Effective Scenario Selection for Preventive Stochastic Unit Commitment during Hurricanes

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***Abstract*—In 2017, four hurricanes made U.S. landfalls, leading to millions of customer outages. Our previous work shows that weather forecast can be used to estimate the failure of transmission lines during hurricanes; these failure estimations can be effectively used in stochastic optimizations and guide preventive operation to reduce outages. However, the large number of possible contingency scenarios, caused by hurricanes, makes preventive operation extremely computationally burdensome. The problem can be practically solved with only a small number of representative scenarios. Thus, the effectiveness of preventive operation would directly depend on the scenario selection process. This paper examines two scenario selection methods, which eliminate (a) the unlikely and (b) the inconsequential scenarios. Simulation studies were carried out on IEEE 118-bus system, mapped to the Texas transmission network, using Hurricane Harvey wind data. The paper sheds light on the effective selection of an appropriate number of scenarios with acceptable computational complexity.**

Keywords—Extreme events, hurricanes, power system reliability, preventive operation, stochastic optimization, unit commitment

I. NOMENCLATURE

Indices

l	Coefficient compared with limit state.
k	Transmission line.
g	Generator.
n	Node.
m	Indices of tower locations in the transmission line.
s	Scenario.
seg	Segment of linearized generator cost function.

Sets

$\sigma^+(n)$	Transmission lines with their "to" bus connected to node n.
$\sigma^-(n)$	Transmission lines with their "from" bus connected to node n.
$g(n)$	Generators connected to node n.

Variables

$F_{k,s,t}$	Real power flow through transmission line $k$in scenarios s at time t.
$F_R(V)$	Structural wind fragility at wind speed V.
$L^L_{n,s,t}$	Load loss at node $n$in scenarios s at time t.
$P_{g,s,t}$	Real power generation of generator g in scenarios s at time t.
$P^O_{g,s,t}$	Over-generation of generator g in scenarios s at time t.
$P^{seg}_{g,s,t}$	Real power generation of generator g in scenarios s in segment seg at time t.
P_m	Damage and failure probability.
$P[FL,k]$	Failure probability of transmission line k.
$P[SL,k]$	Survival probability of transmission line k.
$v_{g,t}$	Startup variable (1: generator g starts up at time t; 0: generator g does not start up at time t.)
V_m	Mean wind speed at the m^{th}tower location.
$w_{g,t}$	Shutdown variable (1: generator g shuts downat time t; 0: generator g does not shut down at time t.)
$\theta_{n,s,t}$	Voltage angle at bus n in scenarios s at time t.
$\theta_{fr,k,s,t}$	Voltage angle at the "from" node of line $k$in scenarios s at time t.
$\theta_{to,k,s,t}$	Voltage angle at the "to" node of line $k$in scenarios s at time t.

Parameters

b_k	Susceptance of transmission line k.
$c^{linear}_{g,seg}$	Linear cost of generator g in segment seg.
c^L	Cost of load loss ($/MWh).
c^{NL}_g	No load cost of generator g.
c^O	Cost of over generation ($/MWh).
c^{SD}_g	Shutdown cost of generator g.
c^{SU}_g	Startup cost of generator g.
F^{max}_k	Thermal/stability limit of transmission line k.
$L_{n,s,t}$	Load at bus $n$in scenario s at time t.
LS	Limit state of structure.
N_b	Number of buses in s system.
N_g	Total number of generators.
N_s	Number of scenarios.
N_{seg}	Number of segments for the linearized generator cost function.
NT	Number of towers in one transmission line.
p_{k,t_k}	Probability of line k to fail at time t_k.
p_s	Probability of scenario s.
P^{max}_g	Upper generation limit of generator g.
P^{min}_g	Lower generation limit of generator g.
$P^{seg,max}_g$	Upper generation limit of generator g in segment seg.
RR_g	Hourly ramp-rate for generator g.
t_H	The time that hurricane starts.
t_k	The time that line k fails.
T	Length of the investigated time period.

