Vaffel - a tool for forecasting transmission line failures based on Bayesian updating, renalysis data and medium range weather forecasts

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Øystein Rognes Solheim
Dept. of Data Science, Statnett SF
Dept. of Electric Power Engineering, NTNU
Oslo, Norway
oysterso@ntnu.no

Ingeborg Ligaarden
Dept. of Data Science, Statnett SF
Oslo, Norway
ingeborg.ligaarden@statnett.no

Boye Annfelt Høverstad
Dept. of Data Science, Statnett SF
Dept. of Computer Science, NTNU
Trondheim, Norway
boye.hoverstad@statnett.no

Thomas Trøtscher
Dept. of Data Science, Statnett SF
Oslo, Norway
thomas.trotscher@statnett.no

Markus Andersen
Dept. of Data Science, Statnett SF
Oslo, Norway
markus.andersen@statnett.no

Magnus Korpås
Dept. of Electric Power Engineering
NTNU
Trondheim, Norway
magnus.korpaas@ntnu.no

***Abstract*—This paper presents a method for forecasting the probability of weather-related transmission line failures. The method combines failure statistics, a Bayesian updating scheme and reanalysis weather data to produce fragility curves that model the relationship between weather exposure for a component and the probability of failure. The fragility curves are combined with medium range weather forecasts extracted at each span of the individual transmission lines to obtain a forecast of the hourly probability of failure for each line. A tool that implements the method has been developed and is currently being tested operationally within the Norwegian TSO Statnett. We show the data requirements and demonstrate the use of a dashboard that expose the forecasts to an end-user.**

***Index Terms*—power system reliability, forecasting, bayesian methods, fragility curves, probabilistic reliability**

I. Introduction

Along with the increased levels of green energy and intermittent production during the last decade, there has been a renewed focus on probabilistic risk assessment in power systems [1], [2], [3]. Natural hazards are the root cause of more than 50 percent of the Energy Not Served (ENS) in the Norwegian transmission system [4]. As climate change most likely leads to more frequent and more intense extreme weather events [5], it becomes even more important to be able to manage the weather-related risks across all levels of society, including the power system.

Many power systems are planned and operated using a deterministic N-1 criterion. However, the effects of "failure bunching" [6], where adverse weather leads to elevated failure probabilities for several transmission lines simultaneously, are not handled satisfactorily within a deterministic framework. Hence, a probabilistic approach where failure probabilities vary with the adversity of the weather is necessary.

At the same time, policymakers in Europe are now enforcing legal obligations for the Transmission System Operators (TSOs) to develop an operational probabilistic risk assessment (PRA) methodology [7], as expressed in the article 44 of the ACER decision on coordinating operational security analysis (CSAM) [8]. The approach and methodology demonstrated in this paper is one possible approach for the European TSOs to fulfil these obligations and operate the European transmission grids more safely and in compliance with future regulations.

In [9] the authors established a tool for online reliability assessment, comparing weather-dependent with constant failure rates. In [3], time-dependent failure rates were explicitly modelled and connected to weather forecasts for the Icelandic power system. In [10] and [11], observed failure data are used in a Bayesian updating scheme together with reanalysis weather data to establish fragility curves as defined in [12] and [13], such that the hourly probability of failure is consistent with the long-term failure rate. Using this Bayesian approach, it is possible to achieve credible failures rates even for the transmission lines without any observed failures.

This paper presents a tool for forecasting hourly weather-dependent transmission line failure probabilities. This paper builds on the work in [10] and [11] where statistical models were built in order to simulate historical failures in the power system. In contrast, the main idea in this paper is to forecast future failures using available short-term weather forecasts in conjunction with the established relationship between weather intensity and probability of failure. This relationship is expressed through fragility curves, individual to each transmission line. A fragility curve contains information on a line's propensity to fail. For each transmission line, we construct a fragility curve for each underlying root cause of failure. In this work, we consider wind and lightning related sources of failure, but the approach is in principle applicable to other underlying sources of failures whenever a forecast is available, such as icing [2] and wildfire [14].

The rest of this paper is organized as follows. In Section II we present the works of [10] and [11] which form a theoretical foundation of the presented tool. We successively go through the Bayesian updating, the fragility curve usage and how the reanalysis data are used in the model. In Section III, we present the forecasting tool and its data requirements. We demonstrate how it works and how it is being used within the Norwegian TSO. In Section IV we summarize the work and present future improvements and alternative use cases.

