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Photovoltaic generation forecasting using convolutional and recurrent neural networks☆

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A R T I C L E I N F O

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A B S T R A C T

Due to climate change consequences, it is very important to replace fossil energy resources with renewable energy resources. Solar energy is one of the main types of renewable energy resources which is harnessed by Photovoltaic (PV) Cells. It is important to accurately forecast how much electricity these energy resources generate to help operate and maintain the electricity grid. But the generation of electricity by PV is often associated with large uncertainty due to varying features like radiation, wind, humidity, and temperature. Deep learning methods have proved useful for this forecasting problem but the spatial information of features for this type of method has not received the due attention for PV generation forecasting. This study aimed to explore how both spatial and temporal information can be considered via a deep learning approach. In this paper, we propose a PV generation forecaster that considers both spatial and temporal information. A convolutional neural network is used as a pre-processing step to capture spatial information. The convolutional neural network is followed by a gated recurrent unit neural network to model temporal characteristics. The proposed model enriches the forecaster model by feeding more meaningful features into the recurrent neural network rather than raw data. The proposed model can predict a horizon for which there is no available information on irradiance, humidity, or wind. We show experimentally that our method is competitive with the state-of-the-art in terms of time and memory requirement while resulting in better prediction performance. The proposed model is applied to real data collected by the research team, and its performance is compared with some state-of-the-art methods. The results show the advantage of the proposed method.

1. Introduction

Power networks and energy consumers are undergoing a fundamental shift in the way traditional energy systems were designed and managed in the past. Having the possibility of energy generation onsite has also enabled flexible consumption, which is transforming consumers from passive users to active services. The prosumer-centric paradigm brings many possibilities by introducing real-time pricing, which creates new opportunities for the local energy exchange. This will eventually allow more prosumers in microgrids creating many new opportunities for aggregation and more importantly, enabling local energy production. This new paradigm requires some new technologies to be developed for the Smart Grid. An accurate forecast of electricity generation from renewable resources is a key aspect of this new paradigm. Generation is required to be accurately forecasted to enable augmentation of grid stability and market feasibility, bringing practical feasibility for an open-market energy trading option. Solar energy is the most popular alternative to conventional energy resources among prosumers (Sobri et al., 2018). Nevertheless, power generation from PV cells is often associated with large uncertainty due to environmental conditions such as cloudiness, temperature, radiation, and humidity (Sobri et al., 2018). A lack of accurate generation forecasts may impact grid stability, power imbalance, frequency responses, and power compensation. The uncertain nature of PV generation imposes some risks by connecting large-scale PV systems to the power grid (Al Khafaf et al., 2022). A solution is the use of battery banks to moderate imbalances (Zhou et al., 2019), but this solution is often costly and not feasible for prosumers. Therefore, it is crucial to develop a highly accurate model which can forecast PV power generation. Eventually, this forecast for the photovoltaic systems (PV) can be integrated within the bidding scheme

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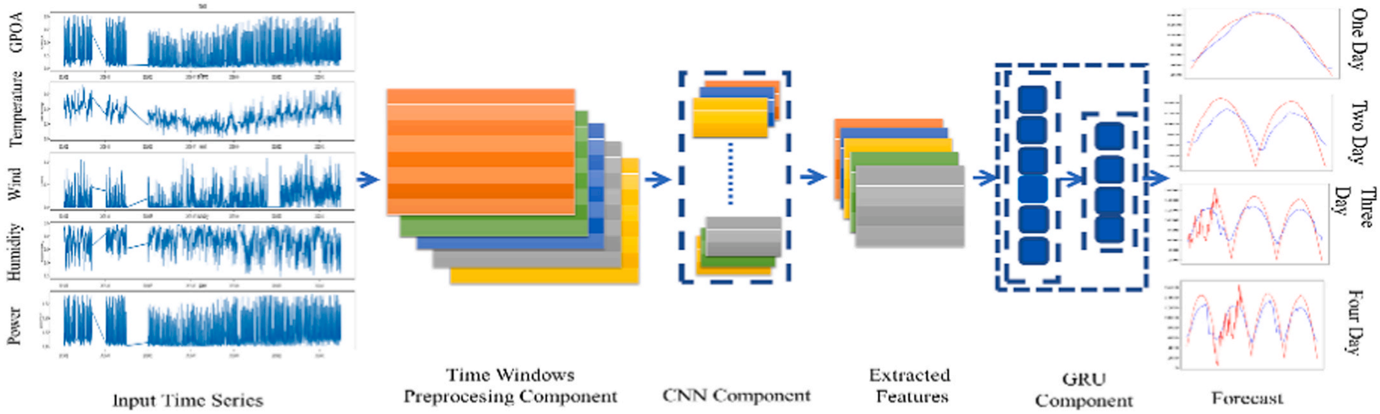

Fig. 1. Framework of the CNN-GRU.

