Forecasting of wind power curtailment events

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***Abstract*—Curtailments due to grid congestions (often called EinsMan or Eisman) are of high (economical) interest especially for direct marketers but also for grid operators and providers of wind power forecasts. To establish a curtailment forecast these stakeholders can benefit from, a method is presented to analyse the importance of several commonly available parameters / features and the interaction between them. The analyses shown are carried out for a wind park located in Schleswig-Holstein, the state with most of the curtailments in Northern Germany and generally concentrated on. Reasons to define the forecast as a binary classification problem are given and the usage of Matthews Correlation Coefficient (*MCC*) is proposed as the cost function for machine learning algorithms to select the best performing model and be able to compare the forecasts of parks with a different curtailment rate. With a model based on an extreme learning machine (ELM) with logistic regression the performance of a day-ahead forecast of the probability for an occurring curtailment is demonstrated (*MCC*: 0.73).**

Keywords: curtailments, EinsMan, wind power, forecasts, machine learning, grid congestion, feature importance, SHAP values

I. Introduction

Wind power has seen a steady growth of capacity in Germany within the last 20 years. By the end of 2018 the installed wind power capacity in Germany reached about 59 GW producing 111.5 TWh of electricity corresponding to a share of 20 % within the German power mix [1]. However, the penetration of such high shares into the existing power grid is challenging due to its weather dependent production usually not correlating with the local demand in the system. While the generation from wind (but also from PV) increased quickly the grid reinforcement and expansion could not keep pace. As a result, the amount of grid congestions within the transmission grid, which could not be solved by re-dispatching conventional power stations, increased as well. Consequently, a frequently used option to ensure grid security by grid operators is to curtail the wind/PV power production in regions with high wind power and less consumption – also called Ei(n)sMan.

In 2018 about 5.4 TWh (2017: 5.5 TWh) of wind power have been curtailed in Germany, resulting in 635 million EUR of financial compensation being paid in the end by the consumers [2], [3]. These numbers by itself indicate a high interest to reduce these costs. In the north of Germany the biggest factor limiting the possible power generation are curtailments due to grid congestions [4]. The problem is not limited to Germany though, Ireland e.g. experiences similar problems [5].

Prior knowledge of situations with high curtailment risks can be a helping tool in several decision making processes of different stakeholders.

This paper provides an insight into this field of research and shows results of curtailment forecasts for wind parks in the region of Schleswig-Holstein (Northern Germany) based on machine learning algorithms such as extreme learning machines (ELM) and random forests. The models are using numerical weather prediction (NWP) inputs in combination with, among others demand forecasts. We focus on a day-ahead forecast (DAF) and the interaction of variables from NWP to gain insight into the basic principle of a curtailment forecast, omitting the actual available power measurements. As target time series, we use the SCADA signal. In case the information is not available from the SCADA system we use the curtailments published by SH-Netz.

In [4] a method was shown to detect curtailments in power measurement data with a short delay and different approaches to improve short-term forecasts (STF) with this information. Although we focus on DAF our method can be used for STF as well.

To the best of our knowledge, so far there has not been any publications on (wind) curtailment forecasts, yet.

II. Benefits and profiteurs of curtailment forecasts

Periods prone to a high risk of curtailments, correlate (mostly, but not alone) with high feed-in from renewable energy sources (RES) and bare the risk of the highest possible forecast errors – forecasting nominal power output while the plant's generation in reality is reduced to zero. Even if it is possible to update a short-term forecast with the incoming power measurements the duration of the curtailment itself stays unclear.

With the information of future curtailments providers of wind/pv power or vertical power flow forecasts can proactively integrate this information into their processes to deliver more precise forecasts of both actual and available power [4]. But these forecasts alone are not necessarily the best solution for all customers of forecasts. While working with actual power forecasts taking into account EinsMan actions, these forecasts include a prediction of the TSOs/DSOs actions he is (at least partly) obtaining from the forecast itself; i.e. the forecast most certainly does not indicate a problem with