T_F	Number of time periods with different probabilities of transmission line failure.
T_g^{down}	Minimum down time for generator g.
T_g^{up}	Minimum up time for generator g.
V	Given wind speed.
V_{10}	Mean wind speed at height10m.
$z_{k,s,t}$	Transmission line k's status at time t in scenario s (1: line is closed; 0: line is open).
$\Delta\theta_k^{max}$	Maximum value of bus voltage angle difference to maintain stability for line k.
$\Delta\theta_k^{min}$	Minimum value of bus voltage angle difference to maintain stability for line k.

II. INTRODUCTION

Severe weather is the leading cause of power outages in the United States [1]. In 2017, four major hurricanes affected U.S. territories – Harvey, Irma, Maria, and Nate, affecting Puerto Rico and at least eight states, including Florida, Georgia, South Carolina, North Carolina, Alabama, Texas, Tennessee, Louisiana and Mississippi [2]-[4]. Due to the damages of Hurricane Maria, nearly all the customers in Puerto Rico lost power by September 20, 2017, affecting more than 1.5 million people [5]. Hurricane Irma also led to millions of customer outages, affecting 48% of the customers in Florida and 22% of the customers in Georgia [3]. The negative impact of hurricanes on power system operation is not only severe, but also long-lasting. An update from the U.S. Department of Energy shows that still about 40% of customers in Puerto Rico are without electricity as of January 10, 2018, almost four months after Hurricane Maria [6]. Thus, it is extremely important to improve the resiliency of power systems in face of extreme weather.

Different strategies have been studied to reduce the adverse impacts of natural disasters on power system reliability. After the extreme event, if the system is islanded, microgrids can be optimally scheduled to locally supply the demand and reduce power outages [7]-[9]. After the damage, power system resources and human resources, performing the restoration tasks can both be optimized to restore the system at the lowest cost or fastest time [10], [11]. Preventive measures can also be taken; the system can be hardened in the planning phase, e.g., installation of underground power lines or reinforcement of transmission towers [12]. Risks of adverse events can also be taken into consideration in the optimization problem in the planning phase, such as transmission expansion, so that a relatively robust future plan under extreme events is chosen [13]. In the operation phase, preventive actions can also be taken, since meteorological data is available to the power system operators. These preventive measures include maintenance scheduling [14] and unit commitment scheduling [15], [16]. Such preventive actions, if properly integrated into the operational models, can drastically reduce the power outages. However, the challenge in finding and implementing these preventive operation measures is that they require solving computationally intensive stochastic optimization models. These models can have a large number of possible scenarios, which further adds to the computational burden of the problem. This is especially important for the day–ahead unit commitment scheduling, which involves binary variables and is computationally burdensome even without preventive operation. Reducing the number of considered scenarios can greatly reduce the computation time; however, the scenarios have to be selected in a way that they represent an appropriately large portion of the uncertain possibilities.

This paper compares two scenario selection methods for preventive power system operation during hurricanes. The first technique is a probability-based selection method, in which only the scenarios with the highest likelihood are chosen. The second method is importance sampling [17], in which the likelihood of selecting a scenario is proportional to its contribution to the expected outage. The two methods are compared in a preventive unit commitment scheduling framework. Simulation studies were carried out on the IEEE 118-bus test system, which was mapped to the Texas transmission network. Transmission component failure scenarios were generated using meteorological data of Hurricane Harvey. In order to generate the scenarios, first, a fragility analysis was carried out, which examines the structural stability of the transmission towers under dynamic wind loading. The analysis takes the system layout and Hurricane Harvey data as input to determine the failure probability of all transmission towers in the system. Then, the probabilities of transmission line failures were calculated based on the transmission tower failure probabilities, and possible contingency scenarios were generated. Each scenario includes information on the transmission lines that fail and the time they fail, along with the probability of the scenario. The total number of scenarios, generated through fragility analysis, turns out to be very large.

We apply the two above-mentioned scenario selection methods to construct a smaller set of representative scenarios. Preventive unit commitment models were solved on these smaller scenario sets, and the solutions, obtained under different scenario sets, were compared. The computational complexity was also analyzed with respect to the number of scenarios and the convergence of the dispatch costs. Results show that the expected dispatch cost, including the value of lost load, converges to a certain level as the number of included scenarios increases. Moreover, the importance sampling technique functions more effectively compared to the probability-based selection method most of the time before the cost converges. It is very important to find the convergence point, so that an effective number of scenarios can be used in the preventive operation without extra computational burden. It is also important to use an appropriate method to select scenarios based on the available computational time in a way that is still representative of the uncertainties.

