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Deterministic proxies for stochastic unit commitment during hurricanes

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Abstract

Severe weather threatens the reliability of the power supply by damaging the network. In
the case of hurricanes, tens of elements may fail, which would lead to power outages.
Under such circumstances, preventive unit commitment methods can model the proba-
bilistic failure forecasts and minimise the power outages. Preventive stochastic unit com-
mitment is an effective method to consider failure forecasts to reduce the power outage.
Although stochastic unit commitment produces high-quality solutions, it is computation-
ally burdensome. Thus, this paper evaluates proxy deterministic methods with lighter
computational compared with stochastic unit commitment on both the solution time
and quality. Adjusted spinning reserve requirements, engineering judgment-based rules,
and robust preventive operation are among the evaluated methods. Numerical results are
obtained for the synthetic grid on the footprint of Texas with 2000 buses. The results
suggest that while some proxy methods, such as standard spinning-reserve and adjusted
spinning-reserve with 6% to 30% of the spinning capacity, may not be as effective as the
stochastic method, others, such as robust optimisation, deliver the majority of the stochas-
tic benefits with substantially less (85%) computational time. Monte Carlo simulations
are used to evaluate the quality of solutions in reducing the expected unserved load and
over-generation.

1 | INTRODUCTION

Historical data indicates that severe weather conditions such as
hurricanes and tornados are the cause of over 90% of black-
outs in the United States [1, 2]. Blackouts occur mainly due
to the unplanned outages of an unforeseen number of grid
components [3]. Any unexpected failure (usually more than a
few components) may result in cascading outages and conclude
in small or large blackouts [4]. Exploring weaknesses and vul-
nerabilities of the network when facing severe weather con-
ditions and planning accordingly to harden relevant compo-
nents, is a long-term solution that can be used in reducing the
impact of hurricanes on power system reliability. How-
ever, short-term emergency plans are needed to better oper-
ate the existing system during severe weather events. This can

be achieved through preventive operation software tools, such
as preventive unit commitment. The preventive unit commit-
ment can be defined as a security-constrained unit commitment
(SCUC) problem, with some modelling of the weather-induced
damages. As was observed and reported by NERC, preventive
SCUC can enhance the stability and reliability of the network
and reduce the unserved load (UL) [3].

SCUC is an essential tool used by system operators, opti-
mising the cost of electricity generation during a certain time,
while satisfying security requirements. The complex nature of
the unit commitment (UC) problem, due to its numerous tech-
nical constraints, necessitates the schedule to be decided reason-
ably ahead of time and be given to the system operators day(s)
in advance. These models involve some degree of uncertainty in
many parameters that need to be handled.

Modelling N-1, N-1-1, N-2, and generally N-k reliability requirements can further complicate SCUC problems, where given the failure of 1 to k elements, the overall stability and reliability of the bulk system should be maintained. Despite all the enhancements and developments over the recent past, the N-k reliable SCUC problems are still deemed too difficult to solve for k larger than two. This becomes even more challenging when k represents transmission lines, and the number of possible futures that should be considered becomes excessive [5].

An excellent example of this challenging problem is when a natural disaster is predicted to impact the network, leading to a relatively large number of element outages. Evaluating the weaknesses of system components reveals that the most vulnerable elements of power systems, when facing severe weather conditions such as hurricanes, are transmission and distribution lines. Modelling such outages can help enhance the reliability of the system and lead preventive dispatch. Unfortunately, state-of-the-art academic and industrial tools can only handle up to a few line outages, for large-scale real power networks [5–7]. This limitation prevents the development of effective tools for power system operation during hurricanes, when tens or hundreds of elements may fail within a few hours. In this effort, the trade-off between computational burden and model effectiveness plays a central role.

Stochastic unit commitment (SUC) is a model that was introduced and developed as a promising technique to schedule power generation in the presence of uncertainties [8–11]. SUC models the uncertainties through a scenario set within the UC problem. Modelling the uncertainties explicitly in the UC problem improves the efficiency and quality of the solution. As a result, the solution offered by SUC is more effective compared to other alternative methods in terms of reliability and economic efficiency. Despite the better quality of the results, two main concerns come with SUC: its high computational burden, and efficient scenario generation.

Unfortunately, both the computational burden and scenario generation complexity are intensified with an increased level of uncertainties. Enhanced handling of SUC computational demands has received much attention over the recent past. Alongside enhancing the formulation of two/multi-stage SUC to reduce the calculation time [12–14], researchers have experimented with other forms of SUC formulation such as interval optimisation [15], taking advantage of parallel computing [16], or using chance-constrained programming techniques [17, 18]. Despite all the enhancements, SUC remains to be a computationally challenging problem, demanding a long run time to be solved. Generally, the calculation time and the quality of the solution depend on the number of modelled scenarios. For any specific scenario generation method, modelling a larger number of scenarios will result in higher quality solutions, but it will cost more in terms of calculation time and required hardware [19]. Hence, the scenario set should be selected in a way that the uncertain future is well represented within a small number of scenarios. Recently, the multidimensional scenario creation method is developed, which is shown to have superior performance compared to many existing techniques for solving preventive unit commitment during severe weather [20].

2 | CONTRIBUTIONS AND MOTIVATIONS

The industry can enhance the reliability and cost of operating the grid in the presence of severe weather risk, if preventive operational scheduling is adopted. While the stochastic methods seem to be among the most effective options, considering all the challenges mentioned above for SUC, it cannot yet be adopted by the industry. Further advancements are needed to speedup SUC solvers, before computational time drops to below acceptable thresholds. Therefore, the development of deterministic proxy rules for preventive SUC is desirable to reduce computational time and enable immediate adoption by the industry. Hence, the objective of this paper is to evaluate and tune proxy deterministic methods to capture the majority of stochastic unit commitment benefits with a substantially less computational burden.

The contribution of this paper is to evaluate a number of deterministic methods for SUC, to enable preventive operation during hurricanes and other predictable disturbances. The paper tunes each method to minimise the outages as well as generation cost. Additionally, the paper compares the results of different approaches, including the stochastic-based methods to illustrate the advantages and shortcomings of each proxy method in the presence of hurricanes. Finally, the paper shows that with fine-tuned deterministic models, which are ready for adoption, power outages can be significantly reduced, under extreme weather conditions, such as hurricanes.

The remainder of this paper is organised as follows. Section 3 describes the severe weather and its impacts on the power system and also offers relevant background information on stochastic unit commitment. Section 4 introduces the candidate proxy deterministic methods that are evaluated in this paper. Section 5 describes the studied test cases, while Section 5 provides the numerical results for each of the test cases. Section 7 offers a further discussion of the objectives of the paper. Finally, Section 8 concludes the paper.

