MACHINE LEARNING APPROACH TO A LOW-COST DAY-AHEAD PHOTOVOLTAIC POWER PREDICTION BASED ON PUBLICLY AVAILABLE WEATHER REPORTS FOR AUTOMATED ENERGY MANAGEMENT SYSTEMS

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ABSTRACT: The fully automated and transferable predictive approach based on the long short-term memory machine learning algorithm is developed for the forecasting of the photovoltaic (PV) power output. The main challenge of this approach is using publicly available weather reports and measured PV power without any technical information about the PV system. Nevertheless, the developed model is able to predict the power output of the various PV systems for all seasons with a reasonably good accuracy. This transferability of the approach is proven by the prediction of the PV power for warm and cold periods and for two different PV systems located in Oldenburg and Munich, Germany. The mean absolute scaled error of the predictions decreases with increasing the size of training set and reaches its minimum by the training with 90 days.

The PV power prediction made with the publicly available weather data is compared to the predictions made with the fee based solar radiation data. The usage of the solar radiation data leads to more accurate predictions even with small training sets. Although the model with the publicly available data needs a greater training set, it still can make reasonably good predictions. Therefore, it can be applied in forecast-based energy management systems.

Key words: PV power prediction, publicly available weather reports, machine learning, long short-term memory, integrated energy systems, smart energy management.

1 INTRODUCTION AND MOTIVATION

The building stock in Germany is aimed to be virtually climate-neutral by 2050 [1]. This goal can be achieved by supporting of different sector coupling solutions and by increasing the self-consumption of locally generated energy. These solutions, in particular the coupling between electricity and mobility sectors, face big challenges especially for small-scale energy systems. One of these challenges is the development and integration of the energy management systems for the buildings.

Such smart energy management system can have a significant impact especially on energy consumption of the commercial buildings, because this type of buildings has an advantage of simultaneity from loads behaviour and locally generated energy such as photovoltaic (PV) systems. But the fluctuating electricity generation from the PV systems challenges the energy management system to use a prediction of PV power output. This type of power prediction leads to increasing the self-consumption, avoiding higher grid fees and efficient controlling of temporal coincidence between integrated energy systems such as PV systems and battery electric vehicles (BEV) or other flexible loads.

As a continuation of the study [2] a predictive model based on machine learning approach is developed within this study for the day-ahead forecasting of the PV power output. This model has the same conditions as in the study [2]: no knowledge about PV system (except measured values) and publicly available weather reports without values of global horizontal irradiance (GHI) should be used as input data. The requirement to use free publicly available weather data can be explained by the assumption that most of the building integrated and grid-connected small-scale PV systems don’t have any business model and they don’t generate enough revenues for an energy management system based on cost-intensive forecast data. Besides using the publicly available weather reports the predictive model should also satisfy other requirements: it should operate fully automatically, be continuously learning, transferable to other PV systems and it should adapt to the changes of weather conditions and the PV system, such as degradation of the solar modules. The transferability of the model is investigated by the comparison between two different scaled PV systems located in Munich and Oldenburg, Germany.

With regard to these requirements different studies are investigated in order to find an appropriate predictive approach. In recent years, more and more machine learning algorithms have been developed and applied for the time series predictions, as [3], [4] and [5] show in their reviews about PV power forecast techniques. In [6] and [7] is discussed, that especially the application of Long Short-Term Memory (LSTM) neural networks provides good results in PV power forecasting.

Taking into account the requirements to the predictive model given above, classical splitting of the data set in training and test sets and training the model only once are not suitable for this study. The data set with the measured values used in this study is regularly updated with current weather data and PV measurements. Therefore, a re-training of the model with new data occurs at regular time intervals. Together with the current data the weather forecast is also updated regularly. After each update of the weather forecast the developed model makes updated prediction of the PV power output for the next 24 h. This procedure can ensure the continuous learning of the predictive model and adaptation to the possible changes.

A benchmark for the developed approach with the publicly available weather data is a model, which uses measurements and prediction of GHI.

2 DATA

In this section, origin, main characteristics and quality of input data are explained. The input data are divided into descriptive and target features. The descriptive features include historical weather measurements and numerical weather predictions. These features are used for prediction of PV power output, which is defined as a target feature.

