Concept for Intra-Hour PV Generation Forecast based on Distributed PV Inverter Data

An Approach Considering Machine Learning Techniques and Distributed Data

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Abstract: The mass-introduction of small scale power generation units like photovoltaic systems at household levels increase the risk for system unbalances, due to their stochastic generation profile. Additionally, upcoming technologies such as electric vehicles, battery storage systems and energy management systems lead to a change from consumer households to prosumers with a significant different residual load profile. For optimizing the profile of future prosumers, especially the forecast for PV generation is crucial. Whilst traditional weather forecasts are based on a few hundred metering locations in the case of Austria, more than 55000 PV systems are currently connected to the Austrian Power grid. Due to the low areal coverage of common metering locations, weather forecasts do not take local phenomena like shadows from clouds into account. An approach using generation data from neighbouring PV systems together with machine learning methods provides a promising alternative for individual location based intra-hour forecasts. This paper describes the requirements and methods of such a concept and concludes with a first proof of concept.

1 INTRODUCTION

The increasing introduction of distributed energy resources (DER) like photovoltaic systems (PV) to medium and low voltage distribution grids creates new challenges but also chances for relevant stakeholders like distribution system operators, energy or service providers but also end customers. Especially the fluctuating generation from PV systems and the difficulties in forecasting changes in power generation are causing increasing risks and also costs in respect to a stable and reliable energy supply and grid operation. Since a large share of PV systems is installed directly at customer (prosumer) premises, strategies for optimization at end customer levels via home energy management systems (HEMS) rely on as precise as possible intraday or short-term forecasts for operating connected devices (e.g. electric car, battery storage system …) as cost efficient as possible. Power generation from PV systems is highly influenced by local conditions (e.g. clouds, temperature, type and setup of the system). Hence, forecasting needs to take local parameters into account which are based on satellite images or stationary metering systems. For metering the relevant parameters, in Austria less than 300 local metering points exist ("Meteorological Network — ZAMG," 2017), which cannot provide the data which is needed for an individual and local power forecasts for PVs (see Figure 1).

Figure 1: Meteorological network of ZAMG ("Meteorological Network — ZAMG," 2017) which offers meteorological data from more than 250 meteorological stations situated in all climate regions and altitudes Austria-wide.

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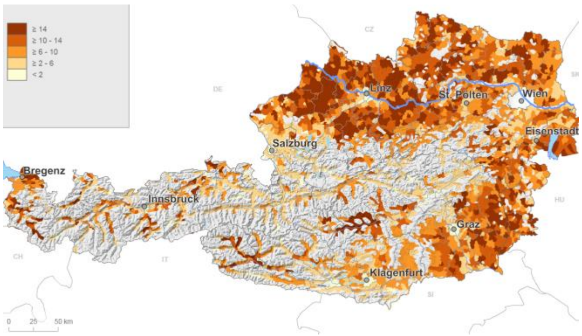

Figure 2: Distribution and number of PV systems in Austria (systems per 1000 inhabitants) ("Photovoltaik Karten," 2017).

In contrast there are currently more than 55.000 individual PV systems installed at the Austrian area and counting. Those systems are spread out among all populated areas of Austria (see Figure 2).

The growing numbers of high-resolution data loggers (at inverters of PV systems) provide a high potential for novel forecasting methods based on such distributed measurements. Therefore, this approach is taking into account spatial phenomena like cloud movement. Using the individual generation data from neighboring PV systems on machine learning methods would enable approaches for local forecasts for each PV site. In this paper a recurrent neural network approach building on the open source software library for machine intelligence TensorFlow™ ("TensorFlow," n.d.) is developed. This approach is taking into account the spatial and temporal dimension of power generation changes. The goal is to show, that with this approach significant improvements over forecasts based on single site time series forecasts can be achieved.

State of the art forecasts for PV generation are summarized in (Antonanzas et al., 2016). Most popular are statistical methods relying on local measurements for short forecast horizons and models building on weather prediction for longer horizons (see Figure 3). There are some approaches to include also the data of neighbouring PV stations into the forecast model. (Bessa et al., 2015) uses a vector autoregressive (VAR) model to forecast 1 to 3 hours ahead, showing improvement over an AR model without other stations. (Lonij et al., 2013) uses a data set of 80 rooftop PV systems on a 50x50 km area for intra hour forecast. One of the problems occurring in both references [5] and [6] are the coarse measurement intervals of 15 minutes, which do not allow following cloud shadows precisely. Furthermore, there exist some larger scale projects, like (Williamson, 2016), where a large number of distributed sensors (PV inverters and fish eye cameras for cloud detection) are connected with machine learning techniques to improve the forecast over the state of Canberra in Australia.