The rest of the paper is organized as follows. Section III describes the preventive unit commitment model, and Section IV presents the procedure that generates and selects scenarios. Simulation results are presented and discussed in Section V, and conclusions are drawn in Section VI.

III. THE PREVENTIVE STOCHASTIC OPTIMIZATION MODEL

The preventive stochastic optimization model is based on a DC power flow unit commitment (UC) formulation, considering different contingency scenarios caused by transmission line outages. The model solves for a uniform unit commitment for all scenarios, while dispatching generation of each unit under each scenario. Over generation and load loss are allowed under each scenario, but are penalized a with a high cost in the objective function. Thus, load will not be shed unless its prevention is impossible or extremely costly.

The formulation of the problem is shown in (1) – (14). The objective function is expressed by (1), which minimizes the expected dispatch cost of the system considering generation dispatch, over generation and load loss under all scenarios. Generation limits are expressed by (2) – (4); generation costs were calculated using a piece-wise linear cost function. DC power flow constraints are expressed by (5) and (6); when a transmission line is out, both its susceptance and thermal limit are set to 0 using the binary integer parameter $z_{k,s,t}$. (7) is the voltage angle stability constraint for each transmission line, and (8) sets the voltage angle of the reference bus to 0. (9) is the node power balance constraint, in which over generation and load loss are included. (10) and (11) calculates the start-up and shut-down variables; (12) is the hourly ramping limit for each generator; and (13) and (14) are the minimum up and down time constraints for each generator. Since contingencies are modelled explicitly, reserves are not modeled in this formulation.

$$\min \left(\sum_{s=1}^{N_s} p_s \sum_{t=1}^{T} \left(\sum_{g=1}^{N_g} \left(\begin{array}{c} \sum_{seg=1}^{N_{seg}} c_{g,seg}^{linear} P_{g,s,t}^{seg} + c_g^{NL} u_{g,t} \\ + c_g^{SU} v_{g,t} + c_g^{SD} w_{g,t} + c^{O} P_{g,s,t}^{O} \end{array} \right) + \sum_{n=1}^{N_b} c^L L_{n,s,t}^L \right) \right) \tag{1}$$

$$P_{g,s,t} = \sum_{seg=1}^{N_{seg}} P_{g,s,t}^{seg} \tag{2}$$

$$0 \le P_{g,s,t}^{seg} \le P_g^{seg,max} \tag{3}$$

$$u_{g,t} P_g^{min} \le P_{g,s,t} \le u_{g,t} P_g^{max} \tag{4}$$

$$-z_{k,s,t} F_k^{max} \le F_{k,s,t} \le z_{k,s,t} F_k^{max} \tag{5}$$

$$z_{k,s,t} b_k \left(\theta_{fr,k,s,t} - \theta_{to,k,s,t} \right) = F_{k,s,t} \tag{6}$$

$$\Delta\theta_k^{min} \le \theta_{fr,k,s,t} - \theta_{to,k,s,t} \le \Delta\theta_k^{max} \tag{7}$$

$$\theta_{1,s,t} = 0 \tag{8}$$

$$\sum_{k \in \sigma^+(n)} F_{k,s,t} - \sum_{k \in \sigma^-(n)} F_{k,s,t} + \sum_{g \in g(n)} P_{g,s,t} - P_{g,s,t}^{O} = L_{n.s.t} - L_{n,s,t}^{L} \tag{9}$$

$$v_{g,t} - w_{g,t} = u_{g,t} - u_{g,t-1} \tag{10}$$

$$v_{g,t} + w_{g,t} \le 1 \tag{11}$$

$$-RR_g \le P_{g,s,t} - P_{g,s,t-1} \le RR_g \tag{12}$$

$$\sum_{t=m}^{m+T_g^{up}-1} u_{g,t} \ge T_g^{up} \left(u_{g,m} - u_{g,m-1} \right), \quad 2 \le m \le T - T_g^{up} + 1 \tag{13}$$

$$\sum_{t=m}^{m+T_g^{down}-1} \left(1 - u_{g,t}\right) \ge T_g^{down} \left(u_{g,m-1} - u_{g,m} \right), \quad 2 \le m \le T - T_g^{down} + 1 \tag{14}$$

