# A Parallel Fast-Track Service Restoration Strategy Relying on Sectionalized Interdependent Power-Gas Distribution Systems

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# A Parallel Fast-Track Service Restoration Strategy Relying on Sectionalized Interdependent Power-Gas Distribution Systems

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***Abstract*—In the distribution networks, catastrophic events especially those caused by natural disasters can result in extensive damage that ordinarily needs a wide range of components to be repaired for keeping the lights on. Since the recovery of system is not technically feasible before making compulsory repairs, the predictive scheduling of available repair crews and black start resources not only minimizes the customer downtime but also speeds up the restoration process. To do so, this paper proposes a novel three-stage buildup restoration planning strategy to combine and coordinate repair crew dispatch problem for the interdependent power and natural gas systems with the primary objective of resiliency enhancement. In the proposed model, the system is sectionalized into autonomous subsystems (i.e., microgrid) with multiple energy resources, and then concurrently restored in parallel considering cold load pick-up conditions. Besides, topology refurbishment and intentional microgrid islanding along with energy storages are applied as remedial actions to further improve the resilience of interdependent systems while unpredicted uncertainties are addressed through stochastic/IGDT method. The theoretical and practical implications of the proposed framework push the research frontier of distribution restoration schemes, while its flexibility and generality support application to various extreme weather incidents.**

***Index Terms*—Distribution System Restoration, Repair Crew Routing, Resiliency, Interdependent Energy System.**

## I. Introduction

### A. Concepts

Concerns over the dramatic rise in weather-related incidents have further increased global attention to the resilience of modern power systems [1]. This becomes even more complicated with high infiltration of *low-inertia* renewable sources (RES) since they bring significant uncertainty and variability into the system and therefore, threaten the strength and stability of the power systems [2]. Despite all efforts performed to maintain the power system performance in emergency situations, widespread blackouts are often unavoidable because of cascading failures. Therefore, the resilience of systems against disturbances is highly dependent on their ability to restore services quickly after a large-area blackout.

The power system restoration (PSR) following a partial or complete collapse is indeed an extremely complicated process, involving multiple variables and steps (i.e., dispatch repair crews, re-establish the generation and transmission systems, pick up loads and bringing the system back to normal) and highly combinatorial operational and technical decisions, which make the restoration scheduling an exponentially challenging task for operators [3]. It should be mentioned that it is not possible to define a generic restoration strategy for all structures without some degree of customization, because the characteristics and conditions of the power networks are often different from each other.

As the interdependency between the power systems and natural gas grids grows gradually (by utilization of *power-to-gas* (P2G) technology or gas-fired DGs), the roles of their coordination in post-disaster restoration scheduling is undeniable to improve the power system resilience. The main reason behind this integration is that energy systems with different spatial and temporal conditions, can give a more favorable response to unforeseen events if connected to each other [4]. In doing so, this paper aims to develop a generic restoration strategy for integrated power-gas distribution systems to reinforce the resilience of the whole system against high-impact low-probability (HILP) natural-related hazards. The propounded strategy is a fast-track *buildup* restoration planning based on sectionalizing into supply-sufficient microgrids ($\mu$G) with energy resources and autonomously restoring each section in parallel considering cold load pickup condition (CLPU). The model establishes an effective toolbox to aid the operators in restoration planning and on-line system recovery guidance.

### B. Literature Review

The restoration scheduling is a sophisticated problem that seeks the secure return of the bulk power system as rapidly as possible to its desirable operating conditions aimed at minimizing economic losses as well as restoration time. Indeed, the rapid system recovery after a widespread blackout is of vital significance to improve the resilience of power systems. In recent years, many works have extensively focused on providing different restoration strategies to improve the resilience of power networks [5]-[14]. Ref. [5] has summed up an overview of the pre-and post-event methods used to distribution system restoration. For convenience, in the literature the restoration planning is broken up into three main categories [6],[7]: *i*) system preparation (including system status diagnosing, black-start power cranking, critical load assigning, and choosing restoration strategy); *ii*) network restoration (comprising system sectionalization, feeder energization, and system reintegration); and *iii*) load recovery (consisting critical load restoring, load pickup scheduling, and system synchronization).

