Comparing a New Power System Preventive Operation Method with a Conventional Industry Practice during Hurricanes

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***Abstract*—Extreme weather is a leading cause of power outages in the U.S., and preventive operation is an effective approach to reduce outages in the operations phase. Currently, a common industry practice for preventive operation is to turn on all the units in a system during extreme weather. In this study, a preventive unit commitment (UC) model is presented to reduce transmission-induced outages during hurricanes. In this model, transmission contingency scenarios are generated based on wind speed, and then these scenarios are used in a stochastic UC model to obtain UC results with a goal of reducing outages in the system. The presented preventive operations method is compared with the business-as-usual model and the turn-on-all-units method, and results show that the presented method can reduce outages from the business-as-usual model as effective as the turn-on-all-units method with a much lower operating cost.**

***Index Terms*—Hurricane, power outage, power system resilience, stochastic optimization, transmission outage.**

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" buses connected to node n.
$\sigma^-(n)$	Transmission lines with their "from" buses 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.
$L^L_{n,s,t}$	Load loss at node $n$in scenario$s$ at time t.
$P_{g,s,t}$	Real power generation of generator g in scenario$s$ at time t.
$P^O_{g,s,t}$	Over-generation of generator g in scenario$s$ at time t.
$P^{seg}_{g,s,t}$	Real power generation of generator g in scenario$s$ in segment seg at time t.
$v_{g,t}$	Startup variable (1: generator g starts up at time t; 0: generator g does not start up at time t.)
$w_{g,t}$	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 scenario$s$ at time t.
$\theta_{fr,k,s,t}$	Voltage angle at the "from" node of line $k$in scenario$s$ at time t.
$\theta_{to,k,s,t}$	Voltage angle at the "to" node of line $k$in scenario$s$ 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.
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.
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.

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RR_g	Hourly ramp-rate for generator g.
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.
$z_{k,s,t}$	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

In the U.S., severe weather is one of the most significant causes of power outages [1]. Outages caused by severe weather can be not only wide-spread but also long-lasting. Take the hurricanes that occurred in 2017 as examples, four strong hurricanes, Harvey, Irma, Maria, and Nate, made U.S. landfalls, and more than eight states were affected. In Florida, 48% of electricity customers experienced outages due to Hurricane Irma, so do 22% of customers in Georgia [2]-[4]. The power system of Puerto Rico was severely damaged by Hurricane Maria, and more than half of its electricity customers experienced outages for more than 3 months [5], [6].

In order to reduce outages, different methods can be adopted. The first one is system hardening, which happens in the planning phase of the power system. Using underground transmission lines and stronger poles, and considering future adverse events in the planning phase both belong to this category [7]-[9]. The second method is through an optimized restoration procedure. When outages occur, different restoration resources can be optimally used to restore power in a relatively fast manner [10]-[15]. The third method is through preventive operation, which means system operators dispatch power considering possible contingencies of the system. Currently, this is an under-explored field, and most system operators perform preventive operations based on engineering judgments, such as turning on all the generation units when a hurricane occurs. A resilience analysis for complex engineering systems is presented in [16], however, the resilience data is not integrated into day-ahead power system operations in the model. A proactive operation method is presented in [17], however, this study uses a generic fragility curve for infrastructure, while in reality infrastructures with different designs have very different fragility curves. A preventive operation method with fragility analysis is briefly discussed in [18], however, it is not compared with other operation heuristics that system operators use. Thus, there is a need to study the preventive operation technique in further detail, and compare it with current industry practices, both in terms of its effectiveness in reducing outages and cost-effectiveness.