3 | PROBLEM DESCRIPTION

The objective of this paper is to compare alternative deterministic methods with SUC during an event with numerous transmission outages. The high-level flowchart for the proposed algorithm is illustrated in Figure 1. After all the data, including the network and uncertainties, are loaded, for each method, including the stochastic and deterministic proxies, the same procedure, as shown in Figure 1 should be performed. Within the first section of Figure 1, "Enhance the Configuration Parameters," for those methods with flexible configuration parameters, the best value of each parameter is determined. Hence, each method is tuned to its best performance when solving test cases with a large number of transmission outages. After the best
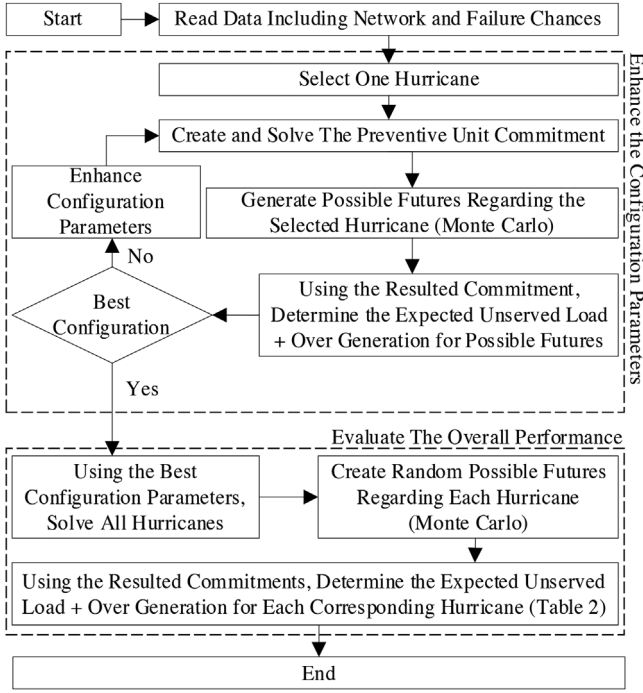
```
┌─────────┐    ┌──────────────────────────────────────────┐
│  Start  │───▶│ Read Data Including Network and Failure Chances │
└─────────┘    └──────────────────────────────────────────┘
```

Enhance the Configuration Parameters

Select One Hurricane

Create and Solve The Preventive Unit Commitment

Enhance Configuration Parameters

Generate Possible Futures Regarding the Selected Hurricane (Monte Carlo)

No

Best Configuration

Using the Resulted Commitment, Determine the Expected Unserved Load + Over Generation for Possible Futures

Yes

Evaluate The Overall Performance

Using the Best Configuration Parameters, Solve All Hurricanes

Create Random Possible Futures Regarding Each Hurricane (Monte Carlo)

Using the Resulted Commitments, Determine the Expected Unserved Load + Over Generation for Each Corresponding Hurricane (Table 2)

End

FIGURE 1 The high-level flowchart of the proposed algorithm to evaluate the best possible performance of each method, when minimising the power outages in the presence of a large number of possible transmission line failures. The same procedure should be performed with the stochastic method and all other deterministic proxies

configuration related to each method is determined, then, within the second section of the flowchart in Figure 1, the numerical results evaluate the quality of solutions for several real-world, large-scale power networks as test cases. For each method, the quality of the solution and the required hardware when solving thousands of randomly generated outages (as a result of possible failures by hurricanes) are compared with other methods. Note that, employing each method on different large-scale test cases necessitates overcoming challenges in their formulation and calculations. However, as the objective of this paper is to compare methods regarding their results and expectations, the formulation and algorithms are not discussed in detail in this paper. Interested readers are referred to [20–22] for further discussions of the mathematical modelling and algorithms.

The remainder of this section, first, briefly discusses the impacts of hurricanes on electric power systems, and, then, presents stochastic unit commitment as an effective tool that has recently been proposed for preventive power system operation during hurricanes [23]. Other deterministic proxies are described in Section 4.

3.1 | Severe weather and power grid

The three main components in the power network include generation units, transmission lines, and distribution networks. While severe weather conditions can impact all three sectors, the

level of damage to each can be different based on the weather conditions. Transmission and distribution networks are more vulnerable to the wind force, and flooding may aggravate the situation. On the generation side, the possibility and intensity of damages to the conventional power plants caused by wind are low due to the presence of structural and building support [24]. In this study, we focus on transmission level damages in developing preventive unit commitment problem. Distribution-level damages are not explicitly modelled as they cause imminent local power outages due to their radial configuration. The preventive generation optimisation is ineffective in reducing the local load loss caused by distribution network failure.

Here, we present an example from Hurricane Irma to justify this assumption. Reference [25] illustrates the power outages over a day during Hurricane Irma's impact on the state of Florida with an animated picture. When the hurricane makes landfall at the southern shore of Florida, not only does it cause outages in the area that is directly damaged, but also causes partial outages in other areas of the state. While the local power outages are likely due to distribution network failures, the power outage in other parts of the system can only be explained by propagation of the problem through the transmission network. This latter category of power outages may be prevented through a preventive generation scheduling, with a reduced reliance on the lines that have failed in southern parts of the system. Preventing this type of outage is what the current paper aims to achieve.

The Hurricane Harvey event analysis report, prepared by the North American Electric Reliability Corporation (NERC) [3], mentions that: "Unit commitment and generator dispatch decisions postured the system to withstand the impact of the storm and recover promptly afterwards that through the preparation processes they were able to reduce the load loss." Although NERC has not specified the method or the practice Electric Reliability Council of Texas used as preventive operation, the unpredictable nature of load loss is named as the primary concern in NERC evaluation that requires further examination. This paper will address NERC's concern by examining different methods to find the most suitable ones for each defined purpose. Interested readers are referred to [26], where the paper investigates the impact of transmission tower damage and failure to the performance of the power transmission network during a hurricane.

3.2 | Stochastic unit commitment

This paper is focused on real-world, large-scale networks with tens of predicted transmission failures. Due to the stochastic nature of the problem, the stochastic-based optimisation methods seem to be promising. Stochastic optimisations have been the subject of interest in the last few decades in its general form [27, 28]. Later, more studies were conducted on stochastic methods based on the scenario tree used in the unit commitment context [17, 29–31], where the model is derived from the idea that a finite number of scenarios is possible to be defined.

The basic idea of solving SUC is to cover as many realisations over the uncertain future as possible, to increase the reliability of the solution while minimising the operating costs. Each realisation is called a scenario and represents a possible state of the network under uncertain conditions. The key advantage of stochastic unit commitment is that uncertainty in each scenario is assumed to be known. Since uncertainty is discretised as one scenario, the deterministic unit commitment formulation can be preserved. In [32], multi-stage stochastic optimisation is compared with deterministic approaches, showing that the stochastic method leads to improved cost. However, the test case in [32] is limited to a few buses and transmission links. Another important fact about SUC that has also been mentioned in [32] is that cost-saving with stochastic optimisation occurs only if the scenario sets represent the underlying uncertainties properly. In this regard, [33] shows that if any uncertainty feature is ignored and not modelled in SUC, a non-negligible effect on the expected cost may be observed. In addition to the computational burden and complexity of scenario generation, as is mentioned in [34], SUC has two more drawbacks. First, obtaining an accurate probability distribution for the uncertainties can be difficult. Second, these solutions provide only probabilistic guarantees. In this regard, it is also useful to mention that for large-scale networks with an unusually high level of uncertainties, the scenario creation, reduction and aggregation is even more challenging, as the number of possible scenarios is practically infinite. The complexity of scenario generation and computational burden of SUC motivate this paper to evaluate proxy deterministic methods with easier modelling procedure and reduced calculation with nearly the same solution quality. These proxy methods are described in Section 4.