Table 1
Implementation details.

	Layers	Neurons	Optimizer	Activation Function	Loss Function	DropOut
GRU	GRU 1	64	adam	Linear	MSE	0.2
	GRU 2	32				
LSTM	LSTM	64	adam	Linear	MSE	0.2
CNN-GRU	Zero Paddinng		adam	Linear	MSE	0.2
	1D-Covolution	32				
	1D-Pooling					
	GRU 1	64				
	GRU 2	32				
CNN-LSTM	Zero Paddinng		adam	Linear	MSE	0.2
	1D-Covolution	32				
	1D-Pooling					
	LSTM	64				

Table 2
Forecasting performance for all horizons (the number between parentheses represents standard deviation over 10 runs).

		MAE	RMSE	MAPE	R2
One–Day	CNN-GRU	**0.076 (±0.015)**	**0.093 (±0.017)**	**10.15 (±1.30)**	**0.93 (±0.028)**
	CNN-LSTM	0.090 (±0.025)	0.115 (±0.029)	12.65 (±2.49)	0.89 (±0.053)
	GRU	0.081 (±0.025)	0.099 (±0.026)	10.83 (±2.14)	0.92 (±0.046)
	LSTM	0.104 (±0.024)	0.125 (±0.029)	14.55 (±2.90)	0.86 (±0.059)
Two-Day	CNN-GRU	**0.19 (±0.019)**	**0.22 (±0.018)**	**27.34 (±1.24)**	**0.60 (±0.078)**
	CNN-LSTM	0.22 (±0.025)	0.24 (±0.025)	28.73 (±3.06)	0.54 (±0.111)
	GRU	0.22 (±0.015)	0.24 (±0.014)	30.15 (±1.91)	0.53 (±0.067)
	LSTM	0.23 (±0.030)	0.25 (±0.027)	30.10 (±6.17)	0.49 (±0.120)
Three-Day	CNN-GRU	**0.18 (±0.016)**	**0.23 (±0.017)**	**25.33 (±1.66)**	**0.59 (±0.062)**
	CNN-LSTM	0.19 (±0.015)	0.24 (±0.011)	25.90 (±2.93)	0.58 (±0.041)
	GRU	0.21 (±0.027)	0.26 (±0.022)	26.62 (±4.07)	0.50 (±0.086)
	LSTM	0.19 (±0.026)	0.23 (±0.026)	25.43 (±4.08)	0.59 (±0.098)
Four-Day	CNN-GRU	**0.19 (±0.018)**	**0.23 (±0.015)**	**34.80 (±3.24)**	**0.63 (±0.049)**
	CNN-LSTM	0.22 (±0.021)	0.26 (±0.021)	41.90 (±5.80)	0.51 (±0.071)
	GRU	0.27 (±0.038)	0.31 (±0.042)	46.39 (±5.66)	0.30 (±0.181)
	LSTM	0.23 (±0.038)	0.27 (±0.037)	40.35 (±4.80)	0.49 (±0.139)

maximizing the prosumer's commitment in the forward market.

PV generation forecasting is crucial to stabilize PV-connected grids (Zhou et al., 2019). particularly, the day-ahead forecast is of high value. It has applications in unit commitment, storage system management, scheduling of transmission (Sangrody et al., 2020), and capacity firming (Keerthisinghe et al., 2020). The other important application of forecasting is the detection of ramps and anomalies by comparing the prediction with real power generation (Ahmad et al., 2018). Generally, methods for PV generation forecasting are divided into three main groups: statistical, machine learning, and ensemble methods (Sobri et al., 2018; Agency, 2019; da Fonseca et al., 2020; Ismail et al., 2015; Lan et al., 2018; Li et al., 2018; Liu and Sun, 2019; Zheng et al., 2018; van der Meer et al., 2018; Zang et al., 2020; Zhou et al., 2020). It has been shown that machine learning and ensemble methods often outperform statistical methods (Ferlito et al., 2017).