II. PROBABILISTIC RELIABILITY

The idea in the Bayesian updating scheme is to use a general failure rate for all transmission lines within a specific category, and then to adjust the failure rates for each line based on observed failures within that category for each line. The updating scheme, as presented in [10] and [11], was used to calculate annual failure rates for transmission lines. This approach is motivated by the observed variation in failure rates for individual transmission lines. These individual variations can be explained by several factors, such as age, technology, weather exposure and maintenance schedules. A Bayesian approach enables us to take all these factors into consideration when building a statistical model for the failure rates.

Based on the Norwegian system of failure reporting FASIT [15], the disturbances in our statistical models are classified according to whether human interaction is necessary to handle the failure. Disturbances that are self-resolved without any human actions (except for a possible restart of a computer) are classified as ”temporary”, whereas events that need some sort of repair or human intervention are classified as ”permanent”. These failure modes typically have very different outage durations, where ”temporary” disturbances usually only last for seconds or minutes whereas ”permanent” disturbances could last for hours up to days or weeks.

As in [10] and [11], we first split the overall failure rate λ_l for a transmission line l into a sum of failure rates based on K categories:

$$\lambda_l = \lambda_l^{\mathrm{c}_1} + \lambda_l^{\mathrm{c}_2} + ... + \lambda_l^{\mathrm{c}_K}. \tag{1}$$

Here c_i denotes category i and these categories consists of the different weather phenomena related to the disturbances and the above-mentioned type classification (”temporary”/”permanent”) in the failure statistics. As an example, with two weather phenomena as root cause (”wind speed”/”lightning”) and two failure types (”temporary”/”permanent”), we have $K = 4$ for our statistical model.

A. Bayesian updating scheme

In the Bayesian approach, for each category c_i we construct the prior distribution by using the observed average for all transmission line as the failure rate $\lambda_l^{\mathrm{c}_i}$. When constructing these historical averages we also take into consideration the voltage level and the length of the transmission line.

For notational simplicity, in the following we let λ denote the annual failure rate for a transmission line l within category c_i and we let the random variable Y denote the number of failures y_i^{c} per year. We model this as a Poisson process with failure rate parameter λ and density $f_{\mathrm{Y}}(y|\lambda)$:

$$f_{\mathrm{Y}}(y|\lambda) = \frac{\lambda^y e^{-\lambda}}{y!}. \tag{2}$$

If we have observed $y_1, y_2, ..., y_n$ failures for subcategory c for each year over a period of n years, the likelihood function thus becomes

$$p(y|\lambda) = \prod_{i=1}^{n} \frac{\lambda^{y_i} e^{-\lambda}}{y_i!} \tag{3}$$

$$\propto \lambda^{\Sigma y_i} e^{-n\lambda}. \tag{4}$$

In the Bayesian scheme, we model the general failure rate as the prior with a gamma distribution given by

$$p(\lambda) = \frac{\beta^{\alpha}\lambda^{\alpha-1}e^{-\lambda\beta}}{\Gamma(\alpha)}, \tag{5}$$

with $\Gamma(\alpha)$ being the Gamma-function and α and β are the parameters of the Gamma distribution. The expectation of a Gamma distributed variable X is given by

$$E[X] = \frac{\alpha}{\beta}. \tag{6}$$

We know that the gamma distribution is the conjugate prior for the Poisson process [16]. This means that the posterior distribution is also gamma distributed, but with new parameters α' and β' such that

$$\alpha' = \alpha + \sum y_i, \tag{7}$$

$$\beta' = \beta + n. \tag{8}$$

Thus we get that the Bayesian adjusted failure rate λ^{B} is given by

$$\lambda^{\mathrm{B}} = \frac{\alpha'}{\beta'} = \frac{\alpha + \sum y_i}{\beta + n}. \tag{9}$$

This means there is a simple formula for correcting the prior failure rates based on the number of observed failures $\sum y_i$ for the time period consisting of n years. In practice, we have chosen $\alpha = 1$ such that the gamma distribution is reduced to the exponential distribution. The reason for this standard choice is that the exponential prior gives a reasonable sensitivity to the observed data.

B. Reanalysis weather data

Reanalysis data are weather data generated by numerical weather prediction models in combination with historical, post processed inputs. Since the reanalysis data are not used in real time, there are opportunities for more elaborate post processing of input data. We refer to Section III-A2 for a further discussion of the reanalysis data used in this tool.

