Reliability Enhancement via Integration of Extreme Weather Forecast in Power System Operation

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***Abstract*—According to US Department of Energy, extreme weather is the leading cause of power outages in the United States. Although all the system operators have access to weather forecast data, no existing automated tool can take advantage of this data to guide preventive operation. This paper presents a framework to close this gap. The framework first forecasts weather with accuracy and resolution required for grid operation. The weather forecast data is, then, passed to a structural analysis module, where the failure likelihood of power system elements is estimated. Finally, the failure probabilities are integrated within a day-ahead stochastic unit commitment model to guide preventive operation. A scenario reduction technique is developed and employed alongside an enhanced formulation to achieve computational tractability. The simulation results on a 2000-bus Texas system suggest that the developed model is effective in reducing power outages, with minor additional dispatch cost. The results also suggest that the developed framework is tractable for large-scale systems.**

Keywords—Extreme weather, power system reliability, power system resilience, stochastic unit commitment, structural stability, weather forecast.

I. Introduction

The future electric power system is expected to operate autonomously and proactively under extreme conditions [1–4]. Hurricanes and tropical storms are one category of extreme weather events that lead to large blackouts, both in terms of lost electric load and number of affected customers [5, 6]. The 2017 hurricane season clearly revealed the vulnerability of the U.S. electric power system to hurricanes. In August 2017, hurricane Harvey caused about 300,000 customer outages in Texas [7]. About two weeks later, in September, hurricane Irma lead to outage of more than 6 million customers in Florida (59% of total FL customers) [8], and just below a million customers in Georgia (22% of total GA customers) [9]. Later in September, hurricane Maria made a devastating landfall in Puerto Rico, which left the entire island in complete darkness [10]. Even a month after the hurricane's landfall, still 73.8% of the customers in Puerto Rico were without power [11]. The question this paper aims to answer is whether or not better software tools can alleviate the impacts of such events on the grid.

Power system reliability is often achieved through implementation of various redundancies, so that the system withstands likely disturbances [12–14]. Reliability standards set by North American Electric Reliability Corporation (NERC) require the operators to prevent blackouts under the random outage of one (N-1) or two (N-1-1) bulk power elements [15,16]. Hurricanes, however, usually lead to outage of multiple elements, well beyond the conditions of NERC standards. For example, Electric Reliability Council of Texas (ERCOT) experienced 97 transmission line outages (139 kV and above) after hurricane Harvey made landfall [17]; similarly, hurricane Sandy caused the outage of over 218 high-voltage (115 kV and above) transmission lines [18]. Thus, it is apparent that the conventional reliability tools, which the industry makes use of, are neither designed for, nor applicable to such extreme conditions.

During extreme weather events, rich meteorological information, such as wind direction and speed, is collected and available to power system operators [18, 19]. Since the reliable delivery of power under such extreme events is not guaranteed, employment of meteorological data by the utilities in order to prevent catastrophic outages is a favorable option [20, 21]. There is a vast body of literature, which aims to estimate the power outage statistics (e.g., number of customers without power, etc.) with the weather forecast data *before the hurricane* [22–32]. Such statistical models, though may produce high-quality results, are only able to provide macro-scale statistics about the outage, without any details on the element-level failures. There also exists a number of studies on optimizing the repair and restoration plan *after the event* [33–39]. *However, the literature on preventive operation during the hurricane, using hurricane forecast information is almost nonexistent.* This is due to a fundamental knowledge gap that limits our ability of incorporating weather forecast data into effective preventive actions [40-43].

To fill the aforementioned knowledge gap, *this paper takes a holistic approach by using the weather data to estimate power system element failure likelihoods. The failure probabilities are, then, integrated within a power system*

This research was funded partly by the NSF ECCS grant # 1839833, and partly by the Utah Science Technology and Research (USTAR) Initiative grant # 18065UTAG0054.

