Operational Resilience Assessment of Power Systems Under Extreme Weather and Loading Conditions

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***Abstract*—In the traditional reliability assessment of power systems, the effect of real-time operating conditions on components' reliability is usually ignored. Nevertheless, as highlighted by historical electrical and weather emergencies, the conditions that power system components experience, i.e. weather and loading conditions, have a significant effect on their reliability. This paper describes an approach for considering the effect of real-time operating conditions when assessing the operational resilience of power systems, with focus on the impact of wind and loading conditions on the failure probability of transmission lines. The concept of fragility curves is used, which express the failure probability of the lines as a function of the wind speed and their loading. The approach is illustrated using a simplified 29-bus version of the Great Britain transmission network. The simulations results help quantify how less resilient the network becomes for extreme wind and loading conditions.**

***Index Terms*—Real-time conditions, Reliability, Resilience, Resiliency**

I. Introduction

Several methodologies have been developed for evaluating the reliability of power systems. However, the majority of these techniques usually ignore the effect of real-time operating conditions, i.e. weather and loading conditions, on the reliability of power system components. This leads to the use of a set of constant and condition-independent reliability data (i.e. failure and repair rates) under any conditions, which does not reflect the real behavior of system components.

As evidenced by historical electrical and weather emergencies, the conditions that power system components experience affect significantly their operation and reliability. For example, during the Northeast USA [1] and Italian blackouts [2] in 2003, transmission lines tripped due to flashovers to trees while they were loaded at 88% and 86% of their nominal rating respectively. This shows that a transmission line can fail under high loading conditions, even without the occurrence of a thermal overload, where it will be automatically disconnected by the protection equipment. A probabilistic approach is described in [3] for estimating the occurrence of critical line temperatures under fluctuating power flows, which ultimately affect their operation and reliability. Furthermore, in addition to historical severe weather events which highlighted the extent of the damage they can cause to transmission and distribution facilities, numerous methodologies have been developed for evaluating the influence of weather on the reliability of power systems, and in particular on the failure and repair rates of power system components, such as [4-7]. The output of these methodologies shows that neglecting the weather conditions that outdoor power system components experience results in an underestimation of the problem.

Operational resilience assessment refers here to the evaluation of power systems resilience by considering the effect of the real-time operating conditions that the system experiences. To the best knowledge of the authors, there is no currently a single methodology that takes into account the impact of both weather and loading conditions on the resilience of power system components and in turn on the resilience on the entire power infrastructure. Under these premises, this paper describes a Sequential Monte Carlo based approach for considering these conditions and evaluating their impact on the frequency and severity of customer interruptions. The concept of fragility curves is used, which express the failure probability of the components as a function of a weather parameter and the components' loading. A different fragility curve is used for these two conditions, as their impact on components is considered independently in these studies. The illustration of the approach focuses on evaluating the effect of wind speed and loading on the failure probability of transmission lines and towers, but the impact of any weather parameter can be modelled if its fragility curve is available. The approach is applied on a 29-bus simplified version of the Great Britain (GB) transmission network.

The paper is organized as follows. The operational resilience assessment approach is discussed in Section II, which provides insights on how the real-time conditions can be taken into account for evaluating the effect of severe wind events and highly loading conditions. Section III describes the simplified 29-bus version of the GB transmission network, the simulation data and the simulations results of this work.

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Section IV concludes the paper and discusses the key outputs of the simulations, along with suggestions to improve the operational resilience of power systems.

II. Operational Resilience Assessment Procedure

As discussed in Section I, the proposed approach uses Sequential Monte Carlo simulation (SMCS) which models the behavior of the system as a sequence of events in chronological order. The Times to Failure (TTF) and Times to Repair (TTR) are generated using the failure (λ) repair (μ) rates of the components, which ultimately provide their operating cycles. Further details on SMCS can be found in [8].

