Int. J. Renew. Energy Dev. 2022, 11(3), 815-828

Contents list available at IJRED website

International Journal of Renewable Energy Development

Journal homepage: https://ijred.undip.ac.id

Research Article

Univariate and Multivariate LSTM Models for One Step and Multistep PV Power Forecasting

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Abstract. The energy demand is increasing due to population growth and economic development. To satisfy this energy demand, the use of renewable energy is essential to face global warming and the depletion of fossil fuels. Photovoltaic energy is one of the renewable energy sources, widely used by several countries over the world. The integration of PV energy into the grid brings significant benefits to the economy and environment, however, high penetration of this energy also brings some challenges to the stability of the electrical grid, due to the intermittency of solar energy. To overcome this issue, the use of a forecasting system is one of the solutions to guarantee an effective integration of PV plants in the electrical grid. In this paper, a PV power ultra short term forecasting has been done by using univariate and multivariate LSTM models. Different combinations of input variables of the models and different timesteps forecasting were tested and compared. The main aim of this work is to study the influence of the different combinations of variables on the accuracy of the LSTM models for one-step forecasting and multistep forecasting and comparing the univariate and multivariate LSTM models with MLP and CNN models . The results show that for one step forecasting, the use of a univariate model based on historical data of PV output power is sufficient to get accurate forecasting with 28.98W in MAE compared to multivariate models that can reach 35.39W. Meanwhile, for multistep forecasting, it is mandatory to use a multivariate model that has historical data of meteorological variables and PV output power in the input of LSTM model. Moreover, The LSTM model shows great accuracy compared to MLP and CNN especially in multistep PV power forecasting.

Keywords: Photovoltaic power forecasting; LSTM model; One step and multistep forecasting; Univariate and Multivariate model; Recurrent neural network; Artificial intelligent

Received: 5th January 2022; Revised: 10th May 2022; Accepted: 30th May 2022; Available online: 10th June 2022

1. Introduction

The development of economic and population growth leads to an increase in energy demand and its consumption. Furthermore, the depletion of fossil fuel resources and the motivation to decrease the carbon emission to face Global Warming, encourage countries to develop new renewable energy power generation (Tsai *et al*., 2018). Photovoltaic power energy is a clean, renewable energy source that can satisfy the increasing clean energy demand (Kabir *et al*., 2018). Photovoltaic power generation is the conversion of solar irradiation into electric energy through the Photovoltaic Effect(Wang, Zhen, *et al*., 2018). In comparison with other energy sources, Photovoltaic power generation has been widely used thanks to its excellent performances such as cleanliness and high efficiency (Yongsheng *et al*., 2020). The installed capacity of solar photovoltaic in all regions increased from 808 MW in 2000 to 707 494 MW in 2020(Statistics Time Series, no date). The creation and installation of the large capacity of PV systems will be a solution to alleviate the peaking pressure of Power grids (Yongsheng *et al*., 2020). The renewable energy sources that PV systems one of them, can be large-scale stations connected to transmission power systems, small-scale distributed generation (DG) connected to medium voltage distribution systems, or very small-scale placed on rooftops and connected to low voltage distribution. The cost of PV systems is decreasing thanks to their high demand and their technology development speed (Fantidis *et al*., 2013; Ghafoor and Munir, 2015). The integration of PV systems indeed brings significant benefits economically and environmentally, but high penetration brings also a lot of challenges for existing grid systems due to the uncertainty and intermittency of solar energy (Stein and Letcher, 2018). Intermittency of PV power generation with high penetration in the grid can cause many technical problems in power systems, like

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https://doi.org/10.14710/ijred.2022.43953
ISSN: 2252-4940/© 2022.The Author(s). Published by CBIORE

power flow and voltage regulation problems (Lim and Tang, 2014; Ding *et al*., 2016). That's why researchers are interested in finding some solutions to integrate PV systems safely and guarantee no financial or economic risk. One of the solutions proposed is to elaborate accurate forecasting of PV power. Moreover, Forecasting of PV power is used to estimate the output power of PV stations from one side and load demand from the other side to guarantee effective energy management (Massaoudi *et al*., 2021). Forecasting of PV power is one of the most economical and feasible solutions and supports other solutions or technologies (Wang, Zhou, *et al*., 2018) like power flow optimization (Biswas, Suganthan and Amaratunga, 2017) and energy storage (Wang, Zhou, *et al*., 2018). However, Accurate forecasting of PV power could be a complex task due to PV power time series that display non-linear and unstable characteristics, and unpredictable meteorological conditions that PV power generation relies on (Li *et al*., 2018). Presently, research efforts focus on PV power forecasting that proposes several methods for different forecast horizons: long-term, medium-term, and short-term PV power forecasting (Voyant *et al*., 2017; Li *et al*., 2018). Long-term forecasting is between one month to one year, medium-term forecasting looks ahead one week to one month and short-term forecasting is forecast one week or less (Li *et al*., 2020a). Long-term Forecasting grants long-term planning and decision-making for PV power generation, transmission, and distribution, and guarantee reliable operation of the power system. For medium-term forecasting, it contributes to medium-term decision support for dispatching of the power system. Short-term forecasting provides support for power system operation and increases the reliability of the power system (Pierro *et al*., 2017). There is also a fourth forecasting horizon which is very short-term or ultra-short term (1 min to several min ahead) (Raza, Nadarajah and Ekanayake, 2016). This forecasting horizon is used for power smoothing, real-time electricity dispatch, and storage control (Das *et al*., 2018). Also, in the background of the electricity trading market, the ultra-short-term plays an essential role in the supervision and regulation of the power market. Ultra-short-term is the forecasting horizon that our models will try to forecast.

In this paper, a PV power ultra short term forecasting has been done by using univariate and multivariate LSTM (Long short-term memory) models. Different combinations of variables in the input of the model (meteorological variables and PV power), and different timesteps forecasting (One-step and multistep forecasting) were tested and compared. The PV power is forecasted 1 (5min), 3 (15min), 6 (30min), 9 (45min) and 12 (1h) steps ahead using the univariate and the multivariate LSTM models. The main goal of this work is to study the influence of variables on the quality of forecasting to select the best combination of variables for a choosing timestep forecast. The influence of input variables for LSTM model for one step and multistep forecasting is not well addressed in literature that will be demonstrated later in the related works section. The LSTM model been compared to MLP (Multi-layer perceptron) and CNN (Convolutional neural network to showcase its accuracy in PV power forecasting for one step and multistep forecast. The benefits from selecting specific input variables for one step and multistep PV power forecasting are as follows:

- Optimizing the accuracy of the PV output power forecasting by eliminating the variables that negatively influence the accuracy of the forecasting model.
- Decreasing the time consumption to training the LSTM model and to preprocessing the dataset.
- Facilitating the data collecting phase by ignoring the factors or variables that are unnecessary for PV output power forecasting.

The rest of the paper is structured as follows: Section 2: present a literature review of PV power forecasting. Section 3: provide the methodology, methods, and data used. Section 4: present and discuss the results obtained. In the last section, the main conclusions and future works are presented.