In this paper, a preventive operation method is discussed in detail. This method includes two parts, one is the fragility analysis of the infrastructure, and the second part is the preventive unit commitment (UC) model. In this method, weather data is used to perform fragility analysis of the critical infrastructure, and then contingency scenarios are generated based on the failure probabilities of the infrastructure. Then the scenarios are used in a stochastic optimization model to provide UC solutions that can effectively reduce outages. The method is compared with a common industry practice, which is turning all generation units on in the face of severe weather, or, the all-units-on method. Case studies were carried out on an IEEE 118-bus test system, part of which was mapped to the Florida transmission system, using historical wind speed data during Hurricane Irma. Results show that the presented preventive operation method can reduce outages by 30%-50% from the business-as-usual model, in which system operators dispatch the generation without considering possible contingencies caused by severe weather, and its effectiveness in reducing outages is similar to that of the all-units-on methods, but the operation cost of achieving such a reduction in outages is about 40% lower than the all-units-on method.

The rest of this paper is organized as follows. The preventive UC model is presented in Section III, and the scenario generation process is presented in detail in Section IV. The presented preventive operation method is compared with the BAU model and the all-units-on method in Section V, and conclusions are drawn in Section VI.

III. THE PREVENTIVE UC MODEL

The preventive optimization model is based on a DC power flow UC formulation, considering different contingency scenarios caused by transmission line outages. Over generation and load loss are allowed but are penalized a with a high cost in the objective function. Using this model, a preventive operation plan can be obtained for day-ahead market to reduce losses caused by load loss or over generation when extreme weather, like a hurricane, occurs.

The formulation of the problem is shown in (1)–(14). The objective function is expressed by (1), which minimizes the dispatch cost of the system considering generation dispatch, over generation and load loss. 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 $z_{k,t}$. (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.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

IV. Contingency Scenario Generation

Since the actual transmission system data of Florida is confidential, case studies were carried out on a synthetic Florida transmission system using real wind speed during Hurricane Irma. In this study, part of an IEEE 118-bus test system was mapped to the Florida transmission system, as Fig. 1 shows, and the historical wind speed during Hurricane Irma was obtained from the National Hurricane Center [19], as Fig. 2 shows.

Using the historical wind speed during Hurricane Irma, a fragility analysis was performed on three types of transmission towers, designed at wind speeds levels, 120 miles per hour (mph), 140 mph, and 150 mph, respectively. The tower is a 220-kV suspension tower, designed based on ASCE Manuals and Reports on Engineering Practice No.74 (Manual 74): Guidelines for Electrical Transmission Line Structural Loading [20]. This basic wind speed is a 3-second gust wind in a 50-year return period.

After designing the transmission towers, the fragility curve of towers is obtained. The fragility analysis of transmission tower includes three steps. First, a finite element model of tower 1 is built by ANSYS. Wind speed is generated by Monte-Carlo simulation and add it on the tower. The damage probability of a transmission tower is obtained as follows.

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

The limit state (LS) of a transmission tower is defined as the transmission tower's top drift. By analyzing the capacity curve of a transmission tower, 1.5% drift is chosen as the limit state. Secondly, the wind field is developed by modeling the horizontal wind profile. The gradient wind speed is simplified as a function of the radius. Finally, as the failure probability of the individual transmission tower is obtained, the transmission line's failure probability can be calculated. As a transmission line is a serial system, the transmission line can only survive when all the transmission towers of this line survive. Therefore, the transmission line's failure probability $P[FL,k]$ can be calculated as follows.

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

$P[SL,k]$ is the survival probability of a transmission line and $F_{R,m}(V_m)$ is m^{th} transmission tower's failure probability of each transmission line.

The three types of towers are named as Tower 1, Tower 2 and Tower 3, respectively, and the probability of failure for each transmission tower was obtained using Equation (16). In the case studies, three conditions were examined. In the first condition, Tower 1 was used for the whole transmission system. In the second condition, Tower 2 was used for the whole transmission system. And in the third condition, Tower 3 was used for the whole transmission system. Based on the probabilities of failure of each type of transmission tower during each hour, the failure probabilities of transmission lines under the three conditions was calculated, shown in TABLE I-TABLE III, respectively.

