Event-Driven Security-Constrained Unit Commitment with Component Outage Estimation Based on Machine Learning Method

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***Abstract*—Hurricanes can cause significant damages to the electric power systems and result in widespread and prolonged loss of electric services. A preventive scheduling of available resources in response to these events can be of significant importance in reducing the related undesirable aftermath. An Event-driven Security-Constrained Unit Commitment (E-SCUC), as discussed in this paper, can be used as a viable tool to schedule available grid resources in minimizing possible supply interruptions during component outages as a consequence of these events. An accurate estimation of the component outages, however, is of ultimate importance in ensuring a viable resource schedule. In this work, a machine learning method, based on regression and data mining, is proposed to model the power system components that can potentially fail during an anticipated extreme event. The proposed model is trained on artificial and historical data of storm-related damages, where the prediction is further used in the proposed E-SCUC problem. Numerical simulations on the standard IEEE 30-bus system in various hurricane path and intensity scenarios illustrate the effectiveness of the proposed model.**

Keywords*— Event-driven operation, extreme events, machine learning, power system resilience, resource scheduling, security-constrained unit commitment.

NOMENCLATURE

Indices and Sets:

b	Index for buses.
B	Set of components connected to bus b.
i	Index for generation units.
s	Index for scenarios.
S	Set of outage scenarios.
t	Index for time.

Parameters:

DR_i	Ramp down rate of unit i.
DT_i	Minimum down time of unit i.
$F_i\,(.)$	Generation cost function of unit i.
M	Large positive constant.
$P_i^{\min}$	Minimum generation capacity of unit i.
$P_i^{\max}$	Maximum generation capacity of unit i.
R	System reserve.
UR_i	Ramp up rate of unit i.
UT_i	Minimum up time of unit i.
x_l	Reactance of line l.

Variables:

a_{lb}	Element of line l and bus b at line-bus incidence matrix.
D_{bt}	Load at bus b at time t.
I_{it}	Commitment state of unit i at time t.
LC_{bts}	Total load curtailment at bus b at time t in scenario s.
P_{its}	Real power generation of unit i at time t in scenario s.
PL_{lts}	Real power flow of line l at time t in scenario s.
T_{it}^{on}	Number of successive ON hours of unit i at time t.
T_{it}^{off}	Number of successive OFF hours of unit i at time t.
UX_{its}	Outage state of unit i at time t in scenario s; 0 if on outage, otherwise 1.
UY_{lts}	Outage state of line l at time t in scenario s; 0 if on outage, otherwise 1.
v_b	Value of lost load at bus b.
Δ_i	Permissible power adjustment of unit i.
θ_{bts}	Phase angle of bus b at time t in scenario s.

I. INTRODUCTION

The extreme weather is one of the major causes of power outages in the United States, resulting in considerable financial losses every year in terms of lost businesses, impeded emergency services, and damaged infrastructure [1]. Among the various kinds of extreme weathers, hurricanes are the most frequent in the United States which cause considerable damages to the power systems by blowing over trees and debris into power lines, breaking conductors, tower structures, insulators, and poles, and displacement of critical substation components [2]. An efficient prediction of the upcoming hurricanes, along with their potential impacts on the system, plays a vital role in preparing the system to be able to respond to such events and accordingly improve the system resilience.

In [3], the general notion of resiliency is introduced as the endurance of a system and its ability to withstand changes. Power grid resilience has become an increasingly important issue as the frequency and the intensity of extreme weather events have considerably increased in the last decade. The mathematical modeling of optimal scheduling of available resources according to weather related incidents considering the resiliency constraint has further emerged as an important topic and worthy of detailed investigation. In [4], a methodology to characterize the behavior of a networked