In our context, the reanalysis data are used to make fragility curves in order to model the historical relationship between weather and failures. In this curve-generating process, hourly historical probabilities of failure for each individual transmission line are computed, such that the probabilities are consistent with the Bayesian failure rates for the line.

C. Fragility curves

As in [10] and [11], the fragility curves connect weather exposure of a transmission line l to probability of failure for each hour. We use a cumulative lognormal distribution to model this relation, such that with a lognormal density function f, defined by

$$f(x;\mu_l,\sigma_l)=\frac{1}{x\sigma_l\sqrt{2\pi}}\exp\left[-\frac{\ln^2(x)-\ln^2(\mu_l)}{2\sigma_l^2}\right], \quad (10)$$

we get that the probability of failure for line segment i of line l at time t with weather exposure $\hat{w}$ is

$$p_{i,l}^t=F(\hat{w};\mu_l,\sigma_l)=\int_0^{\hat{w}} f(\xi;\mu_l,\sigma_l)d\xi. \quad (11)$$

The total probability of failure for this line at time t is then given by

$$p_l^t=1-\prod_{i=1}^{N}(1-p_{i,l}^t), \quad (12)$$

where $p_{i,l}^t$ is the probability of failure of line segment i at time t and N is the number of segments. We thus assume that the fragility is the same for all line segments, but the failure rates will differ due to different weather exposure for each line segment.

D. Weather exposure

In this paper, we consider two sources of weather related failure, namely wind speed and lightning activity.

1) Wind: As in [10], we define a threshold wind speed w_{thresh} below which failures are not classified as related to wind. And similarly, we model the wind exposure as a cubed function of the wind speed w_i^t above the wind threshold at time t for line segment i. This relationship is motivated by the fact that the energy of the wind is proportional to the wind speed cubed. This gives us the following expression for wind exposure for line segment i with length l_i at time t:

$$\hat{w}_{\text{wind}}^{i,t}=\begin{cases}\alpha_{\text{w}} l_i(w_i^t-w_{\text{thresh}})^3, & w_i^t\geq w_{\text{thresh}},\\ 0 & w_i^t< w_{\text{thresh}}.\end{cases} \quad (13)$$

Here α_{w} is a scale factor used to normalize the input to the fragility curve for wind speed.

2) Lightning: For lightning related failures we use a combination of two established lightning indices, namely the K index [17] and the Total Totals TT index [18]. These are defined as

$$K=(T_{850}-T_{500})+D_{850}-(T_{700}+D_{700}) \quad (14)$$

and

$$TT=(T_{850}-T_{500})+(D_{850}-T_{500}), \quad (15)$$

where T_p is the temperature and D_p is the dew point temperature at pressure level p.

As in [11], we define the lightning exposure for line segment i at time t by

$$\begin{aligned}\hat{w}_{\text{lightning}}^{i,t}=\ &\alpha_K\max(0,K_i^t-K_{\text{thresh}})^2+\\ &\alpha_{TT}\max(0,TT_i^t-TT_{\text{thresh}})^2,\end{aligned} \quad (16)$$

where K_i^t and TT_i^t are the values of the K and TT index at time t for segment i, K_{thresh} and TT_{thresh} are threshold values below which the index does not contribute to the failure probability, and α_K and α_{TT} are scale parameters

In order to find the parameters μ_l and σ_l of the fragility curve for line l in (10), we first compute historical hourly time series of weather exposure based on the reanalysis data for each line segment. Then we use these weather exposure data as input to the fragility curves and get historical values of failure probabilities. By considering each time step as a Bernoulli experiment with failure of probability equal to the fragility value, we find the values of μ_l and σ_l by letting the mean yearly number of failures be equal to the Bayesian failure rate,

$$\lambda^{\text{B}}=\frac{1}{N}\sum_t p_l^t. \quad (17)$$

Here p_l^t is defined by (10) and (11). As in [10] and [11], this is done by optimization where we minimize the squared difference of these two terms.

III. The Vaffel tool

In this section we will present the Vaffel tool[1].