However, in this traditional approach, the failure and repair rates used are usually condition- and time-independent. In contrast to this approach, weather- and loading-dependent (i.e. condition-dependent) failure probabilities are attached here to power system components. The weather-dependent failure probabilities are obtained by mapping the time-series weather profile to weather fragility curves, like the generic one shown in Figure 1. The shape of the weather fragility curve varies and depends on the relation of the component's failure probability and the weather parameter. Similarly, the loading-dependent failure probabilities of the components are obtained by mapping their loading on the loading fragility curve. Again, the shape of this curve varies, as discussed in [9]. A linear relation between the transmission line's loading and its failure probability is shown in Figure 2 [10]. The time resolution of this sampling depends on the desired requirements or on the available time resolution of the weather profile and power flow estimation. Any time resolution can be used in the proposed approach. The highest failure probability between the weather- and loading-dependent failure probabilities is assigned to each component at every simulation step. Next, in order to determine if the component is going to trip at the next simulation step, its failure probability is compared with a uniformly distributed randomly generated number in the range [0,1]. If the failure probability is larger than the randomly generated number, then the component will trip. Otherwise, it will not trip. The TTR are randomly generated when a component outage occurs. This procedure ultimately gives the operating cycles of the components, which can be used in the SMCS.

Following this procedure, the condition- and time-dependent operating states of the components at every simulation step are obtained. This is critically important in order to reflect the real behavior of the components depending on the evolving weather and system conditions. An AC OPF is used for assessing the network performance at every simulation step. The Loss of Load Frequency (LOLF) and Expected Energy Not Supplied (EENS) are used as resilience indices in this study.

It also has to be noticed that a more accurate way of reflecting the impact of weather and loading conditions on the failure probability of the components would possibly be using one single fragility curve, which would express the correlated impact of these factors. This requires a vast amount of historical operational data in order to extract the relation between these two factors. However, even if these historical data were available, it may not be possible to determine a clear and meaningful relation, mainly because of the low frequency of such events, especially of severe weather events.

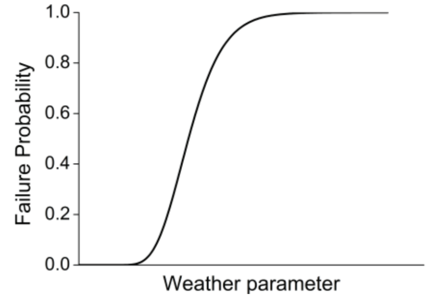


Figure 1. Generic weather fragility curve

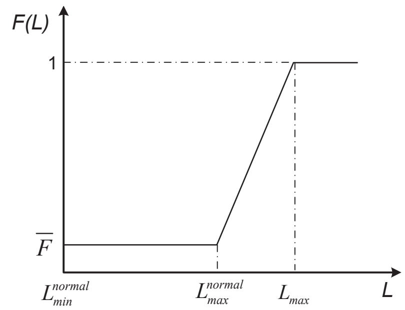


Figure 2. Line Failure probability-Loading fragility curve: F = Failure probability, $\overline{F}$ = Constant Failure Probability, L = Transfer capacity, $L_{\min}^{normal}$ = lower limit of transfer capacity, L_{max}^{normal} = upper limit of transfer capacity, L_{max} = tripping transfer capacity [10]

III. Simulation Data and Results

The proposed approach is illustrated using a simplified 29-bus version of the GB transmission network. This section discusses the simulation data and results of this study.

A. Simulation Data

Figure 3 shows the simplified 29-bus version of the GB transmission network, which consists of 29 buses, 98 overhead transmission lines in double circuit configuration and one single transmission line (between nodes 2 and 3).

Since the aim of this study is to evaluate the effect of wind and loading conditions, the loading and wind fragility curves of the components are required. As discussed in Section I, the effect of these real-time system conditions on transmission lines is used as an illustrative case study. In the case of the wind conditions, their impact on the transmission towers is also considered.

Regarding the loading fragility of transmission lines, the curve of Figure 2 [10] is used. This curve is used only for illustration purpose and it is not implied that it represents the actual relation between a transmission line's failure probability and its loading. The range [L_{max}^{normal}, $L_{\max}$] in Figure 2 is varied as shown in Table I to evaluate the effect of different lines' loading conditions (and consequently of different lines' failure probabilities) on the resilience of the entire infrastructure. These levels of loading conditions are considered realistic based on historical blackouts, as the ones in Northeast USA [1] and Italy [2] in 2003 mentioned in Section I where transmission lines tripped while loaded well below their emergency rating.

