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Proactive Recovery of Electric Power Assets for Resiliency Enhancement

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ABSTRACT This paper presents a significant change in current electric power grid response and recovery schemes by developing a framework for proactive recovery of electric power assets with the primary objective of resiliency enhancement. Within the proposed framework, which can potentially present the next generation decision-making tool for proactive recovery, several coordinated models will be developed including: 1) the outage models to indicate the impact of hurricanes on power system components; 2) a stochastic pre-hurricane crew mobilization model for managing resources before the event; and 3) a deterministic post-hurricane recovery model for managing resources after the event. Proposed models will be extended to ensure applicability to a variety of electric power grids with different technologies and regulatory issues. The theoretical and practical implications of the developed models will push the research frontier of proactive response and recovery schemes in electric power grids, while its flexibility will support application to a variety of infrastructures, in response to a wide range of extreme weather events and natural disasters.

INDEX TERMS Natural disaster, recovery, resiliency, restoration, smart grid.

I. INTRODUCTION

Natural disasters, particularly the storms are still the vulnerable point of the electricity infrastructure as one of the most critical lifeline systems and of utmost importance to our daily lives. After over half a century from publication of one of the earliest studies on efficient response to hurricanes, motivated by Hurricane Carla that slammed into the Gulf Coast and moved onward into the United States and Canada [1], the issue of efficient response to hurricanes and other natural disasters still seems to remain in its immature stage. Storms can result in significant economic, social, and physical disruptions, and cause considerable inconvenience for residents living in disaster areas due to loss of electricity, water and communication [2]. Even the notion of *"after a storm comes a calm,"* is not the case for the electric power systems. The electric power grid transfers the electricity generated by large-scale power plants to a variety of industrial, commercial, and residential customers via transmission and distribution networks, and hence it can be disrupted over a vast geographical area when a hurricane strikes. For instance, following Hurricane Ike in 2008, more than 2.8 million customers in the Greater Houston area experienced a power outage, which lasted from a few days to several weeks. The total damage from Hurricane Ike in the U.S. coastal and inland areas was estimated at $24.9 billion [3]. Therefore, dealing with the aftermath of such disasters is of great concern of utilities and governments.

The level of complexity and interdependency of systems, either in urban or rural settings, increases with time. These complex and interdependent systems are extremely vulnerable to disasters. Development of mitigation strategies which outflanks the process of risk transference of mega-disasters is the key to successful management of disasters. In this context, *resistance* refers to the capacity to withstand disaster without change, while *resilience* refers to its capacity to *"bounce back"* to a pre-disaster condition [4]. Based on definition from [5], *"local resiliency with regard to disasters means that a locale is able to withstand an extreme natural event without suffering devastating losses, damage, diminished productivity, or quality of life and without a large amount of assistance from outside the community."* The term *storm* can alternatively be used for *hurricane*, *typhoon*, and *cyclone*. According to the National Oceanic and Atmospheric Adminstration [6], hurricanes, cyclones, and typhoons are

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the same phenomenon, but they can be classified depending upon the location the storms originate. The term *hurricane* is used in the Atlantic and Northeast Pacific; while it is called *typhoon* in the Northwest Pacific; and *cyclone* is used for the same phenomenon in the South Pacific and Indian Ocean.

A. LITERATURE REVIEW

There is a limited number of studies on the emergency operation of electric power grids in case of extreme weather events and natural disasters. The literature can be studied in four distinct contexts: emergency planning, physical behavior analysis, outage prediction, and resource allocation.

1) EMERGENCY PLANNING

In this context, reference [7] reviewed the models for substations and distribution feeders planning under normal and emergency conditions. A case study on hurricane planning and rebuilding the electrical infrastructure along the Gulf Coast for hurricane Katrina was presented in [8]. A risk assessment method to infrastructure technology planning for improving the power supply resiliency to natural disasters was proposed in [9]. Reduced cost as well as power supply availability were considered as two fundamental decision factors in their hurricane planning approach. In [10], a stochastic integer program was proposed to find the optimal schedule for inspection, damage evaluation, and repair in post-earthquake restoration of an electric power system. The aim was to minimize the time that each customer is without power in average. Reference [11] studied three approaches for joint damage assessment and restoration of the power systems after natural disaster. The proposed approaches include i) an online stochastic combinatorial optimization algorithm which dynamically makes the restoration decisions once each potentially damaged site is visited, ii) a two-stage method that first evaluates the extent of the damage and then restores the system, and iii) a hybrid algorithm of both approaches which simultaneously performs the damage evaluation and system restoration tasks. The results indicate that the first approach is able to provide solutions with higher quality for the joint damage assessment and recovery problems. Reference [12] proposed a general multi-objective linear-integer spatial optimization model for arcs and nodes restoration of disrupted networked infrastructure after disaster. The proposed model addresses the tradeoff between maximization of the system flow and minimization of system cost. In [13], an integrated network design and scheduling problem for restoration of the interdependent civil infrastructures was proposed. The problem was formulated using integer programming, and analyzed on realistic dataset of power infrastructure of the Lower Manhattan in New York City and New Hanover County, North Carolina. The results indicate that the proposed model can be used for real-time as well as long-term restoration planning. Reference [14] considered the last-mile restoration of power systems, i.e., how to schedule and allocate the routes to fleets of repair crews to recover the damaged power system as fast as possible. The power restoration and vehicle routing were decoupled to improve the computational efficiency of the model. The result indicates that the proposed model outperforms the models which are practiced in the field in terms of solution quality and scalability. This work was extended in [15] by applying randomized adaptive vehicle decomposition technique in order to improve the scalability of the model for large-scale disaster restoration of the power networks with more than 24000 components. A comprehensive survey of models and algorithms for emergency response logistics in electric distribution systems, including reliability planning with fault considerations and contingency planning models were presented in [16] and [17].