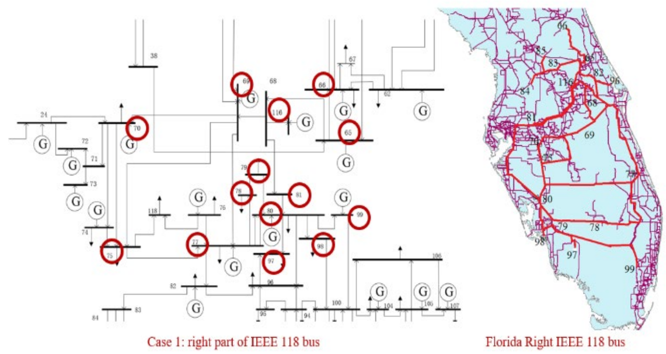

Fig. 1. The mapping of the IEEE 118-bus test system

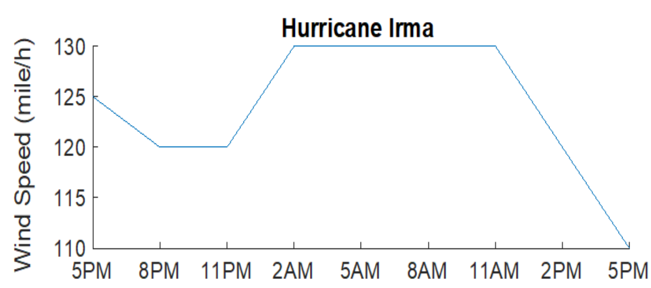

Fig. 2. Wind speed during Hurricane Irma

TABLE I

TRANSMISSION LINE FAILURE PROBABILITIES IN CONDITION 1

Line Number	5PM	8PM	11 PM	2AM	5AM	After 8AM
69-70	0.00	0.00	0.00	0.00	0.00	0.91
69-75	0.00	0.00	0.00	0.00	0.00	0.97
69-77	0.00	0.00	0.99	1.00	1.00	1.00
78-77	0.00	0.00	0.90	1.00	1.00	1.00
82-77	0.00	0.00	0.83	1.00	1.00	1.00
82-96	0.00	0.00	0.08	1.00	1.00	1.00
82-83	0.00	0.00	0.76	1.00	1.00	1.00
85-83	0.00	0.00	0.04	1.00	1.00	1.00
84-83	0.00	0.00	0.53	1.00	1.00	1.00
77-80	0.00	0.00	1.00	1.00	1.00	1.00
97-80	1.00	1.00	1.00	1.00	1.00	1.00
98-80	1.00	1.00	1.00	1.00	1.00	1.00
99-80	1.00	1.00	1.00	1.00	1.00	1.00
80-79	0.04	0.04	0.99	1.00	1.00	1.00
80-81	0.04	0.04	1.00	1.00	1.00	1.00
65-68	1.00	1.00	1.00	1.00	1.00	1.00
68-116	1.00	1.00	1.00	1.00	1.00	1.00
66-65	0.00	0.24	0.81	0.99	0.99	0.99
69-68	0.09	0.95	0.98	1.00	1.00	1.00

TABLE II

TRANSMISSION LINE FAILURE PROBABILITIES IN CONDITION 2

Line Number	5PM	8PM	11PM	2AM	5AM	After 8AM
69-70	0.00	0.00	0.00	0.00	0.00	0.71
69-75	0.00	0.00	0.00	0.00	0.00	0.86
69-77	0.00	0.00	0.86	1.00	1.00	1.00
78-77	0.00	0.00	0.79	1.00	1.00	1.00
82-77	0.00	0.00	0.58	1.00	1.00	1.00
82-96	0.00	0.00	0.04	1.00	1.00	1.00
82-83	0.00	0.00	0.42	1.00	1.00	1.00
85-83	0.00	0.00	0.02	1.00	1.00	1.00
84-83	0.00	0.00	0.31	1.00	1.00	1.00
77-80	0.00	0.00	0.98	1.00	1.00	1.00
97-80	1.00	1.00	1.00	1.00	1.00	1.00
98-80	1.00	1.00	1.00	1.00	1.00	1.00
99-80	1.00	1.00	1.00	1.00	1.00	1.00
80-79	0.02	0.02	0.92	1.00	1.00	1.00
80-81	0.02	0.02	1.00	1.00	1.00	1.00
65-68	1.00	1.00	1.00	1.00	1.00	1.00
68-116	1.00	1.00	1.00	1.00	1.00	1.00
66-65	0.00	0.12	0.66	0.97	0.97	0.97
69-68	0.05	0.82	0.89	1.00	1.00	1.00