2. Related works

Forecasting techniques can be classified as physical techniques and statistical techniques(Ramsami and Oree, 2015). Physical techniques model the PV cell as a function that contains different independent variables like PV cell characteristics, solar radiance, and cell temperature. Many physical models come from conventional solar cell equivalent circuits(Ramsami and Oree, 2015).The most popular physical model is the numeric weather predictor (NWP). This method is based on mathematical equations that show and describe the atmosphere's physical state and dynamic motion(Raza, Nadarajah and Ekanayake, 2016).The forecast accuracy of the physical model is higher when the weather is stable and is highly affected when there is a sharp change in meteorological conditions (Soman *et al*., 2010) . Ayompe *et al*. (Ayompe *et al*., 2010)presented a comparative study to forecast PV output power by studying different PV cell temperature and efficiency models. Dolara *et al*. (Dolara, Leva and Manzolini, 2015) evaluated different physical models by comparing three models describing the PV cell. Each model has respectively three, four, and five parameters equivalent electric circuit, and two thermal models for the cell temperature estimation. Statistical approaches for forecasting can be divided into two classes which are statistical methods and Machine learning methods(Nath, no date). Statistical methods are used in literature to forecast the output power of PV and solar irradiance. Y. Li *et al*. (Li, Su and Shu, 2014) proposed a time series model for forecasting PV power output named ARMAX (Autoregressive–moving-average model with exogenous inputs), which is similar to ARIMA (auto-regressive integrated moving average) by its simplicity and doesn't require solar irradiance. Unlike ARIMA, ARMAX can use exogenous input to forecast PV power output. The results show that ARMAX outperforms greatly ARIMA and other methods like Double moving average single, exponential smoothing, double exponential smoothing, Holt-Winter's additive, Holt-Winter's multiplicative, single moving average in the accuracy of forecasting. Kushwaha & Pindoriya(Kushwaha and Pindoriya, 2017) presented a model named SARIMA (Seasonal Autoregressive Integrated Moving Average) for a very short-term forecast of solar PV generation data (multistep forecasting). The persistence model is used to compare the performance. The error of the SARIMA model is found to be less than that of the persistence model. Although the model's performance is seen satisfactory on sunny days, it may degrade on cloudy days when solar PV generation is more intermittent. Thus, the model may not be suitable for very short-term forecasting in the months having cloudy or rainy days. Almadhor *et al.* (Almadhor, Matin and Gao, 2019) developed triple exponential-smoothing (TES) based forecasting for short-term forecasting of solar irradiance and compare the proposed method with persistence forecasting and average forecasting. Results show that the TES has a better forecasting performance, and it can capture the changing of solar irradiance.

The machine learning techniques are widely used to forecast PV output power and solar irradiance in literature. Shi *et al.* (Shi *et al.*, 2012) proposed a weather classification algorithm to increase the accuracy of SVM (Support-vector machine) results for PV output power forecasting. The weather is divided into four types which are clear sky, cloudy day, foggy day, and rainy day. The SVM is applied in every type of weather. Results show that the proposed model has promising results for one day ahead of PV output power forecasting. Ahmad *et al.*(Ahmad, Mourshed and Rezgui, 2018) evaluated the use of tree-based ensemble methods (which are random forest and Extra trees) for PV output power forecasting by investigating their accuracy, stability, and computational cost and comparing them with the support vector regression model. the results show that RF and ET perform better than SVR. Also, ET outperforms other models in computational costs. Authors conclude that ET is the ideal candidate for PV output power forecasting thanks to its stability and its algorithmic efficiency. Huertas Tato & Centeno Brito (Huertas Tato and Centeno Brito, 2018) presented a PV output power forecasting model by using smart persistence, random forest, historical PV production, and irradiance. results show that using smart persistence as input for the random forest model greatly improves the accuracy of short-term forecasting. Sivaneasan *et al.* (Sivaneasan, Yu and Goh, 2017) propose a model based on Artificial Neural Network (ANN) with a preprocessing model named fuzzy logic and error correction factor for very short-term solar forecasting. the architecture of the training model consists of three layers (input layer, hidden layer, output layer) feed-forward with a back-propagation model. ANN uses all similar day's data to learn the trend of similarity. However, it's complex especially if the weather changes on the same day. For that reason, the authors add a Fuzzy preprocessing toolbox to find data correlation meteorological data with solar irradiance. results show that the proposed model outperforms pure ANN and ANN-Fuzzy without error correction factor. Sharma *et al.*(Sharma *et al.*, 2016)present a mix of ANN and Wavelet transform (WT) for short-term solar irradiance forecasting. Results show that WNN has better forecasting skills in comparison with others forecasting techniques like ARIMA, Persistence, ANN. Chu *et al.* (Chu *et al.*, 2015) present ANN with GA (Genetic Algorithm) optimization to forecast real-time output prediction. The results show that the presented model forecasting accuracy is superior to the physical model based on cloud tracking technique, ARIMA, and kNN (k-nearest neighbors algorithm) models. Lu & Chang (Lu and Chang, 2018) proposed a model for day-ahead PV power generation forecast which is radial basis function neural network with a decoupling method. Results show that the proposed method leads to a more accurate and computational efficient forecast comparing to other techniques like Autoregressive integrated moving average (ARIMA), backpropagation neural network (BPNN), and radial basis function neural network (RBFNN) without decoupling method. LSTM model is a deep learning model, used by a lot of researchers thanks to its promising results in forecasting PV power and solar irradiation in different forecast horizons (Short-term, middle-term, long-term). Pan *et al.* (Pan *et al.*, 2019) propose a novel method to forecast solar generation (one step = 5 min ahead) for very short-term forecasting by using the LSTM model and two algorithms named Temporal attention and partial autocorrelation for more accuracy in forecasting results. Y. Yu *et al.*(Yu, Cao and Zhu, 2019) present a short term solar irradiation forecasting model by using LSTM with clearness index (an index that shows the clearness in the sky for cloudy days) for more accuracy in forecasting GHI (Global Horizontal Irradiance). a comparison was made with different deep learning models and statistical models (LSTM is the more accurate forecasting models with clearness index). Aslam *et al.*(Aslam *et al.*, 2019) The comparison between different deep learning and machine learning models which are LSTM, GRU(Gated Recurrent Units), RNN (Recurrent neural network), FFNN(Feedforward neural network), SVR, and RFR(random forest regression) to forecast a long term solar radiation. results show that LSTM and GRU perform better. Ospina *et al.* (Ospina, Newaz and Faruque, 2019) propose a novel method for medium and long-term PV power forecasting by combining stationary wavelet transform (WT) to extract useful features or information from Data with LSTM and DNN(Deep neural network) models. Results show that the method outperforms LSTM, Naive method, some deep learning methods (DNN, WT+BPNN, WT+RBFNN), and SVR. Hossain & Mahmood (Hossain and Mahmood, 2020) propose two algorithms, the first for one-step forecasting and the second for multistep forecasting by using the LSTM model, time of day, and the month of the season as predictors for more accuracy in forecasting results. Acharya *et al.* (Acharya, Wi and Lee, 2020) propose a different way to train the LSTM model for PV power forecasting by selecting the days where the weather condition is the same to not disturb the training phase of the model. P. Li *et al.* (Li *et al.*, 2020b) present a PV power forecasting for short term forecast by using the LSTM model and Wavelet packet decomposition (WPD decompose PV power series into sub-series with different frequencies). Results show that the proposed model outperforms the individual LSTM, GRU, RNN, and MLP(multilayer perceptron). Chen *et al.* (Chen *et al.*, 2020) use an LSTM with grey relational analysis (GRA) to extract the similarity of the hour for different data parameters, to forecast an hour ahead of PV power. The results show that this combination outperforms GRA BPNN, GRA RBFNN, GRA-Elman, and LSTM individually.

