Assessment of the Resilience of Transmission Networks to Extreme Wind Events

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***Abstract*—Extreme weather may have a significant influence on the resilience of transmission systems. However, modelling the impact of weather is very challenging due to its stochastic and unpredicted nature and behaviour. To cope with these challenges, this paper presents a Sequential Monte Carlo based time-series model for evaluating the effect of weather on power system components, with focus on the wind effect on transmission lines and towers, and in turn on the entire transmission power infrastructure. The concept of fragility curves is used, which express the failure probabilities of the components as a continuous function of the wind speed. The mapping of the wind profile on these fragility curves provides the weather-affected operational state of the transmission lines and towers at every simulation time step. The model is illustrated using a simplified 29-bus model of the transmission network of Great Britain (GB). The simulation results highlight and quantify how the GB test network becomes less resilient for extreme wind events, and the effectiveness of mitigation strategies such as network reinforcement or redundancy.**

***Index Terms*—Extreme Weather, Fragility Curves, Power Systems, Resilience**

I. INTRODUCTION

Extreme weather events have a significant impact on the resilience of power systems. In USA, for example, the annual impact from weather-related loss-of-supply events ranges from \$20 to \$55 billion US dollars [1, 2]. These events tend to be of substantial duration because of the high damage to the transmission and distribution facilities. Therefore, despite their low probability, their impact is so high that methodologies have to be developed for evaluating their effect on power systems resilience and resilience enhancement measures have to be applied for preventing or mitigating their impact.

In the context of power systems, resilience is defined as the ability of a power system to withstand high-impact low-probability events, such as extreme weather events, rapidly recover from such events and adapt its operation and structure to be better prepared for similar events in the future [3-5]. According to the National Infrastructure Advisory Council (NIAC), USA [4] and Cabinet Office, UK [5], the key features of a resilient critical infrastructure, including power systems, are *robustness/ resistance*, which refers to the ability of the system to keep operating in the face of a disaster, *resourcefulness/ redundancy*, which shows the ability to use the available assets to deal with a disaster as it unfolds, *rapid recovery* and *adaptability*. A comprehensive framework for conceptualizing resilience in the context of power systems is provided in [6] and [7].

Assessing the effect of weather events on power systems has attracted the interest of several researchers, which resulted in the development of numerous methodologies. The majority of these methodologies such as [8] and [9] use analytical techniques, with Markov modelling being the dominant technique. Nevertheless, despite the simplicity of these approaches, the simulation techniques, i.e. Monte Carlo simulations [10-12], are considered more suitable for weather-related power system resilience studies because of the stochastic and space- and time-dependent nature of the weather events and the size and complexity of real power systems.

A Sequential Monte Carlo based time-series simulation model has been developed and is presented in this paper for capturing the stochasticity of weather and evaluating its effect on the resilience of power systems [13]. To reflect the influence of weather on power system components, the concept of fragility curves is used, which express the failure probability of the components as a function of a weather parameter, e.g. wind speed or rain intensity. The influence of extreme wind events on power systems resilience is used as an illustrative case study in this paper, but the proposed methodology is generic enough to model the effect for any weather parameter, if the relevant fragility curve is available. The model is applied on a 29-bus simplified version model of the Great Britain (GB) transmission network (Figure 1) to

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evaluate its resilience to extreme wind events. Even though the method is illustrated using a simplified model, by capturing the impact on the main transmission corridors the numerical results provide important insights on the reliability performance of the GB transmission system. In addition, the method can also be applied to distribution networks, if the relevant data are available, e.g. fragility curves of distribution poles and lines.

This paper is organized as follows. Section II discusses the methodology for assessing the impact of weather on power systems resilience. Section III presents the test network, simulation data and simulation results of applying the proposed methodology to the simplified 29-bus version of the GB transmission network. The studies performed include assessing the impact for increasing wind speeds and the performance of resilience "boosting" options such as network reinforcement and redundancy. Section IV summarizes and concludes the paper.