2) PHYSICAL BEHAVIOR

In the context of physical behavior analysis of power system infrastructure in hurricanes, [18] analyzed the resilience of power distribution systems based on the power distribution infrastructure and its interaction with the biophysical environment, and the way that restoration processes are prioritized. It was concluded that even though the infrastructure does not have any significant effect on outage duration, the interaction between infrastructure and the biophysical environment significantly affects outage duration. Reference [19] proposed a comprehensive strategy for mitigation of hazards with the aim of creating resilient cities which are able to withstand disasters. The hazard mitigation practices, the definition of the resilient city, and discussion on importance of resilience, and the ways that these principles can be applied to physical and social elements of cities were presented, as well. In [20], a data mining approach was proposed to evaluate the impact of soil and topographic variables on accuracy of the power outage prediction models in hurricane events. The results indicated that certain land cover variables could be reasonable proxies for the power system and could be incorporated in the model when detailed information about the power system is not available. In [21], a method for characterization of the behavior of networked infrastructure, including power delivery systems in natural hazard events such as hurricanes was presented. The model also included resilience and interdependency measures. The proposed model could be utilized to develop design strategies for improved power infrastructure resiliency in natural disasters. Reference [22] proposed a probabilistic framework for vulnerability analysis of distribution poles subject to hurricane hazards considering the impact of a changing climate. The results indicate that changing climate and the age of the poles significantly increases the failure rate of distribution poles. The impact of tropical cyclones on United States power systems, under climate change scenarios was analyzed in [23].

3) OUTAGE PREDICTION

Outage prediction is an important tool for ensuring an efficient response to hurricanes. In this context, [24] introduced a method for estimating the restoration time of electric power systems after hurricanes and ice storms. Using large dataset of six hurricanes and eight ice storms, accelerated failure time models were developed to forecast the duration of each probable outage. In [25], negative binomial regression models for prediction of outages due to hurricane were developed. The number of transformers in the area, maximum wind gust speed, the power company affected, and a hurricane effect turned out to be the most explanatory variables. Diagnostic statistics such as pseudo R-squared values were used for model selection purposes. The adopted zip code-based analysis was used for prediction of the likely outage rates prior to the hurricane events. In [26], regression analysis and data mining were employed to develop models for estimating the number of utility poles that will be damaged based on damage data from past storms. Results indicated that hurricane-related damages to the poles can be predicted in an accurate manner, given that past damage data are available and adequate. However, the availability of past data could be a challenging issue which limits the model practicality. Reference [27] compared the regression methods and data mining techniques for predicting power outage durations during hurricanes. The accuracy of Bayesian additive regression trees (BART) outperformed the other models in their study. In [28], an outage-forecasting model which is able to accurately estimate the hurricane-induced outages using fewer number of input variables was proposed. The power outage duration models and the key variables along with their degree of influence on predicting hurricane-induced outage durations were proposed in [29]. The development of a hurricane power outage prediction model for U.S. coastlines using publicly available data was proposed by [30]. The application of the model for Hurricane Sandy was demonstrated, and the impacts of some historic storms on U.S. energy infrastructure were analyzed.

4) RESOURCE ALLOCATION

In this context, [31] presented three mathematical goal programming models for locating the repair units and restoring the transmission and distribution lines in an efficient manner. The first model can find the optimal repair-unit dispatch tactical plan with a forecast of adverse weather conditions. The second model is able to derive the optimal repair-unit location for a short-term strategic plan under normal weather conditions. The third model finds the optimal number of repair units for a long-term strategic plan. A mixed-integer programming model and a general column-generation approach for inventory decision making of power system components throughout a populated area in order to maximize the amount of power served after disaster restoration was proposed in [32]. In [33], the service restoration considering the restrictions on emergency-response logistics was studied with the objective of minimizing the customers interruption cost. The reconfiguration and the resource dispatching issues were considered in a systematic way for deriving the optimal time sequence in every step of the restoration plan. In [34], a decision-making model to manage the required resources for economic power restoration operation was proposed. The optimal number of depots, the optimal location of depots, and the optimal number of repair crews were determined by their model in order to minimize the transportation cost associated with restoration operation. In [35], a decision support tool for improvement of information used by electric utilities for managing restoration of power distribution components damaged due to large-scale storms was described. The circuit layout, the placement of protective and switching devices, and the location of customers were taken into account to allocate the crew resources to manage the storm outage in a cost-effective manner.