By and large, the proactive strategies available in the literature for restoration of distribution networks could be nearly divided into two main groups: centralized models and decentralized models. Several centralized restoration strategies have been developed in the prior references [8]-[10], which their basic core is based on step-by-step decision-making through situational awareness and wide-area measurement systems. For example, Arab *et al*. [8] proposed a stochastic cost-effective model for resource allocation to apply the repairs required for proper restoration of infrastructure. In [9], a two-stage program is presented in which the first stage determines repair crew routing for outages while executing system restoration by DGs in the second stage. A two-stage hierarchical load restoration framework is reported in [10] on the basis of synchrophasors that optimally specifies the size and site of load pickups in a time-efficient manner.

Contrary to the centralized models, which mainly emphasize on hierarchical restoration of whole system, the decentralized methods endeavor to split the network into a set of small-scale zones and then simultaneously recover them in parallel. In particular, Ref. [11] has proposed a multi-time step service restoration model by optimal dispatch of controllable switches, energy storages, and DG units in order to minimize the curtailed load considering inter-temporal constraints of resources and CLPU conditions. For the sake of convexity, a mixed-integer second-order cone programming is outlined in [12] to optimize the process of critical load restoration through the formation of $\mu$G and benefiting from grid modernization. In [13], a post-hurricane plan for distribution grid restoration has been extended based on networked $\mu$Gs. In this paper, the Dijkstra's algorithm has been utilized to find the shortest path for delivering mobile emergency resources and uncertainties are also taken into account by unscented transform approach. This paper presents an advanced feeder restoration method to restore critical loads using distributed energy resources (DERs). Authors in [14] have introduced a joint optimization problem that not only maximizes the amount of restored load, but also minimizes the restoration time. In this paper, tie-switches are employed to reconfigure the topology of system in order to change the power flow path and provide opportunities for restoring critical loads.

The use of new cutting-edge technologies can play an effective role in increasing the efficiency of recovery schemes. For this purpose, Ref. [15] presented a post-disaster restoration approach along with dispatching of fast-charge electric buses to not only maximize the resilience of the system, but also to minimize the electric buses rental cost. The authors in [16] have developed an expansion planning model relying on deep reinforcement learning to reinforce the resilience of distribution systems using hardening strategies. A restoration framework based on distributed energy resources is also reported in [17] to restore the critical loads that is done by shortest path method. Jiang, *et al* [18] have proposed a service restoration scheme via reconfiguration, mobile resources, and repair crew to minimize the load curtailment. Besides, Ref. [19] examined a graph-reinforcement learning technique to link the power system topology with a graph convolutional network, which captures the complex mechanism of network restoration in power networks and understands the mutual interactions among controllable devices.

Although there is rich scientific literature in the field of PSR, the impact of other energy grids such as natural-gas network on the recovery of power systems has not been thoroughly evaluated [9]-[10],[12]-[13]. Apart from this, previous articles have mainly used simplistic and inconsistent indices (like those suggested for reliability assessment studies) to measure the effectiveness and performance of restoration approaches to improve resilience, which cannot properly characterize the multidimensional behavior of the power systems in critical situations. For example, value of loss of load [8], expected energy not supplied [9], curtailed critical load [12], and unrecovered load points [14] have been frequently employed to measure the resilience of power system, while these indicators cannot give a proper understanding about the robustness and adequacy of system against extreme events.

### C. Discussion and Contributions

Although the extreme weather-related events are unlikely to occur and cannot be exactly forecasted (they are indeed "*Black Swan*"), the severity of their harmful effects, especially in the low-inertia power systems, necessitates the development of an effective plan to restore the system as quickly as possible after their occurrence. Even though there are valuable works that have been done on the restoration of distribution networks, however, there are still important questions that need to be addressed. The first question that arises is *how to correctly quantify the resilience of distribution networks and what the desired resilience should be*? Besides, the second question that this article seeks to answer is *how to exploit the potential capabilities of the natural gas network to improve the restoration process of power networks*?