II. Time-Series Resilience Assessment Methodology

The proposed model uses Sequential Monte Carlo Simulation (MCS), which models the behaviour of a system as a sequence of events affecting each other as the system progresses in time. It is based on the random generation of Times To Failure (TTF) and Times to Repair (TTR) using the failure and repair rates of the components respectively (or the Mean TTF, MTTF, and Mean TTR, MTTR), which are usually considered constant. This gives the operating cycles of the components. Additional details can be found in [14].

In contrast to this traditional approach, the proposed methodology applies weather- and time-dependent failure probabilities to the components of a power system. This is achieved using fragility curves and time-series weather profiles, as shown in Figure 2. A generic fragility curve can be seen in Figure 2, whose shape varies and depends on the relation between the components' failure probability and the weather parameter. Empirical data could ideally be used for building highly accurate fragility curves; however as the number of failures of transmission towers is so low, analytical methods may need to be used.

By mapping the time-series weather profile to the fragility curve, the weather-affected failure probabilities of the components can be obtained at every simulation step. In this way, the components' failure probabilities will not be constant, but they will depend on the evolving weather conditions. This allows the modelling of the weather effect in a realistic and continuously fluctuating way. The time resolution of this sampling depends on the desired requirements or on the available time resolution of the weather profile. Any time resolution can be used in the proposed methodology, e.g. 15mins or hourly, if the relevant information is available, e.g. time-series wind profile.

After obtaining the weather-dependent failure probability of each component, it is compared with a uniformly randomly generated number $r \in [0,1]$. If the failure probability is larger than r, then the component will trip. Otherwise, it will not trip. Only the permanent line outages are considered here which could take several hours or days to restore, as the temporary outages are usually quickly restored by auto- or manual-reclose without causing any serious problems. The TTR are then randomly generated when a component outage occurs. The restoration times can also be adjusted to reflect the increasing damage on the components for higher intensities of weather conditions, as will be discussed later in Section III.

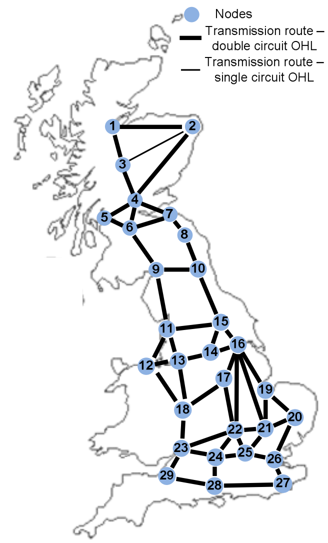


Figure 1. The simplified 29-bus GB transmission network

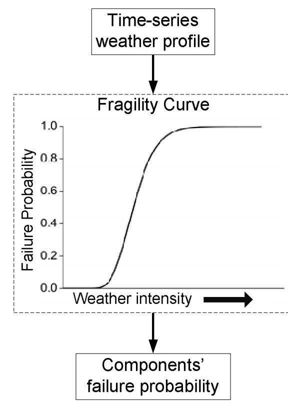
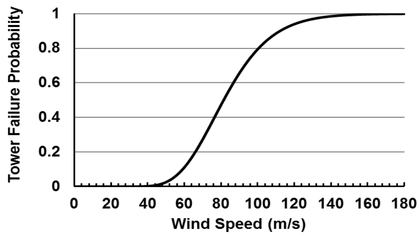
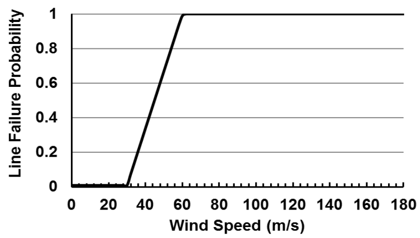