B. CONTRIBUTIONS

Although variety of problems for electric power grid recovery in natural disasters events have been addressed in the literature, few provide a comprehensive and generic approach for resource allocation which simultaneously considers the physics of the power grid along with the economic aspects of the power system. In our previous work [36], we proposed a post-hurricane restoration scheduling model for a restructured electricity market using mixed-integer programming. In [37], we proposed a proactive pre-hurricane restoration and resource planning model using a two-stage stochastic program with recourse. In [38], we used stochastic dynamic programming to model a dynamic asset management strategy for power systems under hurricane effects.

The existing literature studies the power systems under extreme weather events and natural disasters from a specific standpoint. However, a generic and comprehensive model is still required which not only accurately model each part of the problem, but also efficiently coordinate these parts. The effect of natural disasters on the electric power grid as one of critical lifeline systems from one side, and the lack of enough research work to keep pace with the increasing trend of such disasters, provide momentous drivers for enhancing research in this area of study. This paper investigates the issue from a new and generic perspective, and accordingly, will provide viable models for enhancing power grid recovery and emergency response planning in natural disasters, particularly hurricanes.

The rest of the paper is organized as follows. Section II outlines and develops the proactive recovery scheme by discussing its modules. Section III provides additional discussions on extending applicability of the proposed scheme, while Section IV concludes the paper.

II. MODEL DEVELOPMENT

Once the hurricane strikes and results in damage to the electric power grid infrastructure, the available crews need to be mobilized to the damage sites to repair the infrastructure and restore the system. The efficiency of this post-hurricane recovery, however, can be significantly improved if the available crews have already been mobilized to the anticipated damage sites. Therefore, the proactive scheme of the pre-hurricane recovery plan precedes the reactive scheme of post-hurricane crew mobilization model. The pre-hurricane model mobilizes available crews based on damage

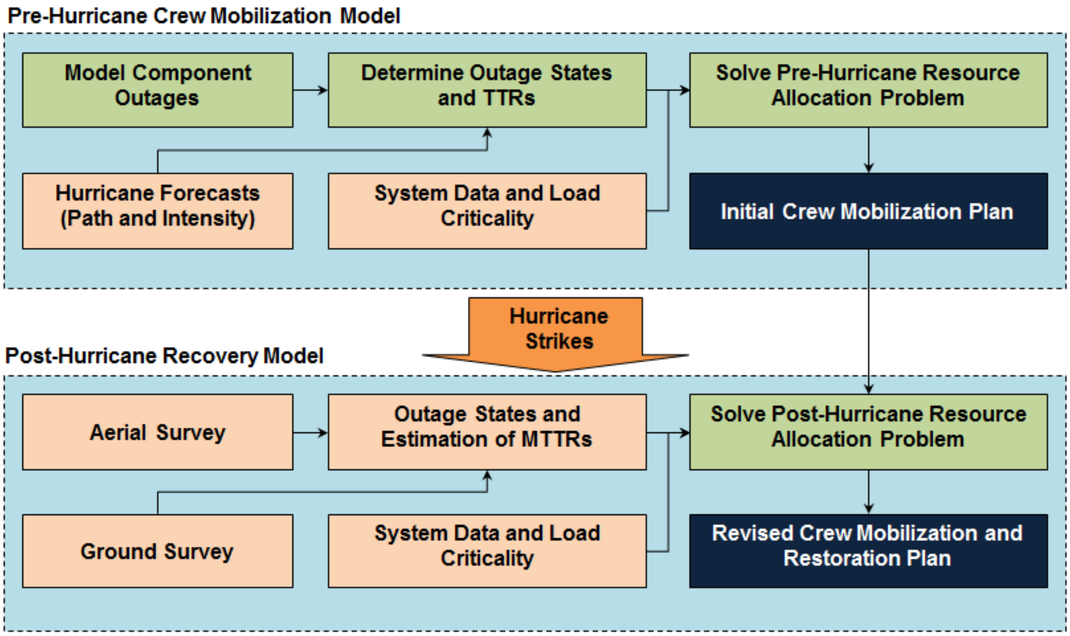

FIGURE 1. Schematic of the proposed proactive recovery scheme.

forecasts and provides an initial solution for the post-hurricane model.

Fig. 1 illustrates the proposed two-level hurricane recovery model which can significantly improve the resiliency of the electric power grid by providing a proactive strategy to cope with the aftermath of an upcoming hurricane. The first stage considers the required preparation before the hurricane, in which the hurricane is forecasted but has not yet hit the electric power grid. In this level, the reliability functions against hurricane for major components of the power infrastructure need to be developed. The weather forecasts are incorporated into the reliability functions to model the effects of upcoming hurricane and its interaction with the physical behavior of the system. Based on that, the outage state is defined as probability of failure along with a random variable which describes the time to repair (TTR) for each damaged component. Based on projected outage states and using the system data and operational characteristics, the optimal pre-hurricane crew mobilization is derived. The obtained values serve as a starting point for the second-level decision making. The second stage is performed after the hurricane in fact strikes. Using aerial inspection through various medium, e.g., satellites, helicopters, and drones, the degree of damage to the infrastructure and the routs to re-mobilize the repair crews are evaluated. Afterwards, in ground inspection, a more accurate evaluation of the damaged infrastructure along with the analysis of the data from Supervisory Control and Data Acquisition (SCADA) systems are performed. Then, the outage states and the system data are determined and set as a single scenario to solve the problem. The solution of the problem intends to provide an efficient restoration plan which considers the resource and physical constraints of the system and incorporates the economic aspects of operation. The combination of these two models introduces an efficient response and recovery scheme for addressing the problem of proactive recovery of the power grid in hurricane events.