Both descriptive and target features are available in the period of time from May 5th 2017 until April 10th 2018 for Oldenburg. This dataset is explored extensively to determine main data quality issues.

2.1 Photovoltaic power output

The origins of the PV power measurements used in this study are roof-top PV systems. The first system is in operation at DLR Institute of Networked Energy Systems in Oldenburg since November 2010. Another system is newly installed on a commercial building in Munich and generates electricity since November 2018.

The investigated PV systems have not only different locations, but different installed capacities, solar cell types, etc. The main technical characteristics of these two systems are presented in Table I.

Table I: Main technical characteristics of the PV systems

Location	Oldenburg	Munich
Installation year	2010	2018
Total capacity	1.14 kW_P	99.9 kW_P
Orientation	237°	177.5°
Inclination	7°	10°
Solar cells type	a-Si	mono-Si
Nominal cell efficiency at standard test conditions	6.6 %	17.9 %

During the investigated period of time (see above) the PV system in Oldenburg generated 675.63 kWh of electricity. The measured values of the PV system in Munich are available since March 5th 2019 and from this time till June 30th 2019 it produced 50,740.14 kWh of energy.

The technical characteristics of the PV systems are not considered in the predictive model and they are given here only for better understanding of the prediction results later. Only measured values of PV power output are used in the prediction model. These measured values for both PV systems are recorded with a time resolution of 5 minutes.

2.2 Weather data

There are two origins of the weather data which are used in the predictive model separate from each other and the prediction results are compared in this paper.

The first origin is an online service "OpenWeatherMap" (OWM) from the company Openweather Ltd. The main company activities profile includes the providing current weather data, historical weather data and weather forecast of different locations to the developers of web services and mobile applications. The current weather and forecast collection is available free to the commercial users which present this meteorological data on their homepages [8]. Because of the public availability of the data from OWM, this data is called in the paper "publicly available weather reports". The second origin is measurements and predictions of solar radiation from DLR Institute of the Networked Energy Systems and Energy Meteorology Group, Institute of Physics, Oldenburg University. This data is called "fee based solar irradiance data". The data and its description for the year 2014 are located in [9]. For this study the solar radiation data is taken from the year 2019.

The investigated weather data has not only different origins but also different meteorological parameters. OWM provides current and forecasted values of various weather parameters, like air temperature, pressure, humidity, cloudiness factor, wind speed, precipitation type, etc. But these publicly available weather reports don't include values of the solar radiation. The fee based data from DLR and Oldenburg University, in turn, includes measured values of global horizontal irradiance (GHI), which are collected by pyranometer. It also contains calculated values of GHI, direct normal irradiance (DNI) and diffuse horizontal irradiance (DHI) for clear sky conditions and angles of solar zenith and azimuth. The GHI prediction is based on an optimized combination of different forecasting methods including satellite cloud images and different numerical weather prediction models [9]. This dataset doesn't include other meteorological parameters, like temperature or humidity.

Another difference between these weather datasets is the time resolution. The current weather data and weather forecast from OWM are available in 30 min and 3 h time resolution respectively. The measured values and prediction of solar radiation in the fee based dataset are presented in 1 h and 15 min time intervals respectively.

2.3 Additional descriptive feature

Because publicly available weather reports from OWM don't provide measured and predicted values of the solar radiation, this descriptive features dataset is extended with an additional descriptive feature. For each time the maximum of PV power is calculated from the measured PV power values of the same time in last five days [2]. Then these values are inserted in the input dataset and used for training the model and making prediction.

Calculation methodology of maximum PV power and optimal number of days to look back are taken from fully automated model in the paper [2].

2.4 Data exploration

The predictive model developed within this study is a data-driven approach and input data, its quality and selection of the appropriate features from the whole input data play key roles for prediction accuracy. Therefore, an exploration of the input data is one of the main steps in the data pre-processing [10].