IV. CONTINGENCY SCENARIO SELECTION

A. Transmission Line Fragility Analysis Under Hurricane

Fragility analysis of transmission line combines three steps. First, the fragility analysis of transmission tower under extreme wind is conducted. A finite element model of the transmission tower is built in ANSYS. By adding a series of wind speed based on Monte-Carlo simulation, the damage and failure probability of a transmission tower can be obtained via equation (15).

$$F_R(V) = P[l > LS \,/\, V_{10} = V] \tag{15}$$

The limit state (LS) of a transmission tower is defined as the transmission tower's top displacement exceeding 1.5%, 2%, 2.5% and 3% of the transmission tower's height. The fragility curves of transmission tower are calculated according to different limit states. In this paper, the limit state of a transmission tower's failure is defined when the top displacement is over 2.5 percent of the tower's height.

Secondly, a horizontal wind profile is modeled to simulate the wind speed distribution. This paper simplifies the gradient wind speed as a function of radius distance. Wind speed increases linearly in a 100 km range to the hurricane center. When it is away from the hurricane center over 100km, it decreases like a parabola.

Finally, the model calculates the transmission line's failure probability. The m^{th} transmission tower's failure probability for each transmission line is expressed as $P_m = F_{R,m}(V_m)$. The k^{th} transmission line's failure and survival probability are denoted as $P[FL,k]$ and $P[SL,k]$ separately. If a transmission line can survive under some wind load, all the transmission towers for this line must survive. Therefore, $P[FL,k]$ is calculated in equation (16).

$$P[FL,k] = 1 - P[SL,k] = 1 - \prod_{m=1}^{NT} F_{R,m}(V_m) \tag{16}$$

B. Generating All Possible Contingency Scenarios

Based on the likelihood of each transmission line to fail, transmission contingency scenarios can be generated and their probabilities can be calculated. Since different lines may fail at different time during the hurricane, each scenario should consider both the locations and time of the lines that fail. The scenario generation procedure is illustrated in Fig. 1.

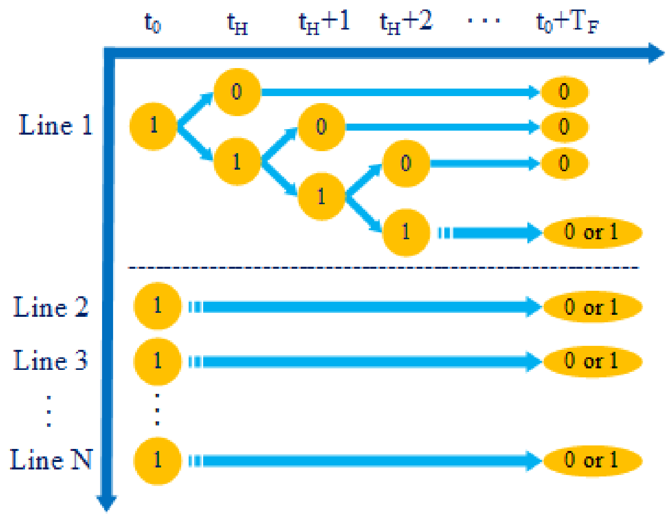

Fig. 1. Illustration of the scenario generation procedure

The total number of scenarios can be calculated as

$$N_s = (T_F + 1)^{N_{br}} \tag{17}$$

Each scenario is a 2-dimensional matrix, including information about the status of each transmission line during each hour in the studied period. Given transmission line k fails at t_k in scenario s, the probability for each scenario can be calculated as shown in (18).

$$p_s = \prod_{k=1}^{N_{br}} \left(p_{k,t_k} \prod_{t=t_H}^{t_k-1} (1 - p_{k,t}) \right). \quad (18)$$

C. Probability-based Scenario Selection

The probability-based scenario selection is a deterministic selection method; it selects the scenarios with the highest probabilities. In order to implement this scenario selection method, all the possible scenarios are ranked according to their likelihood, and a desired number of scenarios with the highest probabilities are selected. This method is easy to implement, but ignores the scenarios with a low probability but high impact.