A. Data requirements

1) Disturbance statistics: In order to compute individual failure rates for each transmission line, it is necessary to have access to comprehensive and systematic disturbance data. Since the failure rates are given according to the underlying exogenous weather related source of failure, the disturbance database and post-processing of individual disturbance events should be carefully examined and classified accordingly. We refer to [19] and [15] for an example of such a system for the Norwegian TSO. Although the statistical models handle all these disturbance types ("temporary"/"permanent") individually, in the final tool we do not make further use of this division, such as computing the outage durations and evaluate consequences. Therefore, the failure probabilities are joined to a single probability per hour for each weather source.

2) Reanalysis data: After adjusting the failure rate for each transmission line through the Bayesian updating scheme, we link these failure rates to hourly weather dependent probabilities of failure. The key to this link is to have finely meshed historical weather data. For the Vaffel tool, we have access to 1km × 1km hourly reanalysis data computed by Kjeller Vindteknikk[2] [20]. They use a model from Weather Research and Forecasting (WRF) [21] to compute the renanalysis data,

[1] The word 'Vaffel' is a Norwegian acronym for 'Varsel Før FeiL', in English equivalent to something like "Warning ahead of failure".

[2] Now aquired by Norconsult, www.norconsult.com.

where they do a upsampling/correction of a 4km $\times$ 4km grid based on a single year statisticial analysis. We assume that in order to capture local topologies critical to the wind exposure of a transmission line it is necessary to have as high resolution as at least 1km $\times$ 1km. As a sidenote, typical transmission line tower distances are in the range 200-300m for the Norwegian transmission grid (300/420kV).

The now deprecated ERA-interim data [22] has a spatial resolution of abut 80km $\times$ 80km with time resolution of 3 hours. The Kjeller Vindteknikk-data is based on the ERA-interim as boundary condition. The ERA-iterim has been replaced with the ERA5 reanalysis models in 2023. The spatial resolution for ERA5 is about 30km with hourly time resolution.

3) Medium range weather forecast: The weather forecast input to the Vaffel tool is delivered by the Norwegian Meteorological Institute, through their Thredds service at thredds.met.no. We use MET Nordic operational real-time, with model spatial resolution of 2.5km, upsampled to 1km [23].

4) Power system model: The power system is in constant change, and the topology of the high-voltage power grid may change due to investments in new equipment or decommissioning of old lines. It is therefore important to update the underlying power grid data set when there are changes. For example, if some power towers for a line are relocated due to excessive weather exposure, the fragility curves have to be regenerated by considering the weather along the new path of the line. In addition, the failure rate has to be reset, with quite possibly no historical failures for the new line.

B. Probability calculations

Once we have fragility curves established for all weather forecasts for the transmission lines available, it is a rather simple procedure to calculate the hourly probabilities of failure for each transmission line. For the wind dependent failure events, we calculate the probability of failure for each line span connecting two towers, with individual weather forecast for each span. For events related to lightning, we make the simplification of using only the maximum of the K-index and the TT-index along the span of a transmission line. We remark that this has to be consistent with the construction of the fragility curves, which for lightning consists of only one curve per line.

C. Model updates

There are various time scales when it comes to updating the model tool. In Figure 1 we illustrate this by dividing the components of the tool into two temporal regions. The upper part of the figure shows updates which are more time-consuming and which are only necessary to compute once a month or on demand. The first model box, termed 'Update reanalysis data' involves the weather data needed for the calculation of the fragility curves. Since this would always be a small extension of the long historical time series, our opinion is that it is sufficient to update these data once a year. The box in

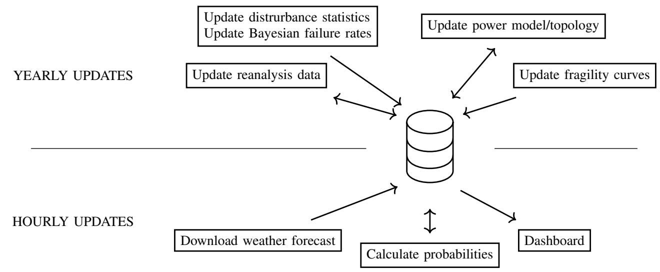

Fig. 1. Vaffel application and data updates overview.

Figure 1 containing disturbance statistics and Bayesian failure rates concerns how to update our model when new failure statistics for a transmission line is available. In principle, the fragility curves could be updated after having post-processed and correctly classified each disturbance. However, the impact of a single failure in the Bayesian updating scheme with a time frame of much less than a year, is often very small. Here also, our experience indicates that a yearly update of all fragility curves based on new disturbance data is sufficient.