Figure 2. Estimating the failure probabilities using fragility curves

Therefore, following this procedure, the weather-affected operating cycles of the components are developed. This is critical in modeling the real behavior of the power system components under the weather conditions they experience. An AC OPF is used here for assessing the performance of the system at every simulation step. The effect of weather on the frequency and duration of power interruptions are used as resilience indices here, i.e., Loss of Load Frequency (LOLF) and Loss of Load Expectation (LOLE) respectively. Based on the output of the resilience assessment, different resilience enhancement actions can be applied, as will be demonstrated in Section III. It also has to be noticed that the model can be extended to model the impact of multiple weather parameters, e.g. snowfall and wind speed. This, however, would require the correlated impact of the weather parameters on the components' failure probabilities, which could possibly be expressed using multi-dimensional fragility curves.



a) Transmission tower



b) Transmission line

Figure 3. Wind fragility curves

III. Simulation Data and Results

The proposed simulation model is illustrated using a 29-bus simplified version of the GB transmission network. The effect of wind on the permanent failure probabilities of transmission lines and towers is used an illustrative case study to demonstrate the efficiency of the proposed methodology.

A. Simulation data

Figure 1 shows the simplified 29-bus GB transmission network model. This network model consists of 29 nodes, 98 overhead transmission lines in double circuit configuration and one overhead singe transmission line (between nodes 2 and 3) and 65 generators of different technologies, e.g. nuclear, CCGT, wind and hydro.

The transmission line and towers wind fragility curves used in this analysis are demonstrated in Figure 3. The tower fragility curve is the preliminary output of the Resilient Electricity Networks for Great Britain (RESNET) project [15], in which the authors are involved. The tower failure probability picks up at approximately 45m/s, while it is considered zero for lower wind speeds. The line fragility curve is assumed here for carrying out the resilience assessment of the GB transmission network. If empirical data were available, a more accurate line fragility curve could be developed. For high wind speeds (>30m/s), a linear relation between the line failure probability and wind speed is assumed. For lower wind speeds (<30m/s), a failure probability equal to $1x10^{-3}$ is used. Further, a transmission tower is assumed every 300m across the line. Next, considering that the towers are in series and that the collapse of a single tower is enough for tripping a transmission line, the overall line outage probability due to a tower collapse is assumed equal to the aggregated failure probability of all individual towers' failure probability.

In the distribution network weather-related resilience studies, it is assumed that the entire network is exposed to the same weather conditions at any given time. This is a valid

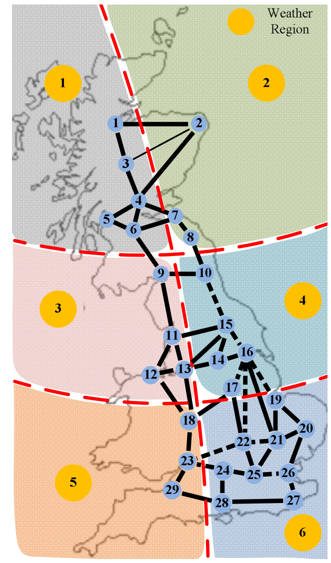


Figure 4. Weather regions of GB transmission network (Dotted lines indicate the critical transmission corridor from North to South GB)

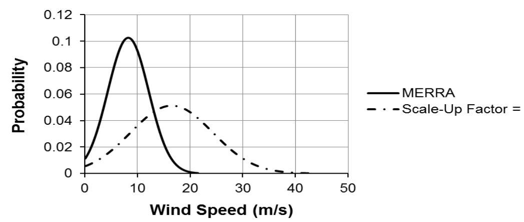


Figure 5. Examples of wind profiles used in the simulations

assumption for distribution networks which cover a small geographic area, but it is not valid for transmission networks which spread across a much larger area. In order to capture the diverse weather impact on the transmission network, the GB transmission network is divided in six weather regions, as shown in Figure 4. In this way, the spatial-temporal impact of the weather event as it moves across the network at any direction can be captured. The same wind conditions are considered within each region for simplifying the analysis. It can be seen that some transmission lines cross two regions (e.g. line 2-4), experiencing different wind conditions in each region. In such cases, the highest wind speed between the two regions is used, in order to obtain the highest line failure probability due to the wind event.