We divide the proposed proactive recovery scheme into three distinct modules: Module 1 analyzes the component outages based on the path and the intensity of the hurricane, and develops probabilistic outage models. The outage models in Module 1 are employed in Module 2 for developing a stochastic pre-hurricane recovery and crew mobilization model. Uncertainty in component outages and time to repairs are captured via multi-stage stochastic programming approach. Module 3 introduces the post-hurricane recovery model, where it uses the solution of pre-hurricane crew mobilization as an initial solution and provides an operational recovery model for repairing the damaged components and restoring the supply of power in the minimum time and cost possible.

The proposed framework aims to address the necessary needs of the utility companies and public administrators by providing an informed decision making tool for efficient and cost-effective restoration of the system in the case of extreme weather events. The main objective is to optimize allocation of the available resources to damage sites in order to minimize the restoration cost and maximize the social welfare by incorporating the opportunity cost of interrupted loads in the decision making process.

A. MODULE 1: COMPONENT OUTAGES

Consider the electric power grid in which a subset of its components are located in the path of an upcoming hurricane.

The forecasted path and intensity of the hurricane can be obtained from weather service agencies. The obtained forecasts are used to indicate the components which are in the risk of damage. Damage models, however, are required to derive the probability and the extent of damage to each component. An accurate mathematical model for the potential damages to electric power grid components due to the hurricane is a key ingredient of an efficient response and recovery plan. Four major components are identified for damage modeling including generation units, transmission lines, distribution lines, and substations. Substations act as the connecting nodes between generation units and transmission lines, as well as between transmission lines and distribution lines. Substations include power transformers which are responsible for voltage level change in the grid and are considered as one of the critical grid components. Various models have already been proposed to the literature for modeling weather related failure rate and probability of damage of electric power grid components [25], [39]–[49]. Damage state can be considered as a random variable with two outcomes: *damaged* and *operational*. Therefore, without loss of generality, we can adopt a Bernoulli random variable for modeling the damaged/operational state of each component. We assume that the Bernoulli random variable, takes the value of 1 when the state of the component is considered operational (with probability p); and takes the value of 0, when the component is considered to be in damaged state (with probability $1 - p$). Therefore, the probability that the system survives during the hurricane time window, i.e., the reliability of the component, plays a central role to model the damage state of each component. To this end, using stress-strength analysis [50], we model the reliability function of each component against hurricane as a dynamic stress-strength model as follows

$$R(\tau) = \sum_{m=0}^{\infty} P\Big\{G_1 < G_1^{'}, G_2 < G_2^{'}, \ldots, G_{N(\tau)} < G_{N(\tau)}^{'},\ |N(\tau) = m\Big\} P\Big(N(\tau) = m\Big), \quad (1)$$

where τ is the time window of upcoming hurricane, $R(\tau)$ is the reliability function, G_i is the outcome of the ith random wind shock from the wind gust speed random variable denoted by G, $G_i^{'}$ is the outcome of the random strength of the component against the ith wind gust denoted by $G^{'}$ (i.e., a random variable for the maximum wind gust speed that the component can withstand), and $N(\tau)$ is the number of hurricane strikes during time window τ. As shown, the total joint probability of the withstanding against wind gust speeds, conditioned on the number of wind gust shocks forms the reliability function of the component. Poisson distribution can be used to model the arrival rates of the wind shocks during the time window of each upcoming hurricane. By plugging in the Poisson distribution into (1), the generalized reliability function for each component can be written as follows

$$\begin{aligned} R(\tau) &= P\Big(N(\tau) = 0\Big) \\ &\quad + \sum_{m=1}^{\infty} \Big[P\Big(G < G^{'}\Big)\Big]^m P\Big(N(\tau) = m\Big) \\ &= \sum_{m=0}^{\infty} \Big[P\Big(G < G^{'}\Big)\Big]^m \frac{\exp\Big(-\lambda\tau\Big)\Big[\lambda\tau\Big]^m}{m!} \\ &= \exp\Big[\lambda\tau\Big(P\Big(G < G^{'}\Big) - 1\Big)\Big], \end{aligned} \quad (2)$$

where λ is the mean of the Poisson distribution, i.e., the average hurricane arrival rate during time window τ. The value of λ can be set based on the historical data. In addition, based on structural and geographical characteristics of each component, appropriate random variables need to be used for G and $G^{'}$ in order to derive a customized reliability function for each major component of the grid, using generalized reliability function (2). The flexibility of the proposed model enables the use of any other existing damage distribution function in a similar way.