TABLE III

TRANSMISSION LINE FAILURE PROBABILITIES IN CONDITION 3

Line Number	5PM	8PM	11PM	2AM	5AM	8AM	After 11AM
69-77	0.00	0.00	0.00	1.00	1.00	1.00	1.00
78-77	0.00	0.00	0.00	1.00	1.00	1.00	1.00
82-77	0.00	0.00	0.69	1.00	1.00	1.00	1.00
82-96	0.00	0.00	0.00	0.30	0.30	0.94	0.99
82-83	0.00	0.00	0.00	1.00	1.00	1.00	1.00
85-83	0.00	0.00	0.00	0.24	0.24	0.25	0.25
84-83	0.00	0.00	0.42	0.99	1.00	1.00	1.00
77-80	0.00	0.00	0.00	0.17	0.45	0.99	0.99
97-80	0.00	0.81	0.81	0.98	1.00	1.00	1.00
98-80	0.80	0.80	0.80	0.80	0.80	0.80	0.80
99-80	0.01	0.01	0.48	1.00	1.00	1.00	1.00
80-79	0.00	0.00	0.00	0.60	0.60	0.86	0.86
80-81	0.00	0.00	0.00	0.17	0.42	0.75	0.75
65-68	0.92	0.92	0.92	0.92	0.92	0.92	0.92
68-116	0.01	0.01	0.01	0.01	0.01	0.01	0.01
66-65	0.00	0.22	0.22	0.22	0.22	0.22	0.22
69-68	0.00	0.00	0.00	0.99	0.99	0.99	0.99

Transmission line contingency scenarios are generated based on the combination of different transmission line failures that happen at different times during the hurricane, illustrated in Fig. 3. The total number of scenarios can be calculated as follows.

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

Given that transmission line k fails at t_k in scenario s, the probability for each scenario can be calculated as follows.

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

According to Equation (15), the total number of scenarios is 1.14×10^{16} in Condition 1 and 2, and 2.24×10^{15} in Condition 3. It is computationally intractable to consider so many scenarios in a stochastic optimization problem, thus, the number of scenarios needs to be reduced to a reasonable level. According to [21], probability-based scenario selection is an effective and computationally efficient method. Thus, in this study, scenarios are selected based on their likelihood to occur. 100 scenarios with the largest probabilities under each condition were considered in the optimization problems.