Firstly, all input data are explored with a goal of determination whether the data suffers from any data quality issues. Both, the current weather data from OWM and dataset with measured PV power output, suffer from missing values. Only 2.9 % of values in the OWM dataset are missing. The dataset with the PV measurements has 5.7 % of missing values. But these amounts are uncritical and both datasets can be used as input data for the predictive model. The next common data quality issue are outliers: OWM has only one outlier (humidity value) within the investigated period and PV dataset doesn't have any outliers in the same period. According to OWM homepage humidity is calculated in percent and varies between zero and hundred. During data exploration was determined, that humidity value on March 12th 2018 at 21:00 is 107%.

Secondly the quality of the numerical weather forecast from OWM can also be evaluated, because the weather forecast is available for the whole investigated period of time. The prediction accuracy of OWM is evaluated with the help of three statistical metrics:

- Mean Absolute Error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\overline{Y_i} - Y_i| \quad (1)$$

- Root Mean Square Error

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\overline{Y_i} - Y_i)^2} \quad (2)$$

- Symmetric Mean Absolute Percentage Error

$$sMAPE = \frac{100\%}{n}\sum_{i=1}^{n}\frac{|\overline{Y_i} - Y_i|}{|\overline{Y_i} + Y_i|} \quad (3)$$

Y_i – measured value
$\overline{Y_i}$ – predicted value
n – number of values

The meteorological parameters cover the different ranges: for example, cloudiness and humidity cover the range [0, 100], temperature covers the range [-10, 29]. In order to compare them with each other, all values are converted into the range [0, 1] using range normalization. Afterwards MAE, RMSE and sMAPE for all meteorological parameters can be calculated. The statistical metrics which indicate the quality of weather forecast from OWM are presented in the Table II.

Table II: Statistical metrics of OWM forecast

	MAE [-]	RMSE [-]	sMAPE [%]
air temperature	0.02	0.03	2.61
humidity	0.22	0.26	15.45
cloudiness	0.24	0.34	33.87
precipitation	0.36	0.60	35.69

Among all meteorological parameters temperature with sMAPE of about 2.6 % has the best prediction accuracy. The statistical errors of the cloudiness and precipitation make sense, because these meteorological parameters are the hardest to predict even nowadays. The accuracy of the humidity forecasting lies between accuracies for temperature and cloudiness.

2.5 Correlation analysis

Because the weather and PV datasets include only continuous features, it is possible to calculate the relationship between them with the help of covariance cov and correlation cor metrics [11]:

$$cov(a,b) = \frac{1}{n-1}\sum_{i=1}^{n}\left((a_i - \bar{a}) \times (b_i - \bar{b})\right) \quad (4)$$

$$corr(a,b) = \frac{cov(a,b)}{sd(a) \times sd(b)} \quad (5)$$

a, b – features a and b
$\bar{a}, \bar{b}$ – means of features a and b
sd – standard deviation

The correlation values between meteorological parameters from OWM and PV power output are presented in Table III.

Table III: Correlation values between descriptive and target features

Feature	Correlation*
Air temperature	0.43
Humidity	-0.57
Cloudiness	-0.11
Precipitation type	-0.14
Max. PV power	0.84

*Values close to -1 mean strong negative correlation, values close to 1 means strong positive correlation and values around 0 mean no correlation [10].

The correlation analysis shows that air temperature and humidity have stronger relationship to the PV power output in comparison with the other meteorological features. Despite the commonly perceived fact that the PV generation strongly depends on the current cloud cover, the given probability for cloudiness from the OWM shows almost no correlation to the measured PV power. The calculated maximum PV power values of the last five days have the strongest positive correlation to PV power output.

3 METHODOLOGY

There are two main approaches for the PV power output forecasts: performance method and machine learning method. The performance or physical method needs technical specification of the PV system and prediction of the solar radiation for this location. But the main aim of the developed predictive approach is obtaining the PV power output without any information about PV system (except historical measured values of the generated power) and without solar radiation prediction. So the performance method cannot be used according to the motivation of this study. The machine learning method doesn't need any information of the system. It is the first reason for choosing the machine learning approach. The second reason is an absence of the solar radiation in the publicly available weather reports.