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infrastructure with an emphasis on post-event infrastructure recovery is proposed. The network resiliency and interdependency of power system transmission and telecommunications is evaluated using limited data of post-landfall for Hurricane Katrina. In [5], a resilience index is proposed along with belief functions and a variety of qualitative features to address and analyze the system vulnerability. In [6], a proactive resource allocation model is proposed to repair and restore damages to power systems resulted by extreme events. The problem is modeled by a stochastic integer program and solved by the Benders' decomposition method to handle computational burden. Post-disaster restoration is an import part of power system resiliency studies. In [7] and [8], proactive recovery of electric power components is investigated by developing component outage models in response to hurricanes, a stochastic pre-hurricane model for managing resources before the event, and a deterministic post-hurricane recovery model for managing resources after the event. In [9] a model based on AC power flow constraints is proposed for power system restoration after natural disasters. The proposed model finds an optimal restoration schedule by using the value of lost load which prioritizes the loads to be restored in order to minimize the load interruptions in the post-disaster phase. A post-disaster decision making model is proposed in [10] to find the optimal repair schedule, unit commitment solution, and system configuration in restoration of the damaged power grid. The model shows that unit commitment model can be considered in economics of disaster for utility companies during the post-disaster restoration process. A comprehensive study of models and algorithms for emergency response in electric distribution systems is presented in [11] and [12].

In the context of data driven approaches to predict power system outages in response to hurricanes, the disruption are studied in terms of number and duration of the outages and customers affected, geographical location, and types of impacted components in [13]. The study is based on large databases of outages in five hurricanes in Carolina. Data logs of an affected urban area which is impacted by four winter storms were plotted in GIS in [14], to study outage duration, and restoration of an urban distribution system located in the U.S. Pacific Northwest. In [15], an ensemble learning method for regression (i.e. random decision forests) is proposed to forecast the power outage durations, caused by Hurricanes Dennis, Katrina, and Ivan in a central Gulf Coast state. In [16], a hurricane power outage prediction model is introduced and claimed to be applicable along the full U.S. coastline. The model is trained on only publicly available data, and is further used to estimate the impacts of Hurricane Sandy and Typhoon Haiyan.

Considering the large number and the frequent occurrence of hurricanes in the U.S., which results in collection of considerable amount of data, machine learning methods could be of significant use. In this paper, a machine learning method is used to analyze the historical hurricane and power system outage data and accordingly estimate the probability of failure for power system components in response to future events based on the center and the category of the hurricane. Kernel Density Estimation (KDE) method, as a non-parametric way to estimate the probability density function of a random variable, is used for this purpose [17]. This method is commonly used in data mining, data smoothing, cluster analysis, image processing, signal processing, and econometrics [18]. As there are only a few publicly available datasets on the impact of the hurricanes on power system components, the proposed method is applied on artificial data to estimate the probability of components failures. The obtained outages are further integrated to a developed E-SCUC model to find the optimal schedule of available resources that not only minimizes the operation cost but also lowers the system total load curtailment.

The rest of the paper is organized as follows. Sections II and III respectively present the model outline and formulation of the proposed outage estimation model and the E-SCUC problem. Section IV presents numerical simulations on the IEEE 30-bus test system. Section V concludes the paper.

II. Proposed E-SCUC Model

The outline of the proposed E-SCUC model is depicted in Fig. 1. The model has three stages. In Stage-1, the category and the path of the potential hurricane that is heading toward the power system is forecasted. This forecast data can be obtained from weather forecast channels. In Stage-2, after knowing the potential regions and the category of the hurricane, the outage probability of each system component is calculated using KDE method on historical hurricane data. As the publicly available data on the impact of hurricanes on power system components is limited, an artificial set of data is generated in this paper to estimate the probability of the component outages. Once the probable damages to system components are estimated, the E-SCUC problem based on the obtained scenarios of outages is solved in Stage-3.