Considering that our test-cases are defined based on large-scale networks, the formulation of the SUC and scenario creation methods are the main challenges in this approach. In this paper, the authors used the complete form of SUC formulation based on power transfer distribution factors as described in [22], and the scenario generation method referred to as "multidimensional scenario selection (MDSS)," which is presented in [20]. In MDSS, multiple dimensions of the available data regarding each uncertainty such as failure chance, transmission capacity, and operation point are taken into account to generate the most efficient set of scenarios. The compact form of SUC, as in [22], is presented here to discuss the key model components briefly. The objective function, which should be minimised, represents the expected cost under all the modelled scenarios, including operating costs and penalty for load shedding and over-generation:

Minimise

$$\sum_s \left\{ \pi_{(s)} \sum_t \left[\sum_g \left(C_{(s,t,g)} \left(x_{s,t}, u_{s,t} \right) \right) + \sum_n \left(c_{(s,t,n)}^{\text{lsh}} \left(x_{s,t}, u_{s,t} \right) \right) \right. \right.$$

$$\left. \left. + \sum_g \left(c_{(s,t,g)}^{\text{og}} \left(x_{s,t}, u_{s,t} \right) \right) \right] \right\}, \tag{1}$$

where s, g, t, and n are the indices for scenario, generation unit, time, and bus number, respectively. Moreover, $C_{(s,t,g)}$, $c_{(s,t,g)}^{\text{og}}$ and $c_{(s,t,n)}^{\text{lsh}}$ represent the generation cost, over-generation penalty, and load shedding penalty, respectively. The generation cost itself is a function of the generated power, no-load fixed cost, start-up and shut-down costs for all units where applicable. It should be mentioned that as the load shedding and over-generation penalties are fairly large in comparison with energy generation cost, the objective function is dominated by penalty components. Hence, solving the SUC essentially minimises the unserved load (UL) and over-generation (OG). The problem includes regular equality and inequality constraints as:

$$g_{s,t} \left(x_{s,t}, u_{s,t} \right) \leq 0, \tag{2}$$

$$h_{s,t} \left(x_{s,t}, u_{s,t} \right) = 0, \tag{3}$$

where $g_{s,t}$ covers constraints regarding the maximum thermal capacity of transmission lines, minimum down and minimum up times of generators, ramping limits of generating units, generation minimum and maximum capacities. $h_{s,t}$ contains nodal or global load balance, power flow equations, and a set of equations that describes the effect of line outages. The main decision variables are commitment status (first stage variable) and generation dispatch (second stage variables) for each unit, $x_{s,t}$, $u_{s,t}$, that minimises the objective cost function. Note that $u_{s,t}$, as first stage variables, should remain the same across all scenarios.

The major difference between the formulation in this study and other two-stage stochastic unit commitment formulations is the inclusion of the effects of line outages in this paper. The final flow of each line, including the normal operation flow plus the effect of outages, should be less than the line's thermal capacity as in Equation (4):

$$-F_{(m)}^{\max} \leq F_{(s,m,t)} \leq F_{(m)}^{\max}, \quad \forall s, \ t, \ m \tag{4}$$

where F is the actual line flow, $F^{\max}$ is the capacity limit of the line, and m is the line index. $F_{(s,m,t)}$ is calculated through the net nodal injection vector and power transfer distribution factor matrix, PTDF [35]. The line outage effect for each s, t and, m is calculated as shown in Equation (5):

$$F_{(s, m, t)} = \left(PTDF_{(m)} \times P_{(s,t)} \right)$$

$$+ \sum_{o \in O_{(s,t)}} \left(PTDF_{(m, frm_{(o)})} - \left(PTDF_{(m, to_{(o)})} \right) \right) FC_{(s,t,o)} \tag{5}$$

The first part of the right-hand side of Equation (5) represents the normal line power flow as a result of nodal injections (includes load, generation, over-generation as load, and load shedding as a negative load). The second part takes the

impact of line outages into account. Note that $FC_{(s,t,o)}$ exemplifies the flow cancelling transaction, which is calculated so that injecting $FC_{(s,t,o)}$ to the "from" bus of line o, and withdrawing $FC_{(s,t,o)}$ from the "to" bus of line "o," has the same effect on the rest of the network as the outage of line "o." To calculate the $FC_{(s,t,o)}$ that is used in Equation (5), a system of equations must be solved. As these equations are dependent on operation point, they are deployed into the problem through equality constraints. This way, they will be automatically solved by the optimiser to calculate $FC_{(s,t,o)}$ for all temporal outages in each scenario that is defined by $O_{(s,t)}$.

$$
\begin{aligned}
&(PIDF_{(o)} \times P_{(s,t)}) - FC_{(s,t,o)} \ \forall, s, \ t \\
&+ \sum_{d \in O_{(s,t)}} \left(PIDF_{(o,frm(d))} \right) \ \forall \ o \in O_{(s,t)} \\
&- \left(PIDF_{(o,to(d))} \right) FC_{(s,t,d)}
\end{aligned}
\tag{6}
$$

For more details on flow cancelling transactions, which is an extension of line outage distribution factors, refer to [29].

4 | CANDIDATE PROXY RULES

Different methods can be employed to handle uncertainties in the preventive unit commitment model. In general, it is possible to divide methods into two main categories: (1) Explicit modelling of the uncertainties, and (2) proxy methods. Generally, the first category yields more efficient solutions but at the cost of more demanding computation and added modelling complexity. In this paper, four proxy methods are evaluated.

4.1 | Standard spinning reserve

A most common approach to address the uncertainties in industrial applications is committing extra generation capacity, known as a spinning reserve [36, 37]. Spinning reserve requirements are simple to implement but not economically efficient, even when the uncertainties are limited [9]. For the case of severe weather, due to a large number of impacted elements, it is expected that relying solely on additional reserve requirements (both spinning and non-spinning reserves) is not going to be efficient. In standard spinning reserve (S-SR) or business as usual method, the operator does not contemplate the information regarding extreme uncertainties and plans the day-ahead generation scheduling as a typical day with some level of uncertainties. Reserve requirements can be used to handle a limited level of uncertainties [36–40]. The main advantage of utilising spinning reserve is the protection it gives against a slight degree of uncertainty while preserving the deterministic interpretation of the problem [41–45]. In this study, the required spinning reserve is assumed to be 6% of the total hourly demand in the network.