In this outlook, this paper attempts to give convincing solutions to the questions by developing a novel tri-level buildup restoration strategy in which the first level dispatches the repair crew routing (preventive actions); the second level performs the remedial actions to recover the system to normal state (corrective actions), and the third level tends to restore critical loads under CLPU. Concisely, this work appends four main contributions to the literature as:

- It quantifies the resilience of system to facilitate the restoration process. The proposed scalable indices measure the rapidity and *resourcefulness* of system facing with extreme events.
- It specifies how the repair crews can be organized to properly manage the resources before the approaching event.
- It also determines the best restoration strategy according to system features to apply various remedial actions after the event considering overcurrent CLPU condition.
- It considers the severe uncertainty of the problem by executing a creative technique so called hybrid stochastic/IGDT method to achieve more conservative and realistic results

### D. Paper Organization

In the continuation of this article, we will first outline an optimized framework for restoration of integrated power and gas distribution systems in Section II. In this section, we mainly focus on repair crew dispatch and system sectionalization to recover the system. After that, a hybrid stochastic/IGDT procedure is developed to refine the restoration plan to makes it practically fast-track. Subsequently, in Section III, three different case studies have been executed to verify the effectiveness of the proposed model. Finally, in Section IV, we point out the main findings and results of the proposed model and potential future research directions.

## II. Mathematical Formulation

### A. Problem Assumptions

To implement the proposed approach, some assumptions have been considered in the problem formulations that are listed here:

1) It is assumed that only renewable units and distribution feeders can be damaged due to the hurricane.
2) The gas-fired DGs and electricity-consumed compressors are in charge of coupling electricity and gas grids to each other.
3) There is a repair crew dispatch center that has access to the information of both power and gas systems and makes the repair decisions and dispatches the crews.
4) It is assumed that remotely controlled switches (RCS) have already been installed on the lines and the operator can determine whether they should be disconnected or connected.
5) There are three automatic tie switches on the network in order to change the power flow paths.
6) The power generation of gas-fired DGs is a linear function of its gas consumption [20]. This is done because the accurate gas-fired DG modelling would impose great challenge on computation efficiency and model tractability, which is not necessary for the restoration problem, where the first priority of which is to maintain the network security and return it to normal conditions.

7) The direction of gas flow is assumed to be fixed, since the structure of the gas network is usually radial [21], because the gas grids are usually operated as radial and we do not actually require that gas flow directions keep changed all day long, especially in the abnormal conditions.

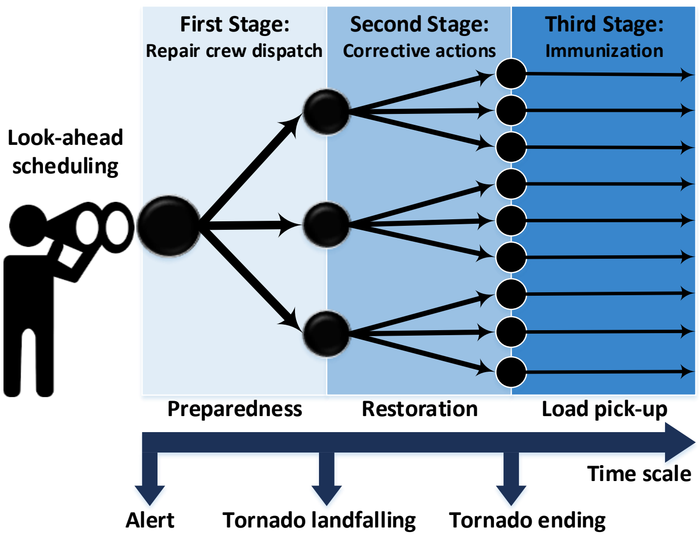



Fig. 1. The overall chronology of the tri-level restoration planning strategy.