Despite the robustness of LSTM models for PV power forecasting, very few research studies have investigated the influence of input data on the accuracy of LSTM models for PV power forecasting. To the best of our knowledge, the only work that exists in literature is presented by Son & Jung (Son and Jung, 2020). These authors propose a modified LSTM model for medium-term and long-term PV power forecasting by comparing the proposed LSTM with traditional LSTM and studying the impact of input factors on forecasting accuracy, however their work has some gaps including the impact of input factors on multistep forecasting and the ultra short-term forecasting horizon. Moreover, as we said earlier, exploring the impact of input variables on the accuracy of the LSTM model has various advantages, and for that reason, our study will be focused on this point and enrich the literature regarding the influence of input factors on forecasting accuracy.

3. Materials and methods

3.1 PV plant description

The data used in this work was published by (Id Omar *et al.*, 2021), it corresponds to a PV plant located at rooftop of National School of Applied Sciences of Safi, Morocco (Latitude and longitude (32.3265°N; -9.2634°W)) (Fig. 1). This PV plant consists of three types of PV technologies, Mono-crystalline, polycrystalline, and amorphous. In our study, we focus on Mono-crystalline (m-si) technology. The plant that has m-si technology has 8 panels and each one has 255 Wp. The PV modules are mounted in metallic structures tilted by 32° and south oriented. The energy produced by this PV plant is injected into the electrical grid through three identical inverters. For further technical information on the PV plant see Table 1. The variables measured by the weather station installed nearby the PV array, are the ones that influence highly on PV plant generation which are solar irradiance, ambient temperature, and PV module temperature. Solar irradiance measured by calibrated crystalline silicon reference cell with calibration uncertainty less than 2.3 % (Erraissi *et al.*, 2018). Ambient temperature was measured with Pt100 sensor with accuracy better than 0.1 °C (Erraissi *et al.*, 2018). Furthermore, PV module temperatures were obtained on the backside of each technology using Pt100 sensors, with accuracy better than 0.1 °C (Erraissi *et al.*, 2018). For DC powers, it was obtained directly from the inverters equipped with maximum power point tracking function (MPPT) (Erraissi *et al.*, 2018). All data were measured in each 5 min.

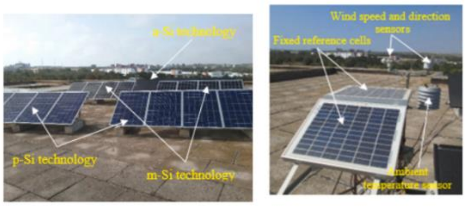


Fig 1. PV plant and measuring instruments
Source : (Omar Nour-eddine *et al.*, 2021)

Table 1
Characteristics of PV plant

Characteristics	PV array
Maximum power of PV array under STC (KWp)	2.04
Nominal power of PV array (KWp)	1.473
Total number of modules	8
Modules set up	8 x 1
PV array's surface (m²)	12.74
Tilted angle (°)	32
Nominal power of each inverter (KVA)	2

Source : (Omar Nour-eddine *et al.*, 2021)

3.2 Methodology

The methodology proposed in this paper is presented in Fig. 2. First, the data is preprocessed by filling missing values, removing zero values from the dataset, and scaling data. Furthermore, the data is split into training data (70%) used to train the model and find patterns and test data (30%) to evaluate the model. Then, the LSTM structure and hyperparameters are defined (the number of neurons, the number of the hidden layer, optimizer, etc.). Next, the time horizon is defined as ultra-short term forecasting. After, two types of Forecasting will be tested: one-step forecasting (1 step) and multistep forecasting (2 steps, 3 steps, etc.). Different combinations of variables will be used to forecast the PV power for one-step and multistep forecasting. After, the tested models will be assessed by using test data to choose the best model in.

3.3 LSTM model

The model used in our work is LSTM, which is a type of RNN, that can learn order dependence in sequence prediction problems by preserving previous information and establishing temporal correlations between sequential data with internal self-looped repeating networks (Luo, Zhang and Zhu, 2021). LSTM outperforms the simple RNN by its capability to learn long-term dependencies (Luo, Zhang and Zhu, 2021). LSTM contains four connected layers, three gate layers and a Tanh layer (Luo, Zhang and Zhu, 2021). LSTM architecture is presented in Fig. 3. Cell state is a core variable that can run straight down the architecture, carrying information of previous steps (Luo, Zhang and Zhu, 2021). The LSTM capable to remove or add information to the cell state, regulated by gates. The first layer is Forget layer; it decides which information of previous steps to forget. The mathematical equation for this gate is (1), the output of

$$f_t = \sigma(W_f \cdot [h_{t-1}, X_t] + b_f \qquad (1)$$

The second layer is the input gate, which decides what new information will be stored in the cell state by using (2) (Luo, Zhang and Zhu, 2021):

$$i_t = \sigma(W_i \cdot [h_{t-1}, X_t] + b_i) \qquad (2)$$

The third layer is the Tanh layer. It generates a vector with new candidate values, defined in (3) (Luo, Zhang and Zhu, 2021):

$$\breve{C}_t = \varphi(W_c \cdot [h_{t-1}, X_t] + b_c) \qquad (3)$$

After the three first layers, the old cell state C_{t-1} is updated by C_t. The update comes from the combination of the output of forget gate and input gate, the first one determines what to forget and the second one determines what to add to the new cell state, as shown in (4)(Luo *et al.*, 2021):