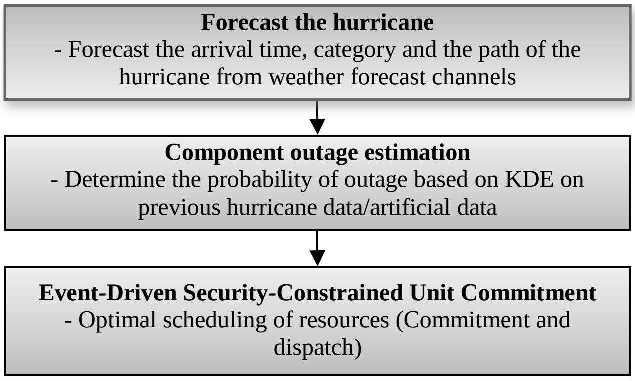

Fig. 1. Proposed E-SCUC model with machine learning-based outage estimation

A. *Categories of Hurricanes*

According to Saffir-Simpson Hurricane Scale, hurricanes are assigned to a category of one to five according to the maximum 1-minute sustained wind speed [19]. The minimum and maximum sustained wind speeds corresponding to each hurricane category are shown in Table I. Category 1 and 2 storms, with sustained winds of 74-95 mph and 96-110 mph, respectively, are less dangerous categories but however require preventive measures. Usually there is no considerable structural damage to most well-constructed permanent structures or there are only minor damages to poorly constructed windows or doors. However extensive power outages may happen lasting from few minutes to several days. The U.S. National Hurricane Center categorizes hurricanes of Category 3 and above as major hurricanes. Category 3 hurricanes can cause some structural damage to small residences and utility buildings, particularly those of wood frame. There is a very high risk of injury or death in Category 4, and catastrophic damage will occur in hurricane Category 5 [19]. A typical hurricane of Category 5 will have three-second gusts that are approximately 25% faster than one-minute sustained wind speeds [2]. Using this 25% gust factor, the minimum and maximum expected three-second gust speeds corresponding to each hurricane category are also shown in Table I.

TABLE I. SAFFIR-SIMPSON HURRICANE SCALE [19]

	1-min sustained (mph)		3-sec gust (mph)	
Category	Min	Max	Min	Max
1	74	95	93	119
2	96	110	120	138
3	111	130	139	163
4	131	155	164	196
5	156	180	195	225

B. *Kernel Density Estimation (KDE)*

The operational/outage state of a component can be considered as a random binary variable. A variety of probability distribution models have been proposed to model the probability of damages on the power system components [20], [21]. Given a sample $x \in \mathbb{R}^d$ from some unknown densities, the general form of a multivariate kernel density estimate at x is computed as

$$\hat{f}_h(x) = \frac{1}{n}\sum_{i=1}^{n} K_h(x - x_i) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{1}$$

where $K(.)$ is d-variate function (the kernel) and h is a smoothing parameter called the *bandwidth*. The bandwidth is a rescaling factor which determines the extent of the region over which the probability mass for a point x_i is spread. The kernel is generally chosen to be an even function, i.e., $K(x)= K(-x)$, which usually integrates to one and has a mean value of zero. The most widely used kernel is the Gaussian of zero mean and unit variance as:

$$K(x) = \frac{1}{\sqrt{2\pi^d}} \exp\left\{-\frac{\|x\|}{2}\right\} \tag{2}$$

KDE methods are not very sensitive to the choice of K, and different functions that produce good results can be used. In practice, the bandwidth plays an important role and has a great effect on the shape of the estimator. If the bandwidth is small, an under-smoothed estimator with high variability will be obtained. On the contrary, a large bandwidth results in an over-smooth estimator and farther from the estimated function. Thus, the quality of a kernel density estimator highly depends on the choice of the smoothing parameter. A common way to estimate an optimum value of the bandwidth is by measuring the mean integrated squared error (MISE) between the density and its estimate integrated over the domain of definition as in (3) [22]:

$$MISE(h) = \int_{\Re^d} \left(\hat{f}_h(x) - f(x)\right)^2 dx \tag{3}$$

Fig. 2 illustrates the effect of bandwidth on KDE of a standard normal distribution. As shown, small bandwidth (h=2) results a higher variability estimation and a large bandwidth (h=20) results in an over-smooth estimator, while the calculated optimal bandwidth can estimate the probability of random samples more accurately.