### B. Problem Formulation

To find the solution within a reasonable amount of computational burden, the model is decomposed into three main interdependent stages including repair crew dispatch, restoration actions, and immunization (as given in Fig. 1). The first stage specifies the optimal repair crew routing, which is characterized by depots, repair crews, damaged components and paths between the damaged components. The second stage is in line with *out-of-merit* order that breaks the distribution system into a set of $\mu$Gs and then runs restoration process in parallel using available resources and network reconfiguration. In the end, the third stage pickups loads of the system and immunizes the scheduling against unpredicted uncertainties by an effective hybrid stochastic/IGDT approach. To mathematically consolidate these three stages together, a tri-level MILP formulation is adopted to maximize the picked-up loads considering CLPU conditions.

#### *B.1. First Stage: Repair Crew Routing*

This stage determines the route for the repair crews and then dispatches their best organization to rapidly repair the damaged components after the hurricane landfalls. This repair process (i.e., reconnecting a wire or replacing a pole, etc.) is modeled as the repair time in the problem.

First of all, the damaged components should be clustered to each depot for reducing the computational burden of the problem (a.1)-(a.3), and then the crews are transported from the nearest depot to the incident site to repair the damaged equipment. To do so, equation (a.1) minimizes the distance between the depots $\sigma$ and damaged equipment $d$, so that each component only can be assigned to one depot (a.2). In these equations, $s_{d,\sigma}$ is a binary variable that clusters the damaged equipment $d$ to depot $\sigma$ as (a.3).

$$\min \sum_{\forall d} \sum_{\forall \sigma} D(d,\sigma).s_{d\sigma} \tag{a.1}$$

$$c.t. \ \sum_{\forall \sigma} s_{d\sigma} = 1, \quad \forall d \in DN \tag{a.2}$$

$$s_{d\sigma} = \begin{cases} 1 & \text{if } d \text{ is clustered to } \sigma \\ 0 & \text{otherwise} \end{cases} \tag{a.3}$$

To optimally dispatch the repair crews, we used a vehicle-routing problem by introducing two binary variables $x_{d,s,c}^{\sigma}$ and $y_{d,c}^{\sigma}$ that specify whether a crew visits a node or not (a.4)-(a.5), where their relationship is given in (a.6). The proposed vehicle-routing problem has some constraints [22] such as each damaged component only can be visited by one crew (a.7), flow conservation (a.8)-(a.9), and subtour elimination (a.10). To prevent subtours formation in the routs, a dummy variable $\varphi$ is incorporated into (a.10) representing the order of the corresponding node in the route.

$$x_{dsc}^{\sigma} = \begin{cases} 1 & \text{if crew } c \text{ travels from } d \text{ to } s \\ 0 & \text{otherwise} \end{cases} \quad d,s,c \in DN \tag{a.4}$$

$$y_{dc}^{\sigma} = \begin{cases} 1 & \text{if crew } c \text{ travels through } d \\ 0 & \text{otherwise} \end{cases} \quad d,c \in DN \tag{a.5}$$

$$y_{dc}^{\sigma} = \sum_{s} x_{dsc}^{\sigma}, \quad d,c \in DN, \sigma \in DP \tag{a.6}$$

$$\sum_{c} y_{dc}^{\sigma} = 1, \quad d \in DN, \sigma \in DP \tag{a.7}$$

$$\sum_{s} x_{dsc}^{\sigma} - \sum_{s} x_{sdc}^{\sigma} = 0, \quad d,s,c \in DN \tag{a.8}$$

$$\sum_{d} x_{dsc}^{\sigma} = 1, \quad d,s \in DN, \forall c \tag{a.9}$$

$$\varphi_d - \varphi_s + n\sum_{c} x_{dsc}^{\sigma} \le n-1, \quad \forall d \ne s \in DN \tag{a.10}$$

The waiting time for repair by crews is modeled linearly based on arrival time $AT_{d,c}$, repair time $RT_{d,c}$, and traveling time $TT_{d,c}$ as shown in equations (a.11)-(a.12).

$$AT_{dc} + RT_{dc} + TT_{dc} \le \left(1 - x_{dsc}^{\sigma}\right).M \tag{a.11}$$

$$0 \le AT_{dc} \le M.y_{dc}^{\sigma} \tag{a.12}$$

#### *B.2. Second Stage: Service Restoration Process*

The main idea of the proposed plan is to break up the distribution network into several independent $\mu$Gs. Sectionalization of the network allows parallel restoration, and thus increases the rapidity of the restoration process. In the service restoration stage, the black start DGs in each subsystem is restarted, feeders are energized, the priority-weighted loads are served, and after them, the grid is resynchronized. It is worth mentioning that the load restoration will be executed considering CLPU conditions.