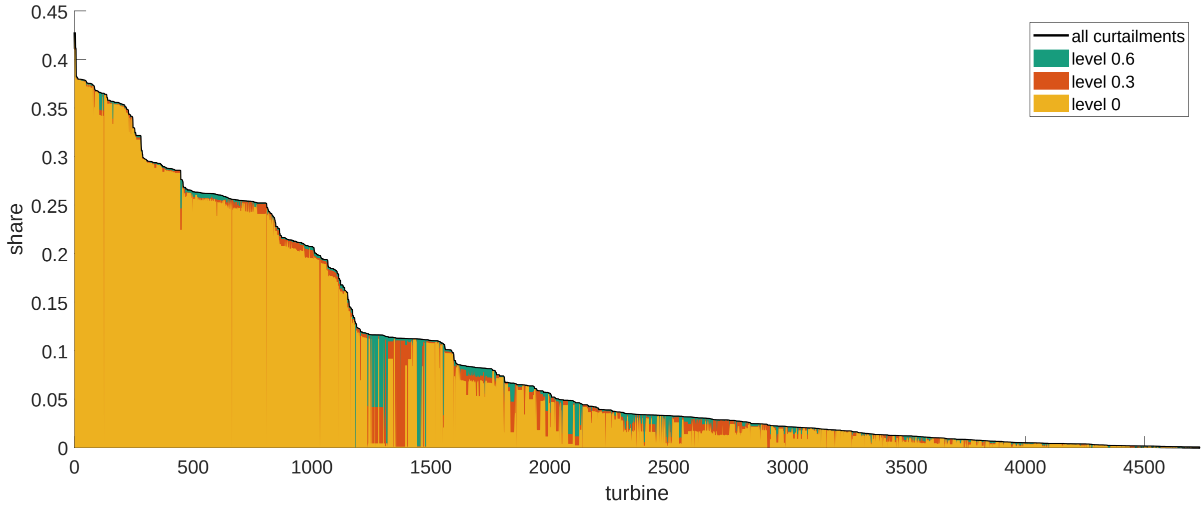

Fig. 1. Share of curtailment level per turbine in SH-Netz region in 2018

a high feed-in the TSO/DSO is supposed to take counter-actions on, because they are already included.

But also in the case of direct marketers a good forecast of available power together with a separately delivered EinsMan-forecast is preferred, as it enables choices based on a more diverse view of the information.

(For now) it is the plant owners who receive the payments for financial losses due to curtailments – as long as the day-ahead prices were not negative for at least six consecutive hours, while the direct marketers themselves have to counter-trade the differences to their priorly traded power at the market. Hence, they have an urge for this information in order to optimize their portfolio and bidding strategies [6].

For the plant operators or their service providers early knowledge of curtailment periods can indicate preferred times for maintenance tasks independent from higher wind speeds.

Furthermore, curtailment forecasts could provide necessary information for a good working demand-side management, hence increasing the share of renewable energies while reducing the amount of curtailed power. Two examples would be optimizing storage options, as proper unit commitment and dispatch plans of classical storage systems as well as batteries and P2X-processes kind of require and rely on curtailment forecasts, or providing consumers with easily accessible information (and incentives) to reduce the pressure on the grid by shifting or reducing their consumption.

All of these stakeholders would profit from a (probabilistic?) curtailment forecast, for either a single power plant, a portfolio, or different aggregation levels like grid nodes.

III. Methodology

To show the feasibility of a meaningful curtailment forecast, relevant input data has to be identified after the target is defined, and a verification process determined. Furthermore, the applicability of different forecasting methods with the given input data has to be proven on a test setup.

A. Target Data

The initial target time-series are the curtailment level the park/plant is reduced to, i.e. a value of ’0’ corresponds to the TSO/DSO curtailing the plant to zero power output, a value of 0.6 means the plant is not allowed to feed-in more than 0.6 times its nominal power.

As mentioned in [4] there are three main ways to obtain a curtailment time series – from SCADA data, with an detection algorithm from the power data and from the public data of the corresponding DSO. The time-series from the DSO though, is given per single plant/turbine, whereas the time-series of the selected turbine might be not sufficient to represent the curtailment behavior of a whole park.

If possible, the curtailment time-series – wherever it stems from – should be checked for plausibility against the measurements, especially if the plant-ID (EEG-ID) is not known.

Analyzing the data from wind turbines curtailed at least once in the region of one DSO (SH-Netz) in the North of Germany reveals the (un-)importance of certain level. Even though technically possible, only a few level are actually used. The analysis gives the level distribution of all curtailed quarter hours (15,343,545) of all wind turbines still operational of the aforementioned DSO for the year 2018 and their frequency of occurrence:

0: 13,690,154 0.3: 973,622 0.6: 679,769

This means that in 89.2 % of all curtailed quarter hours the turbines feed-in was set to zero.