The first category, statistical models, relies on historical data. Statistical models are often sensitive to the noise in data. As such, they are not robust to unpredictable noises caused by rainy or cloudy days (Pieri et al., 2017). Linear models like Autoregressive (AR) and AR moving-average (ARMA) have been applied for PV generation forecasting (Pieri et al., 2017). They are being used for time series forecasting as well. However, the assumption of linear relationships may not work well for many real-world applications. Maximum Lyapunov Exponent (MLE) is a non-linear time series analysis method. It does not directly model the relation between input and output, but it models the dynamic evolution of the data based on the exponential separation characteristic of the data. Zheng et al. (2018) employ MLE for PV forecast on a real-world dataset from China.

The second category, Machine learning models have proved to be useful in modeling non-linear relations between historical data and target forecasts. They have been used in many applications; see a review in Voyant et al. (2017). Machine learning models, unlike physical or

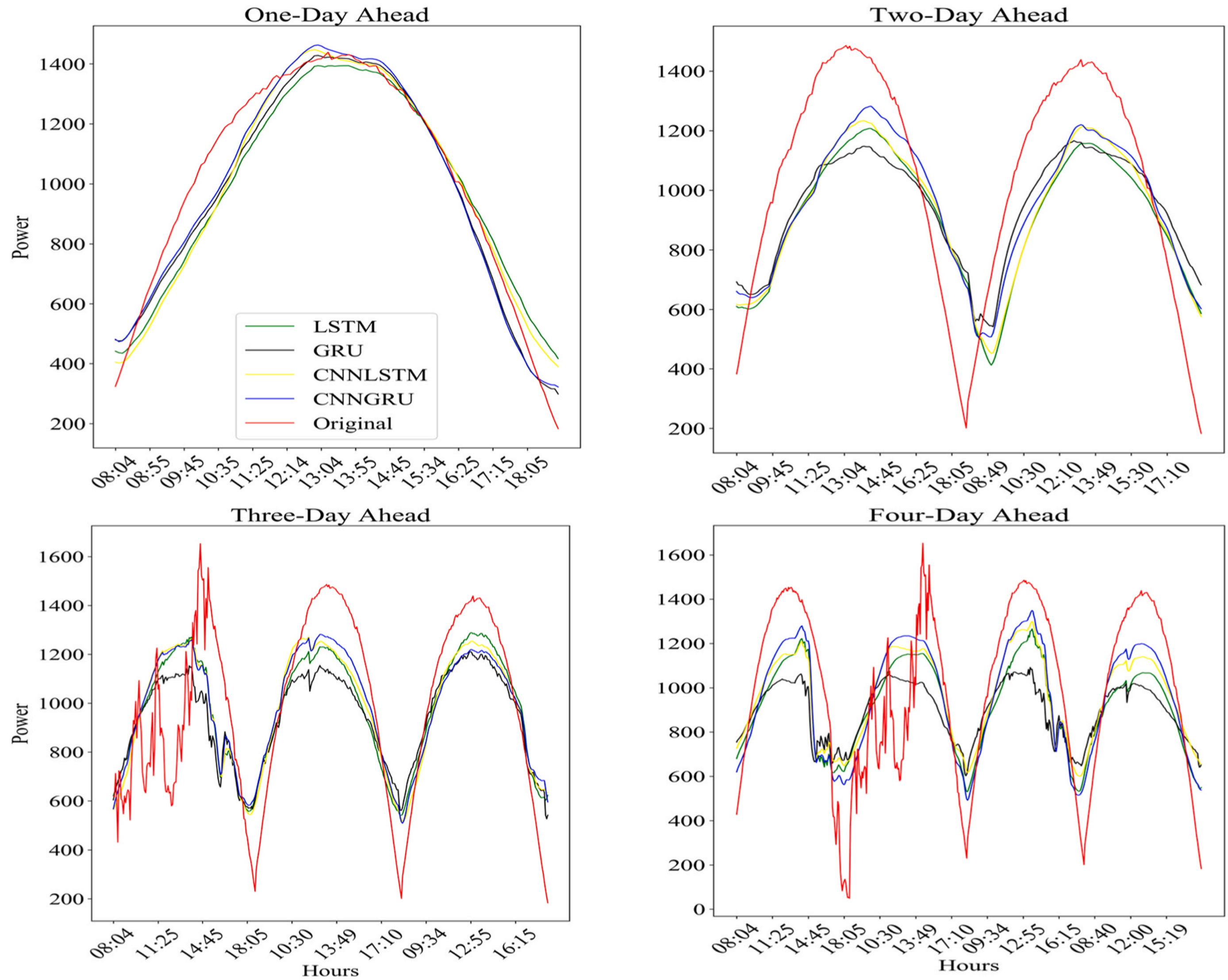

Fig. 2. All models forecasting against ground truth over the horizons. CNN-GRU show gain over all methods in all horizons. In all horizons, we don't use available features associated with the horizons as input. We only use past information to do forecasting.