The time to repair damaged components is defined by the *Weibull* density function (4) [23]:

$$f(t) = \begin{cases} \dfrac{\rho}{\lambda}\left(\dfrac{t}{\lambda}\right)^{\rho-1} e^{-(t/\lambda)^{\rho}} & \text{if } t \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where ρ and λ are the shape parameter and the scale parameter, respectively. In practice, each component has different repair time and required set of skilled crews. For the sake of simplicity, a same shape parameter and scale parameter is considered for different components (i.e. line, substations, and generation units).

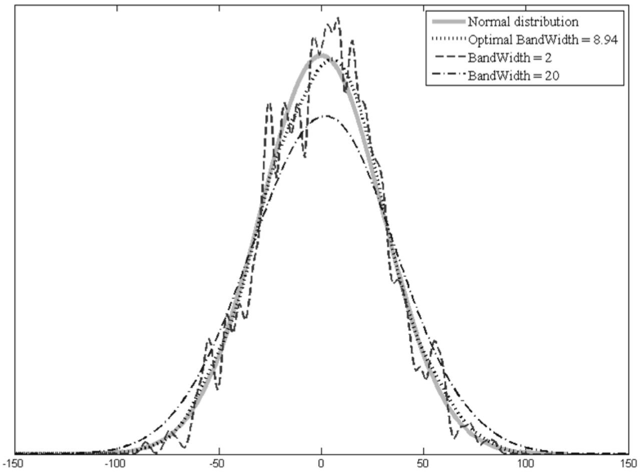

Fig. 2. Kernel density estimation (KDE) with a small bandwidth (h=2), optimal bandwidth (h=8.94) and a large bandwidth (h=20) to estimate a random sample points from a standard normal distribution.

III. E-SCUC PROBLEM FORMULATION

The objective of the E-SCUC problem is defined as:

$$\min \sum_{t}\sum_{i} F(P_{it0}, I_{it}) + \sum_{t}\sum_{s}\sum_{b} vLC_{bts} \tag{5}$$

where $F(P_{it0},I_{it})$ is the operation cost in normal system operation (which includes the generation cost and startup/shut down costs) and LC_{bts} is the cost of unserved energy at bus b at time t during contingency scenarios s. The value of lost load, v, is defined as the average cost that a customer is willing to pay in order to avoid load interruptions [24]. Assuming UX_{its} as the outage state of unit i at time t in scenario s (1 when operating and 0 when on outage) and UY_{lts} as the outage state of line l at time t in scenario s (1 when operating and 0 when on outage), the proposed objective function is subject to the following operational constraints:

$$\sum_{i \in B} P_{its} + \sum_{i \in B} PL_{its} + LC_{bts} = D_{bt} \qquad \forall b, \forall s, \forall t \tag{6}$$

$$P_i^{\min} I_{it} UX_{its} \leq P_{its} \leq P_i^{\max} I_{it} UX_{its} \qquad \forall i, \forall s, \forall t \tag{7}$$

$$P_{its} - P_{i(t-1)s} \leq UR_i \qquad \forall i, \forall s, \forall t \tag{8}$$

$$P_{i(t-1)s} - P_{its} \leq DR_i \qquad \forall i, \forall s, \forall t \tag{9}$$

$$T_{it}^{\text{on}} \geq UT_i\left(I_{it} - I_{i(t-1)}\right) \qquad \forall i, \forall t \tag{10}$$

$$T_{it}^{\text{off}} \geq DT_i\left(I_{i(t-1)} - I_{it}\right) \qquad \forall i, \forall t \tag{11}$$

$$\sum_{i} P_i^{\max} I_{it} \geq D_t + R_t \qquad \forall i, \forall t \tag{12}$$

$$\left|P_{it0} - P_{its}\right| \in \Delta_i \qquad \forall i, \forall s, \forall t \tag{13}$$

$$PL_l^{\min} UY_{lts} \leq PL_{lts} \leq PL_l^{\max} UX_{lts} \qquad \forall l, \forall s, \forall t \qquad (14)$$

$$\left| PL_{lts} - \frac{\sum_b a_{lb} \theta_{bts}}{x_l} \right| \leq M\left(1 - UY_{lts}\right) \qquad \forall l, \forall s, \forall t \qquad (15)$$