4.2 | Optimised spinning reserve

Optimised spinning reserve (O-SR) is similar to the S-SR method, except that the level of required spinning reserve is optimised to compensate hurricane-induced line outages. Generally, the deterministic constraints can be adjusted in order to handle a defined uncertainty [38, 46, 47]. For this study, as the deterministic constraint is the level of the reserve requirement, and the predicted outages are more than usual, the required reserve should be higher than the standard value and needs to be optimised for the test case.

More than a few studies have concentrated on optimising the spinning reserve requirements in order to reduce the value of lost load (unserved load) [8], and [18]. In [48], the objective is to optimise the spinning reserve in a system with high penetration of wind power. In [49], (meta-) heuristic methods are used for optimising the reserve requirement. References [50] and [51] are studies that include more details and involve constraints such as consumer's required reliability. In [52], the same as in this study, authors claim that with the modern requirements in the power network, the generation cost minimisation cannot be assumed as the best goal to solve the UC problem when minimising the generation cost may apply other costs such as pollution to the total operation cost. Authors of [52] try to evaluate the reliability of the unit commitment problem with spinning reserve through the swarm intelligent methods. In [52], it is mentioned that as the future scope of their work, stochastic approaches can be utilised to consider multiple scenarios to improve the overall efficiency. However, the difference between [52] and the current study is that in [52] the probability of generation failures are included while in this paper focuses on multiple possible line failures.

In O-SR, the spinning reserve is flexible and can be any value from 0% of the hourly load to the maximum level that the network is capable of supplying. For our test cases, the maximum possible spinning reserve is set to 33% of the total hourly load. The network and generation constraints do not allow for reserves, more than 33% of the hourly demand, as it does not yield a feasible solution. Note that 33% is the maximum possible value of reserve when there is no line outage in the network, and any line outage may reduce this threshold.

4.3 | Worst possible case

The worst possible case (WPC) is a method defined based on robust optimisation [53, 54]. While robust optimisation and dynamic robust optimisation are extremely conservative methods, defined minimisation of maximums [55–57], it is not possible to evaluate all the possible futures representing all the uncertainties, as mentioned before. Based on the concept of multi-stage robust unit commitment as introduced and used in [34, 58–60], in this paper, the integer commitment variables are assumed to be the first-stage variables, and real-generation scheduled power as the second-stage variables.

It is assumed that the worst future case in terms of UL and OG happens when the maximum possible number of lines fail. With this assumption, the worst case occurs when any line with a minimum failure chance is taken out of the network. The result is a deterministic temporal configuration for the network, with the topology changing over time when each line collapses. The failures, though, are deterministic, leading to only one topology trajectory. Hence, the model is comparable to the preventive stochastic optimisation with one scenario, and that single scenario is the worst possible case. It should be mentioned that in the above definition, the failure threshold is assumed to be 0%, which means any failure chance of more than 0% at any time will be assumed as a certain failure. However, it is possible to consider the value assigned to the threshold as a configuration parameter. Whenever the failure chance of any line is more than the defined threshold, that line would be assumed offline. Increasing the value of the mentioned configuration parameter from 0% to 100% means shifting from applying extremely conservative constraints to applying no constraint at all (this is later explained with examples). This may help in enhancing the overall efficiency of the WPC method by reducing the unnecessary level of conservativeness and the overall cost of system operation [61].

4.4 | Engineering judgment

As tens of line outages are predicted for the network, a suggested solution by experienced operators can be to ignore the operation cost and solve the problem just to minimise the unserved load. We refer to this as "engineering judgment" in this paper. While tens of lines may fail, a sensible decision can be to keep all the generation units available at all times. Hence, engineering judgment (EJ) reflects a strategy where all units are available. While EJ supports the minimisation of the unserved load, it can harm the network with side effects such as over-generation. Over-generation happens because of the sudden disconnection of operating generation units, and its adverse impacts on the system can be as bad as the unserved loads.

In EJ, we assume all generation units are available to generate at any time except for those that are already disconnected from the network or operating in the islanded part of the network. The least time to shut down the unit is assumed to be one step of defined time (mostly an hour), and during that one unit of time, the generated power is assumed as OG. Note that the generation units should somehow waste OG on site.

5 | TEST CASES

The network that is studied in this paper is a synthetic grid on the footprint of Texas. This system includes 2000 buses, 3206 transmission lines, and 540 generators with characteristics as described in [62, 63]. Different test cases are outcomes of different simulated hurricanes that impact the grid. Hence, in addition to electrical data, the geographical data that represents the
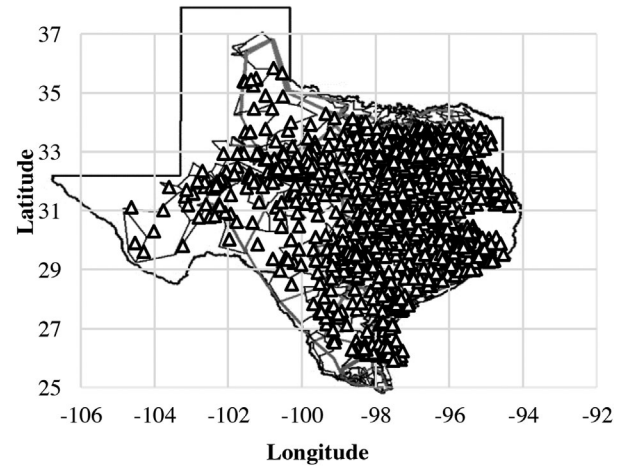

FIGURE 2 The default layout of the power network used in test cases. For each test case, the effect of one simulated hurricane on this network is estimated
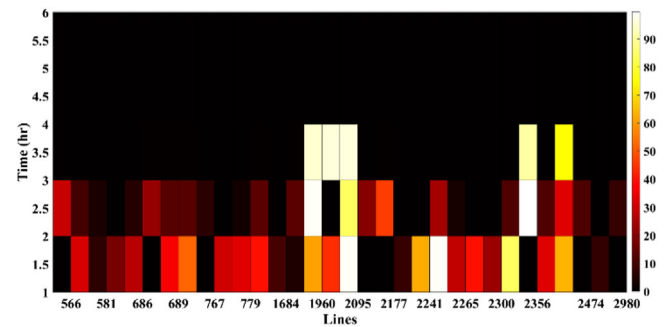

FIGURE 3 Temporal lines failure chances (%) corresponding to test case 1. A total number of affected transmission lines is 33. Assuming the effective-time duration of hurricane is equal to three hours, the total number of possible futures is 7.4E + 19

location of each element must be included as well. The electrical components of the network are shown in Figure 2.

For a comprehensive evaluation, different synthetic hurricanes are considered to pass through the network from different sides and affect the network. It is consistent with the historical data available to assume that the hurricane does not damage the generators directly; instead, their outages are modelled through the transmission lines connecting them to the bulk system. The chance of damage to different elements of the transmission network is then calculated as a temporal failure probability curve for every transmission line, as is shown in Figure 3 related to the first hurricane.

