Physics informed graph neural networks for multi-site solar forecasting

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PHYSICS INFORMED GRAPH NEURAL NETWORKS FOR MULTI-SITE SOLAR FORECASTING

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ABSTRACT: Accurate forecasting of photovoltaic (PV) power generation is crucial for efficient electricity management and market trading. Traditional data-driven models, while providing state-of-the-art accuracy for short-term forecasts, often suffer from limited generalization when facing data that deviates from their training distribution. Additionally, these models typically produce smooth forecasts that fail to capture the intricate dynamics of cloud movements, crucial for predicting solar irradiance, a primary driver of PV output. To address these challenges, we introduced a physics-informed graph neural network (PING) model that estimates the particle velocities of the historical input data, in an unsupervised fashion, and forecasts the future particle concentration values of advection-diffusion processes. In this paper we propose the combination of PING with our previously developed model, the Graph Convolutional Long-short term memory (GCLSTM) network, for multi-site PV power forecasting tasks. Numerical results showed that PING + GCLSTM outperforms all benchmarks on the entire horizon showing a daytime normalized root-mean-square error, overall sites, between 7% and 13% for 15 minutes and 6 hours ahead prediction, respectively.
Keywords: Physically informed neural network, machine learning, power forecasting

1 INTRODUCTION

Accurate forecasting of photovoltaic (PV) power generation is vital for improving electricity management, power system scheduling and trading on the electricity market. Cloud formation and movement directly influence irradiance, the main driver of PV power generation. Since they are guided by advection-diffusion processes, predicting such processes is essential for accurate forecasting of PV power.

Numerical solvers, which are traditionally used to solve the physical equations that describe the advection-diffusion processes, are computationally expensive [1]. For forecasting purposes, pure data-driven methods are attractive since they accelerate inference by a factor 40 to 80 [2] but their ability to reliably generalize is limited. To improve physical consistency, physics-informed neural networks (PINNs) are trained with a loss function that incorporates physical equations describing the underlying process [3]. However, most PINN models solve the tasks on regular grids, while forecasting data from sensor networks represents a problem that inherently lies on an irregular grid. On the other hand, data-driven methods, as recently proposed in [4]–[8], usually encounter limitations in terms of their generalization capabilities if the input data is out of the data distribution from the training set. Another drawback is that the forecasts from pure data-driven models are usually smooth and, as such, do not fully capture cloud dynamics by neglecting the underlying physical processes [9].

To address these challenges, we recently introduced a physics-informed graph neural network (PING) model that estimates the particle velocities of the historical input data, in an unsupervised fashion, and forecasts the future particle concentration values of advection-diffusion processes [9]. In this paper we propose the combination of PING with our previously developed model, the Graph Convolutional Long-short term memory (GCLSTM) network [7], for multi-site PV power forecasting tasks. We term the proposed model PING + GCLSTM. The combination of purely data-driven approaches and PING presents several advantages apart from improving the prediction accuracy. First, physically informed models offer insights into the dynamics of the historical input data, opening the door for prediction of rare weather events, which requires not only estimation but also propagation of the future dynamics. Second, the combination of ground measurements and satellite data offers the possibility of extending the forecasting horizons (e.g., to 24 hours ahead) since satellite data might provide information from a wider geographical area while ground measurements provide local high-resolution data to preserve high prediction accuracy for short time horizons.

In this work, short-term prediction horizons from 15 minutes to 6 hours ahead, with a temporal resolution of 15 minutes, ahead are considered. In the proposed approach, PING uses past cloud index concentration to predict future cloud concentration. These predictions are an additional input (inductive bias) to the GCLSTM model, which also uses past PV power production data. The PING + GCLSTM model was evaluated on a dataset of 304 PV systems distributed in Switzerland for a complete year. Apart from the power production data, PING + GCLSTM used cloud index data derived from the ERA5 dataset.

2 METHODOLOGY

2.1 Forecasting model

CSEM has developed a physics-informed graph neural network (PING) model that forecasts the future particle concentration values of advection-diffusion processes such as cloud formation and movement [9]. First, PING estimates the velocities and acceleration features of particles from past satellite images. Then, these estimations and input data are used to find the correlation between the input points from satellite images, using the attention module [10]. Finally, once flow estimations and correlations within the acceleration and velocity flows are calculated, flows are aggregated and future particles' concentration is forecasted, see Figure 1.