D. Importance-sampling-based Scenario Selection

The importance sampling method is a stochastic scenario selection method. In this method, the likelihood of selecting a scenario is proportional to its contribution to the expected generation dispatch cost. In order to implement this method, first, deterministic unit commitment is solved for each possible scenario, and the dispatch cost is obtained from each deterministic unit commitment case. It should be noted that the dispatch cost is dominated by its penalty component, when over generation and load shedding occurs. Thus, a high cost scenario should be interpreted as a scenario with high violations, i.e., load shedding and over generation. Then, considering the probability of each scenario, an expected dispatch cost can be calculated. Finally, scenarios are selected with a likelihood in proportion to their expected cost [17]. This method is more complicated than the probability-based selection method, and it adds randomness to the selection method. This method is not guaranteed to select the most representative scenarios; however, it makes it possible to consider scenarios that has a low probability but significant impact on the system.

V. Simulation Results and Analysis

A. Test System Layout and Scenario Generation

Simulations in this study were carried out on the IEEE 118-bus test system [18], which was mapped to the transmission system of Texas, under Hurricane Harvey. Hurricane Harvey made landfall around 4:00 am and wind speed were collected every three hours according to data from the National Hurricane Center [19]. The wind speed is shown in Fig. 2.

Since the IEEE 118 test system is mapped to the Texas transmission system, using the horizontal wind profile of Hurricane Harvey, the displacement of every transmission tower can be calculated, from which the failure probability for transmission towers can be obtained. Consequently, probability of transmission line failures during each three-hour period can be calculated [15]. Results show that the hurricane was able to cause transmission line failures only in the first three-hour period. During this period, 22 lines may fail with different probabilities; the 22 lines and their "from" and "to" buses are shown in Fig. 3 and their failure probabilities are shown in TABLE I. In this table, the lines are denoted with their "from" and "to" buses. With 22 lines possible to fail in one period, according Equation (17), a total number of 4,194,304 scenarios can be generated.