The time-series wind profiles at the different locations of the GB weather regions shown in Figure 4 are obtained using MERRA re-analysis [16]. In order to simulate a wide range of wind speeds, the wind profiles obtained by MERRA re-analysis are scaled up and down for generating several wind profiles. This results in wind profiles with increasing maximum wind speeds. Figure 5 shows an example of the probability distribution of a wind profile in weather region 1 as obtained by MERRA re-analysis and scaled-up with a multiplication factor equal to 2. According to Met Office, UK [17], the highest wind speed ever recorded in low-level sites in GB, which is where the transmission facilities usually reside, is about 63m/s, so it was considered reasonable to generate wind profiles with maximum wind speeds close to

TABLE I. INCREASING MTTR UNDER SEVERE WIND CONDITIONS

Maximum wind speed of the wind profile, V_{wind_max} (m/s)	MTTR multiplication factor
V_{wind_max} <= 20	0 (equal to normal MTTR)
20 < V_{wind_max} <= 40	Random between 2-4
40 < V_{wind_max} <= 60	Random between 5-7

the historical one. This enables the impact modelling of the worst possible wind conditions that transmission components might experience. This is particularly important because the aim of this study is to evaluate the effect of the highest possible wind speeds that the transmission components might experience during a wind event, which have the highest effect on their failure probability.

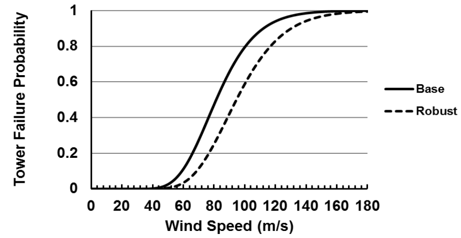
A MTTR equal to 10hrs and 50hrs is assumed for the transmission lines and towers respectively (refer to as "normal" MTTR). In order to reflect the increasing damage to the transmission towers and lines and difficulty in restoring the damaged components under severe wind conditions, a MTTR that increases with wind speeds is used. Precisely, a multiplication factor uniformly randomly generated within a predetermined range is used to multiply "normal" MTTR depending on the maximum wind speed (V_{wind_max}) experienced in each wind profile used in the simulations (Table I). It has to be noted that these restoration times are assumed here for illustration purposes.

A severe wind event, depending on its intensity, can cause a single line failure, or a double-circuit failure as a result of a tower collapse. The latter is considered a common cause failure (CCF). In order thus to model the effect of CCF due to extreme winds, it is considered that the double circuit lines are on the same tower. Therefore, a tower collapse would result in a CCF, i.e. double circuit failure.

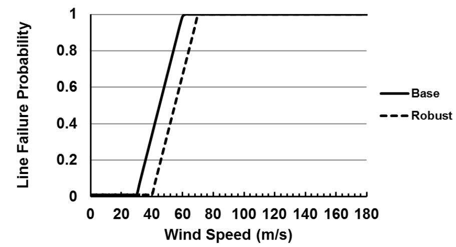
An hourly simulation step is used in the studies, but as mentioned any time resolution can be used if the relevant information is available, e.g. wind profile. The hourly node demand profile is obtained from the historical demand database available in National Grid website [18] (the GB transmission system operator). A simulation time of one week is used. A winter week is used, where the peak demand and extreme winds are expected in GB. Therefore, LOLE and LOLF express here the average number of hours of customer disconnection per week and the number of occurrences of such events per week respectively.

