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Multidimensional Scenario Selection for Power Systems with Stochastic Failures

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Abstract—Stochastic optimization can be used to model predictable but uncertain element failures, in an attempt to enhance system reliability in power system operation and planning. In practical applications, such as preventive operation during severe weather, the uncertainty set is often very large. This will lead to two challenges: (i) every possible scenario cannot be practically identified; and (ii) the computational demands of stochastic optimization with a large scenario set cannot be met. To address these challenges, this paper develops a multidimensional scenario selection method, which creates a rather small but representative set of scenarios. The developed method makes use of failure features as well as network features of the elements that may fail, to achieve a superior performance. The simulations studies on a synthetic large-scale Texas system, show the dominant performance of the method compared to existing algorithms in the literature, as well as common industry practices. Due to its effectiveness, the method presented in this paper enables computationally efficient implementation of stochastic power system operation and planning software tools. Such stochastic tools will improve system reliability and efficiency through enhanced use of the existing resources, without requiring any expensive system upgrade.

***Index Terms*—Large-scale systems, load shedding, power outage, power system reliability, preventive operation, scenario creation, scenario reduction, severe weather, stochastic unit commitment, stochastic optimization, transmission outage.**

I. INTRODUCTION

The National Academy of Engineering refers to the North American power grid as the largest and most complex machine ever built by humans [1]. In order to supply the electric load reliably, numerous decisions should be made at different time scales, each of which can change the operating conditions and the cost of grid operation. Such decisions are made based on the available information that describes the state of the system. With perfect information, system reliability would be achieved with ease, through the use of appropriate decision support systems. In reality, however, power systems are stochastic in nature, and there are many sources of uncertainty that affect the system in different ways. Failure of decision-makers in accounting for the uncertainties can lead to inefficiencies in operation, power outages, and even widespread blackouts in extreme cases. Uncertainties in power systems include but are not limited to random human errors, unplanned element failures, load forecast error, and renewable generation forecast error. The focus of this paper is the uncertainty associated with the element failures, when such failures are predictable. Severe weather is an example of such events, during which many power system elements fail.

Statistical analysis shows that during the past ten years, equipment failure, during predictable extreme weather events, has been the leading cause of power outages in the United States [2]–[4]. Different studies are focused on evaluating the adverse impacts of severe weather on power system reliability, using different techniques such as fuzzy systems [5], and fragility modeling and impact assessment [6]. While severe weather events, such as hurricanes, are predictable in advance, the forecasts often involve a large degree of uncertainty. This uncertainty propagates through the element failure estimation models that take weather forecast as input. Handling such a large uncertainty set in power system operation and planning is a challenging task due to two main reasons: (i) analyzing the uncertainties is often not straightforward and requires complex processes; and (ii) operation and planning tools with explicit modeling of uncertainties become extremely computationally demanding [7]. This is even more challenging for short-term operation models such as unit commitment and economic dispatch, where computational time is extremely scarce. Thus, industry implementation of operation models does not explicitly model many of the uncertainties. Instead, energy and market management system software tools, by in large, use a combination of proxy deterministic rules and engineering judgment for uncertainty management [8]–[10]. These methods do not necessarily use the available resources efficiently, and in extreme cases, fail to supply the load reliably.

Over the last two decades, power system research community has attempted to improve the modeling of uncertainties. With improvements in computer hardware and software, new and more efficient software tools for power system operation and planning, based on stochastic optimization have been introduced [8], [11], [12]. In short-term operation, stochastic unit commitment (SUC) is developed as a scenario-based optimization method that explicitly models uncertainties. As a result, the solution to SUC is more efficient than that of deterministic UC, both in terms of reliability and economic efficiency.

Despite these anticipated and suitable advantages, imple-

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mentation of SUC is computationally burdensome. Additionally, efficient scenario creation is often a complex and challenging process. Scenario creation is extremely important as the computational complexity of stochastic optimization is typically a function of the number of scenarios. Hence, modeling more scenarios, though may result in an improved solution, will increase the computational demand of the model. Furthermore, for many realistic problems, modeling of all the possible scenarios is an impossible task. Thus, an appropriate scenario creation method is needed to identify a manageable set of scenarios that effectively represents the uncertainty space. It should be noted that with any scenario creation method, there will always be a trade-off between the number of modeled scenarios and the solution quality. Thus, not only is the formulation for the calculations within each scenario important, but also the methods for scenario creation, reduction, and aggregation are critical steps in implementation of an effective SUC.

The purpose of this paper is to enable practical implementation of SUC, in presence of many predictable but uncertain element failures. In [13], we have developed a formulation that is able to reduce UC computational time by a factor of more than 90%, in comparison with common academic methods, with many simultaneous line failures. This paper develops an enhanced algorithm for scenario creation, for the case of many uncertain element failures. As shown in the simulation results, the two methods together enable practical implementation of SUC, with predictable stochastic failures.

A proper set of scenarios should be able to represent the most critical and influential possibilities, within a limited number of scenarios. The process of scenario creation can be based on complex computational methods or simple human decisions. For example, in [14], where the uncertainty of generating units is the subject of interest, the first and the second scenarios are defined as the outage of the largest and the second-largest generation units. While this scenario creation method is simple and straightforward, it is not efficient in terms of representing all the possible futures. There are several mathematical methods such as fast forward selection (FFS) [15], [16], simultaneous backward reduction method [15], [17], and forward selection in recourse clusters (FSRC) [18], which create, reduce, and aggregate scenarios for a general stochastic optimization problem. In [19], Monte Carlo method is used to create scenarios, while FFS and backward techniques are employed for scenario reduction. Authors of [20] combine the two-stage stochastic programming with chance-constrained stochastic methods to create a joint formulation, which uses Monte Carlo principle and new formulation to solve the unit commitment problem with uncertain wind power penetration. Reference [21] reviews some of known methods and proposes an algorithm for scenario creation and reduction with applications in power management problems. The algorithm is based on fast forward selection and backward reduction when number of scenarios is many but finite. [19] and [21] both assume that the possibility of each scenario and the distance between the scenarios are both computable or known. In some cases, however, it is difficult to determine all possible individual scenarios or their corresponding possibilities. This will be a challenge for many existing methods, which first, create a scenario tree, and, then, use statistical data, to reduce the number of scenarios [15], [22]–[24]. As will be shown in our simulation studies, the above-mentioned random-based methods are not efficient for the application discussed in this paper.