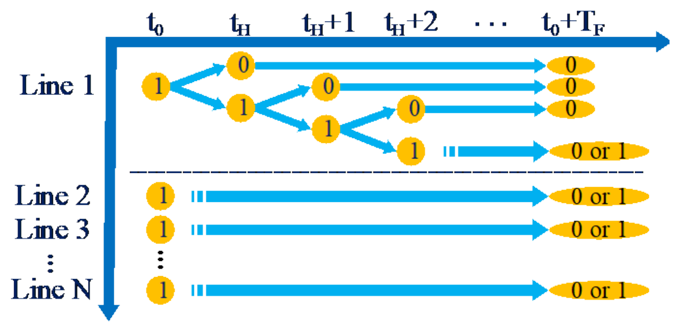

Fig. 3. Contingency scenario generation method

V. OUTAGE COMPARISON FOR THREE OPERATION METHODS

Based on the selected 100 scenarios, the preventive operation model presented in Section III can be implemented to obtain the UC results that help reduce transmission-induced outages. Then the UC is adopted in a large number of scenarios which cover more than 95% of the scenarios with probabilities of larger or equal to 1×10^{-5}. The numbers of scenarios tested under the three conditions are shown in TABLE IV. Scenarios with a probability of less than 1×10^{-5} are not tested, because it is computationally intractable to test it over a number of 10^{15}-10^{16} scenarios. In these test cases, load shedding was penalized with a cost of \$10,000/MWh. Under the three conditions, the expected outage, generation dispatch cost without penalties, and generation dispatch cost with penalties are obtained under each condition, as TABLE V shows.

TABLE IV

NUMBER OF SCENARIOS TESTED UNDER THE THREE CONDITIONS

Condition	Number of Scenarios	Probability covered among scenarios with probabilities of $\geq 1 \times 10^{-5}$
Condition 1	1000	98.78%
Condition 2	2000	95.84%
Condition 3	7000	95.10%

TABLE V
THE EXPECTED OUTAGE AND GENERATION DISPATCH COST FROM THE PREVENTIVE OPERATION CASES

Conditions	Expected load shedding (MWh/day)	Expected dispatch cost with penalty (million $/day)	Expected dispatch cost with penalty (million $/day)
Condition 1	5880.48	59.97	1.16
Condition 2	5810.57	59.26	1.16
Condition 3	2586.54	27.02	1.16

In order to validate the effectiveness of the preventive operation method, expected load shedding and dispatch costs are also obtained using two other operation methods: (1) the BAU method, in which the generation units are committed without considering the possible contingencies that may be caused by the upcoming severe weather; (2) the all-units-on method, in which all the generation units are committed all through the day to deal with the severe weather. The expected outage and dispatch costs are obtained using the same number of scenarios presented in TABLE IV, and the results from the two operation methods are shown in TABLE VI and TABLE VII, respectively. From the results, it can be seen that, with a penalty level of $10,000/MWh for load shedding, the presented preventive operation method provides a lower expected generation dispatch cost with penalties included than the all-units-on method, which means the presented preventive operation method has a better overall economic benefit than the all-units-on method in this case.

The expected load shedding is compared intuitively in Fig. 4, and the dispatch costs from the system operator's perspective are compared in Fig. 5. From the two figures, it can be seen that both the preventive UC model and the all-units-on methods can significantly reduce transmission-induced outages compared to the BAU method, and their effectiveness in reducing outages is at a similar level. However, the outage reduction from the all-units-on method comes at a cost of high generation dispatch cost, while the preventive UC model is able to effectively reduce outages at a much lower operating cost than the all-units-on method.

TABLE VI
THE EXPECTED OUTAGE AND GENERATION DISPATCH COST FROM THE BAU CASES

Conditions	Expected load shedding (MWh/day)	Expected dispatch cost with penalty (million $/day)	Expected dispatch cost with penalty (million $/day)
Condition 1	8879.16	89.80	1.01
Condition 2	8707.47	88.09	1.02
Condition 3	4736.63	48.41	1.05

TABLE VII
THE EXPECTED OUTAGE AND GENERATION DISPATCH COST FROM THE ALL-UNITS-ON CASES

Conditions	Expected load shedding (MWh/day)	Expected dispatch cost with penalty (million $/day)	Expected dispatch cost with penalty (million $/day)
Condition 1	5879.34	60.67	1.88
Condition 2	5808.85	59.96	1.88
Condition 3	2562.94	27.48	1.85