$$C_t = f_t * C_{t-1} + i_t * \breve{C}_t \qquad (4)$$

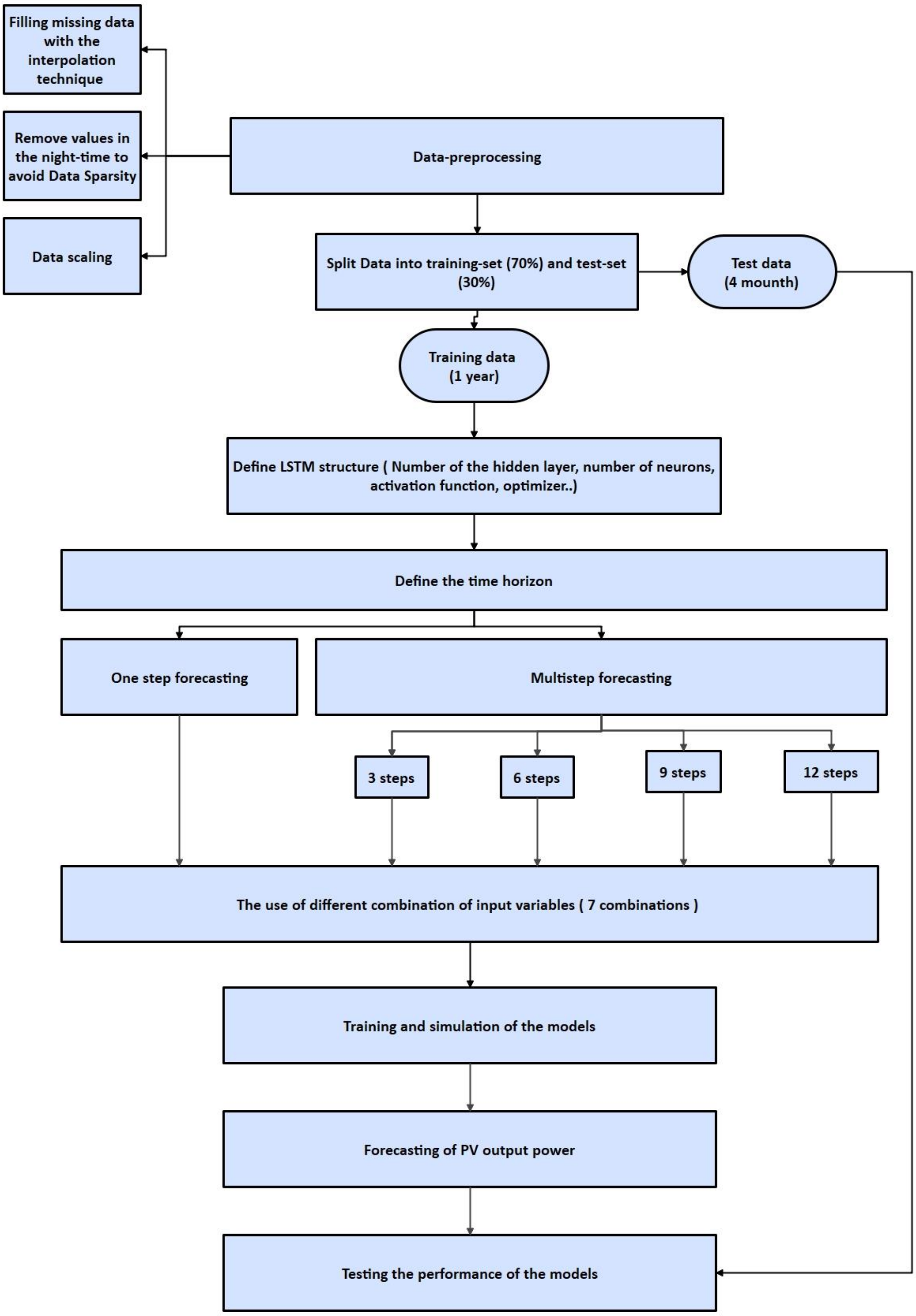


Fig 2. Methodology flow chart

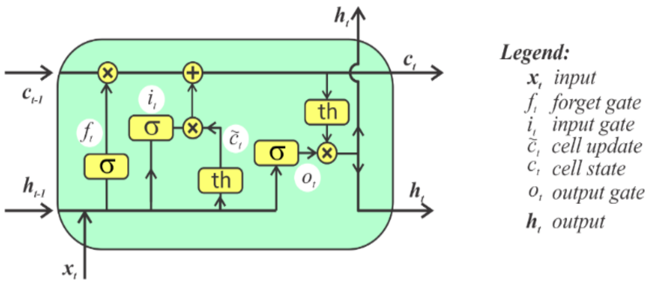


Fig 3. LSTM architecture
Source : (Predicting weather using LSTM)

The final layer is the output gate. it's generating the final output according to the updated cell. (5) shows the process of output gate (Luo et al., 2021):

$$o_t = \sigma(W_o \cdot [h_{t-1}, X_t] + b_o) * \varphi(C_t) \quad (5)$$

Where σ is a sigmoid function, φ is tanh function, W_o , W_f, W_i, W_c and b_o, b_f, b_i, b_c are the weight and bias of each layer. The weights and bias are tuned by using optimizers like Adam and stochastic gradient descent (SGD) to minimize the loss function.

3.4 Data description and pre-processing

The data records were collected on a 5 min time basis. The dataset consists of four parameters: DC PV power, module temperature, temperature ambient, and global irradiance. Data covers the period from 18 June 2016 to 29 October 2017. To Optimize model training, computational cost, and improving the accuracy of the model, pre-processing of input data is a must (Das *et al.*, 2018). There are different techniques for pre-processing input data to handle missing data, sparsity, and other issues.

Missing data

Dataset presents some missing values due to:

- Electrical breakdowns: The PV plant is connected to the grid, so it's synchronized with the same frequency (Grid frequency), and when the power in the grid is off, the data acquisition system is also off. (Id Omar *et al.*, 2021)
- Inverters failure: If the inverter malfunctions, electrical records are set to zero. (Id Omar *et al.*, 2021)
- Burned or disarmed fuse: In this situation, the values that were recorded are null or have errors. (Id Omar *et al.*, 2021)

The existence of missing values in a dataset disturbs the forecasting model to make a precise prediction for a time series problem where continuously measured data is a requirement. To fill gaps in the dataset, we calculate an estimated value for each missing value in a particular time step by using the interpolation technique especially the "Time" method that is more appropriate for that type of problem. The Fig. 4 shows an example of interpolation technique that fills some missing values for each parameter.

Data sparsity

Data sparsity is the term used to describe the phenomenon of not observing enough data in a dataset (Nasiri, Minaei and Sharifi, 2017). Since The values of PV power and global irradiance are null in the night-time, data sparsity will occur and will lead to a bad training model which negatively influences the model performance. To avoid this issue, night-time values are eliminated from the dataset and keeping values that exist between 07:00-18:00 in each day.

Scaling Data

Data variables used have a different scale. To avoid the domination of the feature that has a high-value range, scaling data is a must to take into consideration all features or variables equally without prioritizing any feature. Furthermore, feature scaling improves the calculation speed of the algorithm in the training phase and helps to converge rapidly. There are different scaling techniques, in our study, we used "Min Max scaler"to rescaled data into a particular range which is between 0 and 1. This technique uses the equation below to rescale data:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (6)$$

where X is the measured value and X_{scaled} is the scaled value.

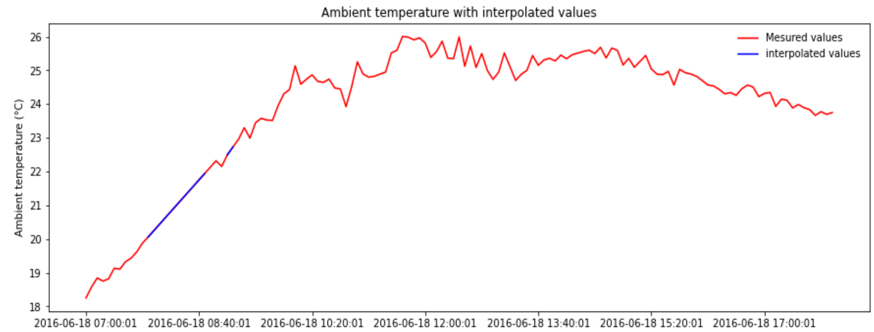
3.5 Proposed models

Univariate and multivariate models

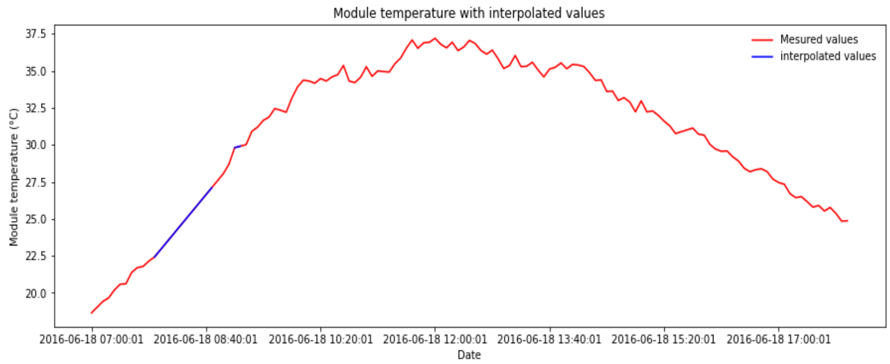
In our study, we used different models: The univariate model and the multivariate model. In the univariate model, we use only the historical PV power as input of the LSTM to forecast PV power. In the multivariate model, we have 7 models created by combining input variables: PV power, module temperature, ambient temperature, global irradiance. The combinations used in the multivariate are shown in Table 2.