The next step is selecting a machine learning technique among many techniques of forecasting the PV power output. The Artificial Neural Network (ANN) is nowadays the most used machine learning approach for the prediction of the PV power: in 24 % of all studies in [4] the researchers predict the PV power using the ANN models. A special architecture of the ANN, namely Long Short-Term Memory network (LSTM), is chosen for the predictive model of this study. The detailed description of LSTM, its functional principal and the main differences from classical ANN are explained in [11] and [12].

The main reason for using of LSTM in this study is its ability to learn long-term dependencies that are typically laying in the time series. And all used input datasets described in chapter 2 are time series. But before training the model with the chosen machine learning technique, namely LSTM, the input data have to be prepared for it. The data preparation, model training and other main steps of the PV power forecasting are presented in a simplified flow chart (see Figure 1).

To initialize the training algorithm the predictive model waits five days to collect enough data for calculation of the maximum power output (see chapter 2.3). The continuous prediction of the PV power occurs in an endless loop, each iteration of which starts with a decision-making about re-training of the model. In case of positive decision, the predictive model is re-trained with the updated weather data and PV measurements. The positive decision occurs twice per day: at 00:00 and at 12:00. As known from the previous chapter all input data used in this study has data quality issues, i.e. missing values and different time resolutions. Therefore, the data pre-processing is an unavoidable step which includes the following functions: detection of the double or completely inconsistent timestamps, imputation of missing values by linear interpolation, transformation of time resolution to 30 min, and normalization of values. The normalization means a scaling of the values into range [0, 1] using range normalization. The descriptive and target features are scaled separate from each other and the scalers are saved for further forecasting process, namely scaling of the input weather forecast values and rescaling of the values of the predicted PV power. After the normalization step the scaled input values can be used for training of the developed predictive model. This model has one input layer, two hidden LSTM layers and one output layer.

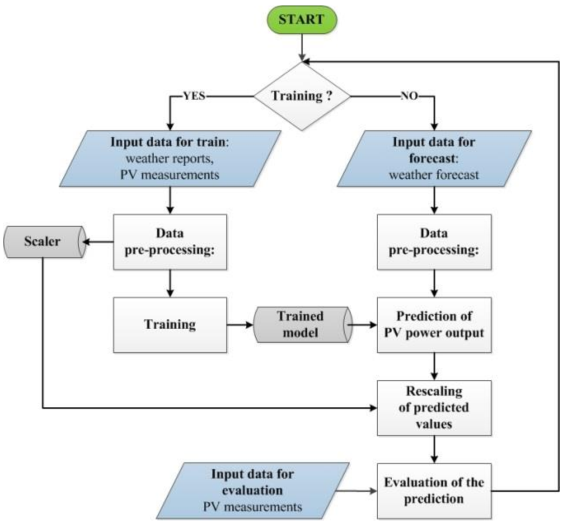

Figure 1: Simplified flow chart of the predictive model

After re-training or in case of negative decision about re-training, the model, which was saved after previous training, is used for making prediction of the PV power for the next 24 h. The last steps in the loop include rescaling of the predicted values and evaluation of the forecast accuracy. The evaluation is done by calculating of the statistical errors (see equations (1), (2), (3)). According to [4], the classical MAPE is adapted for the forecasting of the PV power output:

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \frac{|P_{pred} - P_{meas}|}{P_0} \qquad (6)$$

where P_0 is the installed capacity of the PV system.

Another measure for estimation of the forecast accuracy is the Mean Absolute Scaled Error (MASE), which is described in [4] and [13].

$$MASE = \frac{MAE}{\frac{1}{n-m}\sum_{i=1}^{n}|P_{meas,i} - P_{meas,i-m}|} \qquad (7)$$

This error differs from classical statistical errors in the fact that MASE is independent from the scale of the data. If MASE is greater than one, the used predictive method has poor forecast accuracy.

Besides statistical errors the difference between the measured and predicted daily energies plays an important role. This measure is called energy forecast error and it’s calculated with the following equation [14]:

$$\Delta E = \frac{E_{daily,model} - E_{daily,measured}}{E_{daily,measured}} \qquad (8)$$

The sign of the energy forecast errors indicates, whether the predictive model overestimates or underestimates the measured values.

