Multi-site PV Forecasting using Spatio-temporal Machine Learning Models

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Accurate photovoltaics forecasting is essential to integrate renewable energy sources into the power grid. CSEM developed data-driven methods for forecasting PV production over a large area with fine temporal and spatial resolution using graph-based methods. These methods outperform the state of the art for horizons up to six hours.

Accurate time-series forecasting of renewable power generation is vital for the improvement of electricity management, power system scheduling and trading on the electricity market [1]. However, photovoltaic power production is dependent on weather conditions, which makes forecasting challenging.

The focus of the project was on intra-day multi-site PV forecasting since it is key to grid scheduling and planning. State-of-the-art methods within this temporal horizon use numerical weather predictions (NWP). However, NWP has a coarse resolution. Therefore, we have not relied on weather data, only on the past PV data and geographical information. However, due to limitations in the data collection and transmission, real-world data usually contains missing values.

CSEM developed a robust solution for time-series PV forecasting. Figure 1 depicts the solution, where the gap reconstruction and pre-processing module is applied to the data, before the forecasting module. Input data are past PV data, which are denoised, normalized, de-trended and imputed. Furthermore, these historical data are passed to the graph model learning module to learn graph embeddings, as well as to the forecaster.

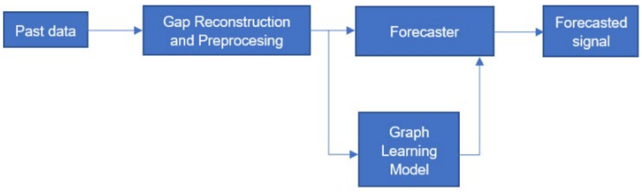

Figure 1: Block diagram of the proposed approach for robust PV production forecasting.

For the forecasting itself, we chose to model spatio-temporal correlations in multi-site PV data with graph structures. PV stations are modelled as nodes and the observed PV production data as signals on the graph.

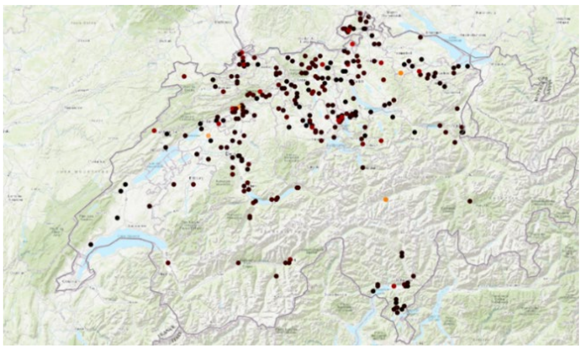

Figure 2: Spatial distribution of the evaluation dataset. Colors indicate the peak production at each site.

One linear and three nonlinear graph-based methods have been developed to capture spatial and temporal correlations between time series. Our models find the nodes which are the most informative and important when making a forecast. The developed non-linear methods use state-of-the-art neural network models that rely on combination of recurrent, graph convolutional, and attention structures. We have compared our graph-based models to the state-of-the-art combination of machine learning (here: support vector regression, SVR) and NWP for two single sites: Bern and for Bätterkinden. To validate our approaches, we have used 300 spatially distributed PV stations across Switzerland (Figure 2). Models were trained on the data from the year 2016 and evaluated on the following year.

Figure 3 shows the evolution of normalized root mean square (NRMSE) error over forecasting horizon. The developed methods outperform methods based on the numerical weather forecast and prove the intuition that graph-based methods can capture nonstationary and stochastic behaviors of the data, by jointly capturing spatial and temporal correlations. What is more, graph-based methods have shown to be powerful in the reconstruction of the missing and noisy data. As a result, the full forecasting pipeline proved very robust against faulty data.

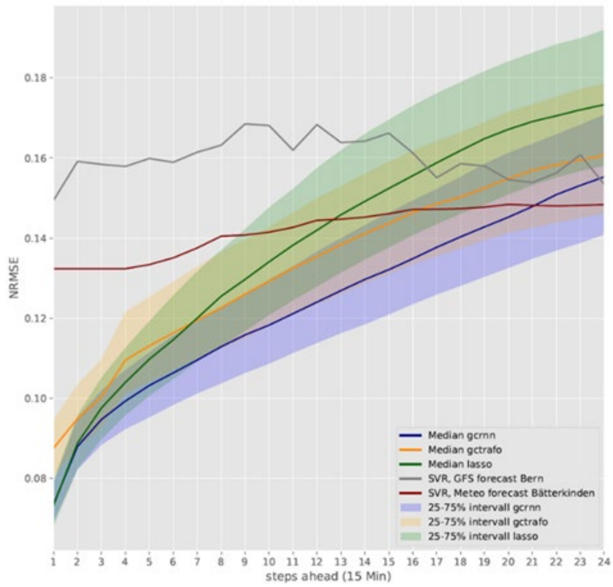

Figure 3: Forecast NMRSE for the real dataset. The forecast horizon is 6 hours in steps of 15 minutes.

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[1] P.-J. Alet, *et al*., “Forecasting and Observability: Critical Technologies for System Operations with High PV Penetration,” in Proceedings of the 32nd European Photovoltaic Solar Energy Conference and Exhibition, pp. 1444–1448, Munich (2016) [doi:10.4229/EUPVSEC20162016-5DP.1.3].