Table 2
Input variables of the univariate model and the multivariate models

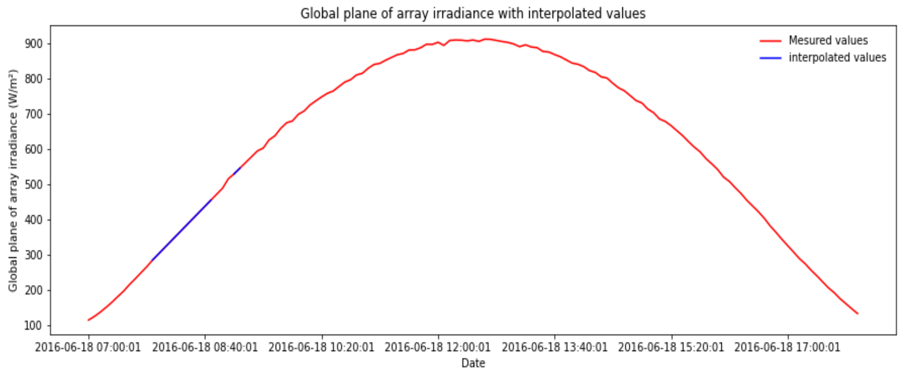
Model	Input variables
Univariate model	PV output power
Multivariate model	PV output power, Global plane of array irradiance
	PV output power, Module temperature
	PV output power, Ambient temperature
	PV output power, Global plane of array irradiance, Module temperature
	PV output power, Global plane of array irradiance, Ambient temperature
	PV output power, Module temperature, Ambient temperature
	PV output power, Global plane of array irradiance, Ambient temperature, Module temperature



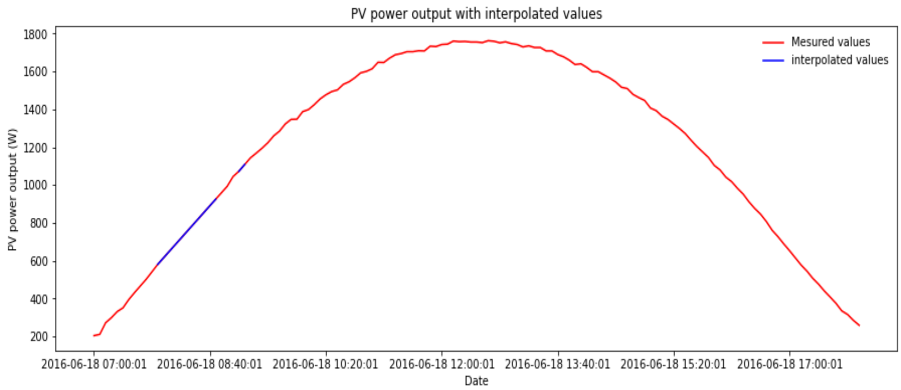
(a)



(b)



(c)



(d)

Fig 4. Variables interpolation for : a) ambient temperature, b)module temperature, c)global plane of array irradiance, d) PV power

Table 3
LSTM hyperparameters:

LSTM hyperparameters	Value
Number of hidden layers	1
Number of neurons	100
Look back	60 steps (5 hours)
Activation function	Tanh
Number of epochs	100
Batch size	200
Learning rate	0.001
Loss function	Mean squared error
Optimizer	Adam

One-step forecasting and multistep forecasting

One step forecasting is the task to forecast a single value in the future (x_{t+1}). For multistep forecasting is when we forecast a sequence of values ($x_{t+1}, x_{t+2}, x_{t+3}..$). one step is 5 min since the observations recorded each 5 min. In our study, we forecasted PV power output from 5 min ahead (1 step) to 1 hour ahead (12 steps) using the univariate model and the multivariate models.

LSTM parameters and setting for training

The hyperparameters of the LSTM model is presented in the Table 3. The structure of the LSTM model consists of one hidden layer, 100 neurons units, 60 values to look back, and the hyperbolic tangent as an activation function. For training setting, the maximum number of epoch or iterations is 100, the batch size is 200, the Learning rate is 0.001, the loss function is Mean Squared Error and the optimizer to reduce the loss is "Adam". It's worth mentioning that different look back has been tested to forecast the PV power, and the best value with low MAE has been chosen which is 60 steps.

3.6 Evaluation metrics

To compare different models, we evaluate the performance and accuracy of each one. The metrics used in our work are Root Mean Squared Error (RMSE) that penalizes large errors in square order, Mean Absolute Error (MAE) that shows the average distance between the measured values and the model predictions, and Coefficient of Determination (R^2) or Pearson's coefficient that indicates how correlated the forecasted and real values are (Alzahrani *et al.*, 2017).

RMSE equation is: (Alzahrani *et al.*, 2017)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_{pred} - P_{meas}\right)^2} \quad (7)$$

MAE equation is: (Alzahrani *et al.*, 2017)

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left| P_{pred} - P_{meas} \right| \quad (8)$$

R^2 equation is: (Alzahrani *et al.*, 2017)

$$R^2 = 1 - \frac{var(P_{pred} - P_{meas})}{var(P_{pred})} \quad (9)$$

Where P_{pred} and P_{meas} represent the predicted and measured values at time i respectively, and var is variance.

4. Results and discussions

4.1 One step and multistep PV power forecasting by using LSTM model

The models are trained by using the training set to give accurate results in PV power forecasting. Each LSTM model has an input combination and a forecasted time step. To evaluate the models, we used the test set data which are unseen data for the model that was not used for training. Furthermore, we calculated RMSE, MAE, and R^2 to measure the accuracy of the models and their performance. To analyze the results, we used figures and tables that showcase the accuracy and errors of the models.

One step forecasting (5 min ahead)

As we said earlier, one-step forecasting is when we forecast a single step in the future, in our case 5 min ahead. The Fig. 5 presents the true and predicted PV power. As shown in the Fig. 5, the models can predict very well the PV power output especially if the weather is stable with no clouds like we see on the day "2017-07-19". Furthermore, on the day "2017-07-18", there are some fluctuations in PV power, the models find some difficult to predict these fluctuations. However, the models still try to follow the trend and capture the global behavior of PV output power. Moreover, there is no significant difference in the predicted curve for different LSTM models. In order to compare the performance of the models, we use the table that presents RMSE, MAE, and R^2 for each model. As demonstrated in the Table 4, each model has a different error metrics value, and the best model, that has low errors and a strong correlation with actual PV power output, according to the table and figure is the univariate model that has only historical data of PV output power in the input of the model with an RMSE of 67.17W, an MAE of 35.52W and an R^2 of 98.53%. The highest error in all models is 74.58W in RMSE and 46.21W in MAE and get it from the model that uses all variables as input in LSTM. All the models have a strong correlation with the true values of PV output power.