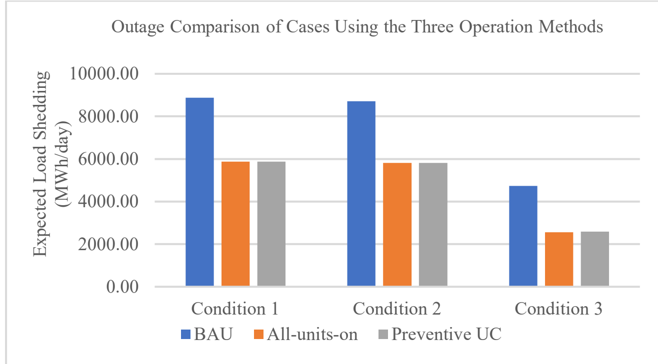

Fig. 4. Outage comparison of cases using the three operation methods

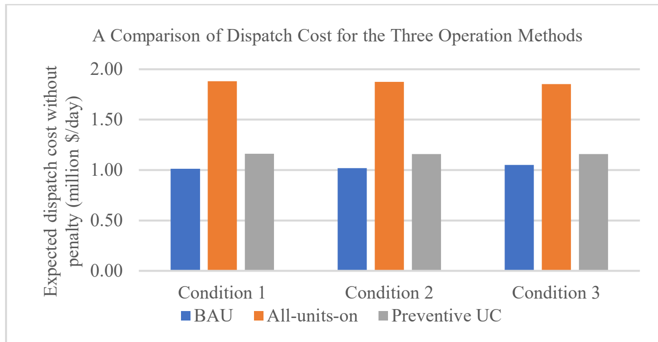

Fig. 5. A comparison of dispatch cost for the three operation methods

VI. CONCLUSIONS

In this paper, a preventive operation method to reduce transmission-induced outages during hurricanes is presented. This method makes full use of the available weather data to perform fragility analysis of the infrastructure, based on which the contingency scenarios can be generated and considered in a stochastic optimization model. This method is compared with two other methods, namely, the BAU and all-units-on methods, and results show that the preventive UC model is able to reduce outages with similar effectiveness as the all-units-on method, but at a much lower operating cost. Future work includes applying this method in large-scale power systems, which will enable the application of this method in real-world systems.

VII. ACKNOWLEDGMENT

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REFERENCES

[1] The President's Council of Economic Advisers and U.S. Department of Energy, "Economic Benefits of Increasing Electric Grid Resilience to Weather Outages," White House Office of Science and Technology, U.S. DOE, Aug. 2013.

[2] Infrastructure Security and Energy Restoration. (September 1, 2017).Tropical Depression Harvey Event Report (Update #14). U.S. Department of Energy, Washington DC.[Online]. Available: https://www.energy.gov/sites/prod/files/2017/09/f36/Hurricane%20Harvey%20Event%20Summary%20%2314.pdf

[3] Infrastructure Security and Energy Restoration. (September 12, 2017).Hurricane Irma & Hurricane Harvey Event Summary (Report #28).U.S. Department of Energy, Washington DC. [Online]. Available:

https://energy.gov/sites/prod/files/2017/10/f37/Hurricanes%20Irma%20and%20Harvey%20Event%20Summary%20%2328.pdf

[4] Infrastructure Security and Energy Restoration. (October 8, 2017).Hurricanes Nate, Maria, Irma, and Harvey October 8 Event Summary (Report #59).U.S. Department of Energy, Washington DC. [Online]. Available:https://energy.gov/sites/prod/files/2017/10/f37/Hurricanes%20Nate%20Maria%20Irma%20Harvey%20Event%20Summary%20October%208.pdf

[5] Infrastructure Security and Energy Restoration.(September 21, 2017).Hurricanes Maria, Irma, and Harvey September 21 Morning Event Summary (Report #40).U.S. Department of Energy, Washington DC. [Online]. Available:https://energy.gov/sites/prod/files/2017/09/f36/Hurricanes%20Maria%20Irma%20%26%20Harvey%20Event%20Summary%20morning%20September%2021%2C%202017.pdf

[6] Infrastructure Security and Energy Restoration. (January 10, 2018). Hurricanes Maria & Irma January 10 Event Summary (Report #86). U.S. Department of Energy, Washington DC. [Online]. Available: https://energy.gov/sites/prod/files/2018/01/f46/Hurricanes%20Maria%20and%20Irma%20Event%20Summary%20January%2010%2C%202018.pdf

[7] W. Yuan, J. Wang, F. Qiu, C. Chen, C. Kang and B. Zeng, "Robust Optimization-Based Resilient Distribution Network Planning Against Natural Disasters," *IEEE Transactions on Smart Grid*, vol. 7, no. 6, pp. 2817-2826, Nov. 2016.