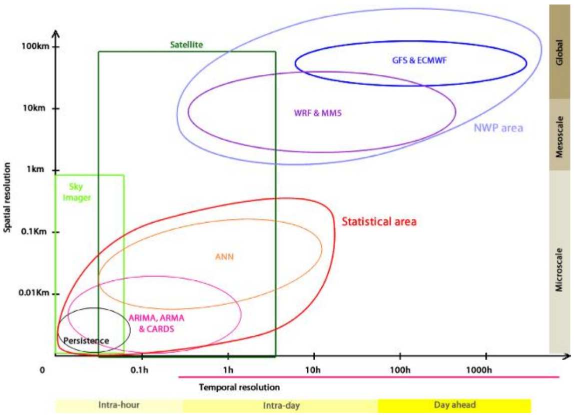

Figure 3: Overview of state of the art forecast methods for PV generation (Antonanzas et al., 2016).

Machine learning techniques are already applied in many publications of PV forecasting, but the application is on a quite basic level up to now. Simple feed-forward neural networks are used often, because they are easily implemented, while advanced architectures are not considered in literature. Areas with advanced use of neural networks are for example image recognition (e.g. for the detection of clouds and wind direction or speed) and language processing. While algorithms from image recognition cannot be used for the concept described in this paper (because they rely on strictly gridded spatial positions), the time domain is represented very well in other areas of research. Recurrent neural networks use the time ordered nature of data for prediction. The long short-term memory (LSTM) recurrent neural network for example reaches outstanding scores at benchmarks for speech recognition tasks (Graves et al., 2013). Hence, the concept described in this work will use recurrent neuronal networks.

The main focus of this paper is to describe the general concept and the developed method and to point out how a neural network method has to be designed to fit this field, which differs in several respects from classical machine learning disciplines. First we apply a simplified scenario for a first proof of concept. In future, special challenges including the day cycle, irregularly spatial distribution of data points, different weather regimes and other parameters will be approached.

2 CONCEPT DESCRIPTION

This position paper aims to describe a concept for an intra-day PV generation forecast based on distributed (neighbouring) PV generation data and machine learning methods. The local generation from PV Systems is influenced by a number of factors. In general, the mathematical model for understanding the PV generation profile can be divided into three main models:

- Irradiation Model:

  It describes the global radiation at a certain location. Extra-terrestrial solar radiation can be calculated based on geometric considerations. Furthermore, the influence of the terrestrial atmosphere on a clear day is often included into this part of the model.
- Statistical Model:

  This model describes the local disturbances caused mainly by local weather phenomena.
- Physical Model:

  The physical model contains the characteristics of the technical system (cell type, inverter, position …).

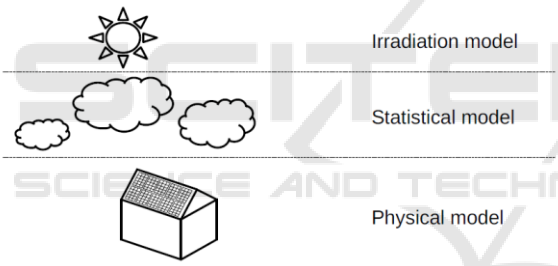

Figure 4: Types of models for the description of influence parameters for PV generation and forecast.

Those three aspects are usually modelled independently due to their diverse nature and characteristics by different mathematical methods. In reality, the effects of these three models are reflected in the power generation profile of each PV system, which can be measured directly at the inverter or grid connection point. Whilst different mathematical approaches were necessary in the past to conquer the individual characteristics and challenges for each model, progress in machine learning methods might provide a new unified tool for the analysis of generation data with respect to local power forecasts.

Figure 5 provides a schematic example of a time-delayed power drop at neighboring PV systems (along the wind direction) caused by a moving cloud. Depending on the distance of the PV systems to each other and the wind speed the probability for a similar power drop at a neighboring PV system in direction of the wind could be calculated.