To conclude, in one step forecasting the use of historical PV output power in LSTM input is sufficient to get accurate forecasting of PV power output. By using the univariate model, the measure and the collect of meteorological factors data is not necessary, which make the forecasting operation more available and easier to execute. The decrease of the input variable can reduce the time-consuming to preprocess the data and to train the LSTM model.

Table 4
Forecasting performance for one step forecasting

Time step	Combination	RMSE (W)	R^2	MAE (W)
	DC Power (W)	60.58	99%	29.03
	DC Power (W) and Global plane of array irradiance (W/m²)	60.7	99%	29.04
	DC Power (W) and Ambient temperature (°C)	60.23	99%	29.16
1	DC Power (W) and Module temperature (°C)	61.54	99%	31.81
	DC Power (W), Global plane of array irradiance (W/m²), Ambient temperature (°C) and Module temperature (°C)	61.51	99%	29.3
	DC Power (W), Ambient temperature (°C) and Module temperature (°C)	60.97	99%	29.18
	DC Power (W), Global plane of array irradiance (W/m²) and Ambient temperature (°C)	64.67	99%	35.39
	DC Power (W), Global plane of array irradiance (W/m²) and Module temperature (°C)	63.35	99%	33.65

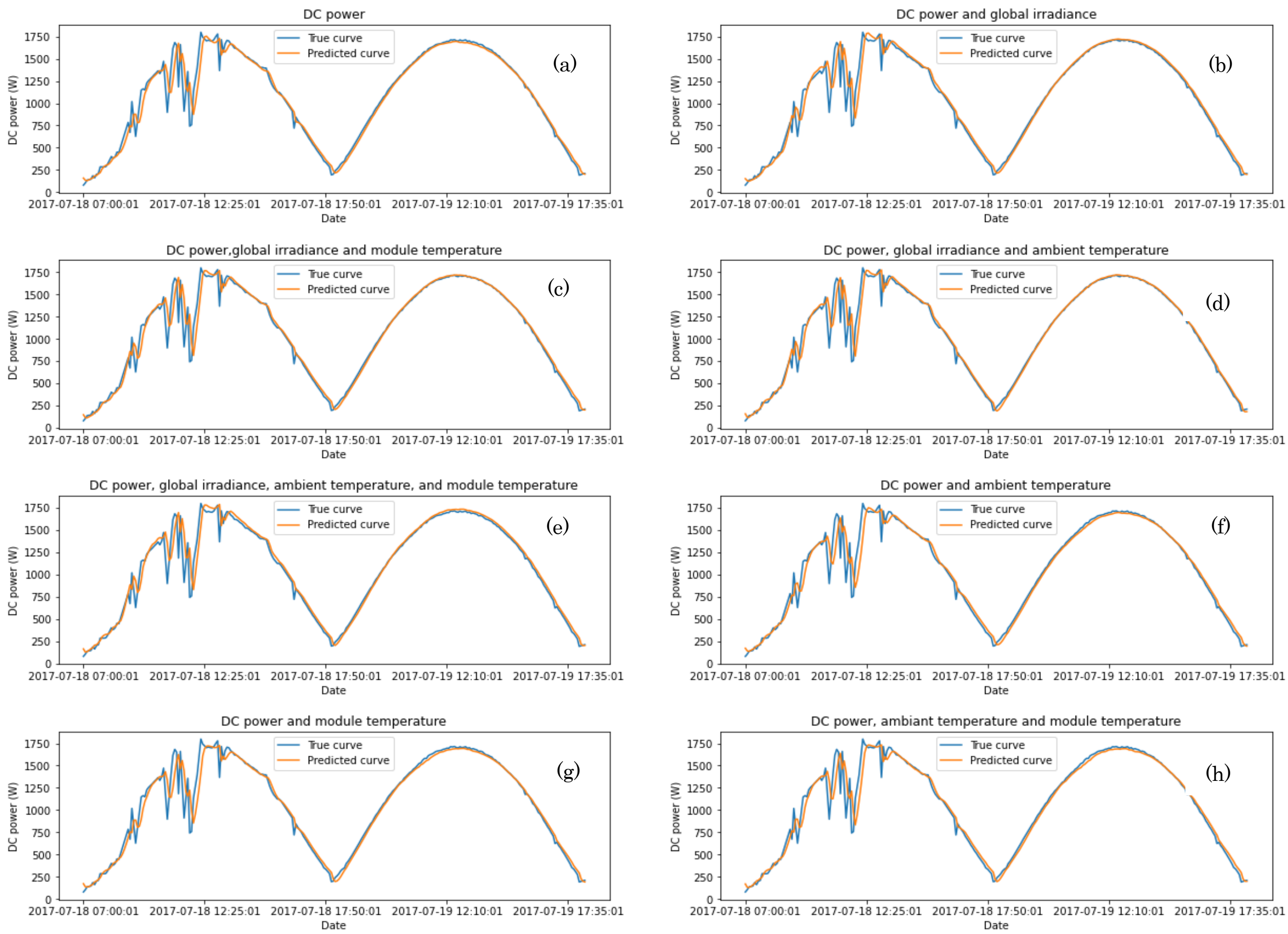


Fig 5. Actual values and predicted values curves by using different combinations of variables in LSTM model: a) DC power, b) DC power and global irradiance, c) DC power, global irradiance and module temperature, d) DC power, global irradiance and ambient temperature, f) DC and ambient temperature, g) DC power and module temperature, h) DC power, ambient temperature and module temperature

Table 5
Forecasting performance for multistep forecasting

Time step	Combination	RMSE (W)	R^2 (%)	MAE (W)
3 (15min)	-DC Power (W)	104.24	97%	66.082
	-DC Power (W) and Global plane of array irradiance (W/m²)	107.5	96%	71.87
	-DC Power (W) and Ambient temperature (°C)	101.91	97%	61.37
	-DC Power (W) and Module temperature (°C)	102.86	97%	64.117
	-DC Power (W), Global plane of array irradiance (W/m²), Ambient temperature (°C) and Module temperature (°C)	104.977	97%	50.97
	-DC Power (W), Ambient temperature (°C) and Module temperature (°C)	107.04	96%	69.64
	-DC Power (W), Global plane of array irradiance (W/m²) and Ambient temperature (°C)	99.85	97%	57.23
	-DC Power (W), Global plane of array irradiance (W/m²) and Module temperature (°C)	99.39	97%	56.7
6 (30 min)	-DC Power (W)	132.95	94%	85.79
	-DC Power (W) and Global plane of array irradiance (W/m²)	148.13	93%	109.36
	-DC Power (W) and Ambient temperature (°C)	134.18	94%	92.13
	-DC Power (W) and Module temperature (°C)	141.68	94%	101.53
	-DC Power (W), Global plane of array irradiance (W/m²), Ambient temperature (°C) and Module temperature (°C)	138.06	94%	85.76
	-DC Power (W), Ambient temperature (°C) and Module temperature (°C)	164.49	91%	128.02
	-DC Power (W), Global plane of array irradiance (W/m²) and Ambient temperature (°C)	127.48	95%	80.16
	-DC Power (W), Global plane of array irradiance (W/m²) and Module temperature (°C)	137.09	94%	96.05
9 (45min)	DC Power (W)	148.98	93%	97.3
	-DC Power (W) and Global plane of array irradiance (W/m²)	167.26	91%	127.45
	-DC Power (W) and Ambient temperature (°C)	114.69	93%	89.85
	-DC Power (W) and Module temperature (°C)	162.8	92%	120.15
	-DC Power (W), Global plane of array irradiance (W/m²), Ambient temperature (°C) and Module temperature (°C)	145.49	93%	104.94
	-DC Power (W), Ambient temperature (°C) and Module temperature (°C)	171.2	91%	129.62
	-DC Power (W), Global plane of array irradiance (W/m²) and Ambient temperature (°C)	160.37	92%	115.79
	-DC Power (W), Global plane of array irradiance (W/m²) and Module temperature (°C)	163.31	92%	120.98
12 (1h)	-DC Power (W)	195.12	88%	151.55
	-DC Power (W) and Global plane of array irradiance (W/m²)	197.99	88%	154.25
	-DC Power (W) and Ambient temperature (°C)	186.36	89%	135.33
	-DC Power (W) and Module temperature (°C)	160.76	91%	95.41
	-DC Power (W), Global plane of array irradiance (W/m²), Ambient temperature (°C) and Module temperature (°C)	185.63	89%	128.91
	-DC Power (W), Ambient temperature (°C) and Module temperature (°C)	191.66	88%	147.45
	-DC Power (W), Global plane of array irradiance (W/m²) and Ambient temperature (°C)	169.83	91%	119.55
	-DC Power (W), Global plane of array irradiance (W/m²) and Module temperature (°C)	172.94	91%	123.27