978-1-7281-2658-6/19/$31.00 ©2019 IEEE

operation model to guide preventive operation. This paper develops an integrated framework to enable preventive operation during hurricanes: first, the wind field (speed and direction) in the hurricane region will be constructed with high-resolution hurricane forecasting models; the failure probability of transmission-level elements will be estimated through dynamic structural analysis, based on the wind field information; then, using a stochastic optimization framework, the failure probabilities will be explicitly modeled within a power system operation problem to discover preventive actions. Fig. 1 provides a schematic overview of the developed platform. This integrated platform will estimate expected energy not served (EENS) due to the hurricane as well as the cost of operation.

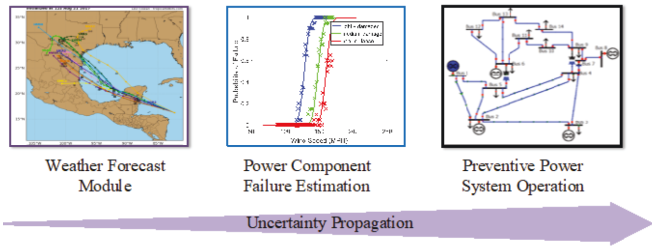

Fig. 1. The architecture of the developed framework.

The remainder of this paper is organized as follows. Section II briefly presents the weather forecast module, while the transmission failure estimation procedure is explained in Section III. Section IV is dedicated to the preventive power system operation model. Section V presents the simulation results. Finally, Section VI concludes this paper. As an example of extreme weather, this paper focuses on the case of hurricanes.

II. Weather Forecast Module

Commercially available weather forecast usually does not meet the quality levels required for power system operation. The quality requirements include accuracy, uncertainty bounds, and resolution. Thus, the first module of the platform performs high resolution and high accuracy weather forecast, customized for preventive power system operation.

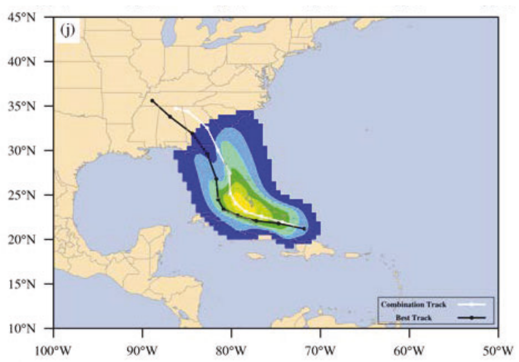

Fig. 2. Hurricane Harvey forecast probability maps at wind speed of 34kt. The figure show 120-h forecast from 00 UTC 8 Sep 2017. The white line shows the forecast and black line denotes the best track (e.g., "observations") as a reference.

For hurricane forecast, in additional to high-resolution numerical forecast field at 2-km horizontal grids, a Monte Carlo Probability [44] has been implemented and further modified by combining it with ensemble forecasts from operational centers [45]. Fig. 2 shows sample probability result. Hurricane Harvey forecasts data, both from high-resolution simulations and probability model are used to conduct the study.

III. Transmission Failure Estimation

Transmission failures in this work are identified based on the response of the towers to the wind load. To estimate the tower's response, a finite element model of transmission towers is developed using ANSYS. The model is further reduced to a 13-degree of freedom lumped mass model to facilitate fast computation. The model is shown in Fig. 3.

Using the developed model, the response of the tower to the wind load can be estimated. The factors that play a role in the response include air density, wind direction, wind speed, steady wind profiles, turbulent wind frequency (spectrum) and the shapes and sizes of the tower members. Our validations show that the lumped mass model accurately predicts the response of the finite element model. The important factor in the response that would determine the failure of the tower is the top drift as shown in Fig 3.

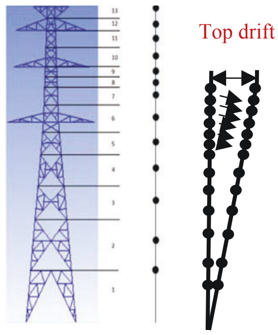

Fig. 3. 13-degree of freedom lumped mass model of transmission towers and the top drift due to wind loading.