When a fault occurs on the system, it is disconnected from the transmission network and therefore, has to meet its demand locally by its available resources. Under these situations, the main goal is to quickly and properly restore the distribution network to a normal state at the lowest possible cost. To do so, we first sectionalize the system into a few small-scale zones based on some technical properties and then recover each section in parallel. In this path, we define a unique objective function as priority-weighted load pick up (b.1) for each section that intends to maximize the recoverable load in the shortest time. The first term indicates the electrical loads recovered in this stage in which the repair time step ($\Delta t$) sets to be 10 minutes. The second term denotes the importance of rapidity in the restoration process that assures all damaged components are repaired in a time-efficient manner.

$$F = \max \sum_{w} \pi_w \sum_{t} \sum_{z} \sum_{i} \omega_i . \varsigma_{iztw} . p^{D}_{iztw} . \Delta t \\ - \gamma \sum_{w} \pi_w \sum_{t} \sum_{\sigma} \sum_{\varepsilon} \xi_t . \tau_{\varepsilon\sigma tw} \tag{b.1}$$

Eq. (b.1) is repeated for all scenarios where $\pi_w$ is the probability of each scenario; $p^{E}_{iztw}$ is the diversified electrical load at $i$th bus of section $z$, in scenario $w$ and time slot $t$; $\omega_i$ is priority weight of load at bus $i$ and $\zeta_{iztw}$ is the connection status of each load point. Also, $\gamma$ denotes the weight of repair duration, $\xi_t$ is repair duration and $\tau_{\varepsilon\sigma tw}$ is a binary variable that shows the time step at which the damaged component is repaired. It is of note that the restoration stage is performed under disjunctive and inter-temporal constraints as explained in the following.

*1) Power system modeling*

For the sake of simplicity and convergence, this paper uses an efficient linearized *DistFlow* technique [23] to compute the integrated power-gas flow problem in radial distribution systems. In the proposed model, some linearized constraints (by enforcing special-order-sets-of-type2 and big-M method) are taken into account such as nodal power equilibrium (b.2)-(b.3), branch flow limitation (b.4)-(b.6), load shedding restrictions (b.7)-(b.8), voltage constraint (b.9), and permissible DG output (b.10)-(b.11). In addition, (b.12)-(b.16) define the operational region of the ESS.

$$p^{DG}_{itw} + p^{\uparrow}_{stw} - \left( p^{L}_{jtw} + p^{\downarrow}_{stw} - p^{Shed}_{jtw} \right) = \sum_{l} p_{ltw}, \ \forall j, \forall t \tag{b.2}$$

$$q^{DG}_{it} - \left( q^{L}_{jt} - q^{Shed}_{jt} \right) = \sum_{l} q_{lt}, \ \forall j, \forall t \tag{b.3}$$

$$-M\left(1 - u\ell_{lt}\right) \le \upsilon_{it} - \upsilon_{jt} - \left( r_l p_{lt} + x_l q_{lt} \right) \le M\left(1 - u\ell_{lt}\right) \tag{b.4}$$

$$-S^{\max}_{l} . u\ell_{lt} \le p_{lt} \le S^{\max}_{l} . u\ell_{lt}, \ \ \forall \ell \in \Re, \forall t \tag{b.5}$$

$$-S^{\max}_{l} . u\ell_{lt} \le q_{l,t} \le S^{\max}_{l} . u\ell_{lt}, \ \ \forall \ell \in \Re, \forall t \tag{b.6}$$