[8] J. M. Arroyo, N. Alguacil and M. Carrion, "A Risk-Based Approach for Transmission Network Expansion Planning Under Deliberate Outages," *IEEE Transactions on Power Systems*, vol. 25, no. 3, pp. 1759-1766, Aug. 2010.

[9] A. Arab, E. Tekin, A. Khodaei, S. K. Khator and Z. Han, "System Hardening and Condition-Based Maintenance for Electric Power Infrastructure Under Hurricane Effects," *IEEE Transactions on Reliability*, vol. 65, no. 3, pp. 1457-1470, Sept. 2016.

[10] A. Arab, A. Khodaei, S. K. Khator, K. Ding, V. A. Emesih and Z. Han, "Stochastic Pre-hurricane Restoration Planning for Electric Power Systems Infrastructure," *IEEE Trans. on Smart Grid*, vol. 6, no. 2, pp. 1046-1054, March 2015.

[11] A. Arab, A. Khodaei, Z. Han and S. K. Khator, "Proactive Recovery of Electric Power Assets for Resiliency Enhancement," *IEEE Access*, vol. 3, pp. 99-109, March 2015.

[12] P. Van Hentenryck and C. Coffrin, "Transmission system repair and restoration," *Math. Program*., vol. 151, no. 1, pp. 347–373, 2015.

[13] C. Coffrin and P. Van Hentenryck, "Transmission system restora-tion with co-optimization of repairs, load pickups, and generation dispatch," *Int. J. Electr. Power Energy Syst*., vol. 72, pp. 144–154, 2015.

[14] A. Golshani, W. Sun, Q. Zhou, Q. P. Zheng, and J. Tong, "Two-Stage Adaptive Restoration Decision Support System for a Self-Healing Power Grid," *IEEE Trans. Ind. Inform*., vol. 13, no. 6, pp. 2802–2812, Dec. 2017.

[15] Y. Fang, N. Pedroni, and E. Zio, "Resilience-Based Component Importance Measures for Critical Infrastructure Network Systems," *IEEE Trans. Reliab*., vol. 65, no. 2, pp. 502–512, Jun. 2016.

[16] N. Yodo, P. Wang, and Z. Zhou, "Predictive Resilience Analysis of Complex Systems Using Dynamic Bayesian Networks," *IEEE Trans. Reliab.,* vol. 66, no. 3, pp. 761–770, Sep. 2017.

[17] C. Wang, Y. Hou, F. Qiu, S. Lei, and K. Liu, "Resilience En-hancement With Sequentially Proactive Operation Strategies," *IEEE Trans. Power Syst.*, vol. 32, no. 4, pp. 2847–2857, 2017.

[18] M. Sahraei-Ardakani, and G. Ou, "Day-Ahead Preventive Scheduling of Power Systems During Natuaral Hazards via Stochastic Optimization," in *Proc. 2017 IEEE PES General Meeting, Chicago*, IL, USA, July 2017.

[19] N. H. Center, "National Hurricane Center." [Online]. Available: http://www.nhc.noaa.gov/. [Accessed: 04-Jan-2018].

[20] C. J. Wong, and M. D. Miller, Guidelines for Electrical Transmission Line Structural Loading., Recon: American Society of Civil Engineering, 2010.

[21] Y. Sang, M. Sahraei-Ardakani, J. Xue and G. Ou, "Effective Scenario Selection for Preventive Stochastic Unit Commitment during Hurricanes," in Proc. *2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, Boise, ID, 2018.