When a component of the electricity grid goes offline due to a damage by hurricane, enough crews are required ro be allocated to repair the component. The time to repair for each damaged component is stochastic in its nature. In [27], it was shown that the repair time is not only a function of the number of crews, but also other factors, e.g., geographical characteristics of the area that limit crews access can affect the repair time. On the other hand, because of the variation in skill level of the repair crew along with the random nature of the degree of damage, the time to repair need to be considered as a random variable. It can be modeled by a random variable and may take various probability distributions. Random variables TTR_b, TTR_i, and TTR_l correspond to time to repair for bus b, generation unit i, and transmission line l, respectively. The probability distributions most often used to model the time to repair are the Exponential, Gamma, Normal, Weibull, and Lognormal [51]. Because of its flexibility, without loss of generality, the time to repair can be modeled as a Weibull random variable as follows

$$f_{TTR_x}(t) = \begin{cases} \frac{\rho_x}{\lambda_x}\left(\frac{t}{\lambda_x}\right)^{\rho_x - 1} e^{-(t/\lambda_x)^{\rho_x}} & \text{if } t \geq 0, \\ 0 \quad \text{otherwise}, \end{cases} \quad (3)$$

where ρ_x is the shape parameter, λ_x is the scale parameter, and $x \in \{b, i, l\}$. Therefore, the outage models help to determine two important pieces of information which will be used in the pre-hurricane model: operating state of each component, and the required time to repair of damaged components.

In order to reduce the complexity, and improve the computational efficiency, the mean time to repair (MTTR) can be used as a reliable substitute for time to repair. The MTTR is defined as the expected value of the time to repair random variable. It is considered as the time required to fully repair a damaged component, or to replace in cases of complete damage, in order to bring the component to the operational state. In the context of scientific management, the time to repair can be modeled with *man-hour* unit which is defined as the amount of work performed by an average worker during one hour [52]. The higher number of crews allocated per hour can result in shorter repair time for the damaged component. However, in this relationship, there is a saturation point in which allocation of more repair crews per hour would not make the repair process any faster. Moreover, there is a minimum number of required crews to repair a damaged component. This relationship is illustrated in Fig. 2. Note that this relationship can vary from one component to another. These pieces of information can be obtained from historical and human resource data of the electric utility company. For a case study on this Module readers are referred to [38].

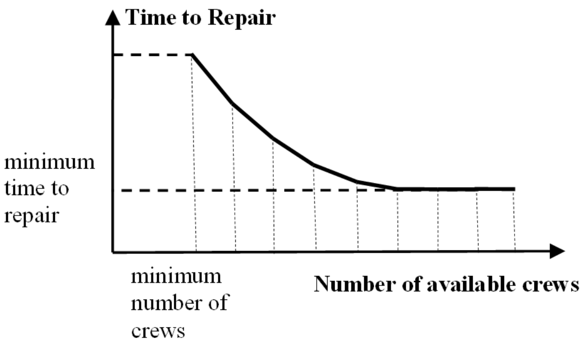

FIGURE 2. Time to repair as a function of number of allocated crews per hour.

B. MODULE 2: PRE-HURRICANE CREW MOBILIZATION MODEL

Once the stochastic damage state of each component in the hurricane path and the associated time to repairs are determined, the pre-hurricane crew mobilization model is solved using prevailing input data. The objective of the pre-hurricane crew mobilization model is to proactively allocate and mobilize the resources in order to enable a quick response capability to repair potential damages to electric power grid components in a way that minimizes the expected system costs, by considering various scenarios for hurricane strikes. The expected costs include the crew cost, the power outage cost, and the power generation cost. The crew cost includes the cost of mobilizing and compensating crews for the repair and restoration process. The crew cost depends on the number of personnel required at the damage site, and the wage of each individual crew. This cost is a function of time which could be adjusted to consider different wages and man-hours for different working shifts. The expected outage cost is modeled as the value of lost load (VOLL), times the amount of power outage. From economic point of view, VOLL is considered as an opportunity cost which is defined as the average amount of money that each type of customer (e.g., residential, commercial, or industrial) is willing to pay for each MWh in order to avoid load interruption [54]. VOLL represents the criticality of loads to be supplied, in which more critical loads, such as hospital and water treatment facilities, have a higher VOLL, and therefore, must be restored and supplied with a higher priority. The expected outage cost considers all load buses in the grid. There is an extensive study in the literature on calculating VOLL for variety of loads and accordingly monetizing power outages [53]–[57].

The proposed representation of power outages ensures that crews are mobilized and allocated to repair and restore damaged components with an emphasis on priority of supplying more critical loads. The proposed objective significantly expedites the supply of prioritized loads, and thus, considerably improves electric power grid reliability and reduces economic losses. Furthermore, the objective is to prioritize large power outages, mostly occurred in densely populated areas. The objective, moreover, includes to minimize expected generation cost. The expected generation cost plays an important role in the repair and recovery process, as more economic generation units has to be repaired with a higher priority to prevent the commitment of uneconomical units. Moreover, it assigns a higher priority to the transmission lines and substations connected to more economic generation units.

