STRATEGIES FOR WIDE-SCALE SHORT-TERM PV POWER FORECASTING IN ENERGY COMMUNITIES - AN AGGREGATOR'S GUIDE TO SAVING MONEY

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Overview

With the proliferation of energy communities, rooftop solar photovoltaics (PV) have the potential to become a major provider of electricity in the European energy system. From the perspective of aggregators and energy suppliers, participating in intraday and day-ahead energy markets, this development is intensifying the need to implement accurate and reliable short-term forecasting methods for PV power of rooftop systems. A determining factor for the selection of these methods is the availability of data, which is often protected by privacy legislation (e.g., GDPR). This research aims to quantify the value of various data types, both in terms of quantity and quality, by economically evaluating the accuracy of physical and machine learning forecasting methods for rooftop PV power timeseries.

Methods

The methodology of this research can be split into two broad categories: *physical* and *data-driven* forecasting models. The former consists of a large collection of empirical models, which convert irradiance to power values, through physical relationships. The model employed in this research is the widely used PVWatts model [1]. The second bucket of models, namely *data-driven* models, refers to a collection of state-of-the-art machine learning models [2], which find function mappings between input and output variables based on historical measurement (sensor) data. By varying the quality and quantity of data inputs (see Figure 1) of these models, and successively evaluating the economic losses due to forecast errors (via imbalance prices), the marginal economic value of a given data stream, for a given year can be quantified.

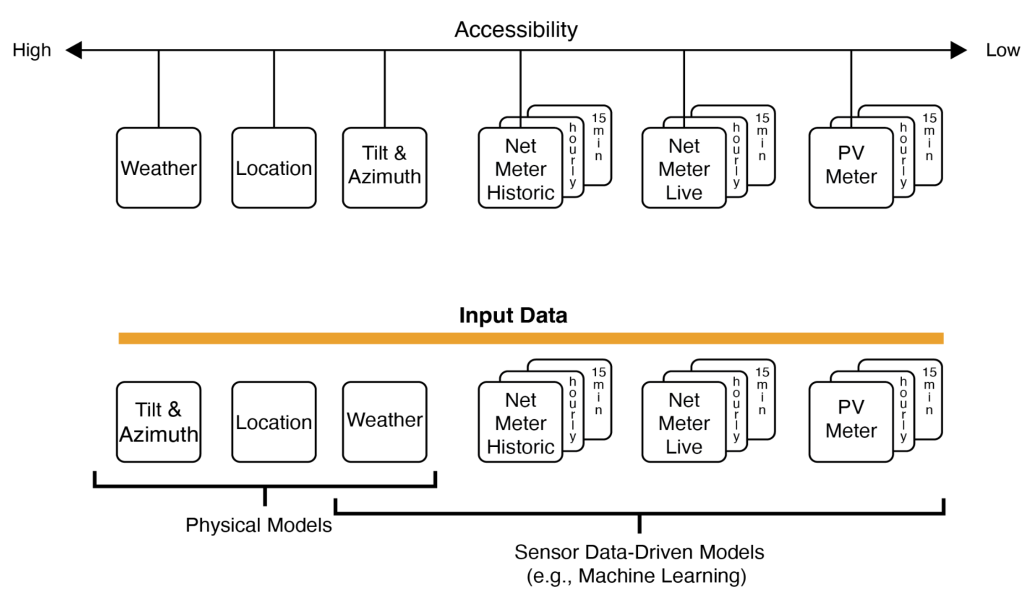

Figure 1: Accessibility of Input Data for PV Power Forecasting for Aggregators

Results

Results are obtained by investigating a case-study of an energy community with 50 households with rooftop PV systems in The Netherlands. The respective data consists of two years of electrical load and PV power output, at a temporal resolution of 30 seconds, as well as meta data on the PV systems. Preliminary results show the relative economic benefit of collecting spatially and temporally granular data to forecast PV power generation. When limited to system meta data, preliminary results show the impact of having correct information of azimuth and tilt angle of PV systems amount to a yearly 20k€ per MWp. The standard deviation of this result is 5k€ per MWp and is strongly related to the irradiance forecast accuracy. Further preliminary results show the relative superiority of data-driven machine learning methods when compared to physical methods. The main reason for this edge is the implicit modelling of shading and other degradation factors. However, the cost savings of using these methods strongly depend on pre-and post-processing of data, which require extensive technical know-how on the aggregator's side.

Conclusions

The conclusions drawn from this research have important implications for data collection and modelling strategies for aggregators that seek to successfully integrate energy communities into their business models. Depending on prevailing privacy laws of the region, the aggregator might opt for a data-driven approach if minimising imbalance costs is a major objective. If, however, privacy laws prevent the collection of granular meter data, azimuth and tilt angles can be sufficient data to receive sufficiently accurate forecasts. Future work will focus on developing machine learning algorithms that use live meter data of neighbouring PV systems to infer high resolution weather conditions that cannot be captured by weather data providers. This will further demonstrate how machine learning algorithms can unlock the economic value of highly granular data, incentivising aggregators to invest in more elaborate data collection and forecasting strategies.

References

[1] Dobos, A. P. (2014). PVWatts version 5 manual (No. NREL/TP-6A20-62641). National Renewable Energy Lab.(NREL), Golden, CO (United States).

[2] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. the Journal of machine Learning research, 12, 2825-2830.