Synthetic hurricanes are inspired by real hurricanes such as Irma and Harvey, to represent realistic test cases. There are seven different tracks for hurricanes; each representing a different path, time, and intensity (wind speed and direction). In Table 1, the label number of lines that are vulnerable for each test case is displayed.

As it can be seen in Table 1, test cases 3 and 4 cover the same set of outages and failure chances; however, in test case 4, the hurricane makes landfall 12 h later than in that of test case 3. Similarly, all the failures in test case 7 are also covered in test

TABLE 1 Test cases and corresponding line failures

Test case	Maximum number of possible outages	Affected lines
1	33	550, 566, 580, 581, 619, 686, 687, 689, 735, 767, 768, 779, 805, 1684, 1795, 1960, 2090, 2095, 2107, 2177, 2240, 2241, 2244, 2265, 2267, 2300, 2355, 2356, 2451, 2453, 2574, 2843, 2980
2	34	549, 550, 566, 581, 619, 686, 687, 689, 736, 767, 768, 779, 805, 816, 1682, 1684, 1795, 1919, 1921, 1960, 2090, 2240, 2241, 2244, 2265, 2267, 2300, 2355, 2356, 2451, 2574, 2843, 2980
3	45	550, 566, 581, 619, 686, 687, 689, 736, 767, 768, 779, 805, 816, 1682, 1684, 1685, 1705, 1718, 1742, 1744, 1756, 1758, 1795, 1919, 1920, 1921, 1960, 1968, 2017, 2068, 2090, 2177, 2240, 2241, 2244, 2265, 2267, 2300, 2355, 2356, 2358, 2451, 2508, 2843, 2980
4	45	550, 566, 581, 619, 686, 687, 689, 736, 767, 768, 779, 805, 816, 1682, 1684, 1685, 1705, 1718, 1742, 1744, 1756, 1758, 1795, 1919, 1920, 1921, 1960, 1968, 2017, 2068, 2090, 2177, 2240, 2241, 2244, 2265, 2267, 2300, 2355, 2356, 2358, 2451, 2508, 2843, 2980
5	28	550, 566, 581, 619, 686, 687, 689, 767, 768, 779, 805, 816, 1684, 1795, 1960, 2090, 2177, 2240, 2241, 2244, 2265, 2267, 2300, 2355, 2356, 2451, 2508, 2980
6	39	566, 581, 619, 686, 687, 689, 767, 768, 773, 779, 805, 816, 1682, 1718, 1743, 1758, 1795, 1815, 1879, 1919, 1921, 1960, 1968, 1971, 1989, 2068, 2071, 2090, 2240, 2241, 2244, 2265, 2267, 2300, 2355, 2356, 2451, 2508, 2980
7	13	689, 816, 1718, 1743, 1795, 2068, 2090, 2240, 2241, 2300, 2355, 2451, 2980

case 6. The difference between these two test cases is that the failure chances covered in test case 7 are not less than 50%. As for the utilised daily load profile, it is obtained from CAISO for a month and calculated to represent hourly load for a day and is available in [64].

6 | NUMERICAL RESULTS

In order to provide a comprehensive evaluation of each method, the impacts of the influencing factor are studied in separate subsections. The first subsection assesses the impacts of different method configurations. To do so, one test case is selected, and the problem is solved using various methods, including SUC and other alternative methods, each with a variety of configurations.

The result of this section helps fine-tune each method in solving preventive unit commitment. In the second subsection, different test cases are picked and solved by all methods, each with its best configuration parameters. The results of this section showcase the overall performance and efficiency of each method in solving preventive unit commitment with a high number of possible line failures. Finally, in the last subsection, other aspects of the results are discussed. It should be mentioned that while the main performance metric of the first two sections is the unserved load plus the over-generation, UL+OG, the last subsection focuses on other indicators, such as computation time and required hardware.

In each subsection, the preventive unit commitment problem is solved using different methods, and the obtained day-ahead commitment is considered as the calculated solution. Then, by deploying the Monte Carlo procedure, the obtained commitment is tested with 1000 randomly selected realisations of the future in order to calculate the expected values of UL, OG, and operation cost. It should be mentioned that to keep the comparison fair, those 1000-realizations are the same for all methods and subsections within each of the test cases.

It worth mentioning that for all the methods, including the SUC and deterministic proxies, the same set of constraints is applied to the unit commitment problem with two exceptions. The common constraints between all methods include: the thermal capacity of lines, generation and demand power balance, generation minimum and maximum capacities, ramp-up and ramp-down of generation units, and minimum up and down times of generation units. The first exception is an additional set of constraints assuring the commitment variable be the same in all scenarios is SUC (as the commitment status variable is assumed as the first stage variable in the stochastic model), and the second exception is an additional set of constraints regarding the minimum required spinning reserves applied to the standard spinning reserve and optimised spinning reserve methods. As mentioned before, all methods are formulated and modelled using power transfer distribution factors. Moreover, for each method, all the constraints must be satisfied.

6.1 | Different configurations for each method

As mentioned above, in this subsection, all the methods are used to solve the same test case (test case #1), and each method has different configurations. In conformity with the nature of the methods, the standard spinning reserve and engineering judgment do not have any adjustable configuration parameter. In the O-SR, the configuration parameter is the level of the required spinning reserve. As the objective is to reduce the UL+OG as much as possible, the test case is solved with different levels of the spinning reserve from 0% to 30% in the steps of 5%. In Figure 4, the green line illustrates the calculated expected value of UL+OG for the O-SR method with different levels of the spinning reserve as the constraint. Based on simulation results, and as was expected, increasing the spinning reserve reduces the expected UL. The expected value of UL+OG also decreases by
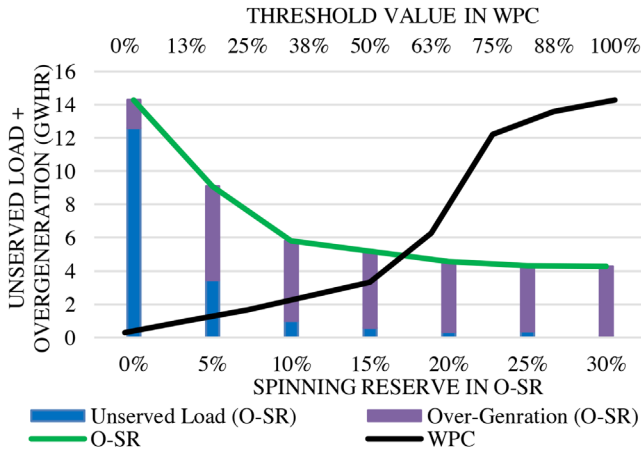
FIGURE 4 Results: Different configurations for O-SR and WPC methods. In O-SR, by increasing the reserve value, the UL+OG drops, UL portion of UL+OG falls, and OG portion raises

FIGURE 5 Effect of increasing the number of scenarios in SUC on UL+OG. Orange bars represent the possible values that were obtained during the Monte Carlo process

increasing the reserve from 0% to 30%. In numbers, the lowest expected value belongs to 30% of reserves, with 4278 MWh of UL+OG.