Inspecting the data more detailed on the turbine level reveals several findings. Figure 1 shows the distribution of curtailment level per turbine sorted by the total share of curtailments over the year 2018. The 1200 most curtailed turbines’ output was almost solely curtailed to zero. Although the curtailment rate reaches up to nearly 40 % the 1000 mostly affected turbines have an average curtailment rate of 28.4 %. On the other hand more than half of the turbines (ca. 2700) have curtailment rates below 5 % with a higher mixture of level. As turbines with high shares of level 0.3 and 0.6 are clustered both in their similar total curtailment rate as well as in their level distribution they are most likely parks positioned geographically close to each other and probably connected to the same transformer station.

It has to be mentioned that the analysis can include turbines installed within the year 2018, therefore not operational throughout whole 2018. In this context those turbines would be showing both a distorted curtailment rate as well as a wrong distribution of level. The total amount of these special cases is assumed to be negligible, though.

The case is completely different for the offshore wind parks (OWP). Instead of three reduction level (0, 0.3 and 0.6 of nominal power) OWP are down-regulated in much finer steps of 0.01, which makes sense regarding their high installed capacity and the resulting change in output. This results in 1000 possible level of which indeed nearly 760 were used for the Tennet OWP in the first eight months of 2019 already [7].

With this information it is decided to concentrate on onshore first, neglect the different level and define the target input as a binary: 'true/1' for a curtailment and 'false/0' for no reduction. Especially from a machine learning point of view this is crucial as with the data being aggregated to parks and an uneven distribution of level over the parks but especially over the year, the absolute amount of data-points for each level per park in the training set shrinks, making it difficult to get sufficient training data. In case the forecast is for one of the turbines/parks with a high share of different level this decision could be reassessed.

This creates a binary-classification problem which is usually easier to handle than a multi-class one. Depending on the forecast model used the output is given as the probability for a curtailment event to happen – providing more information than a binary output would.

B. Input Data / Features

As wind turbines are hit with curtailments by a huge margin (72 % on-, 25.1 % offshore wind vs 2.2 % pv of down-regulated GWh in 2018 [3]) the conclusion of possible wind power production being the decisive factor for curtailments is easily to be drawn but still has to be proven first. The high share of curtailments could also simply be due to a high share of installed capacity.

Nevertheless, it makes sense that other factors are playing a role for a precise curtailment forecast, as well. With the same possible wind power generation e.g. the load can be the difference between a curtailment enforced and an operation without any intervention necessary. The first case results in an amount of energy being generated exceeding the demand (including transmission line capacities to other regions) whereas in a higher load scenario the system might stay balanced.

Besides the meteorological ones (most importantly wind-speed) there are more parameters, that at least potentially can play a role in a congestion case and can therefore be of interest as input features from a machine learning point of view. These are among others: load forecasts, day-ahead and intra-day prices (as forecasts), day-of-week or time-of-day.

But the data is not always easy to obtain and the availability of features are depending on the customer, the use case and the time the forecast is needed; e.g. if the forecast is due as DAF shortly before 12:00 day-ahead prices are not yet available and only forecasts can be used for them (which will already account for possible curtailments), while for the clearing of the intra-day market at 15:00 those numbers are available.

Hence, here the importance of commonly available input data for the prediction model is analyzed beforehand to concentrate further research on those with a big decisive impact and get a rough estimate of the lost potential of a potentially unavailable feature.

C. Feature Importance

The suspect of wind speed being one if not the biggest drivers of curtailments in the examined region additional to the aforementioned evidences can be supported with Fig. 2.