To further facilitate computation, we develop the fragility curves for transmission towers based on the lumped mass model. The particular fragility curve identifies the failure probability of a transmission tower at a given wind speed. A probability of failure P at a certain wind speed indicates the top displacement of transmission tower exceeds its failure/collapse threshold P*N times in running N simulation at the specific wind speed. Fig. 4 demonstrates different fragility curves of a prototype transmission tower under different wind profiles.

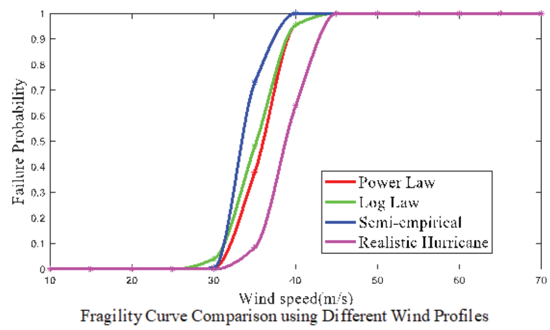

Fig. 4. Fragility curve for transmission towers based on wind loading.

The reliability of the transmission line is equivalent to the reliability of a series system considering the individual transmission towers as components. Therefore, eventually, the failure probably of the transmission line in an extreme wind event can be calculated with the fragility curve of the tower and the known wind field.

IV. Preventive Day-Ahead Scheduling

Given the hurricane forecast, the transmission failure estimation module will calculate the probability of line failures at each hour of the day. Such probabilities can be integrated in a day-ahead security constrained unit commitment (SCUC) model, to enable preventive operation. The solution to the preventive SCUC will reflect the possibility of line failures in a way that the dispatch will rely less on the lines that are prone to failure. However, due to stochastic nature of the failures, the model will be a stochastic SCUC as shown in (1)-(3):

$$\text{minimize } \sum_{s=1}^{S}\sum_{t=1}^{T}\left(\Pr(s)\, C_t\big(X(t,s),Y(t,s),U(t,s)\big)\right) \quad (1)$$

$$\text{s.t.} \quad G\big(X(t,s),Y(t,s),U(t,s)\big)=0 \quad (2)$$

$$H\big(X(t,s),Y(t,s),U(t,s)\big)\le 0 \quad (3)$$

where $\Pr(s)$ is the probability of scenario s; C_t is the cost of dispatch in period t, X is the vector of state variables, Y is the vector of model parameters and U includes the decision variables such as commitment and dispatch. The constraints of the problem are shown in (2)-(3), which include power balance constraints, power flow equations, line capacity limits, generator capacity limits, ramping constraints, etc [41-43].

To represent the failure probabilities in scenarios, one can use a failure vector for each scenario, $F=[t_1 \dots t_L]^T$, in which t_i shows the time when line i fails. Given the estimated probability of failures for each line, the probability of each scenario, $\Pr(s)$, can also be calculated as shown in (4):

$$\Pr(t_1,\dots,T_L)=\prod_{l=1}^{L}\left(P_l(t_l)\prod_{t=1}^{t-1}\big(1-P_l(t-1)\big)\right) \quad (4)$$

where P_l is the probability of failure of line l, at time t_l.

The simplest way of integrating failure estimations within stochastic SCUC is to generate all the possible scenario vectors F, and calculate the likelihood of their occurrence. However, such formulation can lead to an extremely large number of scenarios. The number of scenarios for a case, where L lines are affected in T periods will be $(T+1)^L$. If the hurricane affects only 30 lines, in 4 hours, the number of scenarios can be as large as 9.3e20, which is more than 2000 times larger than the age of the universe, measured in seconds, since the Big Bang.