Load balance equation (6) ensures that the total injected power to each bus from generation units and line flows is equal to the total consumed load at each load bus. Load curtailment variable (LC_{bts}) is further added to the load balance equation to ensure a feasible solution when there is not sufficient generation to supply loads (due to outage of power system components). Load curtailment will be zero under normal operation conditions. Generation unit output power is limited by its capacity limit and will be set to zero depending on its commitment and outage states (7). Generation units are further subject to prevailing technical constraints including ramp up and down rate limits (8)-(9), minimum up and down time limits (10)-(11). System operating reserve requirement is represented in (12). The change in unit generation is further limited by the maximum permissible limit between normal and contingency scenarios (13). Transmission line capacity limits and power flow constraints are modeled by (14) and (15), respectively, in which the outage state is included to effectively model the line outages in contingency scenarios.

IV. Numercial Simulations

The proposed E-SCUC problem is applied to the IEEE 30-bus test system. We assume that a hurricane passes through three hypothetical paths with different categories as shown in Fig. 3 [25]. Five hundred samples with different wind gust speeds around the center of the hurricane are generated following a normal distribution with a small noise. Accordingly, a Gaussian kernel is applied on the center of the hurricane to estimate the probability of failure of each component. MISE is used to obtain the optimal bandwidth. Fig. 4 shows the estimated probability of component failure for each hurricane category. The optimal bandwidth is estimated as 4.86 (Category 1 & 2), 9.76 (Category 3), 16.22 (Category 4), and 26.75 (Category 5). The proposed probability distribution functions can be better estimated if more significant and reliable data from previous hurricanes were available; however, the proposed model is a general framework that can be applied to any available set of data, with different degrees of accuracy, without loss of generality. In each hurricane path, based on the distance of each component to the center of the hurricane and the category of the hurricane, the probability of survival is determined. Tables II-IV show the probability of failure for different components in each studied area (shown in Fig. 3) based on data mining and KDE on artificial data. Probability of component failure over a threshold of 0.1 is considered for component failure (shown bold in Tables II-IV). In order to exhibit the effectiveness of the proposed model, three cases are studied as follows:

A. *Case 1: SCUC with N-1 Reliability*

In this case, *N*-1 reliability criterion is considered in each contingency scenario. The operation cost is obtained as \$10,730. No load curtailment has occurred in this case, and the system is secure against any single component outage.

B. *Case 2: SCUC with N-1 Reliability against m Ouatges*

The purpose of this case study is to identify how much load curtailment will occur if the system is scheduled for *N*-1 but multiple components outage happen due to an extreme event. In other words, the calculated commitment in Case 1 is used to solve the problem for the *m* component outages in each contingency scenario. Component outages along each hurricane path (contingency scenario) are shown bold in Tables II-IV. A cut-off probability of 0.1 is considered, i.e., any failure probability larger than this will result in component outage, while probabilities less than this will ensure that the component will continue to operate in the functional state.

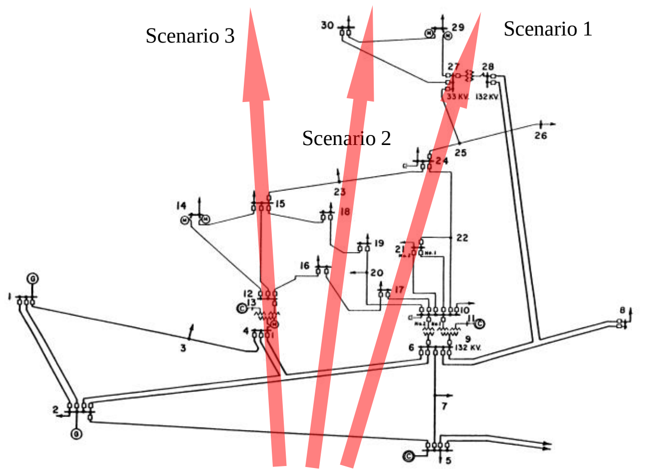

Fig. 3. Schematic of a forecasted hurricane passing through three possible paths over the IEEE 30-bus test system.