B. *Illustrative case studies*

The aim of the illustrative case studies is to first evaluate the impact of extreme wind events on the resilience of the GB transmission network model and then to evaluate different resilience enhancement measures. The case studies presented here focus mainly on the hardening and reinforcement measures that can be applied for mitigating the impact of weather events. Examples of measures that can be taken for boosting the resilience of power systems to severe weather events can be found in [19].



a) Transmission Tower



b) Transsmission Line

Figure 6. Base and robust wind-related fragility curves

Following extensive power flow and resilience studies, it was identified that one of the critical transmission corridors for preserving the resilience of the entire GB transmission network is the one shown in Figure 4 with dotted lines, i.e. the transmission corridor from North GB to South GB and more specifically to London (node 25), the main demand node of GB. It can be seen that this corridor includes transmission lines in central GB (i.e. weather region 4) for transferring the power generated in the North GB to South GB, and also lines in South GB within weather region 6 for supplying London.

Based on this observation, the following illustrative case studies are used here:

- *Base case,* where the simulation data of the previous section are used, with no resilience enhancement measures applied.
- *Robust case,* where the lines of the critical transmission corridor shown in Figure 4 are made more robust to the wind event. This is done by shifting the fragility curves to the right, as demonstrated in Figure 6, and can be achieved, for example, by upgrading the materials of the transmission lines and towers.
- *Redundant case,* where redundant, parallel lines are added to the critical transmission corridor of Figure 4.

These case studies aim at enhancing some of the key features of resilience. In particular, the robust case improves the robustness of the network to the wind events, so it can withstand more severe winds. The redundant case improves the resourcefulness feature of resilience, as additional transmission assets are available to the transmission system operators for coping with the evolving weather conditions. An additional way of enhancing resilience is by improving the operational procedures during and after the weather event, which is however an object of future work.

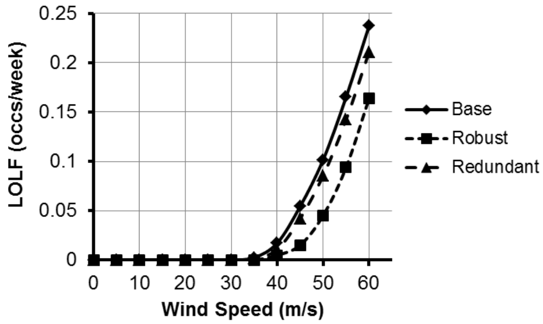


Figure 7. LOLF as a function of the maximum wind speed experienced in each wind profile

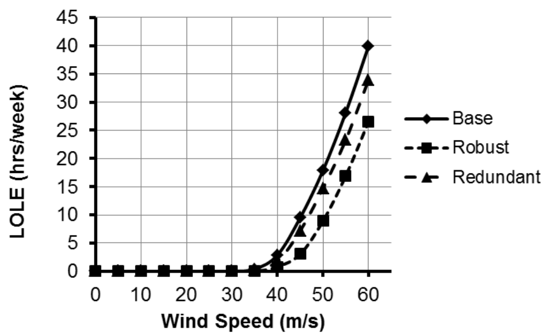


Figure 8. LOLE as a function of the maximum wind speed experienced in each wind profile

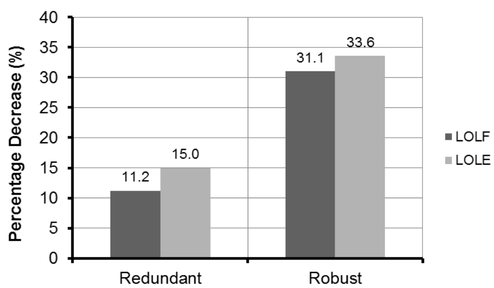


Figure 9. Percentage decrease in LOLF and LOLE when compared to base case, V_{wind_max} = 60m/s

C. Simulation Results

As discussed, the GB transmission network is imposed to several wind profiles with increasing maximum wind speeds to determine when it becomes less resilient, i.e. higher LOLF and LOLE, to transmission outages due to extreme wind events. Figures 7 and 8 show the LOLF and LOLE respectively as a function of the maximum wind speeds experienced in the wind profiles used in the simulations. Figure 9 shows the percentage decrease in LOLF and LOLE for the robust and redundant case studies when compared with the base case study for V_{wind_max} = 60m/s.