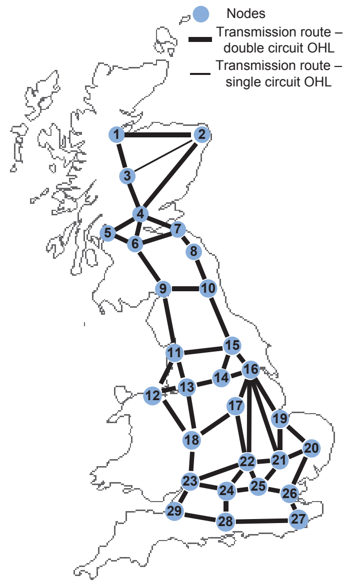


Figure 3. The simplified 29-bus GB transmission network

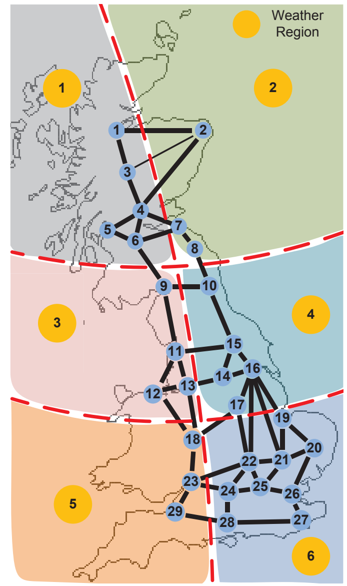


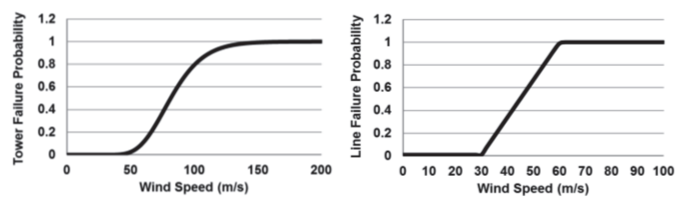
Figure 4. Weather regions of GB transmission network

TABLE I. LEVELS OF LINES' LOADING CONDITIONS IN P.U. OF THEIR NOMINAL CAPACITY

A/A	L_{max}^{normal} (p.u.)	L_{max} (p.u.)
1	0.95	1.05
2	0.9	1.1
3	0.85	1.15

The weather-related reliability studies usually consider that the entire system is exposed to the same weather conditions at any given time. This is a valid assumption for distribution networks which cover a small geographic area [11, 12], but it is not applicable in transmission networks which spread across a much larger area and the weather events traverse in both space and time. This results in a diverse weather impact in different parts of the network. In order to consider the time- and spatial-varying weather impact on different transmission areas, the GB network is divided into six weather regions, as shown in Figure 4. The same wind conditions are assumed within each region. The wind profiles at different locations in GB are obtained using MERRA re-analysis [13].

The transmission tower and line wind fragility curves used in this study are shown in Figure 5. The tower fragility curve is the output of the Resilient Electricity Networks for Great Britain (RESNET) project [14], in which the authors are involved. The line fragility curve is assumed here for illustration purposes. Empirical data would help develop a more accurate wind fragility curve for the transmission lines. For high wind speeds (>30m/s), a linear relation is assumed. For lower wind speeds (≤30m/s), a failure probability equal to 1×10^{-3} is used. The same probability is used for loadings lower than L_{max}^{normal} in Figure 2 (i.e. $\overline{F} = 1\times10^{-3}$). Further, a transmission tower is assumed every 300m across the line. Next, considering that the towers are in series, the overall line outage probability due to a tower collapse is assumed equal to the aggregated failure probability of all individual towers' failure probability.



a) Transmission Tower b) Transmission Line

Fig. 5: Wind Fragility Curves

As can be seen in Figure 4, there are some transmission lines crossing more than one weather regions (e.g. line 1-2), experiencing different wind conditions in each region. This will result in different line failure probabilities due to the wind events in each weather region. In such cases, the highest wind speed among the regions that the line is crossing is used, in order to estimate the worst (i.e. highest) failure probability due to the wind event. This wind speed is then mapped to the transmission lines and towers fragility curves to obtain the failure probabilities at every simulation step.

A severe wind event can result in an independent/single circuit outage of a transmission line, or in a double-circuit transmission line outage due to a tower collapse. The latter is considered a common cause failure (CCF), which is a significant and common threat to network resilience during weather extremes. In order to model CCF, it is considered that the double-circuit lines are on the same tower. Based on discussions with National Grid (the GB transmission system operator), this is the usual configuration of the double-circuit lines in the GB transmission network.