Thus, thus simple implementation of the stochastic SCUC is not possible with a few exceptions, as listed below:

1. The number of affected lines and important hours are both small, which is common for tornados and uncommon for hurricanes.
2. The failure probabilities are close to extremes of 0 and 1, and probabilistic transitions are rare or negligible.

In other cases, representation of all the possible scenarios is not practical and a scenario selection method is required.

A. Scenario Selection

As mentioned above, scenario selection is an essential module within the developed platform. Without appropriate scenario selection, the tool will not be able to practically handle large systems. In designing any scenario selection method, it is important to sample the space in a way that the selected set is representative of the scenario space. This is not at all a trivial task as the scenario space is extremely large.

We base our scenario selection technique on two attributes of the failure probabilities: 1) the likelihood of the failure and 2) the criticality of the transmission lines. Each line with a nonzero failure probability is evaluated based on these two attributes, as shown in Fig. 5. The failure probability is a direct product of the fragility analysis, explained in Section 3. The criticality of the lines, is measured based on the line outage distribution factors and the loading of the line in a simple SCUC. The criticality includes information on the number of lines that would get overloaded after the line under study fails; criticality also accounts for the severity of post outage overloads.

In Fig. 5, each star represents a vulnerable line, with its failure probability and criticality. To generate scenarios, the space is divided into a grid. Each corner point in this grid represents a scenario, in which lines with higher failure likelihood and higher criticality are included. A sample scenario is shown in Fig. 5, with a red dot. In this figure the origin represents a scenario, where all the lines with any possibility of failure are assumed to be out. The point at the right-top corner represents a scenario, where all the lines survive. Another challenge in scenario selection is assignment of probability to each scenario. In this paper, we assign equal probabilities to each of the scenarios.

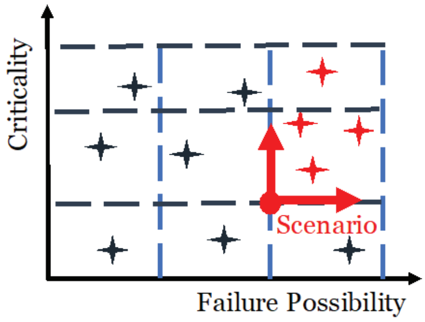

Fig. 5. The scenario selection method, based on failure probability and criticality of the transmission lines; the red dot represents a scenario, in which any outage with higher failure likelihood and higher criticality is included.

B. Enhanced Formulation

Even with a small scenario set, stochastic SCUC can be extremely computationally demanding for large scale systems. Academic formulation of the problem, based on $b-\theta$ representation of the power flows is not tractable. Here we use three techniques to reduce the computational burden of the problem. These techniques are described below:

1. Flow calculations: Instead of $b-\theta$ representation of the flows, we use shift factors. With shift factors, the line flows can be calculated by multiplying the shift factor matrix, φ, with the nodal injection vector, $\boldsymbol{I}$, as shown in (5). This formulation enables isolated calculation of select line flows, unlike the $b-\theta$

formulation, where all the flows need to be calculated simultaneously. Thus, shift factor structure will allow elimination of a majority of line flow constraints for the lines, whose flows are not close to the limits. Moreover, voltage angles are eliminated entirely from the formulation, which again improves computational performance.

$$\boldsymbol{f} = \varphi \boldsymbol{I}; \quad f_l = \varphi_l \boldsymbol{I} \tag{5}$$

2. Line outage modeling: As the shift factor matrix depends on the network topology, line outages change the shift factor matrix. Recalculation of the shift factor matrix is unfortunately computationally expensive. To properly model line outages without having to recalculate the shift factor matrix, we use flow canceling transactions, as described in [46,47]. Flow canceling transactions are an injection pair placed at the two ends of the line, which represent the outage of that line. Unlike the conventional line outage distribution factors, flow canceling transactions can properly model multiple line outages.

3. Iterative constraint selection: To improve the computational performance, the model starts without modeling transmission limits and then calculates the flows after a solution is achieves. The model, then, adds the violated limits as constraints to the problem, and resolves the model. This process is repeated until no violation remains.