4 RESULTS

In this chapter the results of the prediction with the publicly available weather reports and fee based solar irradiance data for two different PV systems are presented and discussed. Moreover, it is also checked whether the developed predictive model meets the defined requirements, like self-learning ability, transferability, etc.

4.1 Content and sizes of the training and test sets

Because the PV power output depends strongly on the weather conditions and seasons, the developed predictive model is checked whether it can forecast the PV power output for different seasons. For this purpose, the model is trained with the weather data of warm and cold periods, and then the trained model is used to make prediction for warm and cold periods respectively.

Not only is the content of the training set varied, but also its size. Figure 2 shows four different sizes of a training set (7 days, 14 days, 30 days and 90 days), one constant size of a test set (23 days) and a general splitting of the whole dataset in the training and test sets.

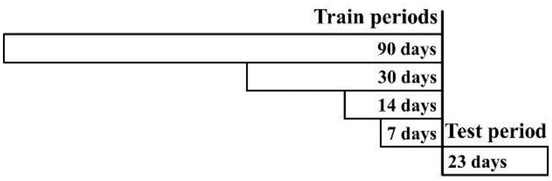

Figure 2: Splitting in the training and test sets

As seen in Figure 2 the first prediction of the PV power output begins always at the same time point independent of the training set size. One after the other, the defined training set sizes are used to train the model and make prediction of the PV power. Then the impact of the training set sizes on the forecasting accuracy is investigated by comparison the predictions with each other.

4.2 Prediction with publicly available weather reports

The developed predictive model with publicly available weather reports as input data must be able to make reasonably good predictions of PV power output. Also, the model must be applied for different seasons of the year, different PV systems, etc. The suitability of the model to different seasons of the year is checked on the PV system in Oldenburg, because this system has enough weather data and weather forecast from OWM. Therefore, the predictive model can be tested for two periods of time with different weather and solar radiation conditions: warm period from 08.08.2017 till 30.08.2017 and cold period from 19.03.2018 till 10.04.2018.

The prediction accuracy for warm and cold periods is displayed in Figure 3. The predictions for both warm and cold periods are made with the predictive model, which is trained with four training set sizes one after the other. All training sets and test sets contain the data from the publicly available weather reports.

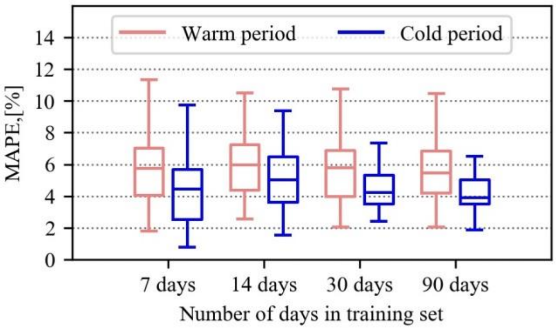

Figure 3: Distribution of daily MAPE-values of warm and cold seasons for four sizes of the training set containing the publicly available weather reports

The prediction accuracies for warm and cold periods are presented in Figure 3 in form of boxplots with distribution of MAPE values. A boxplot is a very representative way of displaying the distribution of the values. The main components of the boxplot are box, median, whiskers and outliers. The box contains the middle 50 % of all values. The line in the box indicates the median. The lower whisker covers the range between the minimum and lower quartile. The upper whisker includes the values between upper quartile and maximum.

The X-axis of the Figure 3 presents four sizes of the training set, which are used to train the model. The Y-axis shows the distribution of the MAPE for the warm and cold period. Because the measured values of PV power in winter are lower than in summer, MAPE for winter are also lower. The scale dependent errors MAE and RMSE have the same disadvantage. For this reason, it's important to calculate the scale-independent metric MASE and to use it for comparison of the prediction accuracy between the different seasons. The distribution of the daily MASE-values for two seasons and four training sets are also presented as boxplots in Figure 4.