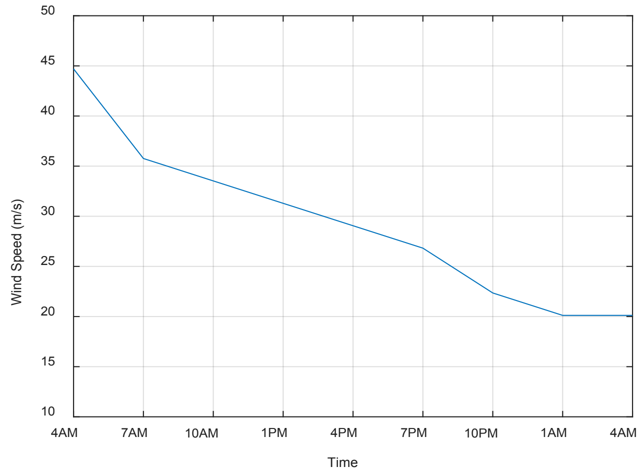

Fig. 2. Wind speed of Hurricane Harvey

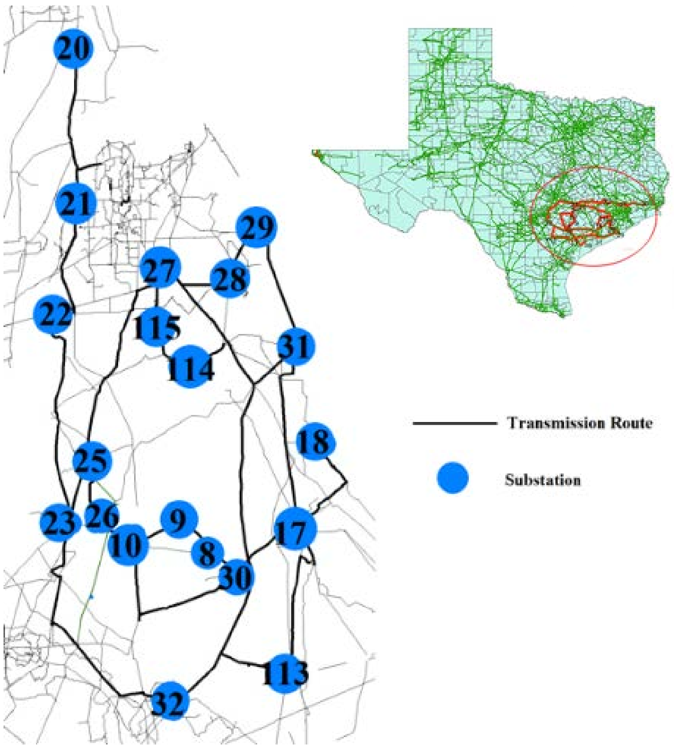

Fig. 3. Test system layout

TABLE I

Lines That May Fail During the First Three-hour Period

Line	Probability	Line	Probability
10-9	0.9493	114-115	0.9888
9-8	0.9583	114-32	0.9775
8-30	0.4877	27-32	0.9858
30-17	0.7417	27-25	0.9995
17-18	0.9552	26-25	0.5973
17-113	0.5535	23-25	0.4235
32-31	0.9596	23-32	0.1364
29-31	0.9982	23-22	0.8777
28-29	0.9953	21-22	0.9355
27-28	0.9923	20-21	0.8873
27-115	0.9867	26-30	0.5106

B. *Scenario Selection Using the Two Methods*

In order to run the stochastic optimization problem efficiently, a scenario set which includes a small number of scenarios, selected from the total 4,194,304 scenarios should be used for each stochastic optimization problem. 42 scenario sets were obtained in this study, including 7 obtained using the probability-based methods and 35 obtained using the importance sampling method.

With the probability-based selection method, a desired number of scenarios can be selected quickly. In this study, seven scenario sets were selected, each of which containing 1, 4, 7, 10, 20, 30 and 40 scenarios, respectively.

The large number of scenarios makes employment of importance sampling extremely computationally demanding. This is because, if importance sampling is used, a unit commitment problem needs to be solved under each scenario. Although each unit commitment problem just takes a few seconds to solve, solving more than 4 million scenarios will take months. In order to reduce computational burden, scenarios with probabilities of less than 0.005% were removed first. This way, the number of scenarios was reduced to 1,492. Then deterministic unit commitment problems were solved under each of the 1,492 scenarios using the model described in [20]. Using the individual dispatch costs and the scenario probabilities, the expected dispatch cost was calculated, and contribution of each scenario to the expected cost was obtained. Due to the stochastic nature of this selection method, 5 scenario sets were obtained using importance sampling for each of the seven numbers of scenarios mentioned above, so that the stochastic optimization can be carried out under different scenario sets with the same number of scenarios to make the results more credible.

C. *Economic Benefit Comparison*

In order to compare the effectiveness of scenario selection, the preventive unit commitment model described in Section III was solved under the 42 scenario sets, respectively and the solutions were obtained. Then, each of the 42 unit commitment solutions was adopted for economic dispatches under the 1,492 scenarios mentioned in Section IV-A, and an expected dispatch cost considering probabilities of the 1,492 scenarios was obtained for each unit commitment solution. The lower the expected dispatch cost, the more economical the unit commitment solution is in face of the hurricane. Again, note that the value of lost load is included in the dispatch cost, with lost load and over generation penalized at a high price. As the dispatch cost is dominated by this penalty component, a cheaper solution really reflects a more reliable solution.

The expected dispatch costs of the 42 cases are shown in Fig. 4. The expected dispatch costs decreased with the increase in the number of scenarios, and they converged to about $33.3 million with 20 or more scenarios, no matter which scenario selection method was used. When only one scenario was selected, the number of scenarios was so small that no method could guarantee selecting a representative scenario, although the probability-based method showed slight advantage in this case. However, when 4 or 7 scenarios were selected, the importance sampling method showed an obvious advantage, and the expected dispatch costs from the importance sampling method were much lower than those from the probability-based method. The results suggest that the importance sampling method is generally more effective before the expected cost converges, but they are very close in effectiveness once the number of scenarios is large enough so that the expected dispatch cost converges.