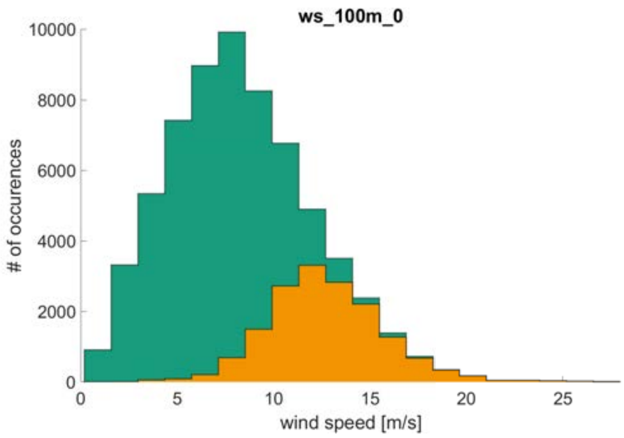

Fig. 2. Distribution of curtailed (orange) and not curtailed (green) wind speed at 100 m height for March 2017 till March 2019

It shows the distribution of wind speeds for one wind park with a quarterly hour resolution. All plots in this section use data from the same park. The orange area marks those quarter hours the park was curtailed at the corresponding wind speeds. It is apparent that from around 14 m/s on more than 90 % of the times are curtailed. The share of curtailments per wind speed bin increases the most from ca. 10 to 13 m/s. This wind speed region falls in the area of wind turbines reaching their nominal power (maximum power generation). With the wind further increasing it is more probable larger regions experience wind speeds high enough to reach nominal power – and therefore chances of grid congestion rise a lot as well. This correlation is probably the explanation/reason that one DSO gave out some kind of 'static' forecast, which only gives a wind speed value for certain transformers. With the exceedance of this value at a turbine connected to the corresponding transformer, a curtailment is supposed to be very likely [8].

Of course, this kind of plot can be made and analysed for each available feature to highlight some correlation (but not necessarily a causation!) between their value and the probability of curtailment at the same time, but this 'method' completely neglects interactions between the features.

An alternative approach is to make use of cooperative game theory methods to 'explain a prediction as a game played by the feature values' [9]. This method can also be used to explain individual predictions of machine learning models while also including the interactions between the features by working with Shapley values [10]. Shapley values can be interpreted as:

> 'Given the current set of feature values, the contribution of a feature value to the difference between the actual prediction and the mean prediction is the estimated Shapley value.' [9]

Here, SHAP (SHapley Additive exPlanations) values and SHAP interaction values are used which are based on the classic Shapley values [11], [12] but are computationally less expensive – especially for trees and ensembles of trees – and are easily obtained from the data via the SHAP package in python. This concept was e.g. shown in [13] to explain the risk factors in real time predictions being made during a surgery on the risk of hypoxaemia.

In this case though the method is applied for a XGBoost model (gradient-boosted decision tree) with the data for one park at a time and a period of two years to analyse the importance of the features and the interactions between them, which gives their significance in the model. The method is applied to several parks to get an indication if there are substantial differences between the parks or if the results can be generally used for all parks in the region. It was decided to not split the data into training, validation and test but to give the model all the data available, as the goal is not to establish a good forecast model but to give advice in the decision-making process of evaluating the importance of certain features in general. Consequently over-fitting is not to be seen as a problem. Not splitting the data prevents seasonal differences in feature importance to distort the overall results. These differences are supposed to be learned by the forecasting method after the features were selected.

Figure 3 shows the positive or negative impact of each features time step colored after the normed value of the feature itself. Its importance as mean of the absolute SHAP values corresponding to the average impact on model output magnitude are displayed as gray bars for one specific park over the whole time period. Meteorological parameters used in this example are: wind speed (*ws*) in different heights and triangularly decomposed wind direction (*wd*), temperature (*t*) and dew point (*d*) at two meters height, pressure at the surface (*p_sfc*), global horizontal irradiance (*Ggh*) as well as *solarAzimuth* and *solarHeight*. In case of *ws** and *ggh** the last number indicates a time shift, '1' for normal, '0' or '2' for minus or plus one hour shift respectively. Non-meteorological features are: a sinus-cosinus-wise decomposition of hour-of-day-time (*hod 1&2*) and day-of-week-time (*dow 1&2*), a load forecast for Germany (*demand_DAF*) and *night_time*, a logical value