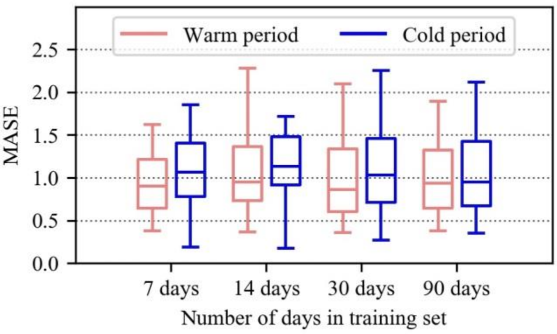

Figure 4: Distribution of daily MASE-values of warm and cold seasons for four sizes of the training set containing the publicly available weather reports

It is obvious from Figure 4 that the prediction of the PV power in the cold period is less accurate than in the warm period: the MASE medians of the cold period lies above 1.0 for almost all training sets except the set with 90 days and the MASE-medians in the warm period are about 0.90 for all training sets. One of the possible reasons for better prediction in the warm period is that solar radiation and, consequently, PV power output in the warm season is more stable, and cold season has a lot of days with strongly fluctuating solar radiation during the day. But the developed predictive model should forecast the PV power output for all seasons of the year equally well. In this case, only the training with 90 days ensures appropriate prediction accuracy for both warm and cold seasons: the MASE-medians of the PV power prediction for this training set are about 0.90 regardless of the season.

After the testing whether the predictive model can make good PV power prediction for different seasons, the same model is also tested whether it can forecast PV power for a completely different PV system. This system is located in Munich, Germany, and its installed capacity is almost hundred times greater than the PV system in Oldenburg. The technical parameters of this PV system are presented in Table I. The power output prediction for the PV system in Munich is made also for 23 days from 08.06.2019 till 30.06.2019. The data set of the Munich's PV system is split in the same way as the data set of the Oldenburg's PV system (see Figure 2).

Because the installed capacity of the Munich's PV systems is much greater than the capacity of the Oldenburg's PV system, only scale-independent statistical metric MASE can be used for comparison of the prediction accuracy of these two systems. The average values of MASE for the whole test periods for two PV systems are displayed as dot chart in Figure 5.

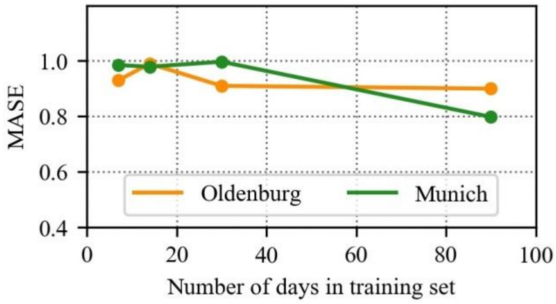

Figure 5: Average of MASE-values for two different PV systems in Oldenburg and Munich

The predicted values of the Munich's PV system have similar average values of MASE, like the predicted values of the Oldenburg's system. The most accurate prediction occurs again after 90 days training, but extension the Munich's training set to 90 days leads to greater improvement of the prediction accuracy. The Figure 5 shows not only the forecasting quality, but it also verifies that the developed predictive model is able to forecast the power output for the different PV systems without any technical information about these systems, except the measured power values.

4.3 Prediction with fee based solar irradiance data

In the following chapter the PV power prediction with the publicly available weather data from OWM is compared to the prediction with the fee based solar irradiance data. This comparison is made for the Munich's PV system.

The main difference between these two data sources lies in the fact, that the publicly available weather reports contain only indirectly values of the GHI like cloudiness, and precipitation while the fee based data already has measurements and predictions of the GHI which are highly correlated with PV power output.

The prediction of the PV power output with the fee based solar irradiance data is made with the same predictive model described in chapter 3. But unlike the previous sub-chapter, the predictive model makes training and forecasting processes with the measurements and predictions of the solar radiation.

Firstly, the MASE values of the PV power predictions with publicly available weather reports and fee based solar irradiance data for all training sets are compared with each other, in order to find out the optimal sizes of the training set for each data origin. Figure 6 shows these values.