$$0 \le p^{Shed}_{jt} \le P^{L}_{jt}, \ \ \forall j, \forall t \tag{b.7}$$

$$q^{Shed}_{jt} = p^{L}_{jt} / pf_{jt}, \ \ \forall j, \forall t \tag{b.8}$$

$$1 - \varepsilon \le v_{jt} \le 1 + \varepsilon, \ \forall j, \forall t \tag{b.9}$$

$$P^{\min}_{i}\left(1 - ug_{itw}\right) \le p^{DG}_{itw} \le \left(1 - ug_{itw}\right) P^{\max}_{i}, \ \forall i \in DG \tag{b.10}$$

$$Q^{\min}_{i}\left(1 - ug_{itw}\right) \le q^{DG}_{it} \le \left(1 - ug_{itw}\right) Q^{\max}_{i}, \ \forall i \in DG \tag{b.11}$$

$$e_{stw} = e_{s(t-1)w} + \eta^{\uparrow}_{s} p^{\uparrow}_{stw} - \eta^{\downarrow}_{s} p^{\downarrow}_{stw}, \forall s, 1 < t < \left|\mathrm{T}\right| \tag{b.12}$$

$$e_{stw} = E^{ini}_{s}, \ \ \forall s, t = 1, t = \left|\mathrm{T}\right| \tag{b.13}$$

$$0 \le p^{\uparrow}_{stw} \le x^{\uparrow}_{stw} \overline{P}^{\uparrow}_{s}, \ \forall s, \forall t, \forall w \tag{b.14}$$

$$0 \le p^{\downarrow}_{stw} \le x^{\downarrow}_{stw} \overline{P}^{\downarrow}_{s}, \ \forall s, \forall t, \forall w \tag{b.15}$$

$$0 \le e_{stw} \le \overline{E}_{s}, \ \forall s, \forall t, \forall w \tag{b.16}$$

In the formulations, subscript $i$ refers to DGs, $s$ is used for storages, $w$ is the index of scenarios, $j$ and $l$ denote the nodes and lines of power system and $t$ shows the time intervals. Accordingly, variables $p^{DG}_{itw}$, $p^{\uparrow}_{stw}$, $p^{\downarrow}_{stw}$, $p^{shed}_{jtw}$, and $p_{ltw}$ respectively, depict the power generated by DG, discharged and charged powers of storages, the load shedding and power flows at lines. Note that here variable $q$ has been used for their reactive powers. Also, $ug_{irw}$ and $x_{srw}$ are both binary variables to determine the on/off of DGs and charging mode of ESS units over the scheduling horizon.

One of the most effective steps towards rapid restoration planning is to confine the extent of the event by sectioning the network into a few islands. In the sectionalization process, two main constraints should be regarded. First, there must be a power balance between the load and generation of each section at all times and second, the network structure must remain radial due to protection schemes. The former condition is applied by the power balance equation (b.2) in each section and the latter one is satisfied by applying some restrictions so that at least one of the lines in each probable loop must be open (b.17). To this end, the probable loops and their related lines are recognized by a depth-first search approach [24] and the radiality structure is guaranteed through the minimum spanning tree method [25] as (b.18)-(b.21).

$$\sum_{\kappa} \tau_{\kappa w} \le \left|\Omega_{K(l)}\right| - 1, \ \ \kappa \in \Omega_{K(l)}, \forall l, t, w \tag{b.17}$$

$$0 \le \rho_{jj'} \le 1, \ \forall i, j \in \Omega, \ \forall t, w \tag{b.18}$$

$$\rho_{jj'} + \rho_{j'j} = \tau_{\kappa w}, \ \ \forall \kappa, t, w \tag{b.19}$$

$$\rho_{jj'} = 0, \ \forall i \in \Omega, \ \forall j \in \Omega', t, w \tag{b.20}$$

$$\sum_{j} \rho_{jj'} \le 1, \ \forall j \in \Omega, t, w \tag{b.21}$$

Where $\tau_{kw}$ specifies lines status at each route and $\Omega_{K(l)}$ shows the number of lines in each loop. To apply the spanning tree method, we defined two binary variables $\rho_{jj'}$ and $\rho_{j'j}$ that express the connection status of lines.