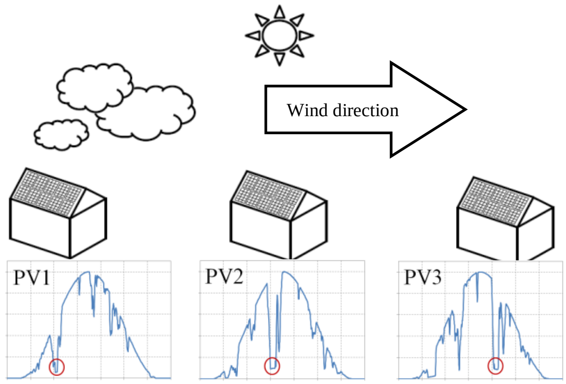

Figure 5: Example of a time-delayed moving power drop at neighbouring PV systems caused by a moving cloud (large images of the PV diagrams in the APPENDIX).

As a requirement for the workability of the approach described in this paper, participating PV Systems are required to share the following data over a centralized cloud based data infrastructure:

- Location [long/lat]: Geographical location of the PV System. This information is necessary to identify neighboring systems in reference to wind direction and speed.
- Timestamp [yyyy-mm-dd hh:mm:ss]: Timestamp of the data transmission consisting of date and time. This information is necessary to calculate forecasts.
- Power [kW]: The actual power output of the PV system at a specific timestamp.

Such data needs to be submitted by each PV system. This could either be done by a peer-to-peer network or a centralized approach as shown in Figure 6.

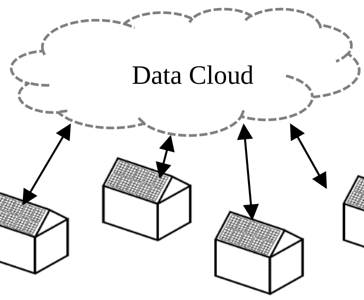

Figure 6: Simplified data transfer between individual PV systems by a centralized cloud system.

3 PROOF OF CONCEPT

Following the idea of the concept description (Section 2) basic requirements, method and a first use-case are defined for a first proof of concept.

3.1 Requirement Analysis

In order to be able to establish a first proof of concept, the requirements for method and use-case have to be analysed. This section will mainly focus on the requirements on data transmission and the geographical distances between neighbouring systems in dependence of wind speeds. As an additional parameter, the forecasting horizon shall be discussed to define the objective of this method.

Depending on the wind speed and the target forecast horizon, the minimum distance to the next neighboring system can be calculated. E.g. for a forecast horizon of 15 minutes, the data signal of a neighboring system would be needed 15 minutes prior the forecasted point in time. This means depending on the wind speed and assuming a real-time signal transmission a minimum distance between sender and receiver is given. Figure 8 shows the minimum distances between neighboring systems for specific data transmission interval periods (from one transmission per second down to every 900 seconds) in reference to wind speeds. According to ("Windatlas Austria," n.d.) average wind speeds at 100 meters above ground level are (depending on the geographic area) between 4 and 7 m/s (see Figure 7).

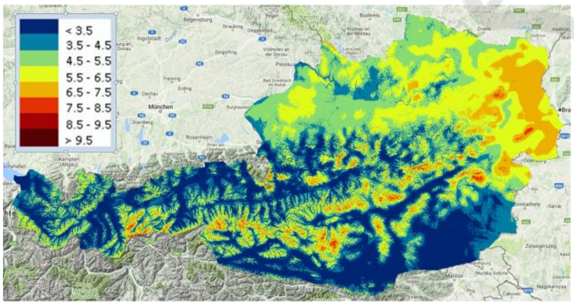

Figure 7: Austrians geographical average annual wind speed distribution (in m/s) ("Windatlas Austria," n.d.).

Since clouds are situated above those heights, for their movement higher wind speeds between 9 and 13 m/s must be considered (Lappalainen and Valkealahti, 2016). From Figure 8 it can be followed that data metering and the corresponding transmission interval should be at least every 60 seconds, since slower intervals increase the distance between systems significantly. This would enable the

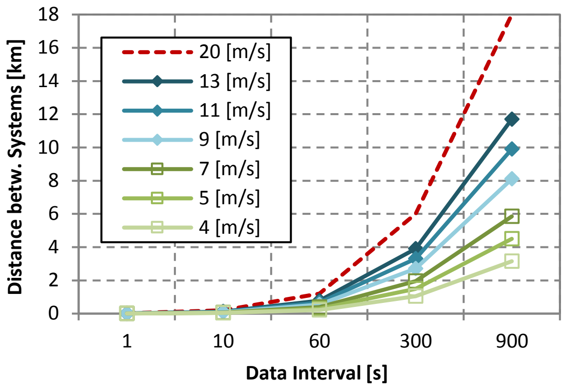

Figure 8: Minimum distance of neighbouring systems depending on data intervals and different wind speeds (4 to 20 m/s).

usage of signals from neighbouring systems of 1 km distance. Even shorter transmission intervals would be beneficial for increasing the forecasting quality and for engaging shorter forecasting horizons (< 15 minutes). The higher the wind speed the more distance is required between sender and receiver. Figure 9 shows the minimum distances in reference to wind speed and different forecast horizons.