We propose the combination of PING, to forecast future cloud index concentration, with our previously developed model Graph Convolutional Long-short term

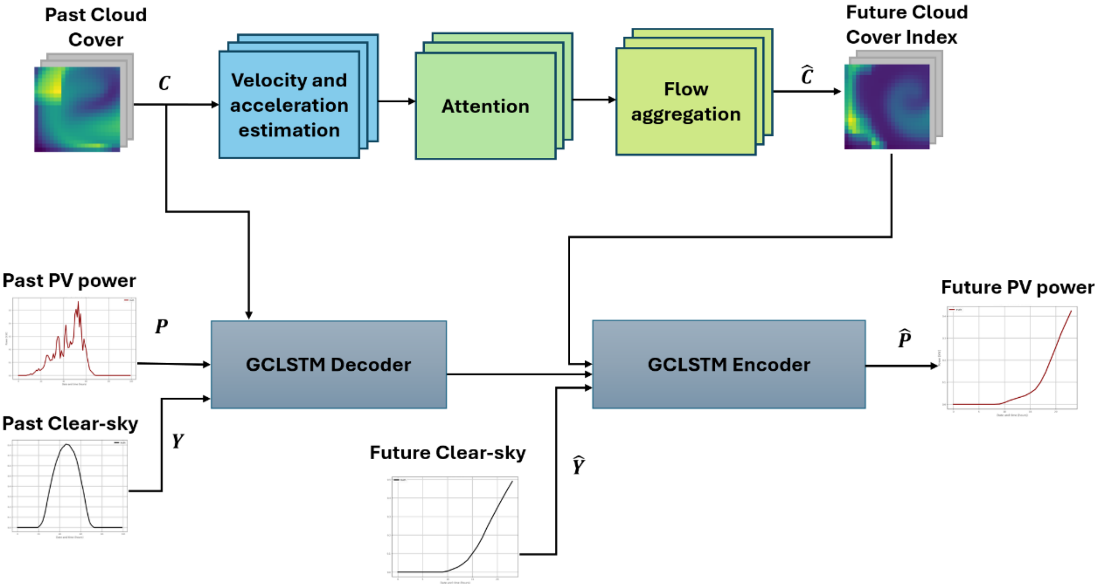

Figure 1. PING model combined with GCLSTM for PV power forecast.

memory (GCLSTM) network and use the predicted cloud index as an additional input (inductive bias) to GCLSTM.

The proposed combination of PING and GCLSTM (coined PING + GCLSTM) is shown in Figure 1. First, PING is used to estimate the cloud movement from past cloud concentration index values $\boldsymbol{C}$ (obtained from satellite data) and to forecast the future cloud concentration index values $\hat{\boldsymbol{C}}$. The past cloud concentration values $\boldsymbol{C}$ are concatenated with the past PV power production $\boldsymbol{P}$ and clear-sky irradiance values $\boldsymbol{Y}_{sky}$ and they are used as inputs to the encoder of GCLSTM. The encoder estimates the state of the system, and those estimations, along with the predicted future cloud concentration values $\hat{\boldsymbol{C}}$, and, future clear-sky irradiance values $\hat{\boldsymbol{Y}}_{sky}$, are the inputs to the decoder.

2.2 Datasets and training

Two datasets are used in our study. The first dataset is the cloud concentration index values from the ERA5 [10] dataset and data from 304 PV systems scattered over Switzerland for both training and evaluation. The PV production dataset has time granularity of 15 minutes while the cloud index dataset has time resolution of 1 hour. Thus, cloud concentration predictions are linearly interpolated to a temporal resolution of 15 minutes.

The training was performed using data from the whole 2016 and the evaluation was performed in 2017.

2.3 Evaluation and metrics

The proposed models are compared over the year 2017. GCLSTM and Smart persistence are used as benchmarks. GCLSTM is trained on the first year of available data (2016). Additionally, the model is benchmarked against a commercial solution based on satellite images, cloud tracking and numerical weather models. The comparison is done on a representative set of 18 locations and 21 days over the year 2017 to cover the whole range of different conditions in Switzerland in terms of weather and terrain. For more details on the selected days and locations, see [11].

The metric used in the evaluation is the normalized root-mean-square error (NRMSE), normalized by the peak production value over the year. Nighttime values were excluded from the error computations.

3 RESULTS

3.1 Forecasting accuracy

The combination of PING and GCLSTM model was evaluated on the PV power generation datasets described in the previous section and compared to the baseline models GCLSTM, Smart Persistence and Cloud Tracking solution. The NRMSE evolution over the forecasting horizon of six hours (with 15 minutes temporal resolution) is shown in Figure 2. The combination of PING and GCLSTM (PING + GCLSTM) outperforms all benchmarks on the entire horizon showing an NRMSE reduction of 2 percentual points in the last hour of the forecasting horizon [9].

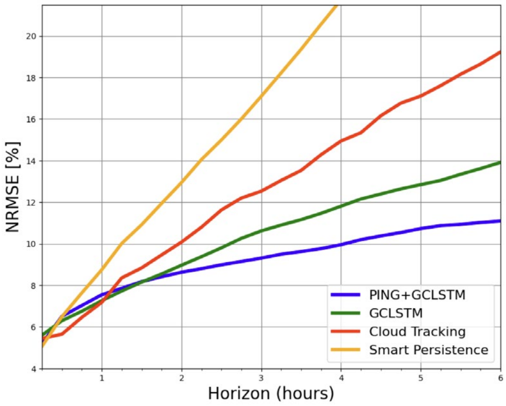

Figure 2. Evolution of the NRMSE between PING+GCLSTM, Smart Persistence, Cloud Tracking and GCLSTM models for six hours ahead for PV power generation, with hourly resolution. The solid line shows the median value among all nodes.