A few alternatives have been introduced in the literature. For instance, [25] claims that the problem can be simplified by ignoring parts of the available information or problem constraints, such as transmission flow limits. It is also suggested that combining SUC with proxy deterministic rules, such as reserve requirements, is an effective way of improving the solution quality [26]; this way, reserve can compensate for the effect of neglected scenarios. However, it is necessary to determine the adequate level of reserve, which in some ways can be arbitrary. In [27], the interval optimization approach is evaluated in comparison with scenario-based stochastic optimization. The study concluded that the interval-based method is faster but may find a less stable; it is also very sensitive to the uncertainty interval. None of the existing methods is efficient enough to solve the problem that this paper focuses on: modeling stochastic element failures within operation and planning problems. An efficient scenario creation method is clearly needed for this problem.

In this paper, we develop a new analytical multidimensional scenario selection (MDSS) algorithm that is able to create a user-identified number of scenarios, in presence of many uncertain element failures. The developed method uses different aspects of information regarding each uncertainty, to create an efficient set of scenarios without missing critical available information. While there are many applications for the proposed method, a predictable substantial disturbance, such as severe weather, would be a suitable use case. The benefits of the MDSS method is more apparent in problems with large uncertainty sets. Other applications, such as *N-k* security-constrained unit commitment, generation expansion planning, and risk management analysis can also benefit from the developed technique.

The remainder of this paper is organized as follows. Section II presents the motivation and contributions of this paper. Section III describes the first step of the developed method: uncertainty evaluation and feature selection. The scenario creation method is presented in Section IV. Simulation studies are offered in Section V to evaluate the performance and effectiveness of the developed method. Finally, Section VI concludes this paper.

II. Motivation and Contribution

To provide a picture of the first challenge in scenario creation, consider only one possible failure in the network with a temporal distribution over the period of operation. For this event, many scenarios can be constructed, as shown in Fig. 1.

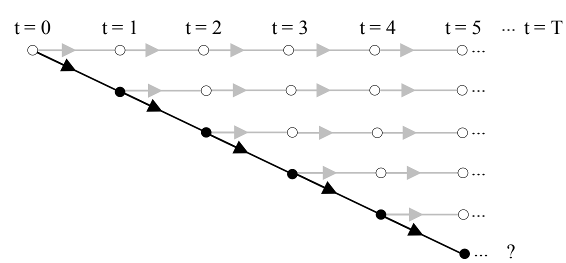

Fig. 1. Possible scenarios for a single element.

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Black dots represent the case, where the element remains online, and gray dots represent failures. It is assumed that a failed element cannot be fixed and go back online during the same operation period. As the figure suggests, even one stochastic failure can lead to many different scenarios, depending on the time when the element fails.

The same is true for any other element in the network with a nonzero failure chance. Hence, the number of different possible scenarios, NS, can be calculated as:

$$NS = (T + 1)^{N_e}, \tag{1}$$

where T is the number of time steps in the duration of the study, and N_e is a number of elements with a nonzero failure chance. For a case with only 36 transmission lines with nonzero failure probabilities over 24 hours, the total number of possible scenarios is about 2E+50. To understand how big this number is, one should notice that the total number of atoms in the earth is estimated to be half of this number. During severe weather events, such as hurricanes, a much larger number of transmission elements can fail, leading to a larger number of possible scenarios. There are four main challenges that come with this large number of possible scenarios. First, it is clearly not possible to evaluate every scenario individually. Second, even using random methods such as Monte Carlo may show low efficiency as the number of randomly evaluated scenarios is extremely limited in comparison to the possibilities. Third, it is not practically possible to calculate the probability of each individual scenario as the individual probabilities are all almost zero. Although the probabilities are not exactly zero, they will be considered as zero within the accuracy of most computer software tools. Finally, even if it was possible to examine each scenario and its possibility, scenario selection based on individual scenario probability would not be efficient. This is due to the reason that many high probability scenarios can be very similar. For example, two scenarios could be exactly the same for the first 23 hours and only a single line outage difference at the 24th hour. In that case, both scenarios represent almost the same conditions and most likely ignoring one would not affect efficiency.

To address all of these challenges, this paper develops an analytical MDSS method to generate an efficient but small scenario set. The method employs information related to the elements that are prone to failure to generate a desired number of scenarios. The method decomposes the information into element level data, such as failure probability, as well as network level data, such as criticality, to provide a holistic view of the future possibilities. The method presented in this paper is fundamentally different from random scenario selection methods, such as Monte Carlo simulation, or those based on evaluation of every possible scenario.

III. Uncertainty Evaluation and Feature Decomposition

The basic goal of solving SUC, instead of a deterministic unit commitment, is to enhance the reliability of the system, while minimizing the operation cost. In SUC, each scenario represents a possible future for the network that can occur due to the existence of different uncertainties. Uncertain element failures can be represented by a failure probability distribution function, often with a temporal distribution.

The failure distribution, though critical to SUC, does not include information on the technical characteristics of the element that indicate its importance for the network. For example, while two generators can have the same value for availability factors, most probably the one with higher capacity or cheaper cost, is more important to the network. Hence, relying solely on the failure probability leads to missing critical information on the element's importance, which reduces the efficiency of the scenario set. An appropriate scenario selection method should take all aspects of information regarding each uncertainty into account.

In this paper, the numerical description of each attribute of information is referred to as a "feature". Describing each uncertainty with several features helps create scenarios based on the element's importance as well as its chance of failure. This way, the scenario creation method is flexible and adjustable, so the operator can decide the attributes that should be considered in scenario creation.

Without losing the generality of the proposed algorithm, here, we define and consider two main features for each uncertainty. These two features include: the network feature and the failure feature. Describing each uncertainty with these two features are later used as the basic step to create efficient scenarios. Note that any other desired feature can be defined and added to the algorithm in the same way. In what follows, the procedure of determining features for the selected elements are described.

A. Network Feature

Network feature or importance factor determines the importance of the element failure to the network. The importance of each element is defined based on its overall effect on other components of the network, should it fail. This feature can vary for different types of elements and should be defined based on the objective of SUC and the role of the element. The procedure of calculating the network feature for the transmission lines and generating units is described below.