As can be seen in Figure 4, adding more reserve capacity after 20% of the predicted demand, does not show any significant improvement. In order to better clarify, in Figure 4, at each value of reserve, the UL and OG are plotted separately as blue and purple bars, respectively. By increasing the assigned reserve value, UL is reduced both in absolute value and as a fraction of total violations (total violations = UL+OG). While the OG fraction of total violations increases at all steps by increasing the reserve capacity, its absolute value does not follow the same pattern. OG jumps up from 1.6 to 5.7 GWh when going from no-reserve to 5%, and then falls steadily until 25% of the reserve and raises again at 30%. The results suggest that 25% of the spinning reserve is a good value to consider in this method as it minimises the OG. Moreover, 25% is a safe value as it is possible that under more extreme circumstances, 30% reserve requirements would result in infeasibility issues, because the system may not have such large capacity margins.

With defined WPC method, the preventive unit commitment is a single scenario deterministic form of stochastic unit commitment, in which any line at high enough risk, is assumed to fail with certainty. As was mentioned before, the value of the acceptable threshold for risk is the configuration parameter of this method. A threshold of 0% would model any failure chance as a certain failure, which results in the worst possible case in the future, with the largest number of failures. Similarly, a threshold of 100% would consider a line as failed only if the predicted failure chance is higher than 100%, and that never happens (no line fails). Thus, 0% is the most conservative and pessimistic approach, while 100% is the most optimistic one. However, any value in between can be assigned to the threshold to achieve a trade-off between conservative and optimistic views. To evaluate the effect of the threshold on the results, the threshold value is increased from 0% to 100% in eight steps, and then the calculated commitments are tested to determine the expected value of UL+OG. The results can be seen as the black line in
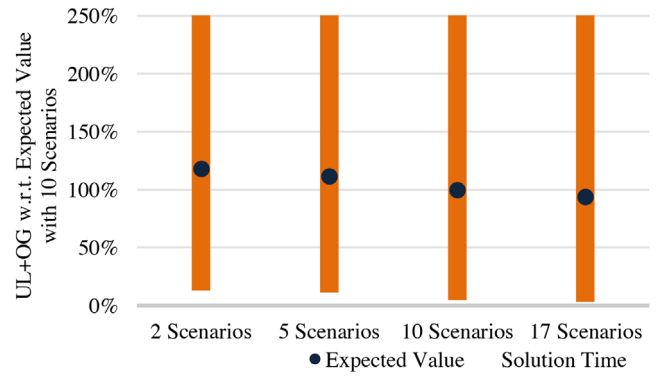
Figure 4. As can be seen, the best outcome is obtained when the threshold is 0%, which means only the most pessimistic future is considered. Considering the best configuration for both O-SR and WPC, the expected value of the UL+OG is less with WPS. From now on, 0% is assumed as the best configuration for the WPC method.

In SUC, while different parameters can be assumed as configuration parameters, the key configuration parameter is considered to be the number of modelled scenarios. Other parameters such as scenario generation algorithm, reduction and aggregation, penalty cost for load shedding and over-generation, and programming technique are assumed to be set at their best configurations for any number of scenarios. It is worth mentioning that different techniques for scenario generation/reduction such as fast forward selection (FFS) [65], simultaneous backward reduction [65, 66], and forward selection in recourse clusters (FSRC) [67] were tested, and multidimensional scenario selection (MDSS) offered the best performance among all [20].

There is always a trade-off between the number of scenarios and the quality of the solution; more scenarios require more calculations but will yield a more efficient solution. Yet, it is necessary to evaluate the quality of the solution, calculation time, and required hardware when selecting the number of scenarios. After running a few assessments, by considering the required calculation power and hardware, authors decided to use ten scenarios for the SUC method. Figure 5 illustrates the effect that the number of scenarios has on the range of calculated UL+OG. By increasing the number of scenarios, not only the expected value of UL+OG reduced but also the minimum and maximum value of the objective function were decreased.

6.2 | Different test cases with each method

As a reminder from the previous section, in O-SR, the reserve requirement is considered 25% of hourly demand; in WPC, the threshold of failure is assumed to be 0%, while the spinning reserve is assumed to be 6%; finally, in SUC, ten scenarios are examined. For each method and each test case, the minimum,

TABLE 2 Expected value of results for all the methods (with their best configurations) and all test cases

Method	Test Case	UL (MWhr)			OG (MWhr)			UL+OG	Cost ($)		
		Min	Average	Max	Min	Average	Max	Average	Total	Energy	Penalty
S-SR	1	77	3,252	15,314	0	5,348	17,916	8,600	$272,776,451	$17,280,935	$255,495,516
O-SR	1	0	377	10,136	0	3,937	17,179	4,313	$145,345,160	$17,205,450	$128,139,710
EJ	1	0	37	2,242	416	4,620	18,651	4,657	$155,802,034	$17,456,807	$138,345,227
WPC	1	0	276	2,264	0	18	341	294	$26,293,707	$17,568,683	$8,725,024
SUC	1	0	61	2,242	0	1	242	62	$19,342,724	$17,499,607	$1,843,117
S-SR	2	229	4,245	9,922	0	7,384	14,036	11,629	$362,877,644	$17,401,916	$345,475,728
O-SR	2	0	303	3,631	0	5,613	12,067	5,916	$193,142,852	$17,388,765	$175,754,087
EJ	2	0	32	2,654	413	6,462	15,294	6,494	$210,494,319	$17,582,540	$192,911,779
WPC	2	173	903	4,349	0	91	1,061	994	$46,997,007	$17,462,072	$29,534,935
SUC	2	0	196	2,657	0	62	945	257	$25,068,379	$17,419,826	$7,648,554
S-SR	3	229	4,245	9,922	308	7,476	40,485	11,721	$365,780,939	$17,568,251	$348,212,689
O-SR	3	0	3,174	25,511	0	2,928	7,297	6,101	$198,447,080	$17,188,629	$181,258,451
EJ	3	0	25	1,591	386	3,518	8,019	3,543	$122,640,177	$17,373,285	$105,266,892
WPC	3	0	463	8,809	0	24	346	487	$31,967,361	$17,510,411	$14,456,951
SUC	3	0	119	5,813	0	27	831	146	$21,744,368	$17,398,438	$4,345,930
S-SR	4	0	3,272	22,799	0	1,976	4,712	5,247	$172,833,021	$16,941,661	$155,891,359
O-SR	4	0	1,418	15,373	0	1,492	3,802	2,910	$103,332,018	$16,888,139	$86,443,880
EJ	4	0	20	1,035	405	1,935	4,263	1,955	$75,311,917	$17,234,445	$58,077,472
WPC	4	0	254	5,488	0	17	333	271	$25,269,269	$17,224,386	$8,044,883
SUC	4	19	92	3,497	0	5	268	97	$20,012,032	$17,116,405	$2,895,627
S-SR	5	0	1,777	19,585	0	2,584	5,412	4,361	$146,587,264	$17,033,305	$129,553,959
O-SR	5	0	380	15,248	0	1,902	4,680	2,282	$84,746,988	$16,947,297	$67,799,691
EJ	5	0	8	1,031	407	2,352	5,269	2,360	$87,426,516	$17,304,465	$70,122,051
WPC	5	0	74	2,614	0	10	201	84	$19,678,268	$17,190,122	$2,488,146
SUC	5	11	26	2,132	0	4	189	31	$18,079,493	$17,171,523	$907,970
S-SR	6	496	9,266	41,774	0	2,326	6,097	11,592	$361,286,189	$16,924,743	$344,361,446
O-SR	6	324	3,293	29,919	0	1,882	5,508	5,174	$170,686,899	$16,963,384	$153,723,515
EJ	6	0	27	1,418	406	2,271	5,169	2,298	$85,585,855	$17,326,296	$68,259,559
WPC	6	0	726	5,171	0	32	482	758	$39,798,018	$17,278,127	$22,519,891
SUC	6	0	220	3,707	0	32	507	252	$24,726,140	$17,236,402	$7,489,738
S-SR	7	529	5,542	10,220	0	2,148	4,359	7,689	245,411,670	$16,972,930	$228,438,740
O-SR	7	377	1,580	2,628	0	1,699	3,119	3,279	114,363,866	$16,937,914	$97,425,952
EJ	7	0	0	13	408	1,977	3,386	1,977	76,003,201	$17,261,850	$58,741,351
WPC	7	0	585	4,035	0	1	36	586	34,463,596	$17,061,624	$17,401,973
SUC	7	0	585	3,828	0	0	11	585	34,434,864	$17,068,748	$17,366,116