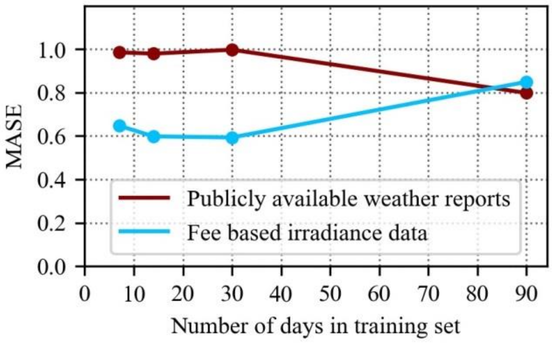

Figure 6: MASE of PV power predictions with publicly available and fee based input data. The prediction is made for the Munich PV system.

Figure 6 shows, that the prediction accuracy of the model with the solar radiation data is much better using shorter training data sets. The extension of the training set with the solar radiation data from 30 days to 90 days leads to the increasing of the MASE. The predictive model makes the most accurate prediction, if the training set contains 14 days of solar radiation data or 90 days of the publicly available data. Further the PV power predictions with exact these training set sizes are compared to each other.

The next measure for the comparison between the predictions, made with two data origins, is the error between the predicted and measured daily energies calculated using equation (8). The normalized distribution of energy forecast errors of the developed model which is trained with 90 days of the publicly available weather data and 14 days of the fee based data is displayed in Figure 7.

There are two main conclusions to be drawn from Figure 7. The first conclusion is that the developed predictive model is slightly inclined to overestimate the measured values no matter what input data is used: about 40 % of the energy forecast errors have negative sigh. The second conclusion is that the predictive model with the fee based solar irradiance data can predict daily energy more accurate than the same model trained with the publicly available weather reports. The energy forecast errors of the prediction with the solar radiation data vary between -10 % and 60 %, but the usage of the publicly available weather reports for the input data leads to increasing of the forecast errors in both directions: overestimating and underestimating.

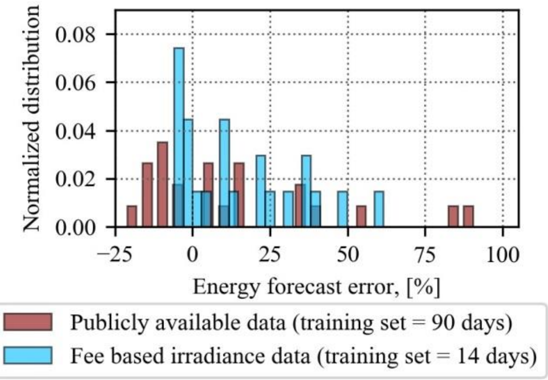

Figure 7: Normalized distribution of the energy forecast errors of predictions with publicly available weather reports (training set with 90 days) and fee based data (training set with 14 days). The prediction is made for the Munich PV system.

It is relevant to consider the predicted PV power output not only for the whole test period, but also for single days. That's why one day with fluctuating PV power is selected from the test set and the PV power values predicted by the model with the publicly available weather reports and fee based solar irradiance data are compared to the measured values. For this purpose, the PV power output at June 20th 2019 is chosen. The predicted and measured power curves for this day are presented in Figure 8.

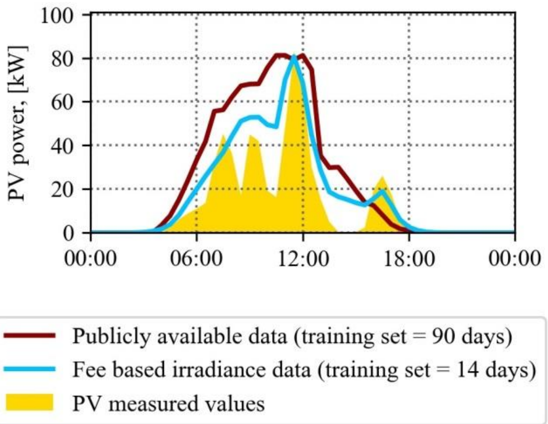

Figure 8: Measured PV power of the Munich PV system in comparison to the PV power predictions made by the model with publicly available weather reports (training set with 90 days) and fee based solar irradiance data (training set with 14 days) at June 20th 2019.

The training with the solar radiation data leads to the fact that the model can predict single peaks and drops of the PV system accurately even by fluctuated PV power production. But the model trained with 90 days of the publicly available weather reports can notice not only the main trend of the day, but it is able to predict the rapid power drop in this day.