1) Network Feature for Transmission Lines

Transmission lines transfer energy/power from the generating units to the loads. Hence, the network feature for the transmission lines should be defined based on transferring energy and its impact on the objective function. There is a number of characteristics that can be used to calculate the network feature for the transmission lines. For example, nominal thermal capacity, capacity utilization of lines at a specific operation point, the physical length of line, or whether it is radial or not. In order to make the algorithm general and applicable to any network, we suggest using a feature that is independent of the operating point and straightforward to calculate, while also considering the main characteristics of line.

Line outage distribution factor (LODF) is a well-known method to analyze the effect of line outage on the network. Each array of LODF, $LODF_{(m,m')}$, determines the fraction of pre-outage flow on line m that will be transferred to line m', should line m fail. Using this definition, each row of the LODF matrix represents the effect of a line outage on the rest of the lines, which fits our needs for defining the network feature. However, there are some additional points that are necessary to be addressed in

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using LODF as the network feature. The sign of LODF can be positive or negative, which describes the direction of the flow change, relative to the direction that is predefined for each line. As the direction of power flow does not matter for our application, we consider only the absolute value. Additionally, as the LODF is a fraction of the pre-outage flow, it is always between -1 and 1, which means the actual capacity of the line is not included. Hence, the following equation is used to calculate the network feature for each line:

$$NF_{line} = F_{line}^{max} \sum_{l=1}^{L} abs(LODF_{(line,l)}), \qquad \forall\, line \in \mathrm{L} \qquad (2)$$

where NF_{line} represents the calculated network feature of *line*, F_{line}^{max} is the capacity of *line* as in [28], and L is the set of all transmission lines.

It is worth mentioning that using actual flows instead of lines' maximum capacity in (2), may more accurately represent the network condition; however, we chose to use line capacity for two main reasons. First, using flows that change over time leads to scenarios that also change over time. Using line capacities, on the other hand, will lead to generation of time-independent scenarios. Note that this is a desirable feature in unit commitment, as the flows change over the duration of the problem and are also dependent on the scenario itself. Second, we assume that the transmission network is planned appropriately and not overbuilt. Thus, transmission capacity limits should be an indication of the line importance and loading during peak hours. Thus, line capacity limits should be a good static proxy to the variable flows, in the sense of the line importance and potential flow.

2) Network Feature for Generation Units

Regardless of network constraints, there are two main characteristics for each generating unit that defines its level of utilization: generation capacity and generation cost.

A generation unit with higher capacity and lower cost is more important in operation, when solving the unit commitment problem. If G is the set of generators with g as a generator index, the network feature of generator g, NF_g , is defined as:

$$NF_g = A \frac{PG_g^{max}}{Max\{PG_g^{max}\}_{\forall g \in \mathrm{G}}} - B \frac{C_g^{max}}{Max\{C_g^{max}\}_{\forall g \in \mathrm{G}}}, \qquad \forall\, g \in \mathrm{G} \qquad (3)$$

where PG_g^{max} and C_g^{max} are the capacity and marginal cost of generation at maximum capacity, respectively. A and B are coefficient indices by which the weight factors of capacity and cost in the final index can be adjusted ($A + B = 100\%$). We suggest $A = B = 50\%$ for the cases with limited number of outages, when supplying all the loads is possible. $A > B$ gives the reliability of supplying load higher priority than the cost, and vice versa. Assuming that the number of failures is large, similar to the operation conditions during hurricanes, picking $A \gg B$ would be a wise decision ($A > 90\%$).

3) Other Uncertainties

For other components of the network, a network feature can be defined similar to generation and transmission. The rest of this paper is applicable to any element, after the network feature is defined in an appropriate way.

B. Failure Feature

Failure feature is simply defined as the best value that describes the failure probability for an element. The failure probability can be defined as a function of time, constant number, or any other form. For the case of a constant failure rate, the rate itself can be used as the failure feature. When the failure probability has a temporal distribution, the failure feature value depends on the distribution of the possibility over time. It can be defined as the maximum value, average value, value at a specific time, median, etc. For the case study presented in this paper, we use the maximum failure chance as the failure feature for transmission lines and generating units.

IV. Scenario Creation Method

The previous section discussed how each element with uncertain failure probability can be described with multiple features. This section explains how those features are used to create an efficient scenario set.

Assume U is an element with uncertain failure probability, and it is described with a pair of features as U = (NF_u , PF_u), in which NF_u and PF_u are network feature and failure feature related to U, respectively. It is possible to represent each feature as a coordinate in a two-dimensional space. Putting all pairs/uncertainties in the two-dimensional space creates an uncertainty space, as shown in Fig. 2. Using this space, uncertainties are automatically sorted based on all features. In Fig. 2, (NF_X , PF_X) is the one with the highest importance to the network and also the highest failure likelihood; in the same way, (NF_m , PF_m) is the one with lowest importance and failure possibility. Note that in a general case, (NF_X , PF_X) and (NF_m , PF_m) may not exist, as one element may not simultaneously have the maximum/minimum value for both features. It is also worth mentioning that the method presented here is general and can handle more than two features. We have chosen two features to enable a graphical representation of the method.

In the next step, multiple thresholds should be considered on each axis (feature). This divides the total space into smaller areas, as shown in Fig. 2.

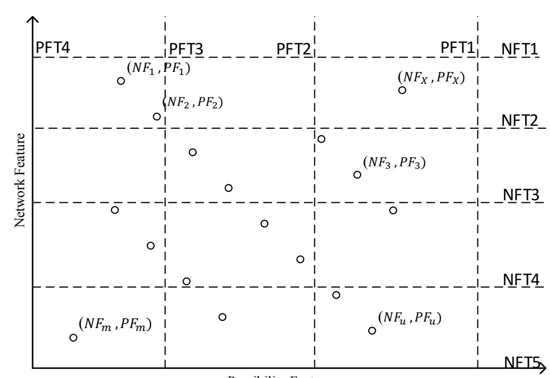

Fig. 2. Multidimensional uncertainty space, and thresholds for each feature.