maximum, and expected value of UL and OG are calculated. In addition to those values, the operation cost is calculated as well. The results are summarised in Table 2, where, min, average, and max represent the minimum, expected, and maximum values among 1000 Monte Carlo random realisations. In economic terms, Table 2 includes the cost of energy denoting the actual cost of electricity generation, penalty cost indicating the economic expense imposed on the system because of UL and OG, and the total cost, which is the summation of energy generation cost and penalty costs.

The first and most evident conclusion from Table 2 is that SUC is always the best method in terms of reducing UL+OG. Calculations show that SUC can reduce the UL+OG by at least

95% in comparison with S-SR. In terms of cost, the real energy generation cost of the SUC solution is slightly higher than that of S-SR, as more load is served in the SUC method. The penalty cost in S-SR is much higher than the SUC and any other method. SUC is also the best method when OG matters more than UL because of possible long-term damages to the generation units. The expected value of OG is negligible when using SUC, in all the test cases.

Knowing that the total daily demand for electricity is 1.3 TWh, the S-SR approach results in UL of 0.33–0.88% of total daily demanded energy. While these numbers do not seem significant, having access to electricity becomes critical during severe weather conditions. Using any other approach can at least

reduce that value by about 50%. This reduction in UL+OG can be as significant as 95% and 91% using SUC and WPC, respectively. These numbers are significant, considering that they are obtained only through better operation software, which does not apply any additional hardening cost to the system.

While the O-SR shares the same principle as S-SR, because of more spinning reserve (25% compared to 6% of hourly demand), the obtained solution is more than 50% improved in terms of the average value of UL+OG. Carefully checking Table 2 also reveals that this improvement mostly occurs because of less UL. Using more reserve leads to a reduction in the expected OG, but the reduction in UL is even more significant.

As expected, engineering judgment (EJ), which keeps all the units available, is the best method among all to minimise the UL. For each test case, the lowest expected value of UL is realised through EJ. The potential of EJ on reducing UL is demonstrated in the last test case, where the expected UL is as low as zero. On the other hand, having all generating units available results in OG value that is not efficient. Overall, the EJ approach is better than the O-SR and S-SR, but it cannot beat WPC and SUC. It should be noted that, before using this approach to reduce the UL, the OG problem should be handled to prevent damage to the generation units, as a damaged generator may need days or weeks to be fixed. This can reduce the reliability of the electricity supply for days after the severe weather event.

The WPC is not the best method in any case, yet its performance is very close to the SUC. A closer look at the last test case exposes that the maximum possible value of UL is the only major difference between SUC and WPC. While the expected (average) value of UL is 585 MWh in both methods, the maximum possible value is better with SUC.

The same advantage for SUC over WPC can be seen in all other test cases. In comparison between SUC and WPC, as the two best methods to improve the reliability of the electricity supply, in most cases, SUC has a non-trivial lead over WPC except for the last test case. To justify that, note that while in the first six test cases, the failure chances can be any value between 0% and 100%, in the last test case, it only includes those predictions with more than 50% of chance of an outage. Having uncertainties with a higher chance of failure makes the uncertain possible future closer to the worst possible case. As in WPC, only the worst possible case is considered, it is efficient for this test case. Note that as one of the modelled scenarios in the SUC is the worst possible case, SUC still shows better efficiency than WPC, but its advantages over WPC are less noticeable than other test cases.

Finally, using the UL+OG as the primary metric of measuring the efficiency of the solutions, Table 2 compares different methods with one another. For example, SUC can reduce the UL+OG by a factor of 59% relative to the WPC. In the same way, using the O-SR will result in 763% more UL+OG relative to the WPC. As can be seen in Table 3, SUC has all negative values in its column, which means it has lower UL+OG in comparison with any other method.

TABLE 3 The efficiency of different methods with respect to each other

| UL + OG in: ↓ | with respect to | | | | |
	S-SR	O-SR	EJ	WPC	SUC
S-SR	—	103%	161%	1652%	4153%
O-SR	−51%	—	29%	763%	1996%
EJ	−62%	−22%	–	570%	1528%
WPC	−94%	−88%	−85%	—	143%
SUC	−98%	−95%	−94%	−59%	—

6.3 | Other aspects of comparison

While the quality of the solution in reducing the expected value of UL+OG is one of the important criteria for method selection, other important features should also be carefully studied. These features include computational time and computational power (required hardware). Among evaluated methods, S-SR and O-SR do not model the failure chance directly into the problem. In those two methods, the operator simply solves the unit commitment problem once, and the solution is utilised for any outage scenario. Although the quality of the solution provided by those methods is not the same as SUC or WPC, they have some significant advantages over the other two methods. As the uncertainty (failure data) is not modelled explicitly in S-SR and O-SR, there is no need to calculate the outage chance of lines by simulating the hurricane and its effect on different components of the network. Not only does this directly reduce the total required calculation load significantly, but it also prevents making bad decisions because of errors in weather/outage prediction and calculation. Moreover, there is no need to recalculate the preventive unit commitment problem for different hurricanes.

As mentioned before, when OG is less critical than UL, the EJ is the best method to minimise the UL. EJ has one more advantage over all others; EJ does not need any computation. It should be noted that while we assumed all the generation units are online in EJ, this may not necessarily be possible. There might be generation units that cannot accept the risk of OG, in which case, the principle can be applied to the maximum number of generating units with the capability of handling OG. Still, the same advantages would be expected for this method over all others.