The pre-hurricane crew mobilization model is subject to uncertain outage states which stem from uncertain hurricane path and intensity forecasts as described in Module 1. Since the problem is subject to uncertainties and the exact value of outage and generation costs cannot be determined, the expected value of these terms must be included in the objective. Thus, the objective will consist of certain and uncertain parts. The certain part minimizes the primary allocation of crews to damage sites by minimizing the crew cost, and the uncertain part minimizes the expected outage costs, the expected generation outage costs, and the expected cost of secondary allocation of the crews which have not been allocated beforehand due to uncertain nature of the forecasts. A two-stage stochastic program with recourse is employed to model the objective function as follows:

$$\begin{aligned}
\min_{u_i,u_b,u_l} & \sum_t \sum_i C_{it} R_i^{min} u_{it} \\
& + \sum_t \sum_b C_{bt} R_b^{min} u_{bt} + \sum_t \sum_l C_{lt} R_l^{min} u_{lt} \\
& + \mathbb{E}_S \Bigg[\min_{LI,I,P,SU,SD,X_l^+,X_b^+} \sum_t \sum_b VOLL_{bt} LI_{bts} \\
& \quad + \sum_t \sum_i \left(C_{it}^g I_{its} P_{its} + SU_{its} + SD_{its} \right) \\
& \quad + \sum_i \sum_t q_{it}^+ X_{its}^+ + \sum_l \sum_t q_{lt}^+ X_{lts}^+ \\
& \quad + \sum_b \sum_t q_{bt}^+ X_{bts}^+ \Bigg],
\end{aligned} \tag{4}$$

where i, b, l, and t are indices for generation units, substations, transmission lines, and time, respectively; C_{xt} is the hourly crew cost per person for component x at time t, C_{it}^g is the generation cost of unit i at time t, $VOLL_{bt}$ is the value of lost load at bus b at time t, q_{xt}^+ is the second-stage cost coefficient of resource allocation to component x,

u_{xt} is the binary variable which represents the restoration resource allocation status to component x at time t (it takes value of 1, if the required resources for restoration of component x is seized during time t; otherwise, it takes value of 0), X^{+}_{xts} is the binary recourse variable for second-stage resource allocation to component x at time t in scenario s of outage state, P_{it} is the real power generation variable for unit i at time t, I_{it} is the unit commitment binary variable for unit i at time t, SU_{it} is the startup cost variable of unit i at time t, SD_{it} is the shutdown cost variable of unit i at time t, and LI_{bt} is the load interruption variable in bus b at time t. The expected value operator represents the expected second-stage (recourse) function, where the first term in the expected value operator is the opportunity cost of load interruption over the restoration planning horizon, and the second term is the total generation cost including fuel costs, the startup costs and the shutdown costs of generating units under scenario s. This term is linearized by replacing $I_{its}P_{its}$ with a new variable, say F_{its} along with the pertinent linearization constraints.

An important constraint which needs to be considered is the inclusion of hazard zones. Although crews are sent to the potential damage sites to quickly repair the damaged components after the hurricane, they must be housed in safe shelters which are sufficiently far from hazard zones to be protected against any high risk condition during the course of the hurricane. This process is currently employed in several utilities across the United States in which employees must reside near forecasted event locations to perform their assigned duties after extreme events. Hazard zones will be determined based on the forecasted information on hurricane path and intensity.

The proposed pre-hurricane crew mobilization problem is solved to determine the time, and the number of crews which need to be mobilized to the potential damage sites. The solution would help the grid operator to ensure that available crews are mobilized in a timely and cost-effective manner with the aim of restoring the power grid in minimum period of time and minimum total restoration cost. Fig. 3 shows a simple electric power grid to help to understand the underlying impacts of hurricanes. Hurricane has damaged the components in its path, including generation unit G_1, lines L_1, L_2, and L_3, and substations B_1 and B_4. The other line in the hurricane path is not damaged and is still operational. After solving the pre-hurricane crew mobilization model, the available repair crews are mobilized to strategic locations in the power grid as shown. For a detailed case study on Module 2, readers are referred to [37].

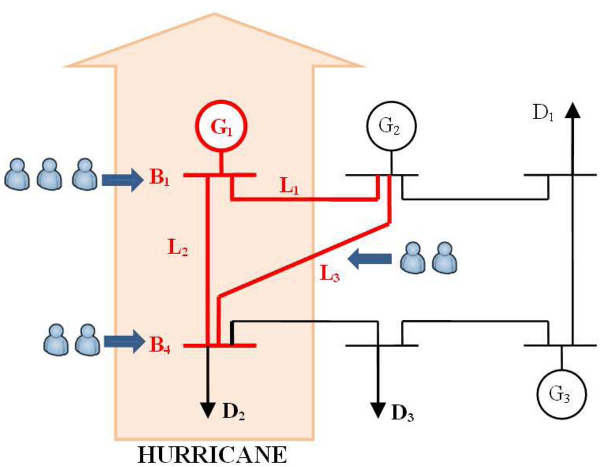

FIGURE 3. Simple example of pre-hurricane crew mobilization.

C. MODULE 3: POST-HURRICANE RECOVERY MODEL

After the hurricane, the grid operator conducts a damage assessment by an aerial survey of the power network in the affected areas as well as a ground check by inspectors [58]. The post-hurricane recovery model determines the optimal number, time, and location of crews to be available at each damage site, as well as the duration of each repair. The proposed model provides a systematic way to dynamically schedule and mobilize crews from one damage site to another, while critical loads are considered to be supplied first. Damage assessment determines whether a component has damaged at all, and if damaged, estimates the required time to repair and restore the component. For locally controlled and operated components, such as generation units, the data on the damage and time to repair will be determined by the local operator to be sent to the grid operator. Similar to the pre-hurricane crew mobilization model, two states are considered for each component: *damaged* and *operational*. However, in contrast to the pre-hurricane crew mobilization model, the outage states are not obtained based on forecasts, and are certain.