As an example, considering five thresholds on the network feature, and four thresholds on possibility features, divides the original space into 12 bounded small areas (areas below NFT1 and left of PFT1), and eight unbounded areas (areas above

NFT1 or right of PFT1), with total number of 20 areas. Each of these areas describes a scenario coverage area and may include several combinations of uncertainties. The number of thresholds on each axis is adjustable; considering a larger number of thresholds on one axis/feature would give higher priority to that feature compared to the others.

Scenario coverage areas are defined at intersections between thresholds of the features and include all the pairs to the right and above that intersection. Fig. 3 represents the scenario coverage area for each scenario, using this definition. In Fig. 3, scenario coverage areas are numbered from S1 to S20 with two arrows showing the direction of the coverage area for each scenario. As an example, the area that is covered by S4 is shown with a solid line U-turn arrow. Similarly, the covered area by S11 is shown with a dotted U-turn arrow. Note that S11 not only covers the bounded area to the right and above of an intersection, but also covers one bounded and four unbounded areas.

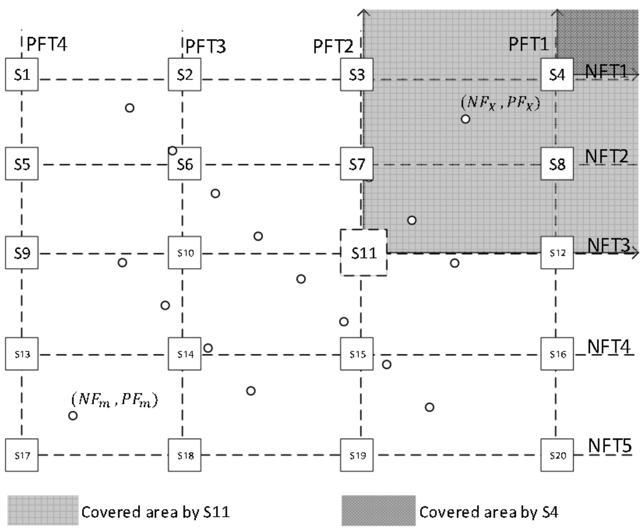

Fig. 3. Scenarios in the multidimensional space.

Generally, any scenario should be defined over time, describing deterministic status for all the elements over the duration of the study. To compute the temporal status of the elements for each scenario, the temporal raw distributions of element's characteristics in the scenario coverage area are examined. The element is considered to be online as long as all the features are below the thresholds, defined by the scenario coverage area. At any time if the element surpasses all the thresholds, it will be transitioned to faulty.

As an example, to identify the scenario for S11, the following steps are taken. 1) The elements that surpass the two thresholds of possibility (PFT2) and network importance (NFT3) for S11 at any point in time are identified, e.g., (NF_X, PF_X) and (NF_3, PF_3). 2) The temporal failure probability for these elements is examined over the duration of the study. 3) The status of these elements, in the scenario, is assumed to be normal until their failure probability exceeds the threshold identified by S11; at that moment the element will transition to be faulty and will remain offline for the remaining hours in the scenario. Note that in this particular example, the network feature does not have a temporal distribution. Thus, whether or not the element exceeds the network threshold is identified in the first step.

Other important observations from Fig. 3 are summarized as:

1. 'S1, S2, S3, S4' and 'S8, S12, S16, S20' all represent the same scenario, which does not include any outage, and thus, can be assumed as the best-case scenario. In the context of unit commitment, this scenario represents business as usual when none of the uncertainties are modeled. This reduces the total number of unique scenarios to 13 for our example. If m features are used for each uncertainty and $n_1, \dots, n_m$ are the number of thresholds on each feature, then the total number of unique scenarios, NRS, can be calculated as:

$$NRS = m + \prod(n_1, \dots, n_m) - \sum(n_1, \dots, n_m) \tag{4}$$

2. 'S17' represents the worst-case scenario. In this scenario, all the elements with nonzero failure possibility are assumed to fail at some point in time. Typically, in robust optimization, this worst-case scenario is considered to obtain a conservative solution.
3. More important uncertainties (in term of network feature or failure feature), will automatically be covered by a larger number of scenarios. For example, in Fig. 3, (NF_X, PF_X) is covered by all scenarios, except for the best-case scenario.
4. The values considered as thresholds (PFT1…PFT4, and NFT1…NFT4), can represent the risk that the operator is willing to accept. In other words, there is no need to divide the entire range of each feature into equal spaces between thresholds; the operator can decide to consider a larger number of thresholds close to high values of each feature to reduce the risk, likely with higher generation cost.

The third observation assists in overcoming the challenge that calculation of individual scenario probabilities is impossible. Assigning equal possibilities to each individual scenario, will automatically give more weight to the more important uncertainties, as it will be included in a larger number of scenarios.

V. Use Case: SUC during Hurricanes

To demonstrate the performance and efficiency of the developed algorithm, we use preventive SUC during hurricanes as a case study. The results are compared with those obtained by other scenario creation methods. To do this, first, we solve a preventive day-ahead SUC in the presence of a hurricane by using different scenario creation methods. Then, the results obtained by each method is tested using Monte Carlo simulations to evaluate the expected power outage. It should be mentioned that for all the methods, the same set of realizations are used for the Monte Carlo analysis.

Hurricanes damage many elements in a power grid; these damages can be predicted in advance with an acceptable level of accuracy. The damage forecasts, however, are probabilistic, due to the uncertainty in weather forecast and fragility analysis. Due to the nature of short-term operation, we assume that if an element fails, it will remain offline for the rest of the day.