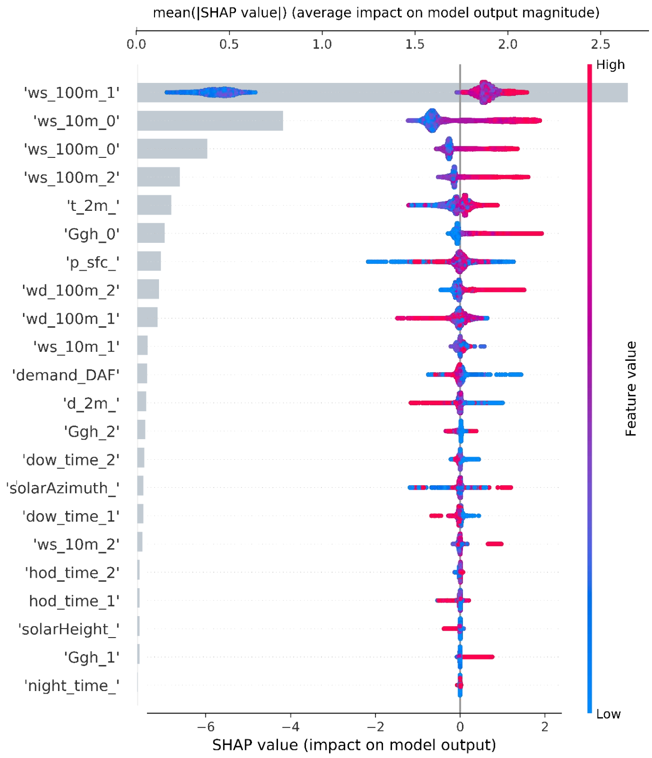

Fig. 3. Importance of features (gray bars, top x-axis) and SHAP values per feature colored after the normed value of the feature itself (bottom x-axis)

representing the times defined as 'night' by German law (important for noise-emission-reductions).

It is to be seen, that the wind speeds are clearly the important features, with the wind speed close to hub height and without any time shift being the most important one. Low values for this feature have a big negative impact on the model – corresponding probabilities for a curtailment are very low, while high wind speeds increase the chances, as expected. The case is similar for *Ggh* whereas a negative time shift of one hour reveals higher importance. Again, high values result in positive SHAP values, but the impact of low *Ggh*-values is very small. This comes from the values not having a lot of influence when being constant '0' during the night – other parameters must be the deciding factors for or against a curtailment. During the day (in combination with *hod, solarAzimut* or *solarHeight*) though, low irradiance values explain small PV-generation and less pressure on the grid. Keep in mind, that the results differ between analysed time periods.

But even though wind speed is the most important parameter, the model relies on more input but wind speed to decide in the transitional region between 'curtailment' or 'no curtailment' being the most probable as can be seen in Figure 5. The figure shows the SHAP values of all features for all time steps (covering 2 years), sorted ascending by the normed wind speed input data without time shift. The output value (probability of curtailment; watch the y-axis' scale) is indicated as the line between all the blue and red areas. Areas marked in red correspond to values pushing the output value from the class average of ca. 23 % upwards while those marked in blue reduce the probability. While

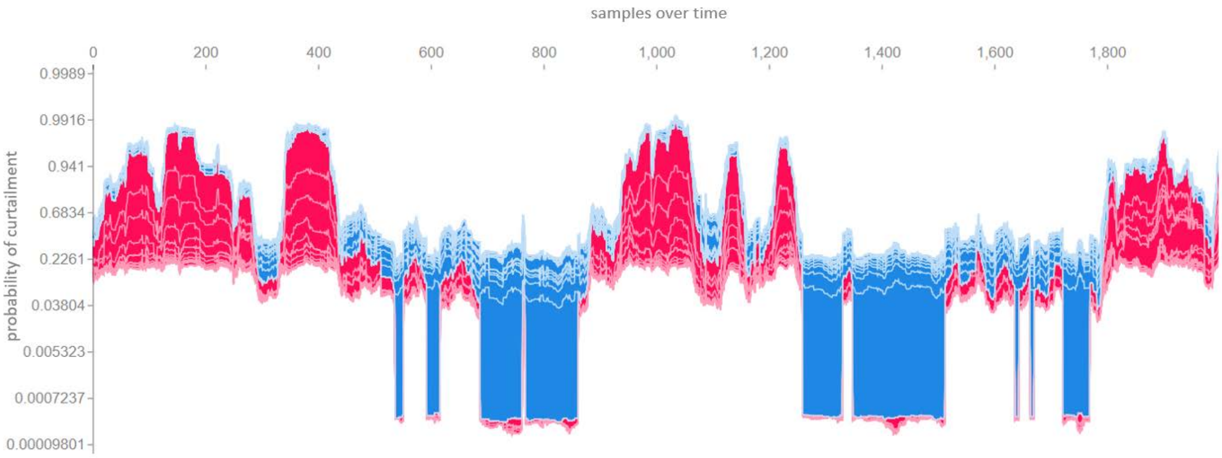

Fig. 4. Effects of features over time. Red areas are features pushing the probability for a curtailment upwards, features marked in blue reduce it.

