Optimization of Power Output Forecasting from Solar PV System using Deep Learning Methods

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Abstract

This research proposes a deep learning method (GA-RNN-LSTM) for forecasting the power output from a solar PV system. The model takes six input parameters, and the output is the power output from the PV system. The proposed model was compared to the conventional RNN-LSTM model in terms of accuracy. The evaluation metrics used were Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R2). The results demonstrate that the GA-RNN-LSTM model demonstrates superior forecasting accuracy and robustness compared to the RNN-LSTM model. Specifically, the proposed model (GA-RNN-LSTM) obtained the best testing results with an RMSE and MAE of 2.581 and 2.065, respectively.

1. Introduction

Humanity faces a severe threat from climate change, especially in areas with a low capacity for adaptation. Clean energy systems that leverage on Internet of Things (IoT) and Artificial Intelligence (AI) to improve efficiency are becoming increasingly important in this context, especially in the context of "smart cities." [1]. Solar energy is a popular renewable energy source due to its environmental benefits and the diminishing availability of traditional energy sources. Deep Learning (DL) methods are being used to forecast the power generated from renewable energy systems because of their improved accuracy. A review of machine learning (ML) and metaheuristic methods for predicting solar radiation and photovoltaic (PV) power found that models could improve forecasting accuracy [2]. In order to enhance the precision of forecasting models, various factors need to be taken into account, including selecting an appropriate algorithm, identifying the crucial input variables, and adjusting model parameters. However, determining the optimal values for these factors can be a challenging task as the ideal values are problem-specific and require multiple trial-and-error experiments to be carried out.

The objective of this research is to improve the precision of forecasting the power generation of a photovoltaic (PV) system by proposing a Genetic Algorithm (GA) to automatically select the optimal parameters for a deep learning model that combines Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) techniques.

The effectiveness of the proposed model will be evaluated using three performance metrics; Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R2).

2. Methodology and Experiment

2.1 Dataset

The dataset was obtained from an open data repository of the Korean government [3]. Preprocessing on the dataset was done to increase data quality. The meteorological data was collected through the Korea Meteorological Agency's Open Weather Portal [4]. The input data are temperature, wind speed, wind direction, humidity, pressure, and solar radiation. The relationship between the input data with the power output is described in Fig. 1.

2.2 Proposed Model

GA is a computational method inspired by biological evolution and genetics principles, which could be used to find the optimal solution to a problem [5]. In this research, we use the genetic algorithm (GA) to find the optimal parameters of a recurrent neural network (RNN) using long short-term memory (LSTM).

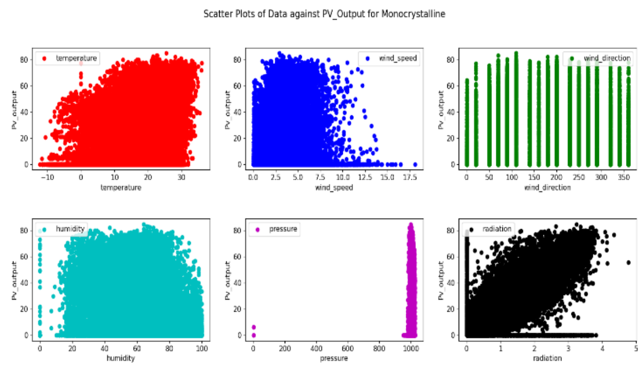

Fig. 1 Relationship of data input data with the PV output

First, we use the Roulette Wheel method for selection. This method compares solutions and chooses the best one to create the next generation. By eliminating the wrong solutions, we were able to find the best solution. Next, we use the crossover to develop new solutions by combining the solutions of two parents. We have a greater opportunity to find the best solution by having various solutions. Finally, we use mutation to increase the diversity of solutions by making small changes to them, such as randomly swapping or turning off bits in the solution. This keeps us from becoming stuck in an optimal local solution and allows us to find the best RNN-LSTM parameters. Table 1 displays the parameters of the proposed model.

Table 1 Parameter value of the proposed model

Parameters	Description	Value or Range
Crossover rate	The probability that a crossover operation will occur	0.6 – 0.9
Mutation rate	The probability that a mutation operation will occur on a solution	0.01 – 0.1
Generation limits	This is the number of iterations that the GA will run for	100 – 1000
Population size	Number of solutions in the population that the GA will operate on	100 – 500

2.3 Experimental Analysis

In this research, we utilized the Keras library in Python for deep learning to develop our model, which was built specifically to run on recurrent neural networks (RNNs). The experimental GPU specification was NVIDIA GTX1080 Ti 11GB-4WAY. Data normalization was performed to improve the data's quality and consistency, with the scaling range from 0 to 1.

3. Result and Discussion

To accurately evaluate the performance of the proposed deep learning technique (GA-RNN-LSTM), the conventional deep learning model RNN-LSTM was introduced for comparison. The dataset was divided into a training set (70%) and a testing set (30%). The result is presented in Table 2; the result shows that the proposed GA-RNN-LSTM model had the lowest RMSE value of 2.733 compared to RNN-LSTM, with an RMSE value of 3.954. The coefficient of determination (R^2) was found to be higher, with a value of 0.993 for GA-RNN-LSTM and 0.982 for the RNN-LSTM model.

Table 2 Result comparison of the proposed algorithm

Models	RMSE (Wh/m2)	MAE (Wh/m2)	R2
GA-RNN-LSTM	2.581	2.065	0.992
RNN-LSTM	3.599	3.043	0.984

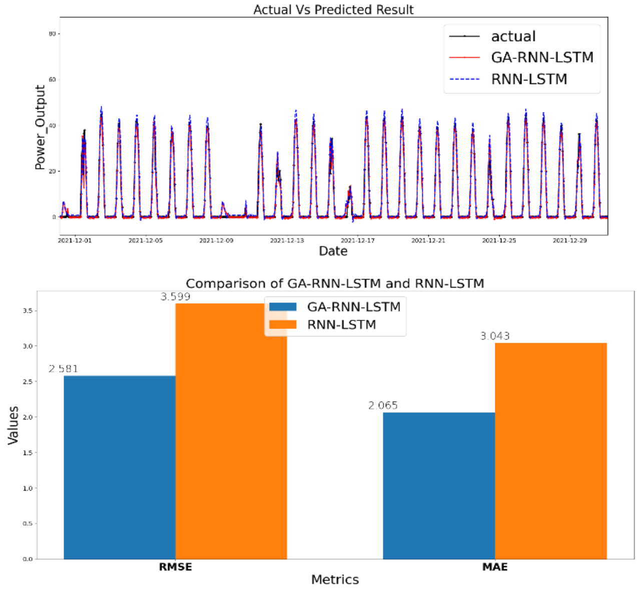

Fig. 2 Comparison of prediction results

The proposed GA-RNN-LSTM model was the most accurate in its predictions, as it closely matched the actual PV output curve, as shown in Fig. 2. However, in some cases, both models produced similar results, and the predicted curves followed a similar pattern as the actual PV output curve.

4. Conclusion

The experiment results in the previous section show that the proposed DL model (GA-RNN-LSTM) provides the most accurate forecasts, with RMSE and MAE values of 2.581 and 2.065, respectively. This proposed model can be utilized for forecasting in real grid-connected PV systems to improve grid dependability and stability. This model can also be used for data from similar and dissimilar climates worldwide.

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