A. Preventive SUC Formulation

While SUC formulation for different applications can be found in the literate, such as in [29], [30], a compact form of the formulation is presented here. The objective is to minimize the cost function:

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$$\textit{Minimize} \quad \sum_s\{\pi_{(s)} \sum_t[\sum_g(C_{(s,t,g)}(x_{s,t}, u_{s,t})) + \sum_n(c^{lsh}_{(s,t,n)}(x_{s,t}, u_{s,t})) + \sum_g(c^{og}_{(s,t,g)}(x_{s,t}, u_{s,t}))]\}, \quad (5)$$

where *s, t, g* and *n* are the indices for scenario, time, generating unit, and bus number, respectively. Moreover, $C_{(s,t,g)}, c^{lsh}_{(s,t,n)}$ *and* $c^{og}_{(s,t,g)}$ represent the generation cost, load shedding penalty, and over-generation penalty, respectively. The generation cost is a function of the output power, no-load cost, start-up and shut-down costs related to each unit. Note that as the load shedding and over-generation penalties are rather large, the objective function is dominated by these penalty components. Thus, the SUC will effectively minimize the load shedding and over-generation. The problem includes a number of equality and inequality constraints:

$$g_{s,t}(x_{s,t}, u_{s,t}) \leq 0, \quad (6)$$

$$h_{s,t}(x_{s,t}, u_{s,t}) = 0, \quad (7)$$

where $g_{s,t}$ includes constraints regarding the thermal capacity of transmission lines, up and down ramping limits of generating units, minimum down and up times of generation units and generation maximum and minimum capacities. $h_{s,t}$ covers the equality constraints, including load balance, power flow calculations, and also a set of equations that describes the effect of possible line outages on the network operation. The main decision variables are commitment status and generation dispatch for each unit, $x_{s,t}$, $u_{s,t}$, that minimize the expected objective function value over all scenarios.

The most important constraint related to uncertainties is the line limits as shown in (8):

$$-F^{max}_{(m)} \leq F_{(s,m,t)} \leq F^{max}_{(m)}, \qquad \forall\, s, t, m \quad (8)$$

where F^{max} is the thermal limit of the line, F is the line flow, and s, m, t, are scenario index, the line index and time index, respectively. $F_{(s,m,t)}$ is calculated by considering the nodal injection vector, power transfer distribution factor matrix ($\boldsymbol{PTDF}$) [31], and line outage effect as shown in (9). The first part of the right-hand side of (9) represents the line flow due to nodal injections, which includes load, generation, over-generation as load, and load shedding as a negative load at each bus. The second part of (9) takes the impact of line outage into account. Note that $FC_{(s,t,o)}$ represents the flow canceling transaction, which is calculated in the way 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*. (10) defines a set of equality constraints, that will be automatically solved by the optimizer to calculate the $FC_{(s,t,o)}$ for all temporal outages in each scenario that are defined by $\mathrm{O}_{(s,t)}$.

$$F_{(s,m,t)} = (\boldsymbol{PTDF}_{(m)} \times \boldsymbol{P}_{(s,t)}) + \sum_{o\in O_{(s,t)}} \Big(PTDF_{(m,frm_{(o)})} - (PTDF_{(m,to_{(o)})}\Big) FC_{(s,t,o)} \qquad \forall\, s,t,m \quad (9)$$

$$(\boldsymbol{PTDF}_{(o)} \times \boldsymbol{P}_{(s,t)}) - FC_{(s,t,o)} + \sum_{o'\in O_{(s,t)}} \Big(PTDF_{(o,frm_{(o')})} - (PTDF_{(o,to_{(o')})}\Big) FC_{(s,t,o')} = 0 \qquad \forall\, s,t \quad \forall\, o \in \mathrm{O}_{(s,t)} \quad (10)$$

For details on flow canceling transactions, which is an extension of line outage distribution factors, refer to [29]. The extended version of the formulation can be found in [13], [31], [32].

In response to the hurricane damage, the operator's corrective decisions are limited by two factors: the commitment status of generators cannot be changed, and all generation units are constrained by their ramping limits. Hence, in order to evaluate the results of the developed MDSS method and compare them with alternative methods, after the main preventive SUC is solved, the commitment variables are fixed; generation levels can be changed only within the ramping limits.

B. Test-Case

A synthetic grid on the footprint of Texas is used here as the test case. The system includes 540 generators, 2,000 buses, and 3,206 transmission lines [28]. For this test case, in addition to electrical characteristics data, the geographical data that represents the location of each element is used as well. The electrical components of the network are shown in Fig. 4 [33].

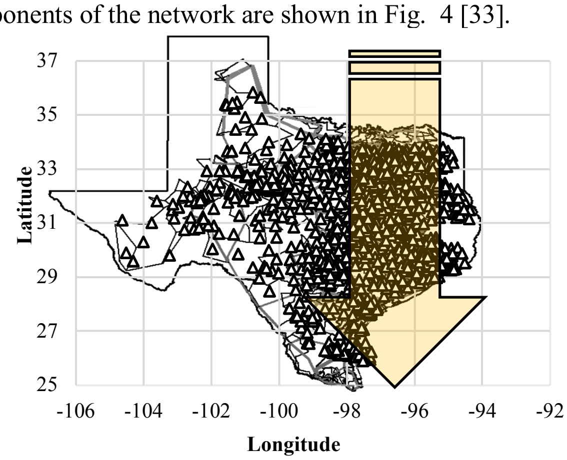

Fig. 4. Network element locations and the hurricane path.

The synthetic hurricane we considered passes through the network from North to South and affects the right side of the network. As the hurricane travels through the network, it has an effective radius, equal to the distance it travels in two hours. The hurricane crosses the network in 24 hours. The most destructive part of hurricane is assumed to be around the center with higher chance of causing equipment failure. Consistent with historical data, it is assumed that the hurricane does not damage the generators. Fig. 4 shows the network elements and the hurricane path.

VI. Simulation Study

As the hurricane gets close to the transmission line (any point from the starting bus to the ending bus), the possibility of its failure gets higher. The number of lines that can fail due to the

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TABLE 1. LOAD-SHEDDING, OVER-GENERATION AND OPERATION COST STATISTICS FOR DIFFERENT SCENARIO SELECTION METHODS

Method ↓	Minimum Lost Load+Over Generation (MWhr)	Expected (Average) Lost Load+Over Generation (MWhr)	Maximum Lost Load+Over Generation (MWhr)	Standard Deviation (WMhr)	Energy Generation Cost ($)
BAU	8,570	33,063	70,119	9,365	19,653,410
Engineering Judgment	1,317	15,020	33,940	5,525	26,502,360
Robust Preventive Operation	4,256	16,386	32,054	4,271	17,032,512
MDSS Method with 2 Scenarios	1,641	15,019	31,408	4,543	23,517,023
MDSS Method with 5 Scenarios	1,440	14,199	30,590	4,738	20,965,170
MDSS Method with 10 Scenarios	614	12,689	29,534	4,662	20,988,462
MDSS Method with 17 Scenarios	404	11,940	27,814	4,574	20,930,119
Fast Forward with 10 Scenarios	5,309	32,702	81,885	12,002	20,437,868

hurricane depends on the line structure and the hurricane power. For the test case we used, the total number of lines with nonzero failure chance is 85. The failure probabilities of those lines are bell-shaped functions of time.