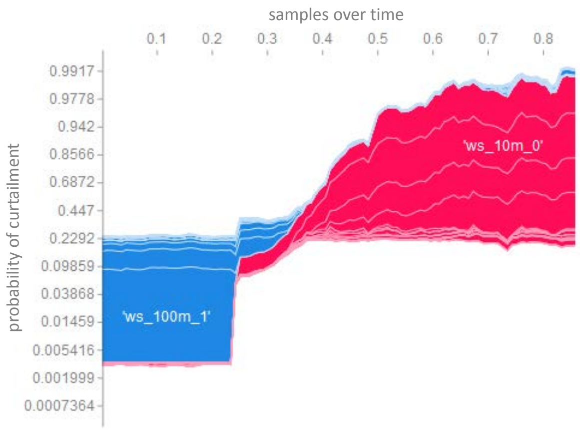

Fig. 5. SHAP values sorted by wind speed value in 100 m height; border between red and blue areas define the probability of a curtailment; watch the y-axis' scale

the output value is similarly low for wind speeds between 0 - 0.23 and relatively high for wind speeds above 0.5 the transitional phase between 0.3 and 0.45 can be seen. Here, the importance of the wind speed is reduced while other parameters are the deciding factors. The conclusion is that as an rough estimate the wind speed seems sufficient to forecast most of the curtailments correctly, while more parameters are necessary to obtain especially the start and end times of a curtailment more precisely and increase certainty in the more uncertain cases.

It is also possible to plot the data over time, either for a single feature or for all features at once. This enables to detect temporal dependencies, e.g. the importance of a certain feature over the seasons or for specific events. Figure 4 shows the contributions of all features to the final output value (probability of a curtailment) over a time period of around 20 days.

Additionally the SHAP interaction values allow to go a little further into details. As an example Figure 6 shows the interaction between the shifted wind speed at 100 m and first un-shifted wind direction component. It illustrates, that the interaction between the two features is low, for low wind speeds – the blue dots gather around zero. Nevertheless some kind of linear behavior from slightly negative to positive interaction values the higher the wind direction component. This changes for high wind speeds: the absolute interaction values are higher and a fitted line would have a negative slope. It would be nice, if the interaction can be directly explained roughly by a line with a fixed point at 0.5 of wind direction and zero interaction, with the slope linearly depending from the wind speed, but the slope. But the slope increases for wind speed values of up to 0.35 then switches signs.

These kind of plots are created for all pairwise combinations of features to find more information on the dependencies between them.

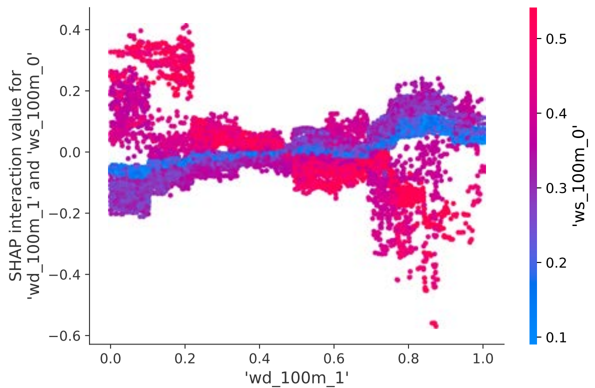

Fig. 6. Interaction values between wind speed and wind direction at 100 m

D. Cost Function / Verification Method

With the target defined as above a binary classification problem has to be solved. Depending on the wind park the classification problem can be quite strongly miss-balanced, more than half of the turbines ever effected in 2018 are curtailed less than 4 % of the year (see Fig. 1). At the same time nearly 20 % experience curtailment rates of more than 20 % and up to 38 %. In case the usage of cross-validation is desired one has to keep the time (especially seasonal) dependency in mind, which can result in a strong miss-balance between the classes, even down to no occurrences of curtailments in some folds.