Multi step forecasting

In multistep forecasting, the models predict multi-timestep of PV output power in the future. In our work, the timesteps when the PV output power is forecasted are 15 min ahead, 30 min ahead, 45 min ahead, and 1h ahead. In multistep forecasting, we have multiple cases. For each timestep, we have 8 models that have different input variables. To avoid plotting plenty of curves for each model to compare their accuracy, we plotted only the best multivariate model predicted curve, the univariate model predicted curve and the actual curve of PV output power. The Table 5 presents the RMSE, MAE, and R^2 of forecasting models. As expected, the error increased with the timestep in all models that has different input variables. To compare between models, we focused on MAE as an indicator of model performance for each forecasted time step. For 15 min (3 steps) forecasting, the best model is a multivariate model that uses all variables as input

which are DC Power (PV output power), Global plane of array irradiance, Ambient temperature, and Module temperature, with an MAE equal to 50.97W, compared to the univariate model that has a value of 66.082W in MAE. As Fig. 6 shown, the multivariate model follows perfectly compared to the univariate model, the true values of PV output power when the weather is stable however if there is some fluctuation the model finds some difficult to follow the trend of actual PV output power. For 30 min (6 steps) forecasting, the best model is the one that uses historical DC power (PV output power), Global plane of array irradiance, and ambient temperature as input with an error equal to 80.16 W, whereas the univariate model has a value of 85.79W. The Fig. 6 shows that the multivariate and univariate models can predict PV output power when weather is stable but incapable of following the trend when there are clouds or fluctuations in the weather. For 45 min (9 steps) forecasting, the best model is the one that uses historical DC power (PV output power) and ambient temperature as input with an error equal to 89.85W, compared to other models especially the univariate model that have a value of 97.3W. As the Fig. 6 demonstrated, the multivariate model follows the actual curve of PV output power better than the univariate model when the weather is stable. For 1h (12 steps) forecasting, the accurate model is the one that uses historical DC Power, and module temperature as input variables to forecast PV output power and has a value of 95.41 in MAE, while the univariate model has a value of 151.55W. And we can see that by using Fig. 6, it shows that the curve of the multivariate model is close to the curve of actual values of PV output power compared to the univariate model curve when the weather is stable.
To sum up, in multistep forecasting of PV output power, the multivariate models that use more than historical PV output power as input in LSTM, are essential to get accurate forecasting of PV output power especially when the weather is stable, meanwhile, the univariate model is unable to predict PV output power accurately in multistep forecasting.

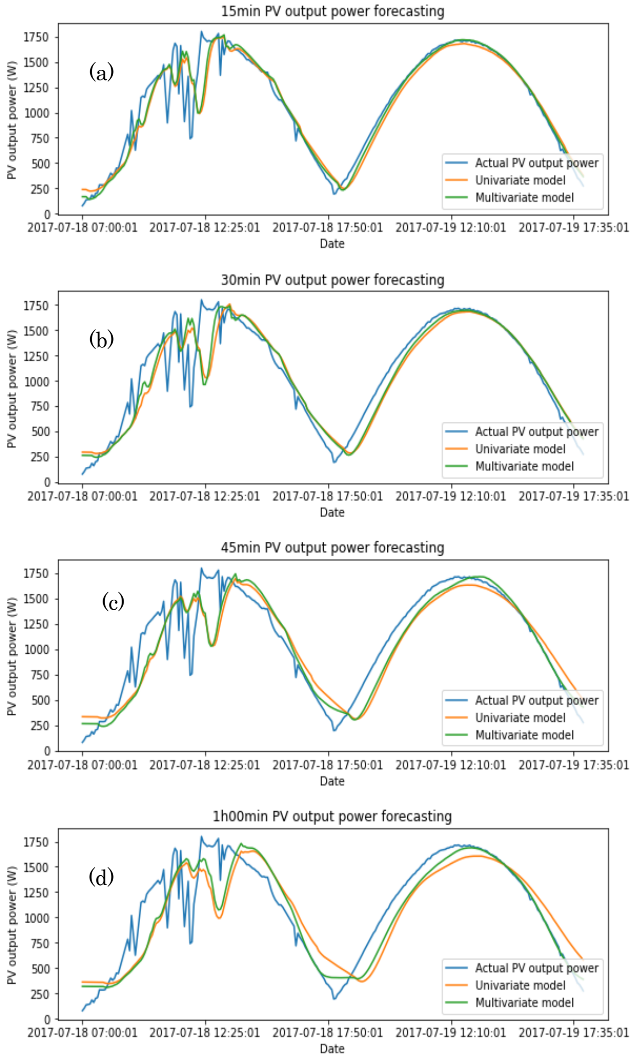


Fig 6. Comparison between the univariate model and the best multivariate model for each predicted timestep: a) 3 steps, b) 6 steps, c) 9 steps, d) 12 steps

4.2 Comparison of the proposed model with other forecasting models

Our proposed model is compared to different forecasting models to demonstrate its performance and accuracy in predicting the PV power. The models used for this comparison are reported in (Mellit *et al.*, 2021) and (Golder *et al.*, 2019), they have been implemented to use our data and forecast the PV power for one step and multistep.

The models are CNN (Convolutional neural network), and MLP (Multilayer perceptron). CNN is a regularized version of the popular feed-forward NNs. It was originally developed for 2D applications. It can also be employed to handle 1-dimensional problems including time series prediction and classification. The structure of CNN is shown in Fig. 6 (Mellit *et al.*, 2021). It has four layers which are convolutional layer, Max Pooling layer, Flatten layer and Dense layer. For MLP, it is a feed forward neural network where the back propagation technique is used for neural network learning (Desai & Shah, 2021). As Fig. 7 shows, The MLP model has an input layer, a hidden layer and an output layer in its structure

The model's parameters used for this work are:

- For CNN: Number of filters is 64, Kernel size is 3, activation function is Relu and Pool size is 2
- For MLP: Number of hidden layers is 1 and number of units is 100

The input used for this work for one step forecasting is historical of PV power only and for multistep is all the parameters (historical of meteorological parameters and PV power) to evaluate the accuracy of univariate and multivariate models for each deep learning model structure. The maximum number of timestep to predict is 12 steps (1h).