3.2 Comparative analysis

We also made a visual inspection of the forecasts made at different times of the day during a variable day for a specific PV system. The results are shown in Figure 3, where we compared PING + GCLSTM and GCLSTM.

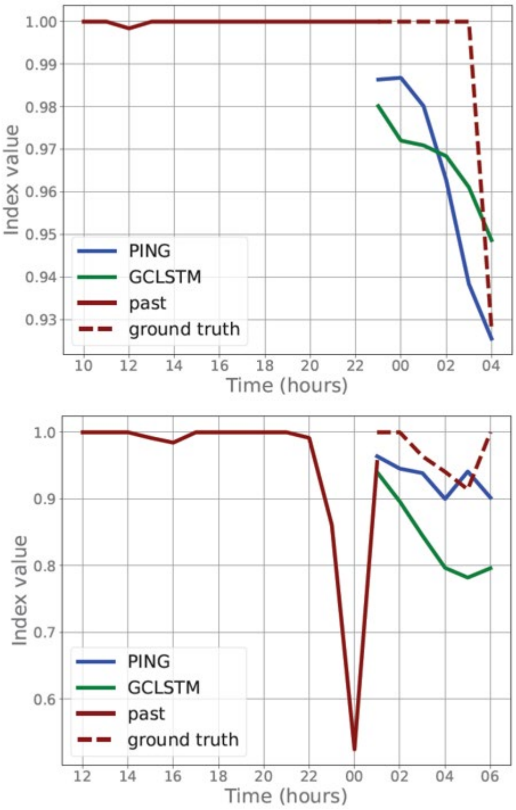

Figure 3. Examples of predictions of cloud index for the entire horizon made at different times of day for a particular location. The forecasted cloud concentration values for GCLSTM and PING models are shown in green and blue, respectively.

These specific instances are selected since they exemplify moments of significant dynamical changes in the cloud coverage. These instances, where the observed value rapidly declines from or exhibits abrupt surges are particularly challenging for forecasting models. However, PING shows better performance compared to GCLSTM.

Furthermore, we have examined the performance of the model made at different times of the day, for the twenty-four horizon values, during a variable day in Figure 4. We have compared the combination of PING + GCLSTM, with the GCLSTM model. The proposed combination of PING + GCLSTM outperforms GCLSTM and makes a closer prediction to the ground truth production during the first half of the day.

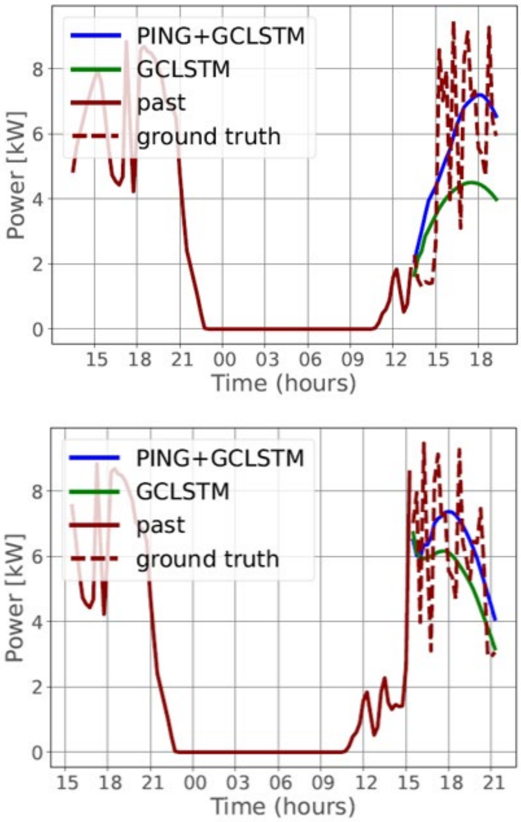

Figure 4. Examples of predictions of PV power production for the entire horizon made at different times during a variable day for a single site. The forecasted production values for GCLSTM and PING + GCLSTM models are shown in green and blue, respectively. Production in the last 24 hours as well as the ground truth production on the predicted horizon are also shown.

GCLSTM has a high error in the first hours of the morning prediction since it has no information on cloud dynamics during the night. Thus, in this situation, GCLSTM relies on the clear-sky profile and local neighborhood information, predicting a sunny day and making a high error when the first part of the day is cloudy. On the other hand, PING + GCLSTM extracts the information of the cloud dynamics during the early morning, allowing it to forecast future values with higher accuracy.

4 CONCLUSIONS

We introduced the PING + GCLSTM framework for multi-site PV power production forecasting. PING's predictions of future cloud concentrations from satellite images are used as additional inputs to the GCLSTM decoder. This allows us to enhance the representation of cloud dynamics in PV power forecasting. Our results demonstrate that this combined approach outperforms existing state-of-the-art PV power forecasting models and commercial cloud tracking solutions by 3% and 8% NRMSE, respectively, for forecasts six hours ahead. Furthermore, these results open the door for forecasting horizons longer than 6 hours ahead since satellite images can provide a wider spatial context than the local network of sensors.

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