A. Scenario Creation/Reduction

As preventive SUC is solved for an entire day, 24-hours, and the number of elements with failure chance is 85, the number of possible scenarios for the future of the network is:

$$NS = (24 + 1)^{85} = 6.7 \times 10^{118}.$$

Clearly, these many scenarios cannot be handled by any machine. Thus, we use the MDSS method as explained in sections III and IV. We further assume that:

- Maximum failure probability is used as the possibility feature (PF);
- Network feature is calculated using (2);
- The number of thresholds on the PF and NF is chosen to be four.

With the above assumptions, there will be ten scenarios, including the best and the worst possible cases and eight scenarios in between. While there is no outage in the best possible case, there are 1,209 line-hours of outage in the worst case. Clearly, the difference between the most optimistic and the most pessimistic future is substantial. Thus, relying only on one extreme, would not properly capture the uncertainties and may lead to inefficient operation. It should be noted that the computational time for the scenario creation method is less than two minutes, using MATLAB on a standard personal computer.

B. Results and Comparison

As mentioned before, to evaluate the efficiency of the proposed algorithm in creating scenarios, the same preventive unit commitment is solved using different approaches. Then, Monte Carlo simulations, with a large number of randomly generated realizations of future, are used to determine the expected cost and lost load over the next day. The standard deviation and average value converge within the first 20% of realizations. Yet, the simulations were continued not only to be confident about the average, but also to have an accurate estimation of the maximum and minimum bounds of the distribution. In addition to MDSS, there are other alternative methods, which can be used to solve the problem, including the following five.

1. Business as Usual: Business-as-usual (BAU) is used to serve as a reference, where a deterministic unit commitment is solved without any modeling of the hurricane damages, and no reserve. The expected value for load shedding (plus over-generation) is 33 GWhr for BAU. Other calculated statistics for BAU are shown in Table 1.

After implementing the developed MDSS method for scenario creation and solving the preventive SUC with 10 scenarios, the expected value of load shedding is substantially reduced to 12.7 GWhr, which is over 62% smaller compared to BAU. The complete set of calculated results are shown in Table 1.

2. Robust Preventive Operation: this approach is defined based on a simple case, in which preventive unit commitment is solved only for the worst possible case (highest number of lines failures). In robust preventive operation, any failure probability is modeled as a certain failure. The main advantage of robust approach over MDSS is its computational efficiency, as it does not include multiple scenarios. Note that weather prediction and calculation of failure probabilities are still needed. Another alternative method to detect the critical components that generate the worst possible case is introduced in [34]. Results are shown in Table 1 and discussed later in this section.

3. MDSS with Different Number of Scenarios: in the presence of computational power or time limits, the number of scenarios can be reduced by reducing the number of thresholds on each feature in the scenario creation algorithm. While reducing the number of scenarios can reduce the computational burden, it will likely decrease the effectiveness of the method. In particular, in the case of one scenario, it can be the same as the robust operation method; with two scenarios, it can cover the business as usual and robust operation simultaneously. Moreover, to show the effect of including a larger number of scenarios, 17 scenarios are created and used to solve the preventive operation problem. The results obtained in this part, are discussed later in a discussion on the sensitivity of the solution to the number of scenarios.

4. Engineering Judgment: in the absence of sophisticated software tools, system operators have relied on engineering judgment for operation in extreme conditions. One judgment-based method that is often used is increasing the available reserves by bringing additional generation online. During severe weather events, the operators often bring all the generator in the storm area online to maximize the reserve margins and reduce the utilization of the transmission network [35]. While this method does not require complex computation, it may not be as effective compared to SUC, both in terms of reliability and economic efficiency. Table 1 presents the obtained results.

5. Fast Forward Selection: this method is described with details in [11], and used in stochastic unit commitment as described in [19]. For this method, based on the predicted outages, first, a set of 1,000 scenarios is created randomly. Then the distance

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between each pair of scenarios is calculated. Note that the difference in outage of lines and outage duration is considered as the distance in this study. At each iteration, one scenario of the pair with minimum distance will be removed from the scenario set, and the distances will be recalculated again. Scenario reduction will continue to the point that the number of remaining scenarios is equal to the desired number. The computational time for scenario creation and reduction with fast forward selection is more than what is required by the MDSS method, developed in this paper. If PTDF and LODF matrices are available, which is the case for most operation and planning applications, the MDSS method would be extremely fast. Calculated results can be found in Table 1.

The comparison between different methods and their capability in preventing lost load and over-generation during the hurricane is shown in Table 1. The maximum and minimum as well as the expected value and standard deviation are shown. Predictably, BAU operation would lead to the highest level of lost load and over-generation. All the other operation methods, in one way or the other, take some measures to improve reliability in the presence of the hurricane. A point that should be emphasized in Table 1 is that fast forward selection is not only worse than the MDSS method with any number of scenarios, but also is worse than robust and engineering judgment in terms of expected unserved load and over-generation. Besides, it is important to consider that the maximum unserved load for fast forward selection is even worse than BAU. The results suggest that randomly generated scenarios, even with well-known methods, can result in worse outcome than simply doing nothing.

Among all the alternative methods, robust preventive operation and engineering judgment led to the lowest expected lost load and over-generation. If the objective of considering the worst case is to increase the reliability, the results clearly show that the goal is not best achieved. In fact, bringing all the generators online produces a slightly better outcome than robust solution.

Using MDSS with only two scenarios, is better than both robust preventive operation and engineering judgment. The best results are achieved by MDSS with seventeen scenarios. The method achieves the lowest expected value as well as the lowest maximum and lowest minimum network violations (lost load plus over-generation) compared to the other methods. This is important as the proposed method is superior over the entire distribution of the network violations, not just the expected value.

It is also worth noting that the cost of operation in BAU is \$19.7 million, while the cost increases to \$21.0 million for the MDSS method. Using engineering judgment, the cost increases to \$26.5 million. While engineering judgment is relatively effective in enhancing the reliability by reducing the unserved load, though not as effective as MDSS, the cost of reliability enhancement for engineering judgment is five times more than that of MDSS.