5 DISCUSSION AND OUTLOOK

The developed predictive approach is a data-driven method, where the quality of input data plays a key role. Therefore, the accuracy of the publicly available weather reports is investigated at the very beginning of the study.

The accuracy of the PV power output prediction cannot be better than the accuracy of the used input data.

The evaluation of the prediction accuracy indicates that the machine learning approach shows suitable results for day-ahead PV power prediction even with the publicly available weather reports. Although the data from OWM is aimed to be used mainly on the websites and mobile applications, it can be also used for the purposes described here. This study proves also that it's possible to predict the PV power output without forecast values of the solar radiation and without any technical information about PV system, except the measured power values.

In the motivation of the study several requirements to the predictive approach are defined. The first requirement is a fully-automated online operation of the day-ahead PV power forecasting. This requirement is proven during the simulation, where the weather forecasts are updated every three hours. In the same time interval the PV power prediction is made for the next 24 h. The constant updating of the training set with current weather data and PV measurements results in a periodic re-training of the predictive model every 12 hours.

The second requirement is a transferability of the model for all seasons and different PV systems. The suitability for different seasons is tested by the simulation with the data set from Oldenburg, which contains weather data for warm and cold periods. The comparison of the simulation results with these two datasets points out influence of seasons on prediction accuracy, and also the ability of the model for the adaptation to the seasonal weather changes. The transferability of the model to the PV systems with different locations, sizes and technical parameters is proven by prediction of the PV power for two completely different PV systems. During checking the transferability of the model, the main disadvantage of MAE, RMSE and MAPE is detected. Therefore, the scale-independent statistical metric MASE is selected to be applied for comparison of the forecasting accuracy between different seasons and PV systems.

Afterwards the PV power predictions with the publicly available weather reports are compared to the predictions with the fee based solar irradiance data. The predictive model fitted with publicly available weather data needs more training data, in order to make relatively good prediction of the PV power. The best accuracy of the prediction with the publicly available weather reports occurs by the training set with data from last 90 days (time resolution of all data is 30 min). If the fee based solar radiation data is used, the training set with last two weeks data leads to the most accurate prediction. The predictive model with the solar radiation data has not only much better prediction accuracy, but it can also forecast single power peaks and drops of the PV system.

In this study the accuracy of the developed predictive model with the publicly available weather reports is improved in different ways: selection the appropriate input features and machine learning algorithm, optimal configuration of the LSTM-network, increasing the training set size, etc. But the prediction accuracy may be also improved in the future, if publicly available weather data sources provide measurements and prediction of the solar irradiance.

The developed predictive approach with the publicly available weather data is not suitable for the applications, which require higher accuracy and finer resolution, i.e. grid stabilization. But the forecasting quality of the developed predictive approach with the publicly available weather reports is suitable for other applications, like forecast-based energy management system for the commercial buildings with small-scale PV systems. This energy management system based on the PV power prediction can increase the self-consumption of PV system and optimize the operation of PV system and flexible loads, as BEVs and heat pumps. Moreover, the distribution of the energy demand over the day considering the predicted PV power output can support the reduction of peak loads, which excludes the exceeding of power limits on the house connection point and avoids high grid fees.

In this study the publicly available weather reports and fee based solar radiation data for the predictive model are compared with each other only regarding to the prediction accuracy. As the optimal training dataset size in dependence of the input data origin strongly influences the prediction accuracy, especially in cases of disruptive changes like snow cover on the modules or failure of strings, an automatic evaluation of the prediction with a consequent automatic adaption of the training dataset length has to be implemented for a universal prediction approach. Additionally, the evaluation of the data origins by different economic metrics has to be conducted in order to evaluate the economic benefits of paying for the solar radiation data. Another goal is the combination of the developed machine learning approach for the PV power prediction with another approach for the load prediction. These two approaches use different descriptive features, different machine learning methods and predict different target features. In order to evaluate this combination of the predictions, error and uncertainty assessment analysis is intended to be done. Afterwards, these two predictive systems can be integrated in the energy management for commercial buildings based on a multi-modal-forecasting approach.

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