Finally, to shed light on the calculation burden and hardware requirements, an average calculation time, the minimum required memory, and dependency of the solution to the change in failure prediction is summarised in Table 4. Note that while the calculation times for the S-SR, O-SR, and EJ are independent of outage data, the calculation times for WPC and SUC highly depend on outage data and failure possibilities. In general, an increase in the number of possible outages results in longer calculation time and more required memory. The reported values for WPC and SUC methods are the average time required to solve all the test cases. For example, in SUC, while

TABLE 4 Calculation requirements of different methods

Method	Calculation time	Required memory	Recalculate if failure prediction changed?
S-SR	14 min	>4 GB	No
O-SR	45 min	>4 GB	No
EJ	0	0	No
WPC	3 h	>24 GB	Yes
SUC	22 h	>32 GB	Yes

the calculation time for the last test case number 7 is less than 2 h, it is more than 30 h for test case number 3.

6.4 | Simulation environment

While there are a number of appropriate software environment options, authors chose to use Oracle Java in combination with IBM CPLEX as the simulation environment. Java is fast and offers flexible memory management [68, 69]. The machine that is used to run the simulations utilises Intel Core i7-7700 CPU @3.60 GHz as a processor combined with 32.0 GB of DDR3 RAM (plus 64 GB of Page-File on a Solid State Drive), which is configured as dual-channel bandwidth @ 2.40 GHz. The software package includes Eclipse Jee ver. 4 (2019-09) and IBM CPLEX ver. 12.8-64bit running on a Windows 10 Pro machine.

7 | DISCUSSION

In the power system, there are circumstances such as natural disasters that may result in multiple element failures. Transmission lines are more vulnerable to more frequent disasters such as hurricanes and tornados. In such situations, improving the reliability of electricity supply by reducing unserved load and over-generation can be achieved through preventive unit commitment. Preventive unit commitment in its original form can be formulated as a stochastic unit commitment. Alternatively, proxy deterministic methods can be used to find an efficient solution. In this paper, different methods were used to solve the same test cases, with predicted transmission failure probabilities due to a hurricane impact. The results were thoroughly presented in the previous section.

A significant result of this paper is that better operation software can improve the reliability of the network with no additional cost. As was shown, even using methods with simple implementation, such as the worst possible case, offers a substantial reduction in UL and OG.

Stochastic preventive unit commitment emerges as the best method among all reducing UL+OG. While other methods may show better performance regarding just UL or OG, the results suggest that stochastic unit commitment is more flexible and offers superior performance. In our test cases, OG and UL have the same negative value to the system, and as a result, methods try to find the best solution to improve both at the same time. As the stochastic solution highly depends on the set of modelled scenarios, scenarios can be defined to give one objective higher priority, and as a result, the solution can be optimised for that specific objective. Hence, stochastic unit commitment can also be adjusted to perform similarly to other methods. Another way of biasing the solver is by manipulating the penalty values relative to each other.

Although stochastic unit commitment is the superior method in terms of performance, it suffers from two major drawbacks. First, the computational burden of the model can become prohibitive for larger systems with more constraints. Second, the industry implementations of SCUC and SCED do not use stochastic optimisation. Thus, a transition to stochastic unit commitment may require substantial adjustment of the existing energy management systems. This paper suggests that there are efficient deterministic alternatives to a stochastic unit commitment that the system operators can use without transitioning to stochastic solvers. Adoption of these proxy deterministic models will provide a significant portion of stochastic unit commitment benefits without leading to issues such as computational burden or incompatibility with energy management systems. Finally, as discussed in detail in the previous sections, the proxy deterministic models discussed in this paper are all rather simple and can seamlessly be added to the existing unit commitment model.

8 | CONCLUSIONS

Severe weather events, such as hurricanes, leading to the outage of many transmission lines. These failures can be predicted in advance as a probability distribution. Recently, a stochastic unit commitment model is proposed that explicitly models such line outage predictions to find a preventive dispatch and reduce network violations. While the method is effective, it is computationally burdensome and not compatible with existing energy management systems. This paper provided a thorough analysis of the effectiveness of a variety of proxy deterministic methods, to replace stochastic unit commitment. Network violations, as the indicator of method effectiveness, were measured as the summation of unserved load and over-generation. The paper showed that while stochastic unit commitment offers superior performance, there exist a number of deterministic alternatives that can offer the majority of stochastic unit commitment's benefits. The results, presented in this paper, suggest that the best deterministic method for minimising the unserved load and over-generation, in most cases, is robust optimisation or worst possible case. This method employs the worst possible failure prediction, thereby eliminating the prediction uncertainty, and offers acceptable results in comparison with stochastic unit commitment. The paper also showed that an engineering judgment rule of keeping all generation units online can minimise the unserved load, but leads to high levels of overgeneration. The method may be used if the overgeneration issues are properly handled by the operators. The deterministic methods are compatible with existing energy management systems and

can be seamlessly adopted. Additionally, they do not substantially add to the computational burden of the current unit commitment models, eliminating the concern about exceeding the available time for computation. This paper demonstrated that better operation software tools could be developed and readily used to improve power system reliability during anticipated severe weather events.

As was shown, among all the evaluated methods, the stochastic method requires the longest calculation time and provides the best quality solution. While the calculation time with the stochastic method may not be acceptable for short time-ahead generation scheduling, it can be useful for long time-ahead generation scheduling and planning where the calculation time has less priority than the quality. In the same way, if the objective is to evaluate the network weaknesses against severe weather conditions, higher quality may better fit. Hence, a decision between the calculation time and the quality of the solution should always be based on the desired application.

Finally, while the authors did not detect any scalability issues with smaller and larger networks, with networks much larger than 2000 buses, the required amount of memory and calculation time may be unreasonably large. It should be noted that the current study is limited to the conditions when no islanding occurs in the network because of the severe weather conditions.

9 | FUTURE RESEARCH

In the current paper, comparisons between the stochastic-based method and proxy deterministic rules were made, when each of the methods was used independently and with their standard format. While in a few methods such as optimised spinning reserve, some tuning was performed, yet other enhancements are possible. It may be possible to combine different methods to create new ones with better efficiency than each method individually. A good example is a stochastic formulation with only two scenarios: one scenario representing the worst possible case, and the second scenario representing the optimised spinning reserve.

In addition to the studied proxies in this paper, there are other promising techniques that can conserve the quality of the stochastic method while may reduce the calculation time. As in this study, all optimisations were made without any warm-start techniques, providing warm-start values (a feasible solution close to final optimised solution) can significantly reduce the calculation time, especially with the stochastic method. Trained supervised machine learning model with the ability to predict the solution may be the best example of these techniques. It should be mentioned that as the predicted values will be used as a feasible solution, the trained model does not need to have perfect accuracy in predictions.

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