statistical models, do not need expensive equipment, and they can model non-linear complex structures. Some methods in this category include Artificial Neural Networks (Alipour et al., 2020; Huang and Kuo, 2019; Lee et al., 2018), Support Vector Machine (SVM) (Jiang and Dong, 2016), and Tree-based methods (Ahmad et al., 2018; Wang et al., 2018). Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) are recent machine learning models that have been applied to forecasting problems. RNN was originally designed to model sequential data due to the memory capacity they possess. Long Short-Term Memory (LSTM) is a recent version of RNN that is more suitable to model long-term dependencies. Wen et al. (2019) have applied it to a PV dataset from Austin, Texas. Keerthisinghe et al. (2020) compared different neural networks including LSTM, encoder-decoder LSTM, and Multi-Layer Perceptron (MLP) on data from Washington, USA. They proved empirically that recurrent neural networks like LSTM work better for PV generation forecasts. Yao et al. (2019) compared CNN and LSTM on data from Alice Spring, Australia. They found again that LSTM works better since it considers temporal information.

In this paper, we propose a novel PV generation forecaster that combines CNN with Gated Recurrent Unit (GRU) network. The CNN automatically extracts the spatial relationships, while the GRU extracts temporal information. To the best of our knowledge, this is the first time that such an automated feature extraction preprocessing is developed to tackle this drawback of RNN models. The contributions of our work are as follows:

- Develop a novel PV generation forecast method that takes advantage of the CNNs integrated with GRU. This combination of CNN and GRU is new in the literature.
- Unlike the previous works, our method is capable of forecasting PV power generation even for horizons without any available feature values. While it results in better prediction performance than state-of-the-art, it is competitive in terms of time and memory complexity.

We apply the proposed prediction algorithm to a high-resolution dataset we collected. The data include the most important features in the literature including the plane of array irradiance (GPOA), humidity, temperature, wind, and power collected with a five-minute resolution.

2. Materials and methods

2.1. Problem definition

Our problem is to forecast power generated by PV cells based on some inputs including GPOA, humidity, temperature, and wind speed. Let $O = \{O_1, O_2, \ldots, O_T\}$ be the historical data sampled for T time steps. Let $O_i = (F_{i,0}, F_{i,1}, \ldots, F_{i,N-1}, P_i)$ be one sample at time step i where F denotes the input vector and P denotes the generated power. For our case, F includes GPOA, humidity, temperature, and wind speed. Let's consider a time window l and horizon h. Also, consider that j is the current time step until which we sample the data. Given $\langle O, l, h\rangle$, our problem is to forecast P_{j+h} using $[O_{j-l}, O_j]$. We express the prediction problem as follows:

$$P_{t+i} = f(P_{t-i}, G_{t-i}, H_{t-i}, T_{t-i}, W_{t-i}); i = 0, \ldots, w \tag{1}$$

$$P_{t+2\times i} = f(P_{t-i}, G_{t-i}, H_{t-i}, T_{t-i}, W_{t-i}); i = 0, \ldots, w \tag{2}$$

$$P_{t+3\times i} = f(P_{t-i}, G_{t-i}, H_{t-i}, T_{t-i}, W_{t-i}); i = 0, \ldots, w \tag{3}$$

$$P_{t+4\times i} = f(P_{t-i}, G_{t-i}, H_{t-i}, T_{t-i}, W_{t-i}); i = 0, \ldots, w \tag{4}$$

Where G is GPOA, H is humidity, T is temperature and W is wind. i ranges from 0 and 130 which means we use the time window including 130 points of the past information from time step t. The number 130 represents the past day, each day is presented via 130 points. Our goal is to estimate the function f and we use deep learning.