These techniques together enable us to achieve a tractable model that can handle large-scale systems within an acceptable time.

V. Simulation Results

To study the effectiveness of the developed model, this section presents the simulation results on a synthetic 2000-bus Texas system [48], as shown in Fig. 6.

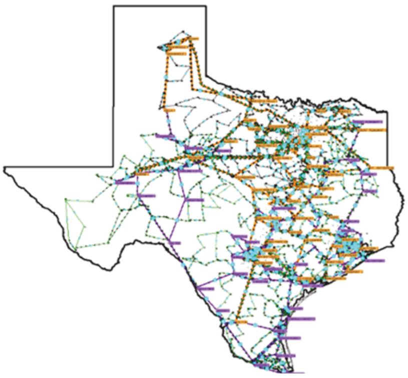

Fig. 6. Synthetic 2000-bus Texas system [48]

Hurricane Harvey forecast data is used to conduct the study, as shown in Fig. 7.

Using the hurricane forecast, and the forecasted wind speed, the developed fragility curves are employed to estimate the failure probability of the transmission lines. The probabilities are then fed into the scenario selection method, explained in the previous section to generate a number of representative scenarios. Finally, the scenarios are used to solve a stochastic SCUC, with the enhanced formulation, discussed in Section 4. The stochastic SCUC produces a solution that only considers the modeled scenarios. To properly understand the performance of the model, the solutions are evaluated through Monte Carlo simulation, where the lines can go out with the probabilities calculated using the fragility curve. In the Monte Carlo simulation, the commitment status of the generation units is fixed to that of the stochastic SCUC solution. The dispatch is allowed to change within the ramping limits. The reason for conducting Monte Carlo simulations is to evaluate the effectiveness of the solution, with line outages in patterns other than those included in the modeled scenarios. The expected power outages are shown in Fig 8.

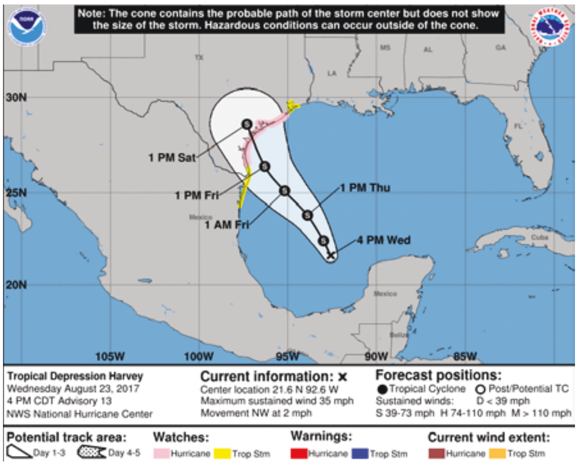

Fig. 7. Hurricane Harvey forecast, taken from National Oceanic and Atmospheric Agency (NOAA).