Perhaps the most important reason for recalculating fragility curves is to reflect permanent changes in the power system structure. As new lines are built and old ones are decommissioned, it is vital to have the quantified results for every transmission line in this system. Thus, the update of the fragility curves based on a change in power system topology should ideally be done on demand. In addition, a transmission line might undergo structural improvements in order to mitigate recurring failures. This could mean that we should only include parts of the failure statistics for the reinforced transmission line.

The lower part of Figure 1 shows the model updates that should be done every hour. The weather forecasts are the main source of information, and should be updated as soon as the data are available. As the new weather forecast is available, new failure probabilities should be calculated and exposed to the user.

D. Dashboard

The Graphical User Interface (GUI) implemented in-house in the Norwegian TSO for the Vaffel tool, makes a significant contribution to visualize the quantified probabilities of disturbances in the power system. This quantification is useful both for the operators in the control center, and when post-analyzing disturbances in the grid. In Figure 2 we show how this dashboard appears at an example date, the 28th of January 2024 at 12:00. At this point in time there was a heavy storm forecasted in northern Norway. In the upper left corner we see the overall probability p of at least one failure of any kind or weather type for the forecast period. This calculation is based on the series expression for reliability, with p being defined as

$$p = 1 - \prod_{l} (1 - p_l), \tag{18}$$

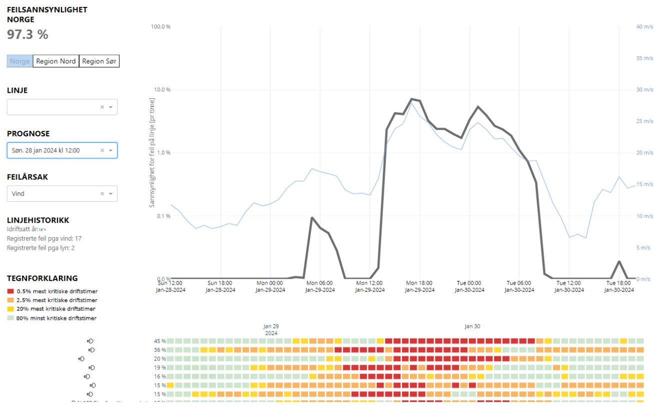

Fig. 2. Dashboard snapshot.

where p_l is the probability of at least one failure in the forecast period for line l. Here the product is over all transmission lines l defined in the system. The probability p_l of at least one failure in the period is equivalently calculated on the basis of the time range in the forecast, with p_l being defined by

$$p_l = 1 - \prod_t (1 - p_{l,t}), \tag{19}$$

where $p_{l,t}$ is the total probability of failure of line l at time t for any weather source or disturbance type. It is also possible to split this total probability for different regions, as in the dashboard for "Region Nord" and "Region Sør" (Norway north and south).

The main window in the dashboard shows the hourly probability of failure for the upcoming time period for the selected line. The line selection is done in the menu on the left side of the dashboard. In this menu it is also possible to choose historical probability forecasts stored in the database. By default, the transmission line with highest individual total probability of failure is selected. Along with the main graph, it is also possible to display the failure probabilities for each weather type, along with relevant weather parameters. When a transmission line has been selected for visualization, the dashboard also displays historical disturbance statistics for the line. In the dashboard display in Figure 2, the selected line has experienced 19 disturbances due to wind and 2 due to lightning. Additional information about when the transmission line was commissioned and operational is also given.

At the bottom of the dashboard there is a complete list of forecasted failure probabilities for all the transmission lines in the system, where each hour for each line is given a color based on the expected caution level for the operator, with red being the most critical.

In Figure 3 we show an example of the probability forecast for two specific lines in northern Norway, namely the two 420kV lines "A" (blue) and "B" (red). In the same figure, we have also shown the actual historical disturbances for these two lines. In the dashboard visualization in Figure 2, they are ranked as number four and seven when it comes to probability of failure. The line "A" experienced a temporary disturbance lasting one second at 21:50 in the evening of the 29th of January. The line "B" experienced three different temporary disturbances at 18:04, 18:08 and 18:47 at the same date, all of them lasting one second.