Another comparison of the different methods is shown in Fig. 5. This figure illustrates the probability distribution of network violations for three of the best methods. A promising point in Fig. 5 is that with MDSS method, the mode of the distribution (shown with a dark blue bin in Fig. 5) is much lower than that of both robust and engineering judgment. For the proposed method, the highest chance for unserved load is a value between 9,347 to 10,465 MWhr. On the other hand, for the other two methods the range between 14,936 to 16,054 MWhr has the highest chance.

Finally, another important factor when deciding to use each of the mentioned methods, is the required calculation time. Table 2 illustrates the required calculation time, and minimum required memory (RAM) for different methods. Note that the computation time for SUC highly depends on outages: larger number of outages requires more computational time. The machine that was used to run different methods has an Intel Core i7 – 7700 processor and 64GB of RAM; the optimization engine that we used was IBM CPLEX [36].

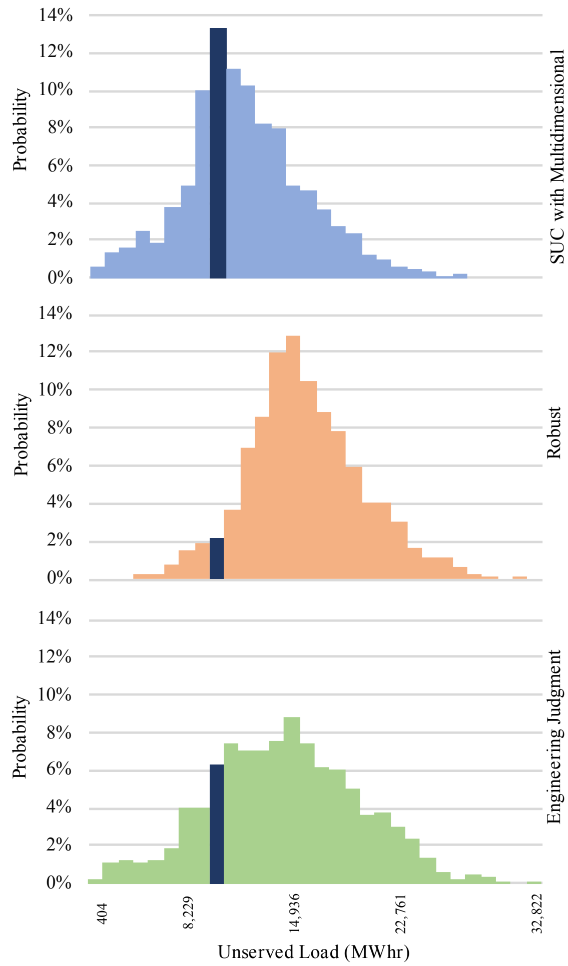

Fig. 5. Distribution of network violations for the three best methods

The engineering judgment needs no unit commitment calculation; hence, as Table 2, shows, the required computational time and memory are reported as None. Generally, more scenarios would lead to longer computational time and more memory use. However, as Table 2 shows, with the same number of scenarios for MDSS and fast forward selection, the computational times are different. This is mainly due to the number of modeled outages in the scenarios. While in MDSS, the worst case is included with highest number of outages, this case is not included in fast forward method as it is based on random selection of the scenarios.

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As Table 2 shows, MDSS similar to other stochastic methods is computationally expensive. However, the results presented in Table 1 shows that MDSS has a superior performance compared to other methods, including robust operation, as it achieves a lower minimum, average (expected), and maximum for unserved load plus over-generation. Moreover, according to Fig. 5, for any uncertain future, MDSS has a higher chance of achieving better performance when minimization of unserved load and over-generation is the objective.

TABLE 2. COMPUTATIONAL TIME AND MINIMUM REQUIRED MEMORY FOR DIFFERENT METHODS

Method ↓	**Computational Time (minutes)**	**Minimum Required Memory (GByte)**
BAU	16	> 1.5
Engineering Judgment	None	None
Robust Preventive Operation	78	> 11
MDSS Method with 2 Scenarios	429	> 16
MDSS Method with 5 Scenarios	579	> 16
MDSS Method with 10 Scenarios	882	> 24
MDSS Method with 17 Scenarios	1,206	> 32
Fast Forward with 10 Scenarios	620	> 18

C. Sensitivity to Number of Scenarios

In order to evaluate the sensitivity of results to the number of created scenarios, we solved the same case by using a different number of scenarios from 2 to 17 scenarios (see Table 1). We observed that by increasing the number of scenarios, enhancement can be achieved on minimum, average and maximum values. The computational time, however, will increase as more scenarios are modeled within the SUC. The computational time that we achieved in our simulations was around 20 hours for the case with 17 scenarios, 15 hours for the case with 10 scenarios, and 10 hours for the case with 5 scenarios. While the computational time seems reasonable, given the size of the test system, further improvements can be achieved through the professional development of the SUC model. While the number of modeled scenarios should be determined based on the required quality of solution and acceptable computation time, for day-ahead unit commitment and large-scale networks, the number of recommended scenarios is between 8 to 20. Note that the temporal distribution of uncertainties can be used to determine the number of scenarios as well. Fast and short-lasting events, such as a strong hurricane that weakens quickly after landfall, require fewer number of scenarios. Slower and long-lasting events, such as a hurricane that maintains strong wind speeds after landfall or makes multiple landfalls, need more scenarios to be properly represented.

D. Scenario Generation Quality Assessment

The quality of stochastic optimization is directly linked to the quality of the scenario set. It is possible to evaluate the quality of the scenario set through, first, solving the stochastic optimization problem, and, then calculating the expected value of the objective function, using a larger sample of the uncertainty set. This, however, can often be very computationally demanding. Hence, it is desirable to evaluate the quality of the generated scenarios, before using them to solve the problem. Note that as long as the scenario set results in quality decisions, the distribution of the generated scenarios in the uncertainty space does not matter. In other words, an unbiased statistical sample of the uncertainty set does not necessarily result in a quality scenario set that performs well in stochastic optimization [37].

For some problems with uncertainty, it is possible to evaluate the quality of the scenarios through the statistical characteristics of the observation data. Such method is used in [38], [39] for assessing wind power scenarios. However, for the problem discussed in this paper, there is often not enough historical data, and it is computationally difficult so simulate a large number of scenarios to compare with one another. Thus, none of the mentioned methods are suitable for the type of problems discussed in this paper.