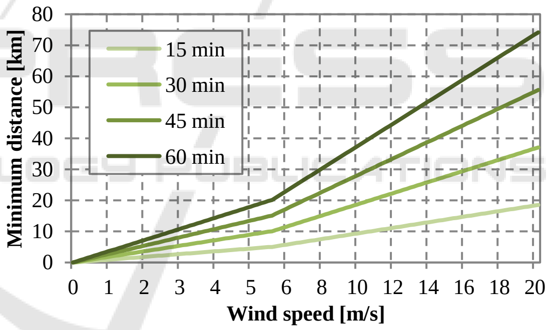

Figure 9: Minimum distance of neighbouring system for different forecast horizons and wind speeds.

The main motivation of spending efforts on forecasting data (in this case generation data) is an advantage and benefit regarding the real-time operation. In case of forecasting PV generation several forecasting horizons could be of specific interest, depending on the application or product. Considering prosumer households in future, which include besides PV systems also electric vehicles and stationary battery electric storage systems, the forecasting horizon will be mainly targeting an intra-hour time period. In specific a 15-minute forecasting horizon could become increasingly important for future prosumers. This assumption is based on current time intervals of Smart Meters and grid connection contracts, which both focus on a 15 minutes interval.

Considering strict power limits in future at households for consumption but also generation in future ("E-Control Position Paper Tarife 2.0," n.d.), a clear objective for forecasting and optimization would be given.

3.2 Method

To analyse the available spatio-temporal measurements of PV inverters, it is important to build a generic model, which can learn from large amounts of data and find relations without explicitly given dependencies between measurement stations. Therefore, machine learning algorithms like neural networks are a good choice for forecasting from such data. Recurrent neural networks were chosen because they directly use the time ordered structure of the data. Inputs are thereby ordered in two dimensions: Different measurement stations make up the first dimension, optionally extended by external data like wind or daytime. Time is handled separately by feeding multiple time steps at once as a second dimension.

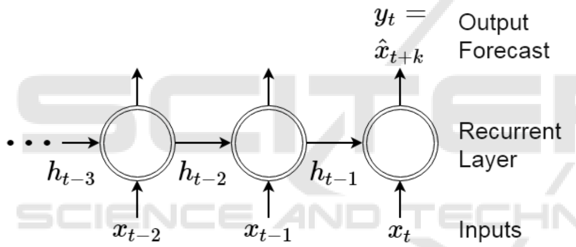

Figure 10: Unrolled representation of an RNN with one recurrent layer. The x are vectors of inputs, the h the hidden layer value vectors and y is the output, in our case a forecast k time steps into the future.

The structure of a recurrent neural network is sketched in Figure 10. For each time step the inputs go to the recurrent layer, together with the outputs of the recurrent layer in the previous time step. This is done up to the last measurement, where the output gives the forecast. The computation in the recurrent layer is identical in each time-step, it consists of several nodes, which can be visualized as in Figure 11. The components of the hidden layer vector $\vec{h}_t$ are calculated by equation 1:

$$h_{j,t} = f_{act}\left(\vec{w}_j^{(i)} \cdot \vec{x}_t + \vec{w}_j^{(h)} \cdot \vec{h}_{t-1} + b_j\right) \tag{1}$$

The $\vec{w}_j$ and b_j are adjustable weights and biases, $\vec{x}_t$ is the input vector and $\vec{h}_{t-1}$ is the output of the recurrent layer of the last time step. f_{act} is an activation function, which has to be monotonically rising. Typically, it is either a sigmoid function, or even more simple, the ReLU function (Rectified Linear Unit), defined by equation 2:

$$f_{act}(x) = \max(0, x). \tag{2}$$

The weights of the inputs and of the hidden layer outputs are shared between time steps. The output is then calculated by a fully connected layer, mapping the hidden layer values on the relevant output features (equation 3):

$$y_t = \sum_j w_j^{(o)} \cdot h_{j,t} + b^{(o)} \tag{3}$$

With a large set of historical data, all weights and biases are adjusted, to give the best fit on the known outputs. This is done with an optimization algorithm called backpropagation (Rumelhart et al., 1985).

