An Icing Forecast for Wind Power Plants A Logistic Regression in Julia

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Motivation and Research Question

Due to an increasing generation of electricity from renewable sources [1] the importance of *generation forecasts* is rising. Icing forecasts for wind power plants are essential. On one hand unplanned outages of wind farms cause imbalances in the electrical grid [2]. On the other hand they can cause imbalance power costs for the operator [3]. The focus of the diploma thesis is on:

- Icing related costs
- Feasibility to predict icing events based on supervisory control and data acquisition (SCADA) and meteorological data

Methodology

For three different wind parks in Lower Austria SCADA data from 2014 to 2017 are analysed. Based on this data empiric power curves (see Figure 1) are determined.

To evaluate the icing costs the binary output of the icing sensor Labko LID-3210C and SCADA data are analised. The period between the indication of one icing event by the icing sensor and the restart of the wind power plant is stated as the icing period. Within this period the lost energy generation is calculated based on the empiric power curve (see Figure 1). All months in which icing occurs are defined as icing month.

The lost energy generation E_{loss} is calculated by equation (1) where $v(t_{i,15})$ is the wind speed for each 15-minute time step, $P_{\mathrm{mean_{EPC}}}$ is the mean active power from the empiric power curve and t is time.

$$E_{\mathrm{loss}} = \sum_{i=0}^{n} \frac{v(t_{i,15}) P_{\mathrm{mean_{EPC}}}}{4} \tag{1}$$

By the equations (2) and (3) the imbalance power costs based on rated power $c_{\mathrm{IP,r}}(t)$ are calculated where $E_{\mathrm{loss}}(t)$ is the lost energy generation, $c_{\mathrm{IP}}(t)$ are the imbalance power costs, $p_{\mathrm{IP}}(t)$ is the imbalance power price and P_{r} is the rated power of the wind power plant.

$$c_{\mathrm{IP}}(t) = E_{\mathrm{loss}}(t) p_{\mathrm{IP}}(t) \tag{2}$$

$$c_{\mathrm{IP,r}}(t) = \frac{c_{\mathrm{IP}}(t)}{P_{\mathrm{r}}} \tag{3}$$

The opportunity costs without an icing forecast $C_{\mathrm{opp}}(t)$ are calculated by equation (4) where $p_{\mathrm{IDAVG}}(t)$ is the intraday average price and $p_{\mathrm{IP}}(t)$ is the imbalance power price.

$$C_{\mathrm{opp}}(t) = E_{\mathrm{loss}}(t)(p_{\mathrm{IDAVG}}(t) - p_{\mathrm{IP}}(t)) \tag{4}$$

The generalized linear forecast model is realised as a **multiple logistic regression** based on a forward selection with a Bayesian information criterion [4] [5]. The economic analysis as well as the multiple logistic regression are written in the programming language **Julia**.

The data is divided into 70 % training and 30 % validation data and randomly shuffled afterwards. To make the results comparable a seed is set.

To validate the results, which the model produces on the unseen validation data, accuracy, precision and recall (Equations (5) – (7) [6]) are used. Table 1 gives an overview of all possible outcomes of the prediction model.

Table 1: Confusion matrix with all four possible outcomes of the prediction model

True Positive (TP)	FalsePositive (FP)	False Negative (FN)	True Negative (TN)
Icing sensor: 1	Icing sensor: 0	Icing sensor: 1	Icing sensor: 0
Model output: 1	Model output: 1	Model output: 0	Model output: 0

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

Results

The predominating wind speed is between 2.5 and 7.5 m/s. Within this interval figure 1 shows a high count of recorded data sets.

There are on average 10 icing events per year. During the icing month from November to April on average 1.67 icing events per month occur. The yearly average downtime is 3 days and 16 hours, which leads to a yearly **average lost energy generation of 344 MWh** hence mean imbalance power costs per installed capacity of 984 €/MW$_r$ per wind park and year.

The yearly average **opportunity costs** in case the wind farms are not subsidised and no icing forecast is used are **9667 €** per year and wind farm. The mean imbalance power price per year is 31.25 €/MWh. In contrast the mean imbalance power price while the wind turbines are not operating due to icing is 55.34 €/MWh.

The accuracy of the forecast model is above 78.8 %, the precision is reaching up to 2 % and the recall is higher than 77.8 %. A rise of the threshold shows a positive impact on the accuracy as well as on the precision.

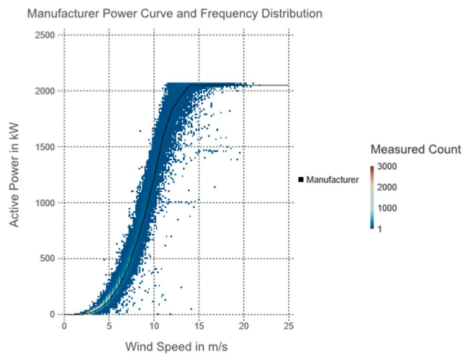

Figure 1 (on the right): Exemplary empiric power curve as a frequency distribution of the measured active power over the wind speed for 2014 - 2017 (squares). The frequency is indicated by the color of the spuares. The manufacturer power curve is respresanted as a black line.

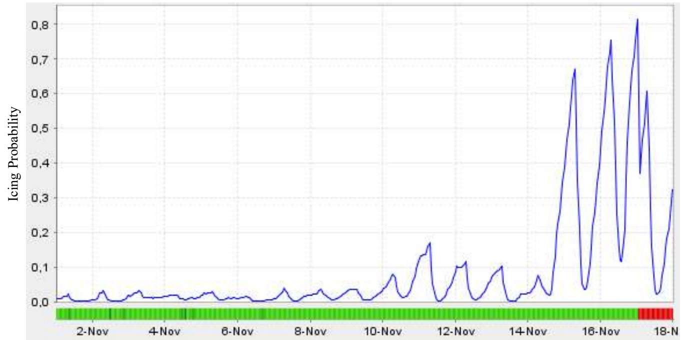

Figure 2 shows the exemplary output of the model for one wind park tested on the live system of EVN AG on 7th of November 2017. The icing probability based on historical data in the period 1st to 6th of November 2018 and on the forecasted input parameter in the period 7th to 17th of November 2018. The green bar above the dates indicates available values. The red bar indicates missing values.

Conclusion

To achieve a more precise forecast the model should be trained on a lager data set including more icing events. To make the model even more accurate liquid water content in the air, droplet median volume diameter, air temperature and air pressure should be measured and forecasted at nacelle hub height.

By the methods described in the diploma thesis it is feasible to estimate the icing related costs and it is possible to predict icing on wind power plants based on SCADA and meteorological data. It can be concluded that the icing related costs for wind power plants amount to approximately 1 % of yearly average contribution margin.

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