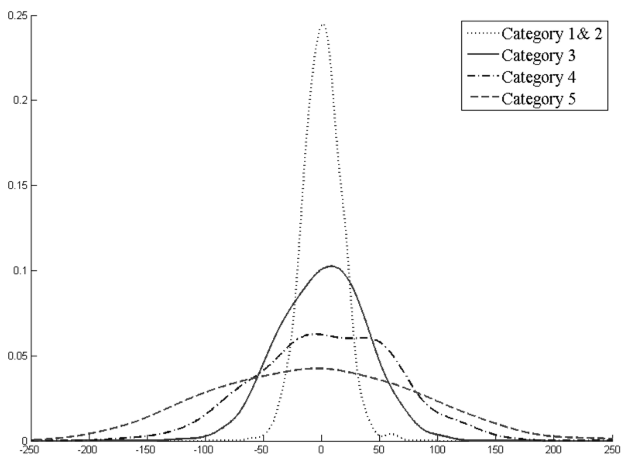

Fig. 4. Estimated probability of component failure for each hurricane category.

TABLE II. Probability Of Failure For Different Components In Hurricane Path 1.

	Category			
	1 & 2	3	4	5
Line 5	**0.3882**	**0.4031**	**0.3646**	**0.3424**
Line 6	0.0393	**0.2623**	**0.3274**	**0.3077**
Line 7	0.0099	**0.2069**	**0.3067**	**0.2892**
Line 25	0.0045	**0.1345**	**0.2722**	**0.2687**
Line 26	0	0.0264	**0.1447**	**0.2091**
Line 27	0	0.0198	**0.1188**	**0.1924**
Line 28	0	0.0006	0.0632	**0.134**
Line 31	0	0.0004	0.0598	**0.1309**

TABLE III. PROBABILITY OF FAILURE FOR DIFFERENT COMPONENTS IN HURRICANE PATH 2.

	Category			
	1 & 2	3	4	5
Line 5	**0.3397**	**0.4383**	**0.3802**	**0.3601**
Line 6	0.0676	**0.292**	**0.3153**	**0.3083**
Line 7	0.0104	**0.1781**	**0.2775**	**0.2816**
Line 21	0.0001	0.0775	**0.2202**	**0.2483**
Line 23	0	0.0661	**0.2088**	**0.2435**
Line 24	0	0.0064	0.0629	**0.1819**
Line 30	0	0.0016	0.0494	**0.1637**
Line 38	0	0.0001	0.0387	**0.1387**

TABLE IV. PROBABILITY OF FAILURE FOR DIFFERENT COMPONENTS IN HURRICANE PATH 3.

	Category			
	1 & 2	3	4	5
Line 5	**0.3875**	**0.4541**	**0.3802**	**0.3053**
Line 6	0.0862	**0.3082**	**0.3395**	**0.3057**
Line 7	0.0629	**0.2769**	**0.3312**	**0.3032**
Line 18	0	0.0583	**0.2253**	**0.2544**
Line 19	0	0.0758	**0.2442**	**0.2638**
Line 21	0	0.0032	0.085	**0.1698**
Line 15	0	0.0008	0.0617	**0.1489**
Line 29	0	0	0.0393	**0.1255**

Table V shows the system operation cost and the load curtailment (LC) in each contingency scenario obtained from solving the SCUC problem based on the identified outages. As the same commitment is used for each number of components on outage (*m*), the total operation cost is constant. However, the results indicate that by increasing the number of simultaneous component outages, the load curtailment increases drastically. For larger amounts of outage i.e. hurricane category 5, the SCUC problem is not able to find a feasible solution. The results indicate that although the *N*-1 criterion is suitable for ensuring power system security in daily operation, but it does not provide a viable solution when dealing with extreme events and multiple component outages.