After determining the damage state of each component, repair crews will be allocated to repair the damaged components, i.e., the initially obtained plan will be revised. Similar to the pre-hurricane model, the objective of the post-hurricane recovery model is defined as the crew cost plus the outage and generation costs. Since, the cost of spare parts and physical components to repair the infrastructure is constant, it can be eliminated from objective function. The objective spans over a longer time period, equal to the maximum time required to completely repair the grid and restore the power supply. The time horizon must be considered as a relatively long period in range of few weeks to incorporate the repair of all components. Despite the pre-hurricane crew mobilization model, the model proposed here is not stochastic since all parameters are known to the grid operator. The post-hurricane recovery model employs the solution of the pre-hurricane crew mobilization model as a starting point, and accordingly revises the resource allocation solution based on the actual obtained data. The objective is to reallocate the resources in order to enable a quick repair and restoration of incurred damages to the electric power grid components in a way that minimizes the expected system costs, after the hurricane hits the power grid.

Both pre-hurricane and post-hurricane problems are subject to resource limitation and physical constraints imposed by the network. These constraints will be accurately modeled for ensuring practicality and enhancing applicability to grid operations. The mixed-integer linear programming can be employed to model the constraints, which will ensure model efficiency and scalability, as well as capability to be solved by commercial solvers. The number of available crews to repair damaged components is limited in each scheduling hour. The resource constraint is added to the models to limit the number of crews to be mobilized during each time period. The physics of the power grid also imposes several constraints to the problem, such as the load balance constraint, generation capacity limits, and power flow constraints. The bus load balance constraint ensures that the injected power to a bus from connected transmission lines and generation units plus the power outage is equal to the bus load. The generation of each generation unit is restricted by its minimum and maximum capacity limits. The power flow constraints determine the flow of power in transmission lines based on power injections [59]. The modeling of these constraints has been extensively discussed in the literature [36]. Efficient outage and repair constraints are proposed based on mixed-integer programming as an essential task in crew mobilization and recovery models developed in Modules 2 and 3. The primary model is nonlinear, but thanks to the binary variables in the model, it can be linearized. By adding linearization constraints, the problem is transformed into an inflated mixed-integer linear program. The original constraints are modeled as follows

$$P_i^{min} z_{it}^G \prod_{b\in B_G} z_{bt}^B \leq P_{it} \leq P_i^{max} z_{it}^G \prod_{b\in B_G} z_{bt}^B, \tag{5}$$

$$|PL_{lt}| \leq PL_l^{max} z_{lt}^L \prod_{b\in B_L} z_{bt}^B, \tag{6}$$

$$\left| PL_{lt} - \frac{\sum_{b\in B_L} \beta_{lb}\delta_{bt}}{x_l} \right| \leq M\Big(3 - z_{lt}^L - \sum_{b\in B_L} z_{bt}^B\Big), \tag{7}$$

$$0 \leq z_{x(t+1)} - \left(\sum_{k=1}^{t} u_{xk} - TTR_x\right)/M + \varepsilon \leq 1, \tag{8}$$

$$\sum_{k=t}^{t+TTR_x-1} u_{xk} \geq TTR_x(u_{xt} - u_{x(t-1)}), \tag{9}$$

where sets B, G, and L include system's buses, generation unites, and transmission lines, respectively. Subset B_G represents connected buses to a particular generation unit, while subset B_L represents associated buses to a particular transmission line. β_{lb} is the element of the line-bus incidence matrix. Parameters P_i^{min} and P_i^{max} are the minimum and the maximum generation capacity of unit i, respectively. Parameters PL_l^{max} and x_l are the maximum power flow capacity and the reactance of line l, respectively. TTR is the expected time to repair for a particular unit, line, or substation. Constant M is a big positive number, while constant ε is a small positive number, where $0 < \varepsilon < 1$. Binary variables z_{bt}^B, z_{it}^G, z_{lt}^L represent the outage state of substation b, unit i, and line l, at time t, respectively. Each of these binary variables takes value of 0 if the component in question is in damaged condition or still is under repair; otherwise it takes value of 1. The continuous variables PL_{lt} and δ_{bt} are the real power generation by unit i and bus voltage angle at substation b, at time t, respectively.

Equation (5) models the generation unit outage. When a generation unit is on outage, its generation must be set to zero. In addition, when the substation connecting the generation unit to the grid is on outage the generation of the unit would be set to zero. Transmission and distribution lines are out of service if the line itself or any of the substations at two sides of the line are on outage, as proposed in (6). Equation (7) is additionally imposed to the model to relax the line flow equation if any of outage states are zero. This constraint guarantees a correct representation of the second Kirchhoff's law when the line is out of service. Based on this constraint, if the line or any of its connected substations, i.e., total of three components, is on outage, the line will be on outage and the associated line flow equation must be relaxed. M in this constraint is a large positive constant which is used for relaxing (7). Outage constraints guarantee that the damaged component is on outage and the associated power generation/flow is zero. Once the repair crews arrive at the damaged site and start repairing the damaged component, the repair constraints are imposed to the model to enable restoration of the damaged component.