As shown in Table 6, MAE, RMSE and R2 have been calculated for one step and multistep PV power forecasting by using different deep learning models. By focusing on MAE, for one step of PV power forecasting (1 step), the LSTM model has an error of 28.9W, while the MAE of MLP and CNN models are respectively 39.94W and 57.76W. Therefore, the univariate LSTM outperformed the other models, also the MLP is more accurate than CNN. For multistep PV power forecasting, the MAE of the LSTM model for 3, 6, 9 and 12 steps forecasted are respectively 50.97W, 85.76W, 104.94W, and 128.91W. For MLP and CNN, they have respectively an MAE equal to 72.26W and

83.27W for 3 steps, 105.74W and 115.36W for 6 steps, 146.44W and 160.26W for 9 steps, 173.01W and 188.33W for 12 steps.

As expected, the error increases by increasing the forecasting horizon. The LSTM still outperformed all other models in multistep especially when the timestep predicted is high as the Table 7 shows for 6 steps, 9 steps and 12 steps. Therefore, The LSTM model can handle very well the long and short dependencies of the features more than other models which explain its capability to predict with great accuracy the PV power for one step and multistep forecasting. The CNN model is incapable of predicting the PV power accurately for all predicted time windows which makes this model unsuitable to be applied to PV power time series. However, by combining the CNN model with another model, especially the LSTM model, its accuracy can be enhanced and increased. The MLP model, shows a good accuracy compared to the CNN model. The MLP model only learns a mapping between inputs and outputs, and it doesn't have a memory, while the LSTM model has memory cells that can learn long dependencies over long sequences which explains its high accuracy.

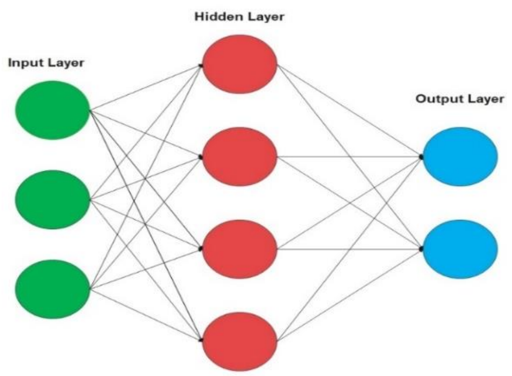


Fig. 7. MLP structure

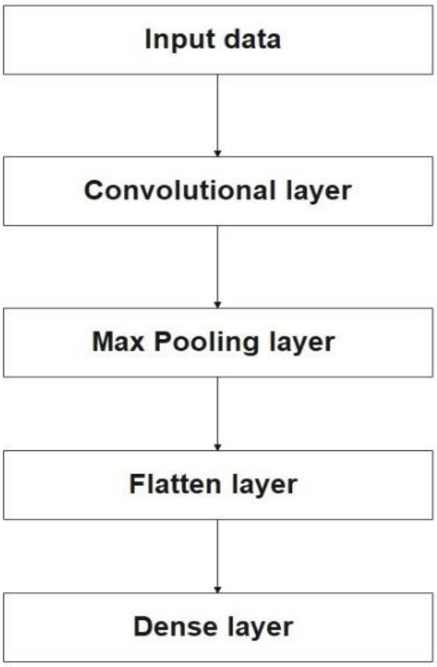


Fig.8. CNN structure

Table 6
Models evaluation

Time step	Model	MAE (W)	RMSE (W)	R2 (%)
1	LSTM	28.9	60.58	99%
	MLP	43.58	69.66	98.47
	CNN	75.41	103.05	96.6
3	LSTM	50.97	104.977	97%
	MLP	72.76	116.82	95.70
	CNN	101.86	130.18	94.67
6	LSTM	85.76	138.06	94%
	MLP	105.74	149.79	92.94
	CNN	117.45	153.85	92.55
9	LSTM	104.94	145.49	93%
	MLP	146.44	186.95	89.01
	CNN	146.94	185.60	89.16
12	LSTM	128.91	185.63	89%
	MLP	173.01	225.11	84.06
	CNN	186.66	230.019	83.36

4. Conclusions and future works

Integration of PV power into the electrical grid poses a great challenge for the stability and security of the electrical grid due to intermittent solar energy. Forecasting of PV output power is one of the solutions to limit the uncertainty of solar energy and integrate it effectively in the electrical grid. In this paper, a PV power ultra-short-term forecasting has been done by using univariate and multivariate LSTM models, different combinations of variables (history of meteorological variables and PV output power), and different time horizons (One step and multistep forecasting). For One step forecasting: the univariate model that has only the history of PV output power in the input of the LSTM model, predicts very well the PV power especially when the weather is stable. The MAE, RMSE, and R^2 of the univariate model are respectively 29.03W, 60.58W, and 99% which represent the best performance compared to the other models (Multivariate models). In this case, the measure of meteorological factors is not mandatory to forecast the PV output power for one step ahead and adding more variables in the input of the LSTM model is not necessarily improve the accuracy of the model. For Multistep forecasting, different timestep has been predicted from 15 min to 1h. the multivariate models that use more than historical PV output power as input in LSTM, are essential to get accurate forecasting of PV output power, and the univariate model isn't sufficient and is unable to forecast PV output power accurately. Moreover, a comparison study between LSTM model and other forecasting models has been done to assess the accuracy of the LSTM model. The results show that LSTM outperform the MLP and CNN models especially in multistep PV power forecasting.

For future works, the use of different meteorological factors will be considered like wind speed, humidity, etc., to study their influence on the accuracy of models for one-step and multistep forecasting of PV output power.

Moreover, the choice of hyperparameters of the LSTM model and parameters of model training will be optimized to get the best accuracy in forecasting results.

Abbreviation

PV	Photovoltaic
LSTM	Long short-term memory
MLP	Multilayer perceptron
CNN	Convolutional neural network
MAE	Mean Absolute Error
DG	Distributed generation
NWP	numeric weather predictor
ARMAX	Autoregressive–moving-average model with exogenous inputs
ARIMA	auto-regressive integrated moving average
SARIMA	Seasonal Autoregressive Integrated Moving Average
TES	triple exponential-smoothing
SVM	Support-vector machine
RF	random forest
ET	Extra trees
SVR	support vector regression
ANN	Artificial Neural Network
WT	Wavelet transform
GA	Genetic Algorithm
kNN	k-nearest neighbors
BPNN	backpropagation neural network
RBFNN	radial basis function neural network
GHI	Global Horizontal Irradiance
GRU	Gated Recurrent Units
RNN	Recurrent neural network
FFNN	Feedforward neural network
RFR	random forest regression
DNN	Deep neural network
WPD	Wavelet packet decomposition
GRA	grey relational analysis
DC	Direct current
MPPT	Maximum power point tracking
Adam	adaptive moment estimation
SGD	stochastic gradient descent
RMSE	Root Mean Squared Error

Funding: The author(s) received no financial support for the research, authorship, and/or publication of this article.

Conflicts of Interest: The authors declare no conflict of interest.

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