values that were gathered after the training. The evaluation metrics value is shown in Tab. I, which shows the evaluation metrics for all models. The LSTM-BNN outperforms other models by having the best metrics compared to other models. The small values of MSE and MAE prove that the error between the ground truth and prediction value is small. Meanwhile, the R^2 value approaching 1 shows that the prediction value has a pattern that is similar to the ground truth. Hence, in this work, the LSTM-BNN works better than other models when used for generating a 24-hour-ahead PV power output forecast using the weather data.

TABLE I
Evaluation metrics from all models

Model	**MSE**	**MAE**	**MAPE**	***R2***
RNN	0.0241	0.1019	2.3585	0.4488
LSTM	0.0479	0.1167	36.5830	0.1792
BiLSTM	0.0436	0.1096	14.3012	0.4071
ConvLSTM	0.0475	0.1177	22.4477	0.4199
LSTM-BNN	**0.0082**	**0.0847**	**0.5299**	**0.5602**

V. Conclusion

The volatility in PV power output is a huge problem when adopting PV power plants in power grid systems. Forecasting the PV power output using deep learning emerges as a solution to the uncertainty when dealing with PV power plants. In this work, it is shown that the PV power output can be forecasted by using the historical weather data of the PV power plant as the input for the deep learning models. Several AI models can be employed to perform the forecasts, and based on the implementation results, the LSTM-BNN model performs better than other models when forecasting the PV power output for 24 hours ahead.

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