TABLE V. OPERATION COST AND LOAD CURTAILEMT OF N-1 SCUC FOR DIFFERENT HURRICANE CATEGORIES

Hurricane Category	Total Cost	LC Scenario 1 (MWh)	LC Scenario 2 (MWh)	LC Scenario 3 (MWh)
1&2	$10,730	0	0	0
3	$10,730	145	128	128
4	$10,730	237	528	128
5	-	-	-	-

C. Case 3: Proposed E-SCUC

In this case, the proposed E-SCUC is used to find optimal scheduling of the simultaneous outage of multiple components along with the *N*-1 reliability criterion. Particularly, 50 scenarios is defined, 47 scenarios representing the single component outage (*N*-1) and 3 representing outage scenarios for each path of the hurricane (*N-1-m*). Component outages along each hurricane path are the same as components that are studied in Case 2 (shown bold in Tables II-IV). Table VI shows the system operation cost and the load curtailment in each contingency scenario obtained as the E-SCUC solution. In addition, the cost increase and average load curtailment decrease compared to the SCUC with *N-m* reliability criterion (Case 2) are shown in this table.

TABLE VI. OPERATION COST AND LOAD CURTAILMENT OF THE PROPOSED E-SCUC FOR STUDIED SCENARIOS.

Category	Total Cost	Cost Increase	LC S1 (MWh)	LC S2 (MWh)	LC S3 (MWh)	Avg. LC Decrease
1&2	$10,759	0.26%	0	0	0	0%
3	$10,847	1.09%	0	0	0	100%
4	$10,937	1.92%	0	87	42	85%
5	$10,943	-	318	373	862	-

The obtained results advocate that for more destructive categories of hurricane (where the number of simultaneous component outages increases), the operation cost increases, as the result of increased number of components that need to be committed in the normal operation. Comparing the results of E-SCUC with SCUC (Case 2) indicates that the proposed E-SCUC model is more resilient against multiple simultaneous component outages as the amount of load curtailment is considerably lower than SCUC problem under similar contingency scenarios. As an example, the load curtailment in response to a category 3 hurricane is reduced to zero when the proposed E-SCUC is utilized.

V. CONCLUSION

In this paper, an event-driven security-constrained unit commitment (E-SCUC) model was proposed by considering the simultaneous outages of multiple system components, representing an *N*-1-*m* reliability criterion. A machine learning method, based on regression and data mining, was used to estimate and model the system components that will likely fail due to a predicted hurricane. An artificial set of data was generated in this paper to estimate the probability of the component outages, as the publicly available data on the impact of hurricanes on power system components is limited. The proposed KDE approach is a general framework, which can ensure more accurate estimations if it is trained on extensive historical data on storm-related damages and their impacts on the system components. The numerical simulations on the standard IEEE 30-bus test system illustrated the merits and applicability of the proposed E-SCUC model. Comparison of the results of the proposed E-SCUC with those from the conventional SCUC without the events modeled indicated that the proposed E-SCUC method can produce a more robust solution that can protect the system against multiple component outages due to a hurricane.

REFERENCES

[1] Executive Office of the President, “Economic Benefits of Increasing Electric Grid Resilience to Weather Outages”, August 2013.

[2] R. E. Brown, “Cost-benefit analysis of the deployment of utility infrastructure upgrades and storm hardening programs,” *Quanta Technology. Raleigh*, 2009.

[3] C. S. Holling, “Resilience and stability of ecological systems,” *Annu. Rev. Ecol. Syst.*, pp. 1–23, 1973.

[4] D. A. Reed, K. C. Kapur, and R. D. Christie, “Methodology for assessing the resilience of networked infrastructure,” *Syst. J. IEEE*, vol. 3, no. 2, pp. 174–180, 2009.

[5] N. O. Attoh-Okine, A. T. Cooper, and S. A. Mensah, “Formulation of resilience index of urban infrastructure using belief functions,” *IEEE Syst. J.*, vol. 3, no. 2, pp. 147–153, 2009.

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

[7] 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, 2015.