2.2. Data

We collect the PV generation data from 1st January 2019–31 st January 2020, between 8 am and 7 pm on a five-minute scale from the city of Mar del Plata in Buenos Aires province of Argentina which is a coastal city. It is the most populated city in the region and has many industrial facilities. It has a great capacity for PV installation. In addition to PV-generated power, we collect some informative features including solar irradiance (GPOA), Humidity, Temperature, and Wind to enhance the performance of the forecasting process. In Argentina, Spring includes September to November. Summer includes December to February, Autumn refers to March to May, and Winter refers to June to August.

2.3. Experimental PV plant

The PV plant includes 18 PV modules, each generating a maximum of 285 W. We install three strings, as shown in Fig. 1, which collectively generate 5.13kWp. The plant provides electricity for the daily consumption of the faculty building. They are north-facing (S38^{0}0′43.35″W57^{0}34′54.11″) inside the Facultad de Ingeniería complex.

2.4. Sensors and data recordings

It is very important to record solar irradiance during the day in all seasons. To that end, we use two different irradiance sensors. The first one, which is horizontal, is installed at Davis Vantage Pro II weather station, 5 m away from PV plant. The second is installed in the tilted surface attached to modules. By doing so, both horizontal and inclined irradiance are recorded. The resolution of horizontal sensors is 1 w/m^2. Its range is 1800 w/m^2 and nominal accuracy is 5 % of the output of the inclined sensor $V_r = (13.9 \pm 0.3)\mu V$ which was calibrated against an Eppley Lab Pyranometer, model PSP,S/N 10566 F4. In general, we use three different types of sensors to record irradiance, meteorological, and power data. To get horizontal irradiance and meterological from Davis station, we use Weatherlink software. External air temperature was also recorded. A PQube device records dc and ac variables of three strings. It averages the data every 10 s and saves it on PQube every 5 min. All three types of sensors were synced via a Network Time Protocol (NTP) with Argentina Time Zone (ART). There is also a nighttime offset in the tilted irradiance sensors.

2.5. Proposed forecasting method

Fig. 1 shows the framework of the proposed model, called CNN-GRU. It starts with passing time series data as input to the first component, i.e., Time Window Preprocess, which converts the raw time series to windows. Then, the windows are fed to CNN component, to process the feature vectors and extract important features regardless of temporal information. Then, the extracted features are fed into GRU component to extract temporal information and complete the prediction task.

2.6. CNN component

The success of CNN in image processing applications served as a motivation to adopt it for feature extraction in time series data (Wang et al., 2019). Unlike fully connected neural networks, i.e., multi-layer perceptrons, CNN is founded on weight-sharing and local connections between neurons. Common CNN mainly consists of three types of layers, convolutional layer, pooled layer, and fully connected layer. The convolutional layer aims to map local feature inputs into a low-dimensional output feature space, called feature map, using a sliding filter. It may use several convolutional kernels (also named filters). In this work, the input of the convolutional layer is a time window of the original features. Then, the pooled layer applies statistical operations on every element of feature map to provide new representations. The statistical operation considers the nearby information of each element in feature map. Eventually, in some cases, one fully connected layer is applied based on the target downstream task. We disregard the last layer and pass the output of the pooling layer to the next component, i.e., GRU.

The operation in the convolutional layer l is formulated as follows:

$$y_j^{(l)} = \left(\sum_{i\in K_j} t_i^{(l-1)} \otimes w_{i,j}^{(l)}\right) + b_j^{(l)} \tag{5}$$

$$t_j^{(l)} = Relu\left(y_j^{(l)}\right) \tag{6}$$

Where $t_j^{(l)}$ is j-th feature map associated with layer l. K_j is the set of feature maps. $y_j^{(l)}$ is the output of convolution operation. $w_{i,j}^{(l)}$ is the convolution kernel. $b_j^{(l)}$ is the bias. The layer runs several convolution operations simultaneously to create different feature maps. Then, a rectified linear activation function is applied on all cells. In pooling layer, we use the average measure as our statistical operation (Wang et al., 2019).