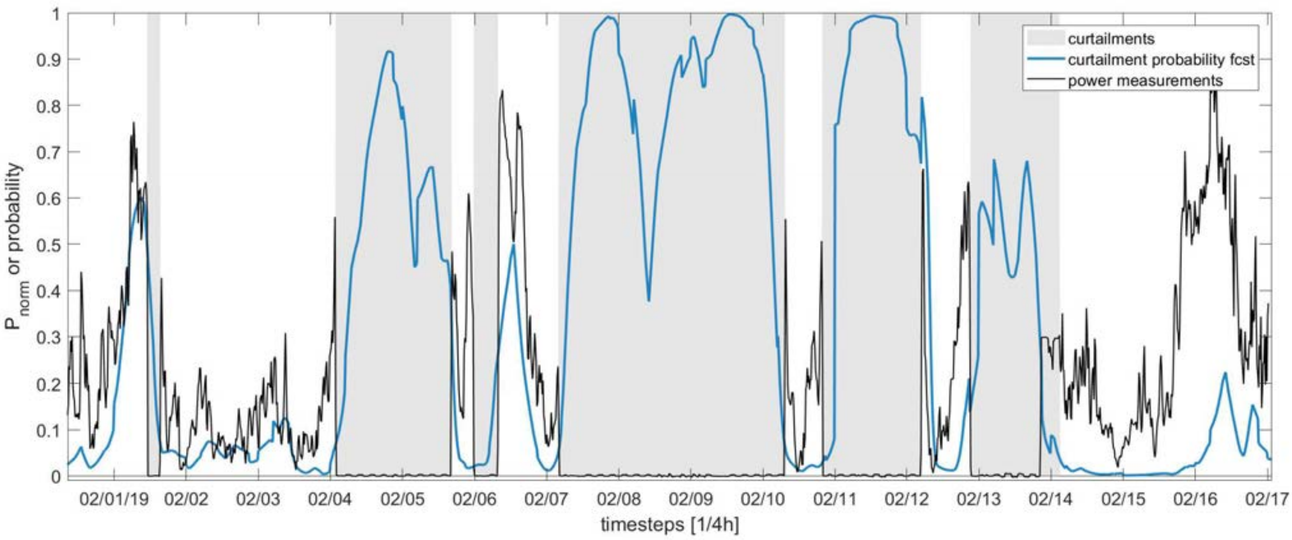

Fig. 7. Day-ahead curtailment probability for one park (blue). The gray areas mark times of curtailments, the black line the actual power measurements.

As described in Section II different ways to take advantage of curtailment forecasts exist. But already this forecast itself – as it is the case for all forecasts – is depending on the chosen error measure / score.

Depending on the customer and his use-case it is more important to get warned for as many events as possible (high true positive rate, tpr) while false alarms (false positive rate, fpr) do not play such a big role while for others false positives rates are the ones to be avoided with all force (low fpr). The weighting between those values can already be taken into account during the training to some extend and has to be discussed with the customer beforehand.

Accuracy and F1-Score are error measures often used in classification problems, with miss-balanced classes though, the classifier will just tend to be biased towards the class with most samples. Similar problems arise with precision or recall, other frequently used error measures, because they can not easily be used as a solitary score [14].

To ensure a score being able to handle miss-balanced classes and hence enabling the comparability of varying time periods and parks with different curtailment rates, Matthews correlation coefficient MCC is used [15], [16].

$$MCC = \frac{tp \cdot tn - fp \cdot fn}{\sqrt{(tp + fp) \cdot (tp + fn) \cdot (tn + fp) \cdot (tn + fn)}}$$

Just like the other previously named scores it works with values of the confusion matrix, namely true positive (tp), true negative (tn), as well as false positive (fp) and false negative (fp) values, respectively. But unlike the others it is indifferent to classes of different sizes. The value ranges from -1 to 1 with one being a perfect forecast.

During the training a threshold of 0.5 is used to convert the forecasted probability into a binary. Depending on the use case the threshold can be set differently in order to modify the entries' weighting of the confusion matrix.