The recurrent neural network can be extended in different ways, for example by using multiple recurrent layers, stacked one after the other. Another, very popular extension is long short-term memory (LSTM) networks. There, the node as shown in Figure 11 is replaced by multiple computation steps. Multiplication of the end values allows to only use nodes when they are appropriate (Hochreiter and Schmidhuber, 1997)(Sak et al., 2014).

The neural network has to be adjusted, to give the best possible results. In our case, optimization is done on the Mean Squared Error of the predicted value (equation 4):

$$MSE = \frac{1}{n}\sum_i^n (\hat{y}_i - y_i)^2 \tag{4}$$

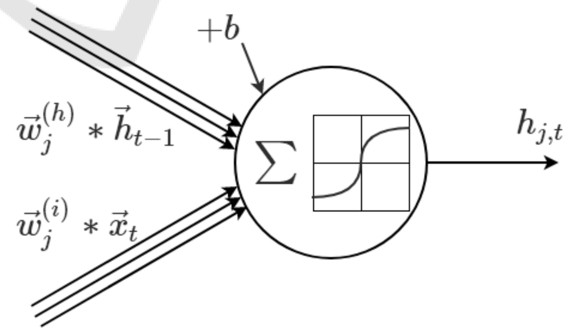

Figure 11: Visualization of the computation in a hidden layer node. w denote weights, b bias, x inputs and h the hidden layer values. j is the index of the node in the layer, while t is the time index.

The performance of the RNN will be compared to a naïve approach. For the naïve approach, forecasts are produced that are equal to the last observed value.

3.3 Use Case Definition

A first use case was defined to show the general applicability of the proposed method. The simulated scenario consists of a time series of partly cloudy days. 10 measurement points are distributed in 5 km distances on a line, with a non-changing cloud speed of 9.3 m/s along this line. An equivalent scenario is visualized in Figure 5. 10000 measurements of minute averages are simulated. Results of forecasts of one station for horizons from 1 to 15 minutes are compared against a naïve forecast, and against results of a neural network only using the local measurements.

This scenario already includes the diurnal cycle of PV production, as well as spatio-temporal relationships and some mostly random differences between the measurement stations. It can be seen as the perfect scenario for the algorithm to be trained: Partly cloudy conditions on a day with a steady wind speed. Of course, there are a lot more influences in a real scenario: Change in wind speed and direction, two-dimensional and unregularly distributed PV systems, differences in PV declination and perturbations of the PV systems. Also cloud formation and dissipation are not included, but should not make a large difference on small time scales, while on clear and overcast days the improvement of the extended method will be minimal. Despite all of this further challenges, the result on the single-dimensional scenario shows already if recurrent neural networks can be a promising approach for forecasting from multiple PV measurement stations.

In a next step, the scenario is extended to two-dimensions, where wind speed and direction changes can be included. This simulation is done in Processing ("Processing.org," n.d.), using a Perlin Noise implementation to simulate moving random cloud fields (Perlin, 1985) (see Figure 12).

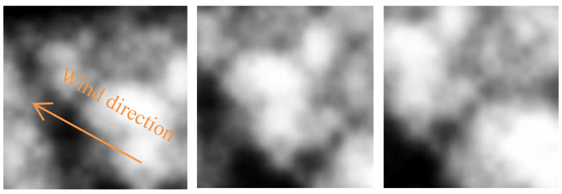

Figure 12: Simulation of a moving cloud field with Perlin Noise and Processing.

3.4 Preliminary Results

Figure 13 shows 10 minute forecasts for half a day of partly cloudy weather. There it can be seen that the RNN with multiple input stations successfully forecasts abrupt PV generation changes. This is facilitated by the measurements of stations, who are reached earlier by the affecting cloud. In contrast the naïve forecast (and similar other local forecast methods) has a delay in the size of the forecasting horizon.