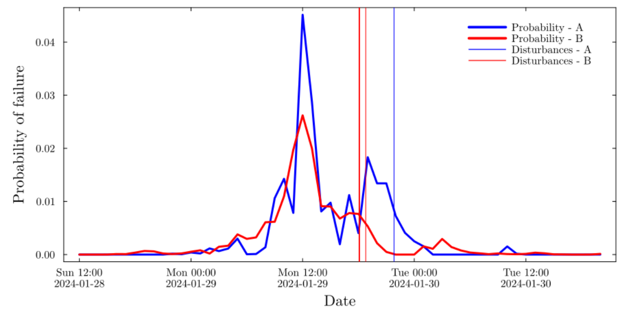

Fig. 3. Visualization of forecast and actual failures.

As we can see, the actual disturbances did not appear at the points in time when the probability was at the highest, but still at a time when the probability of failure was significantly larger than zero. Is this behavior to be expected? In our opinion, this lies at the heart of a probabilistic forecast. For every hour in the forecast period, there is a given probability of a disturbance for a transmission line. Even for severe storms, it is extremely rare to have hourly probabilities above 0.1 for any transmission line. Thus, it is the combination of duration and the geographical distribution of the severe weather that decides the overall probability of disturbances. From an operational perspective, this means that rather than focusing on specific transmission lines, it is necessary to be on general alert for a region. In addition, it is also possible to see this from another perspective in terms of operational risk, namely the useful fact that the forecast can quantify which regions that are *not* exposed to elevated disturbance probability.

Due to lack of historical forecast data, we use a different model for generating the fragility curves than for predicting the probabilities of failure. However, in Figure 4 we compare the wind-based Bayesian failure rates with the output of the Vaffel tool computed from historical wind forecasts for the period 2020-2023. In orange color, we plot the transmission lines in descending order, ordered by the annual Bayesian failure rate. In blue, we have plotted the actual average annual failure rate computed implicitly by the Vaffel tool based on the wind forecast and the fragility curves. As the lines with failure rates substantially above zero are the most interesting ones, we only plot the top 50 percent of the transmission lines. The average failure rate from the Vaffel tool for these 115 lines is 0.33 while the corresponding average of the Bayesian rates is 0.30. The equivalent numbers for all the transmission lines are 0.164 for the Vaffel tool and 0.165 for the Bayesian rates. Even though we do not consider the actual wind levels compared to a meteorological normal, these numbers are nevertheless reassuring, supporting the view that the underlying weather models are consistent.

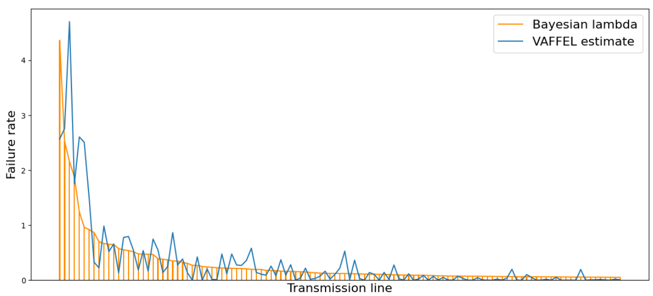

Fig. 4. Visualization of Bayesian failure rates and Vaffel estimated failure rates based on weather forecast for 2020-2023.

IV. Summary and Future Work

In this paper we have presented a tool that is increasingly useful when in comes to assessing the online probability of failure for transmission lines. Based on a Bayesian updating scheme and real-time weather forecasts we get short term probabilities of failure that are consistent with long time annual failure rates.

There are several directions for future developments for this tool. Due to lack of historical forecast data, we use a different model for generating the fragility curves than for predicting the probabilities of failure. From a theoretical and computational point of view, it could be beneficial to have consistent weather models within the tool such that the fragility curves and the weather forecast are based on the same numerical model. Moreover, the tool currently does not include any calculation of the consequence of failure. A promising extension to the tool would therefore be to include a Monte Carlo simulation contingency analysis module, where disturbance events are simulated according to the tool's probability and where the induced socio-economic costs are calculated by a consequence analysis. This would give TSOs an extended view of the current risk in the system. Currently, our Vaffel tool only includes disturbance events related to wind speed and lightning. Expanding the model to other factors, such as wind direction and gusts, snow and icing, and even human activity, would be interesting areas of research. Finally, in Statnett we have ongoing work of monitoring and validating the results of the probability forecasts. This work would also enable us to compare future alternate statistical models for the tool.

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