[8] A. Arab, A. Khodaei, S. K. Khator, K. Ding, and Z. Han, "Post-hurricane transmission network outage management," in *Proc. IEEE Great Lakes Symp. Smart Grid New Energy Econ*, 2013, pp. 1–6.

[9] A. Arab, A. Khodaei, S. K. Khator, and Z. Han, "Transmission network restoration considering AC power flow constraints," in *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, 2015, pp. 816–821.

[10] A. Arab, A. Khodaei, S. Khator, and Z. Han, "Electric Power Grid Restoration Considering Disaster Economics," *IEEE Access*, 2016.

[11] N. Perrier, B. Agard, P. Baptiste, J.-M. Frayret, A. Langevin, R. Pellerin, D. Riopel, and M. Trépanier, "A survey of models and algorithms for emergency response logistics in electric distribution systems. Part I: Reliability planning with fault considerations," *Comput. Oper. Res.*, vol. 40, no. 7, pp. 1895–1906, 2013.

[12] N. Perrier, B. Agard, P. Baptiste, J.-M. Frayret, A. Langevin, R. Pellerin, D. Riopel, and M. Trépanier, "A survey of models and algorithms for emergency response logistics in electric distribution systems. Part II: Contingency planning level," *Comput. Oper. Res.*, vol. 40, no. 7, pp. 1907–1922, 2013.

[13] R. A. Davidson, H. Liu, I. K. Sarpong, P. Sparks, and D. V. Rosowsky, "Electric power distribution system performance in Carolina hurricanes," *Nat. Hazards Rev.*, vol. 4, no. 1, pp. 36–45, 2003.

[14] D. A. Reed, "Electric utility distribution analysis for extreme winds," *J. Wind Eng. Ind. Aerodyn.*, vol. 96, no. 1, pp. 123–140, 2008.

[15] R. Nateghi, S. D. Guikema, and S. M. Quiring, "Forecasting hurricane-induced power outage durations," *Nat. Hazards*, vol. 74, no. 3, pp. 1795–1811, 2014.

[16] S. D. Guikema, R. Nateghi, S. M. Quiring, A. Staid, A. C. Reilly, and M.-L. Gao, "Predicting hurricane power outages to support storm response planning," *IEEE Access*, vol. 2, pp. 1364–1373, 2014.

[17] E. Parzen, "On estimation of a probability density function and mode," *Ann. Math. Stat.*, vol. 33, no. 3, pp. 1065–1076, 1962.

[18] A. C. Guidoum, "Kernel Estimator and Bandwidth Selection for Density and its Derivatives," 2013.

[19] T. Schott, C. Landsea, G. Hafele, J. Lorens, A. Taylor, H. Thurm, B. Ward, M. Willis, and W. Zaleski, "The Saffir-Simpson hurricane wind scale," *Natl. Weather Serv.*, 2012.

[20] A. Arab, E. Tekin, A. Khodaei, S. K. Khator, and Z. Han, "Dynamic maintenance scheduling for power systems incorporating hurricane effects," in *Smart Grid Communications (SmartGridComm), IEEE International Conference on*, 2014, pp. 85–90.

[21] A. Abiri-Jahromi, M. Parvania, F. Bouffard, and M. Fotuhi-Firuzabad, "A two-stage framework for power transformer asset maintenance management—Part I: Models and formulations," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1395–1403, 2013.

[22] S. J. Sheather and M. C. Jones, "A reliable data-based bandwidth selection method for kernel density estimation," *J. R. Stat. Soc. Ser. B Methodol.*, pp. 683–690, 1991.

[23] R. Billinton and P. Wang, "Teaching distribution system reliability evaluation using Monte Carlo simulation," *IEEE Trans. Power Syst.* vol. 14, no. 2, pp. 397–403, 1999.

[24] L. Economics, "Estimating the value of lost load," *Brief. Pap. Prep. ERCOT 17 June 2013*, 2013.

[25] "Power Systems Test Case Archive" [Online]. Available: http://www.ee.washington.edu/research/pstca/pf30/pg_tca30bus.htm.