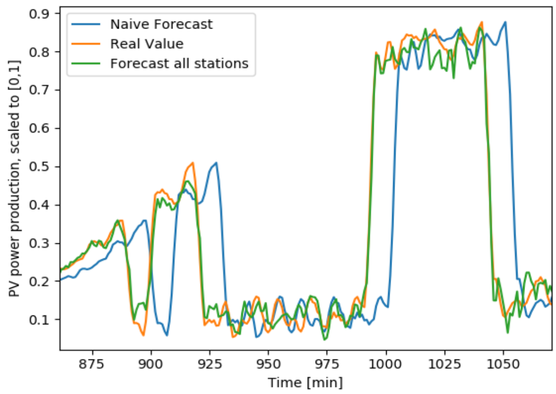

Figure 13: Exemplary forecast for half a day, with a forecast horizon of 10 mins. The RNN Forecast with all stations manages to predict sudden changes quite precise.

Table 1: Mean squared error for three different models and forecast horizons between 1 and 15 minutes.

	RNN Multiple inp	RNN Single inp	Naïve
1 min	0.0558	0.0493	0.1473
3 min	0.1106	0.8299	0.9773
5 min	0.1064	1.5868	1.8033
10 min	0.1712	3.0243	2.8901
15 min	0.1277	3.8968	3.3475

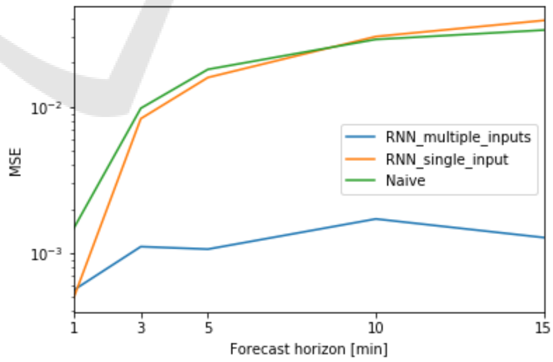

Figure 14: Mean squared error of different forecast models, plotted over the forecast horizon. MSE calculated excluding night periods.

The Mean Squared Error (MSE) for multiple forecasting horizons are shown in Table 1 and Figure 14. The RNN results are compared with the naïve method, which takes the last measured value as forecast, and an RNN with only the local PV inverter measurements and the hour of day as an input. The simple RNN beats the naïve method only for really short forecast horizons, as the temporal relationship in our simulated data set is mostly random on longer time scales. This is supposed to change for real data, as there the network can learn time trends for different weather regimes.

In comparison to those two methods, the RNN with all 10 stations as input manages a big improvement, especially for longer time horizons. For horizons above 5 minutes the MSE is reduced to less than 1/10. This is a significant improvement, indicating that there also may be an improvement for more difficult scenarios.

The final model uses the last 50 time steps and one hidden layer with 40 neurons for prediction. Furthermore, the hour of the day is included as an input variable. LSTM models were tested in this scenario and gave similar results as the RNN. For more difficult scenarios it would be important to include more training data, then also the differences between LSTM and RNN could get more obvious.

4 DISCUSSION & OUTLOOK

A concept for an intra-hour forecast method using distributed data from PV inverters and machine learning techniques was introduced in this paper. The concept assumes the option for PV systems to broadcast their real-time power generation values and the ability to receive such values from neighbouring PV systems. As forecasting method, recurrent neuronal networks were used. A simplified use-case for a first proof of concept was created, by using generic cloud movement at a constant wind speed and direction.

The requirement analysis stresses the need for data submissions from PV systems for at least every minute for intra hour forecasts. The specific minimum distances between neighboring systems are depending on wind speed, data transmission rate and a specific forecast horizon. For a 15 minutes forecast horizon, distances would range from 5 up to 12 km between systems, depending on the wind speed and the corresponding movement of clouds.

A simplified use-case for a first proof of concept was created, by using generic cloud movement at a constant wind speed and direction. As forecasting method, recurrent neuronal networks were used, as they are designed to handle time series data. The network can adapt to the time delayed relationship between different PV stations and increases forecasting accuracy by a factor of 10 in our simplified scenario for forecasting horizons between 5 and 15 minutes (in comparison to the Naïve forecast). Building on these promising results tests on more realistic scenarios will follow in future. Also, the kind and design of the neural network used for this application shall be reviewed in more depth.

The next step in development will focus on adapting the methods on a two-dimensional model of 25 PV systems arranged in a 5x5 grid. The movement of clouds will again be simulated by using Processing and Perlin Noise including changes of wind direction and speed. Presumed that the neuronal networks training on the data of this advanced use-case show good results, a training set consisting of real measured inverter data will be prepared for further developments of the method.

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APPENDIX