In [40], the author proposes a new way of evaluating the scenario generation quality with application to stochastic unit commitment, which seems appropriate for MDSS quality assessment. To use the method, the unit commitment problem is solved with each of the scenarios as a deterministic unit commitment. Then, the commitment variables are fixed and the economic dispatch variables are solved for, when the network configuration is determined by other scenarios. For a 10-scenario set, 10 unit-commitment problems are solved. Each commitment solution is passed to 10 economic dispatch models, resulting in a total of 100 events. According to [40] a ranking histogram can be produced to determine the distribution of errors (over generation plus unserved load) between results of different cases with respect to each other. The shape of the distribution can, then, be used to assess the scenario generation quality.

Here, in addition to what is claimed to be a good metric for quality of scenarios in [40], we investigate two other features that seem suitable for the purpose of this study. Thus, three factors are used in this paper to evaluate the quality of scenario generation. First, we look at the distribution of different scenarios in the uncertainty space. Then, through running deterministic optimizations as explained in [40], a set of objective function values are calculated. These values are used to evaluate two other metrics. For the second metric, an initial value of expected cost, which is dominated by unserved load and over-generation, is calculated through averaging the calculated values for each scenario creation method. A histogram of the results is used as the third metric, as described in [40].

Note that the entire computation time for each scenario method would be less than an hour, which is relatively shorter in comparison with the Monte Carlo simulations, which were used as the main performance evaluation method. Fig. 6 illustrates the covered outages in different scenarios for the two main scenario generation methods. As the figure suggests, while scenarios that are generated by MDSS are distributed from minimum outage (zero outage) to maximum outage, fast forward selection failed to achieve the same distribution. Thus, MDSS samples a wider range of possibilities. In terms of initial value of the objective function, MDSS results in 4.8 GWhr of unserved load and over generation, and fast forward selection results in 11.3 GWhr, showing a better expected quality for MDSS. This was shown before in Table 1. Finally, Fig. 7 shows the distribution of results in the value of unserved load plus over-generation as a scatter plot (top), and the histogram of the objective values (bottom) in deterministic solutions, as suggested by [38]. According to [40], while the histogram of results corresponding to fast forward selection shows a non-reliable and low quality scenario set, due to its wider distribution, the histogram related to MDSS represents a reliable and high quality scenario set.

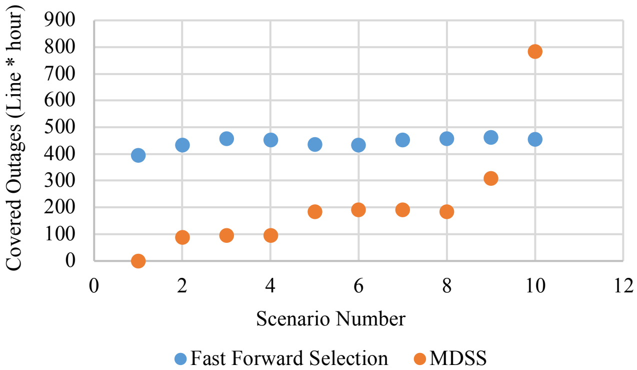

Fig. 6. Covered outages in different scenarios for MDSS and fast forward selection methods.

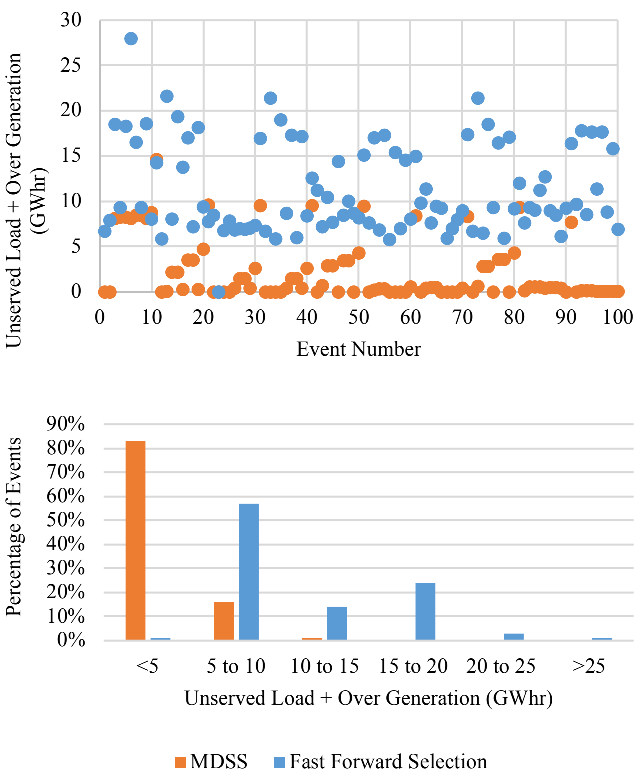

Fig. 7. Scatter plot (top) and histogram (bottom) of results for quality assessment of MDSS and fast forward selection methods.

VII. Conclusion

Existing industry practices rely on proxy deterministic rules as well as engineering judgment to achieve reliability in face of uncertainties. Decades of research and development show that stochastic optimization can enhance uncertainty management and achieve improved reliability and system efficiency. The main challenge for adoption of stochastic models remains to be their computational burden. This paper focuses on the case of predictable but uncertain element failures. In practical applications, such as preventive operation during severe weather, the uncertainty set associated to element failures is rather large. Not only is it impossible to solve a stochastic optimization problem with such a large uncertainty set, but also the identification of all the possible scenarios is impractical. This paper develops an effective scenario selection method to address these challenges. The method, makes use of both the failure feature as well as the network feature to effectively identify a small but representative set of scenarios. To show the effectiveness of the method, it was used to implement a preventive stochastic unit commitment model during hurricanes. The method was, then, compared to alternative scenario selection methods as well as industry practices. The simulation results clearly show that the developed method is superior to its alternatives in terms of performance. As the final scenario set is small, the developed method will enable practical implementation of stochastic power system operation and planning software tools. These tools will improve uncertainty management, which will lead to enhanced reliability without requiring expensive system hardening.

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