Based on the simulation results obtained by the proposed methodology, it can be seen that the GB transmission network model is very resilient to wind speeds up to 30m/s, as LOLF and LOLE are close to zero. According to the Beaufort wind force scale provided by Met Office, UK [20], this wind speed corresponds to violent storms. The operational resilience of the GB network (i.e. operation in "N-2" secure state) can effectively withstand a limited number of transmission outages.

For wind speeds higher than 30m/s, e.g. 35m/s, which is the tipping point of the line fragility curves and correspond to more severe wind events, i.e. hurricanes (V_{wind}>33m/s) [20], a sharp, nonlinear increase in LOLF and LOLE is observed. This shows the sensitivity of the resilience of the entire network to the robustness of the individual transmission components. The increase in LOLF and LOLE becomes much sharper for extremely high wind speeds, i.e. higher than approximately 50m/s. This is because a larger number of transmission lines and towers outages are expected for extreme wind speeds, as can be seen from their fragility curves (Figure 3), which increases the probability of cascading line outages leading to a more frequent and longer customer interruption. These results show that the GB transmission network model is resilient for the expected normal and high wind events as expected by a well-designed and operated system, but it is less resilient for the unexpected severe winds. Further, after discussions with National Grid, the GB transmission operator, the estimated expected duration of customer interruptions is close to the one expected if the GB transmission network is hit by such severe wind events (e.g. V_{wind_max} = 60m/s).

When applying the resilience enhancement measures, an improvement in LOLF and LOLE is observed. Comparing the robust and redundant case studies, it can be seen that a higher improvement is achieved when the components are made more robust than redundant. This again demonstrates the sensitivity of the network resilience to the robustness of the individual components. Figure 9 shows that a 31.1% (33.6%) decrease in LOLF (LOLE) is observed for the robust case, while an 11.2% (15%) decrease is observed for the redundant case. This shows that making the network "bigger" by adding redundancy, even though it provides additional assets to the operators contributing thus to the "resourcefulness" feature of resilience, it does not necessarily have the desired effect as the redundant lines are also similarly susceptible to the extreme wind conditions. On the contrary, making the components more resistant to higher wind speeds helps prevent the transmission outages due to severe winds, which reduces the probability of triggering cascading phenomena leading to customer interruptions.

IV. CONCLUSIONS

A time-series resilience assessment methodology using the concept of fragility curves and Monte Carlo simulation has been presented in this paper for evaluating the weather effect on power systems. The influence of wind is used here, but the proposed model is flexible and generic enough to model the effect of any weather parameter, if its fragility curve is available.

The illustration of the methodology using the simplified 29-bus version of the GB transmission network shows that the test network is resilient for the expected and more frequent range of wind conditions, but it is less resilient to the high-impact low-probability extreme wind events (>50m/s). Even though GB does not currently experience events of such intensity, it is important to evaluate such severe wind events due to the uncertainty associated with the projection of future wind speed levels. Further, it is possible that the frequency and intensity of extreme weather events will be increased in the future as a direct impact of climate change [1].

Therefore, actions have to be taken for boosting the resilience of future power systems to extreme weather events. In this paper, the impact of making the transmission components more robust and adding redundancy has been evaluated. It is shown that making the components stronger to higher wind events results in higher resilience than adding redundancy. However, before applying any resilience enhancement measures, a cost/benefit analysis has to be performed to weight the benefits of each approach over its cost. This would provide the optimum solution for achieving both the resilience and cost goals. Such an analysis is an object of future work. In addition, the effect of different operational measures on the network resilience, e.g. improving the restoration times of the damaged components, will be evaluated and compared with the contribution of hardening and reinforcement measures, such as the ones evaluated here.

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