The Mean TTR (MTTR) of transmission lines and towers are assumed 10hrs and 50hrs respectively (i.e. "normal" MTTR). However, the restoration time depends on the damage caused by the wind event. Therefore, in order to reflect the increasing damage and difficulty in restoring the faulted components under severe wind events, a MTTR which increases with wind speed is used for high wind speeds. More

TABLE II. 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 in the range [2,4]
40 < V_{wind_max} <= 60	Random in the range [5,7]

specifically, a multiplication factor uniformly randomly generated within a predetermined range is used to multiply the "normal" MTTR, depending on the maximum wind speed experienced in each wind profile used in the simulations (Table II). Therefore, for example, following this approach the restoration of a transmission tower can last from a few to several days depending on the severity of and the damage by the wind event. It has to be noted that due to lack of actual restoration times, they are assumed for illustration purposes.

An hourly simulation step is used in the studies. A simulation time of one week is used and a winter week is chosen, where the peak demand and severe wind events are expected in GB. Therefore, in these studies, LOLF and EENS express the frequency of customer disconnection and the expected energy not supplied per week. The hourly demand profile is obtained from the historical demand data available in National Grid's website [15]. An hourly wind profile is considered sufficient for modelling any type of wind events, ranging from moderate to severe wind events and hurricanes.

B. Simulation Results

The following case studies are considered in the simulation studies:

- considering only the wind impact ("Wind Only"), and
- considering both the wind (W) and loading (L) impact: Here the three case studies of Table I are examined (referred to as WL1, WL2 and WL3 respectively).

It has to be noted here that the effect of evaluating only the loading impact on the resilience of the test system has been investigated, but no significant impact on the network resilience has been observed, as the test system is very reliable. This is expected as National Grid operates the network in "N-2" security under normal weather conditions.

In order to obtain wind profiles that in the future might threaten the robustness of the transmission lines and towers, the wind profiles obtained by MERRA re-analysis are scaled-up. This led to the generation of multiple wind profiles, with increasing maximum wind speeds experienced in each wind profile. Figures 6 and 7 show the LOLF and EENS respectively as a function of the maximum wind speed of every wind profile used in the simulation. This helps determine the threshold at which the GB transmission network becomes less resilient, i.e. higher LOLF and EENS.

It can be seen that for wind speeds lower than the tipping point of the line wind fragility curves of Figure 5.b (30m/s), the network is very reliable as the reliability indices are close to zero. However, for wind speeds higher than 30m/s, LOLF increases sharply while EENS picks up at a bit higher wind speeds. This nonlinear sharp increase in the resilience indices is because of the much higher probability of transmission line outages during extreme wind events, either single circuit (i.e.

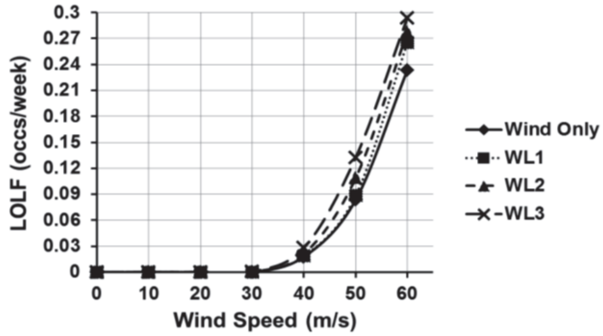


Figure 6. LOLF as a function of maximum wind speed in wind profiles

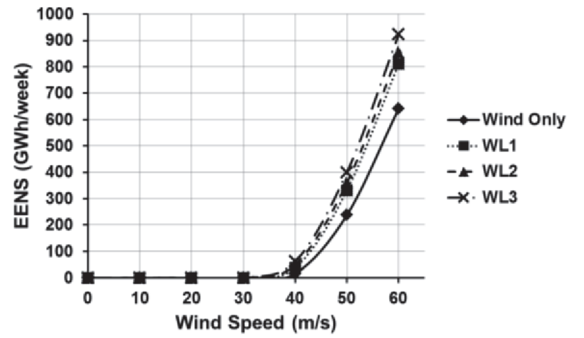


Figure 7. EENS as a function of maximum wind speed in wind profiles

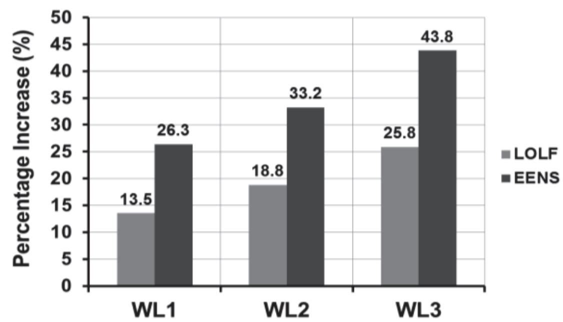


Figure 8. Percentage increase in LOLF and EENS in comparison with the "Wind Only" case study for V_{wind} = 60m/s