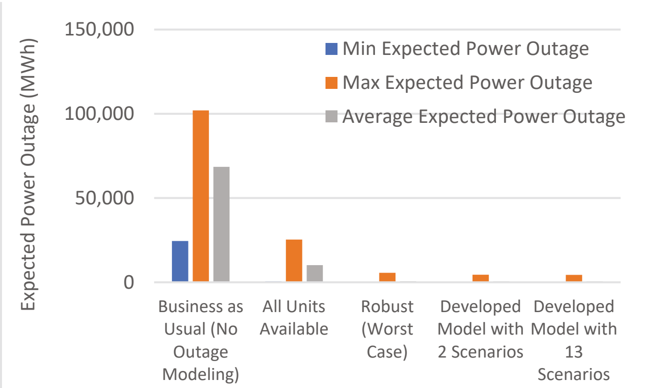

Fig. 8. Simulation results on Texas 2000-bus system

The results show the expected power outages, which is the average of MWh of unserved load over the Monte Carlo simulations. The simulations are repeated, up to 11,000 times, until the results stabilized. The first set of the results belong to a regular SCUC, where line outage estimations are not used. As one would expect, ignoring the fact that a hurricane will hit the system will lead to high levels of power outage. The second set of the results represent a case where the system operator decides to turn all the units on as a response to the hurricane. Engineering judgment adjustments such as turning all the units on is used widely today in response to extreme events. The results suggest that using engineering judgment, though maybe expensive, can substantially reduce the expected power outages. The last three sets of results are obtained with the developed stochastic SCUC. To better see the difference between the results, same plot is presented in Fig. 9, excluding business as usual.

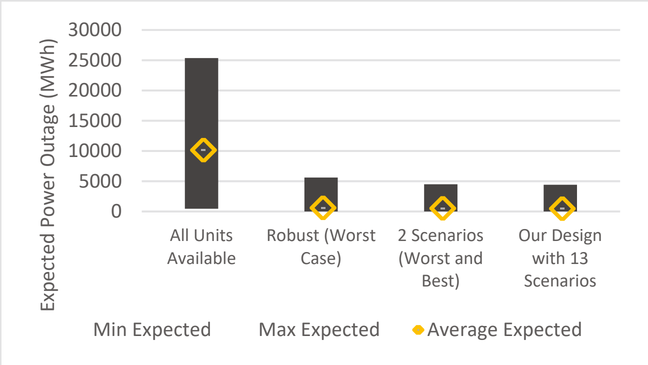

Fig. 9. Performance of stochastic SCUC on the 2000-bus Texas system.

In the results, shown in Fig. 9, the robust case only models the worst case-scenario, which considers all the lines with any probability of failure as out. The case with 2 scenarios combines the worst and best (no line outage) scenarios. The last case, considers 13 different scenarios, which is significantly more computationally demanding. While the maximum and minimum power outages seem to be consistent in the last three cases, the expected outage (yellow diamond) decreases as the number of scenarios increase: from 622 MWh to 518 MWh and finally to 489 MWh for the case with 13 scenarios.

It is also important to look at the cost of the dispatch for each case. The cost information is presented in Table 1. Obviously, the business as usual case has the lowest dispatch cost; however, the cheap dispatch comes with the penalty of large expected power outages. The engineering judgment of turning all the units on is relatively simple to implement; however, it will lead to a rather high dispatch cost and is not as effective as the developed stochastic SCUC. As shown in the table, the model developed in this paper, was able to substantially reduce the power outages, with minimally adding to the dispatch cost.

TABLE I. THE DISPATCH COST

Case	Energy Cost
All Units Available	$26,790,674
Business as Usual (Best Case)	$19,748,334
Robust (Worst Case)	$21,301,729
Developed Model with 2 Scenarios	$21,293,998
Developed Model with 13 Scenarios	$21,306,401

The last factor that is important to investigate is the solution time. In the simulation studies conducted in this paper, our model was able to solver the Texas 2000-bus system with 13 scenarios in less than 18 hours using standard hardware with no parallelization. This confirms that the developed formulation is tractable on a large-scale system. The performance can be further improved through better coding practices as well as parallel computing.

VI. CONCLUSIONS

Today, weather forecast data is not properly integrated in power system operation during extreme events. This paper presented an integrated platform, which enables preventive operation of power systems during extreme weather. The platform first forecasts weather with accuracy and resolution required for grid operation. Weather forecast data is, then, passed to a transmission failure estimation module, which forecasts the failure probability of the transmission lines. Finally, the results of this analysis are used in a power system operation model to guide preventive operation. The preventive power system operation problem was formulated as a stochastic SCUC. A scenario reduction method was developed and employed alongside enhanced formulation to achieve tractability. The simulation results, conducted on a 2000-bus Texas system, confirmed that the developed model is effective in reducing power outages with minimally adding to the dispatch cost. The computational time was also acceptable given the size of the system and the available hardware.

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