2.7. GRU component

After extracting spatial features using CNN component, we employ GRU for prediction purposes. GRU and LSTM are the most common variants of RNN models due to their capability in addressing gradient vanishing/exploiting the challenge of vanilla RNNs. In comparison with LSTM, GRU has fewer gates which reduce the complexity of GRU, while it gives a competitive or even better performance compared to LSTM. There are two types of gates in a GRU cell, a reset gate r that decides whether to ignore the previous hidden state and an update gate z that selects whether the output of the current state is updated via $\widetilde{h}$. We express the process as follows:

$$z^{(t)} = \sigma\left(w_z \bullet \left(h^{(t-1)}, x^{(t)}\right) + b_z\right) \tag{7}$$

$$r^{(t)} = \sigma\left(w_r \bullet \left(h^{(t-1)}, x^{(t)}\right) + b_r\right) \tag{8}$$

$$\widetilde{h}^{(t)} = \tanh\left(w_{\widetilde{h}^{(t)}} \bullet \left(h^{(t-1)} \odot r^{(t)}\right) + u_{\widetilde{h}^{(t)}} x^{(t)} + b_g\right) \tag{9}$$

$$h^{(t)} = z^{(t)} \odot h^{(t-1)} + \left(1 - z^{(t)}\right) \odot \widetilde{h}^{(t)} \tag{10}$$

Where $z, r, \widetilde{h}$ and h are results of update gate, reset gate, candidate activation and output gate respectively. σ is the sigmoid activation function and $\tanh$ is the hyperbolic tangent activation function.

2.8. Implementation details

We use python 3.7.6 in Spyder 4.0.1 platform. We use Tensorflow 1.14.0 and Keras library to develop the neural network. The implementation details of each network are explained in Table 1.

3. Results and discussion

In this section, we discuss the results of the proposed method CNN-GRU, and three state-of-the-art baselines including LSTM, GRU, and CNN-LSTM. For evaluating the performance of our method and other baselines, we use three widely used performance measures including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R2 measure. First, we compare the performance of models on four short-term horizons, i.e., one-, two-, three-, and four-day ahead with the resolution of 5 min, according to historical data we used. Then, we visualize the Power Generation predictions of the models for one day to illustrate the better capability of our model. Means and standard deviations are obtained by the results of 10 independent runs. We apply a grid search over the hyperparameters including the number of neurons $\in \{16, 32, 64, 128\}$, number of layers $\in \{1, 2, 3, 4\}$, the optimizer $\in \{Adam, SGD, RMSProp, Adagrad\}$, and the activation function $\in \{Linear, Relu, Sigmoid, Tanh\}$ for training the model.

Table 2 demonstrates that for all horizons the proposed model constantly improves the performance of predictions overall metrics. CNN-GRU, as the name implies, utilizes GRU model for RNN component of the proposed method. GRU has less structural complexity compared with the other variant of RNN (i.e. LSTM), allowing it to better increase the model generalizability and deal with the over-fitting problem. In essence, the higher structural complexity of LSTM is due to the higher number of parameters of neuronal units. The results show that using CNN component as a feature pre-processing step in CNN-LSTM considerably improves the forecasting performance of LSTM by facilitating the process of fitting the model parameters. Yet, CNN-LSTM suffers from a lack of model generalizability and it is more prone to overfitting due to higher complexity.

As a rule of thumb, PV generation forecasting models use all the features, like humidity, temperature, irradiance, not only for training the models but also during the prediction process. This means that for a specific horizon, they exclude PV power generation information from the data, and feed the rest of the features to the model for predicting PV generation. Our model disregards all features for the intended horizon during the prediction process. Fig. 2 illustrates the predicted and real values, where the predictions made by CNN-GRU are the closest to the real values. CNN-LSTM achieves the second-best forecasting results.

4. Conclusion

Climate change affects the way we generate power. Renewable energy is an important alternative to conventional power resources. PV is one of the main tools to generate power from renewable energy. But there is a great deal of uncertainty associated with PV power generation, due to dependency on varying features like temperature, wind, humidity, etc. This uncertainty might affect the power grid and create instability. Therefore, it is important to have an accurate forecast of the power generated by PVs. In this paper, we developed a novel PV generation forecasting, called CNN-GRU, by integrating CNNs with GRUs. The former learns the spatial features, and the latter captures temporal information associated with the data. We collected high-resolution data from the city of Mar del Plata in Buenos Aires province of Argentina which is a coastal city with five minutes of granularity. The data included six measurement features including generated power, irradiance, humidity, temperature, and wind, features over one year. For model evaluation, we compared the proposed model with three state-of-the-art methods, including LSTM, GRU, and CNN-LSTM. Our experiments showed that the proposed method outperforms all baselines.

Declaration of Competing Interest

The authors declare no conflict of interest.