independent) or double circuit due to a CCF outage. Particularly the probability of tower collapses is higher for wind speeds larger than 50m/s, resulting thus in a higher probability of CCF.

When considering the loading impact on the failure probabilities of the components (i.e. WL1, WL2 and WL3 case studies), the LOLF and EENS become significantly higher. Further, the increase in EENS is much sharper than the increase in LOLF, as shown in Figure 8 which shows the percentage increase in LOLF and EENS for WL1, WL2 and WL3, in comparison with the "Wind Only" case study for V_{wind} = 60m/s. Further, as can be seen in Figure 8, as the range [L_{max}^{normal}, $L_{\max}$] increases, the increase in LOLF and EENS becomes larger. For example, EENS increases from 26.3% for WL1 to 43.8% for WL3, which shows the significant impact of the loading-dependability of the lines' failure probabilities. This is because for severe wind events, more transmission line failures take place, pushing the network closer to its limits, which means higher power flows on the lines (e.g. ≥0.85p.u.). Therefore, when considering the impact of lines' loading on their failure probability, the lines are more likely to trip during these highly loaded events, which results in further cascading line outages and higher frequency and severity of customer interruption. During normal wind conditions where series of line outages are very rare to occur, high line loadings do not usually occur due to the operational security arrangements of the GB system, which results in low loading-related line failure probabilities.

The magnitude of the estimated EENS is considered reasonable as the network will possibly experience a wide-area blackout under the severe wind conditions simulated here. Further, the simulation results clearly show that the real-time operating conditions have a significant effect on the operational resilience of the test system. Therefore, neglecting these factors in the resilience assessment of power systems would result in the underestimation of the problem.

IV. Discussion and Conclusions

Unlike the majority of existing methods which ignore the effect of real-time operating conditions, this paper has described an approach for assessing the real-time operational resilience of power systems taking into account the impact of both weather and loading conditions, with focus on the impact of these system conditions on the failure probability of transmission lines. This has been achieved using fragility curves, which express the lines' failure probability as a function of wind speed and their loading. Any power system component and real-time operating condition can be included in this approach, if its fragility curve is available.

The simulation results show that the GB transmission network becomes less resilient for extreme wind speeds, e.g. V_{wind}>50m/s. Even though such severe wind conditions are currently rare (the highest recorded wind speed in GB is 63.5m/s in 1989 [16]), these wind speeds are to be considered in resilience studies due the uncertainty associated with future wind conditions as a direct impact of the climate change. This would help get an understanding of the challenges that the GB transmission network may face in the future.

If such an understanding is achieved, then hardening measures can be applied for boosting the grid resilience to such catastrophic events, as the simulation results show that extreme wind events have a great impact on the network resilience. This is because as the wind speed increases, the components become less resistant to the fluctuating weather conditions, so it is more likely to trip and trigger cascading outages. The hardening measures refer to the structural and topology reinforcement measures, such as building the components exposed to the weather conditions with stronger materials, undergrounding the overhead lines and adding redundant transmission facilities. These measures will provide network resistance and additional assets to the system operators for coping with the unfolding disaster.

The simulation results of the loading-dependent studies show that if the effect of loading on the components' failure probability is considered, then the network becomes less resilient. This indicates the need for preventive operational measures. An example is the vegetation management for clearing the right-of-way paths of the transmission lines, which would reduce the probability of flashovers to trees as happened in blackouts of the last decade.

The approach described in this paper is generic and can be applied to any power system. This would provide an indication of the network resilience to severe weather and highly loaded conditions, which is of vital importance for achieving operational resilience. Especially if historical data are available for relating the components' failure probabilities with these real-time operating conditions, then more accurate fragility curves can be developed, which would enhance the confidence in the simulation output.

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