Equations (8) and (9) ensure that damaged components are not repaired until the repair crews are available at the damage site for at least the duration of time to repair, TTR. Once the crews are available at the damage site for the duration of time to repair, the outage state of the component would be set to 1, which means that the component is repaired and is ready to be used by the grid operator. For any extent of time during the scheduling horizon that crews are at the damage site for duration of time less than the time to repair, the outage state will remain zero, therefore, the component will be out of service. Note that in Module 2, the initial damage state of each component x, i.e., z_{x0} is considered as a random variable. Therefore the system in Module 2 is restricted to a set of chance constraints. For a case study for deregulated power market using Module 3 readers are referred to [36].

III. ADDITIONAL DISCUSSIONS

A. INTEGRATION OF SMART GRID TECHNOLOGIES IN GRID RESPONSE AND RECOVERY

Recent rapid changes in electric power grids by large-scale deployment of measurement and monitoring devices and by integration of information and communication technologies, has made the case to evolve to a more intelligent and responsive electric power grid. These changes, which are taking place under the umbrella of *smart grid*, enable a distributed and more intelligent decision making process in the control and operation of the electric power grid to enhance power grids economy, reliability, sustainability, and resiliency. As a promising technology, smart grids are anticipated to promote the self-healing capability of the power grid, in which the grid could intelligently respond to undesirable and unplanned events in order to minimize system impacts and power outages, and return to normal operating state in a reasonable amount of time. As extension to the proposed recovery model, it is important to consider the impacts of smart grid technologies on grid recovery in response to hurricane events and other natural disasters. Two major issues should be studied in detail: demand-side management and adaptive topology control. Through demand-side management, electricity customers are able to respond to electricity price variations and financial incentives to efficiently adjust their energy consumption profile. This goal can be achieved using demand response schemes (i.e., to partially curtail less sensitive loads or shift adjustable loads to other operating hours), or deploying distributed energy resources (such as local generation units or energy storage systems). By revising the consumption profile, the amount of power outage will be significantly lowered at customers premises. Subsequently, the transmission and distribution network usage by these customers will be reduced. Therefore, more room for grid operator is provided to reroute the flow of power and supply other customers during normal grid operation as well as emergencies. Adaptive topology control is also a very efficient method in rerouting the flow of power in distribution and transmission networks, and accordingly reducing the power outages, by switching specific transmission and distribution components off. The integration of smart switches with a capability of fast acting as well as communication with other switches, phasor measurement units with a capability of high resolution data measurement and transfer, and high reliability distribution networks based on loop connection, have facilitated the utilization of adaptive topology control schemes for the electric power grid operation and control.

B. IMPACT OF POWER SYSTEM DEREGULATION

In the proposed proactive recovery scheme all grid components are centrally operated by a grid operator. This is the case for regulated power systems with a vertically integrated architecture [60]. However, the deregulation of power systems, which started in 1990s and was adopted by several power systems in the United States and all over the world, restructures the power system architecture by decomposing different sectors. Under this architecture, various sectors of the power system, including generation, transmission, and distribution, are owned and operated by different entities. This privatized architecture enhances competition among different market players, particularly in the generation sector, which results in lower electricity prices and improved reliability. The physical operation and control of transmission and distribution networks under the market environment is performed by an electric utility company. The electric utility company is also responsible for maintenance and upgrade of the local transmission and distribution infrastructure, including the planning for extreme weather events. Under the market environment, electric utilities do not have the generation data, as it is submitted by generation companies to the market operator. Since all the required data to perform proposed proactive recovery scheme are not available to a single entity, a coordination scheme is required to transfer the nonproprietary data among these entities and accordingly enable an efficient hurricane recovery. In this case, the proposed models will need to be further revised and extended to consider the impact of deregulation, in which coordination among several entities is required. This modification ensures that the proposed models will be applicable to all power grids independent of their structure.

IV. CONCLUSION

This paper investigated the development of a comprehensive framework and the supporting theory for increasing resiliency of the critical electric power grid infrastructure in response to hurricanes and other natural disasters. The aim is to expedite the recovery process and minimize the associated economic, social, and physical disruptions. The proposed proactive recovery model can result in profound impacts on local and national energy security, reliability, and sustainability by promoting the sound development of advanced techniques related to extreme weather events and natural disasters which are identified as the second cause of the largest blackouts in the United States. A successful implementation of the proposed model will directly impact the society through helping electric power grid operators to better manage the available resources, and minimize the aftermath of hurricanes and other natural disasters, and accordingly saving billions of dollars in electric power grid outage and recovery related costs.

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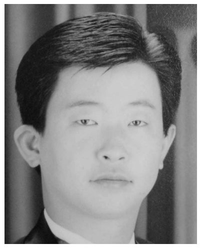

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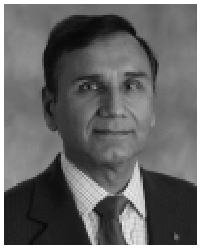

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