IV. Results

In Fig. 7 a day-ahead curtailment forecast for one park for a time period of several curtailments is demonstrated. The model (ELM) is trained with the feature data listed in Fig. 3 of only one year (including a test and validation periods). The curtailment rate for the training and validation period is 22 % which places the park just in the upper quarter of most curtailed turbines (Fig. 1). The measurements are displayed in black and the curtailments are visualized with the highlighted gray areas. The blue line shows the probability of a curtailment itself. Though not perfect, overall the forecasted probabilities correlate quite well with the actual curtailed times. The high power output (corresponding to high wind speeds) combined with a curtailment probability of max. 20 % around the 16th of February shows that curtailments can not be predicted by the power output of a turbine/park or the corresponding wind speed alone. Another interesting detail is the (seldom) reduction to 0.3 of nominal power on the 14th while at the same time the probability starts to decrease immediately before, which is even more interesting as the turbines can not produce up to that level at all times.

	Curtailed	not-curtailed
curt.-pred.	1586 (tp)	102 (fp)
no curt. pred.	542 (fn)	2401 (tn)

With in total 4613 values from the confusion matrix the MCC value of the forecast for the test period of mid February to mid March 2019 results in: 0.73. One has to keep in mind though, that the binary evaluation values are obtained with a threshold of 0.5 but they can be tuned in desired direction, either towards more correctly predicted curtailments while increasing the amount of fp or in the direction of less fp with the trade-off of fewer correctly forecasted curtailments.

V. Discussion / Outlook

So far it is reasonable to define a curtailment forecast as a binary class problem but for offshore parks and maybe in the future also onshore more level than 0/0.3/0.6/(1) are set by the grid operator and change with a higher frequency. The problem gets more complicated: it is multi-class target and very few samples per level are likely to be found in the relevant input data set.

It can be difficult to assure enough curtailed training samples for parks with very low curtailment rates, especially considering the unbalanced distribution over a year and possible splits of the training data. Yet the focus is first on the parks with high rates as curtailment forecasts should have the highest value for them. Therefore a park with a curtailment rate of 22 % – just in the upper quarter of most curtailed turbines – was picked. Nevertheless, it is important to test the method also with parks being less curtailed or located in different regions.

Besides the load forecast all the features are based on the forecast of local conditions (excluding the time based variables dow, hod or $night\_time$). One of the next steps is to analyse the benefit of information not directly connected to the parks location. These are e.g. meteorological conditions for other wind parks, especially offshore wind parks (the conditions differ, but they can still contribute to the grids' congestion) and add spatio-temporal information. Also the interconnector capacities to other countries (DK and after the completion of NordLink NO) and their renewable energy generation can be helpful. But not only transmission capacities to other countries are of interest and subject to changes, with reinforced transmission lines inside of Germany these characteristics are going to alter and it will be the challenge to adapt the forecast models accordingly. Also in those cases knowledge of grid regions can provide further information on the characteristics of curtailments.

At the same time the aspect of adding locally restricted demand forecasts is assumed to get more important in the future, due to the regions different capacities of demand side management (industry, storage systems, PtX, etc.).

Additional to the challenges based on the input features or the changes in the grid infrastructure another development will add complexity to the topic. As of fall 2021 an amendment of the curtailment regulation is supposed to enter into force [17]. From then on renewable energy will be part of the re-dispatch process in case of grid congestion (loses part of its feed-in priority during the re-dispatch process). This marked based solution is supposed to reduce the amount of curtailed power and reduce the costs for society until the grid is sufficiently reinforced to cope with (most of) the available power, but the power will not be feed-in anyway.

Instead of calling it a curtailment forecast small tweaks should do to transform/adjust the curtailment forecast to a congestion forecast, which would still be important, less so for the grid operators but for the direct marketers even more so. Most of the factors will stay the same – the grid would be congested nevertheless, if all the power available would be fed-in. But the price levels at which power generation creates a loss for the direct marketer and a down-regulation is triggered is going to change (probably rise).

While the results seem to have a quite static behavior we assume curtailment forecasts to get more complex with the aforementioned changes.

VI. Conclusion

Curtailments due to grid congestions are a topic of high interest especially for direct marketers, forecast providers and grid operators. To establish a curtailment forecast, these stakeholders can benefit from, a method is presented to analyse the importance of several commonly available parameters / features and the interaction between them for a wind park in the examined region of SH-Netz. The usage of Matthews Correlation Coefficient (MCC) is proposed as a cost function for machine learning algorithms to select the best performing model and be able to compare the forecasts of parks with a different curtailment rate. With a model based on an extreme learning machine (ELM) with logistic regression a working day-ahead forecast for the probability of an occurring curtailment is shown. A short-term forecast should deliver even better results.

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