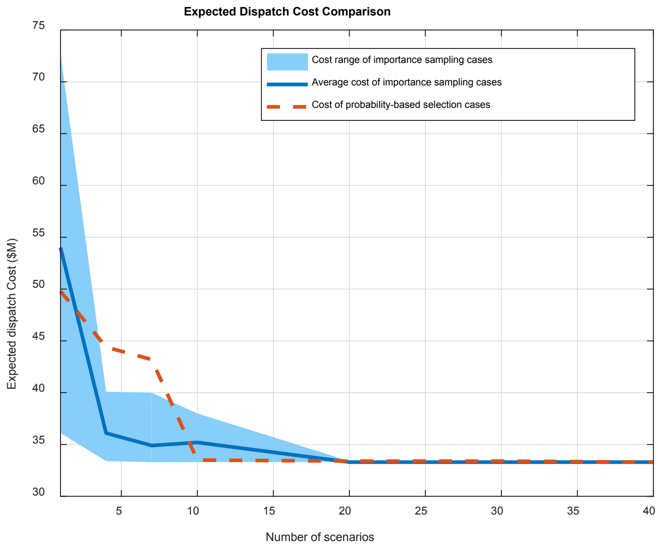

Fig. 4. Comparison of expected cost considering all possible scenarios

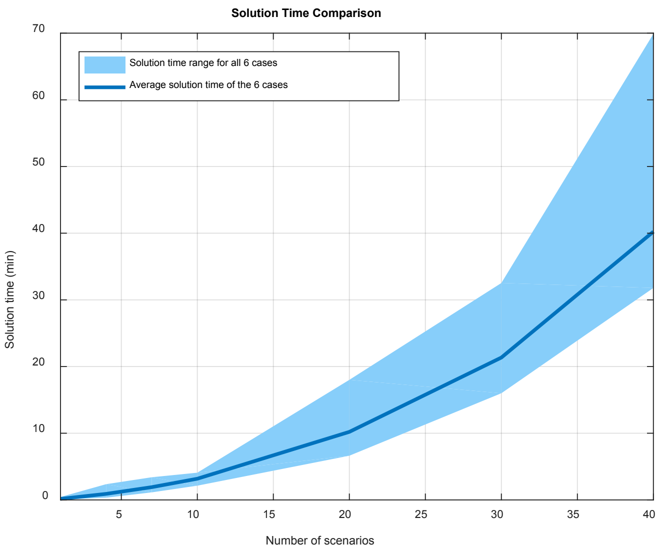

Fig. 5. Solution time comparison under different numbers of scenarios

D. *Computational Complexity Comparison*

The computational complexity of the preventive stochastic optimization model is highly correlated with the number of scenarios considered. The solution times of the 42 cases are shown in Fig. 5, with a light-blue-colored area. Since 6 cases were solved under each number of scenarios, an average solution time was calculated for each of the 7 numbers of scenarios. It can be seen that the solution time increases significantly with the increasing number of scenarios, although randomness in solution time existed with the same number of scenarios. Thus, it is very important to find the number of scenarios at which the expected dispatch cost converges, so that a cost-effective unit commitment solution can be found without taking unnecessarily long computation time.

VI. Conclusion

This paper compared two contingency scenario selection methods, namely, probability-based and importance sampling methods, for stochastic preventive operation in face of hurricanes. Results show that the expected dispatch cost, including high penalty costs for lost load and over generation, obtained under each unit commitment solution, decreases with the increasing number of scenarios. The expected dispatch cost converges to a certain level as the number of scenarios increase. With an extremely small number of scenarios, such as one scenario, neither of the two methods is guaranteed to select a representative scenario set. With a relatively small number of scenarios, the importance sampling method is more effective; but when the number of scenarios is large enough for expected dispatch cost to converge, both scenario selection methods are similar in effectiveness. With similar effectiveness, the probability-based selection method is preferred, because it is much easier to implement compared to the importance sampling method. The computational complexity is highly correlated to the number of scenarios considered; thus, it is ideal to use the number of scenarios right at the convergence of expected dispatch costs. However, in case that only a relatively small number of scenarios can be chosen due to the limitation of computational resources, the importance sampling method is more effective than the probability-based method in general.

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