Data availability

The authors do not have permission to share data.

References

Agency, I.E., Trends in PV applications 2019.
Ahmad, M.W., Mourshed, M., Rezgui, Y., 2018. Tree-based ensemble methods for predicting PV power generation and their comparison with support vector regression. Energy 164, 465–474.
Al Khafaf, N., et al., 2022. Impact of battery storage on residential energy consumption: an Australian case study based on smart meter data. Renew. Energy 182, 390–400.
Alipour, M., et al., 2020. A novel electrical net-load forecasting model based on deep neural networks and wavelet transform integration. Energy, 118106.
da Fonseca, J.E.F., et al., 2020. Degradation analysis of a photovoltaic generator after operating for 15 years in southern Brazil. Sol. Energy 196, 196–206.
Ferlito, S., Adinolfi, G., Graditi, G., 2017. Comparative analysis of data-driven methods online and offline trained to the forecasting of grid-connected photovoltaic plant production. Appl. Energy 205, 116–129.
Huang, C.-J., Kuo, P.-H., 2019. Multiple-input deep convolutional neural network model for short-term photovoltaic power forecasting. IEEE Access 7, 74822–74834.
Ismail, A.M., et al., 2015. Progress of solar photovoltaic in ASEAN countries: a review. Renew. Sustain. Energy Rev. 48, 399–412.
Jiang, H., Dong, Y., 2016. A nonlinear support vector machine model with hard penalty function based on glowworm swarm optimization for forecasting daily global solar radiation. Energy Convers. Manag. 126, 991–1002.
Keerthisinghe, C., et al., 2020. Improved PV forecasts for capacity firming. IEEE Access 8, 152173–152182.
Lan, H., et al., 2018. Day-ahead spatio-temporal forecasting of solar irradiation along a navigation route. Appl. Energy 211, 15–27.
Lee, W., et al., 2018. Forecasting solar power using long-short term memory and convolutional neural networks. IEEE Access 6, 73068–73080.
Li, Q., Wu, Z., Xia, X., 2018. Estimate and characterize PV power at demand-side hybrid system. Appl. Energy 218, 66–77.
Liu, D., Sun, K., 2019. Random forest solar power forecast based on classification optimization. Energy 187, 115940.
Pieri, E., et al., 2017. Forecasting degradation rates of different photovoltaic systems using robust principal component analysis and ARIMA. IET Renew. Power Gen. 11 (10), 1245–1252.
Sangrody, H., Zhou, N., Zhang, Z., 2020. Similarity-based models for day-ahead solar PV generation forecasting. IEEE Access 8, 104469–104478.
Sobri, S., Koohi-Kamali, S., Rahim, N.A., 2018. Solar photovoltaic generation forecasting methods: a review. Energy Convers. Manag. 156, 459–497.
van der Meer, D.W., et al., 2018. Probabilistic forecasting of electricity consumption, photovoltaic power generation and net demand of an individual building using Gaussian processes. Appl. Energy 213, 195–207.
Voyant, C., et al., 2017. Machine learning methods for solar radiation forecasting: a review. Renew. Energy 105, 569–582.
Wang, J., et al., 2018. A short-term photovoltaic power prediction model based on the gradient boost decision tree. Appl. Sci. 8 (5), 689.
Wang, K., Qi, X., Liu, H., 2019. Photovoltaic power forecasting based LSTM-Convolutional Network. Energy 189, 116225.
Wen, L., et al., 2019. Optimal load dispatch of community microgrid with deep learning based solar power and load forecasting. Energy 171, 1053–1065.
Yao, X., Wang, Z., Zhang, H., 2019. A novel photovoltaic power forecasting model based on echo state network. Neurocomputing 325, 182–189.
Zang, H., et al., 2020. Day-ahead photovoltaic power forecasting approach based on deep convolutional neural networks and meta learning. Int. J. Electric. Power Energy Syst. 118, 105790.
Zheng, L., et al., 2018. Very short-term maximum Lyapunov exponent forecasting tool for distributed photovoltaic output. Appl. Energy 229, 1128–1139.
Zhou, H., et al., 2019. Short-term photovoltaic power forecasting based on long short term memory neural network and attention mechanism. IEEE Access 7, 78063–78074.
Zhou, Y., et al., 2020. Prediction of photovoltaic power output based on similar day analysis, genetic algorithm and extreme learning machine. Energy, 117894.