*2) Natural gas system modeling*

In this paper, the steady-state model of natural gas system is modeled by Weymouth which describes the relationship between gas flows and nodal pressures, so that the pipelines are passive if they do not have a compressor and those pipelines that have a compressor are assumed to be active [26]. Different constraints are taken into account for gas system modeling such as gas supply ($g^{G}_{mt}$) limits (c.1), nodal gas balance (c.2), and pipeline flow ($f_{zt}$) restrictions (c.3)-(c.12). In particular, (c.3)-(c.6) illustrate the Weymouth equations that limit the active and passive gas pipeline flows, respectively. Since in passive pipelines the gas flow direction is fixed, we can replace $\pi^2 = \mu$ in (c.7)-(c.8) and apply piecewise linearization [27] by incorporating continuous variable $\delta$ and binary variable $\eta$ in (c.9)-(c.12). Here, $uz_{zt}$ shows the on/off status of $z$th gas pipeline, $\pi_{mt}$ and $\mu_{mt}$ are nodal gas pressure and squared nodal gas pressure, respectively.

$$G^{\min}_{m} \le g^{G}_{mt} \le G^{\max}_{m}, \ \ \forall m \in G, \forall t \tag{c.1}$$

$$g^{G}_{mt} - \left( g^{L}_{mt} - g^{Shed}_{mt} \right) = \sum_{z} f_{zt}, \ \forall m \in \Omega, \forall t \tag{c.2}$$

$$\pi_{mt} \le \pi_{nt} \le \lambda_z \pi_{mt}, \ \ \forall z \in Z_{act}, \forall t \tag{c.3}$$

$$0 \le f_{zt} \le F^{\max}_{z}\left(1 - uz_{zt}\right), \ \ \forall z \in Z_{act}, \forall t \tag{c.4}$$

$$f_{zt}\left|f_{zt}\right| - \phi_z\left(\pi^2_{mt} - \pi^2_{nt}\right) = 0, \ \forall z \in Z_{ina}, \forall t \tag{c.5}$$

$$-F^{\min}_{z}\left(1 - uz_{zt}\right) \le f_{zt} \le \left(1 - uz_{zt}\right) F^{\max}_{z}, \ \ \forall z \in Z_{ina}, \forall t \tag{c.6}$$

$$f^2_{zt} - \phi_z\left(\mu_{mt} - \mu_{nt}\right) = 0, \ \ \forall z \in Z_{ina}, \forall t \tag{c.7}$$

$$0 \le f_{zt} \le F^{\max}_{z}\left(1 - uz_{zt}\right), \ \ \forall z \in Z_{ina}, \forall t \tag{c.8}$$

$$f^2_{ztl} + \sum_{k}\left( f^2_{zt(k+1)} - f^2_{ztk} \right)\delta_{ztk} - \phi_z\left(\mu_{mt} - \mu_{nt}\right), \forall Z_{ina} \tag{c.9}$$

$$f_{zt} = f_{ztl} + \sum_{k}\left( f_{zt(k+1)} - f_{ztk} \right)\delta_{ztk}, \forall z \in Z_{ina}, \forall t \tag{c.10}$$

$$\delta_{zt(k+1)} \le \eta_{ztk} \le \delta_{ztk}, \ \forall z \in Z_{ina}, \forall t, k \in \{1, 2, ..., NP\} \tag{c.11}$$

$$0 \le \delta_{z,t,k} \le 1, \quad \eta_{z,t,k} \in \{0,1\}, \ \forall z \in Z_{ina}, \forall t, \forall k \tag{c.12}$$

It is noteworthy to mention that the power system and natural gas network are coupled with each other by P2G technologies, gas-fired DGs and electricity-consumed compressors. The gas-fired DGs are seen as a gas load with coefficients $\lambda_i$ and $\theta_i$ in the respective gas node (c.13), and reciprocally the electricity-consumed compressors are seen as power load with coefficient $\xi_z$ to the respective electric node (c.14). Finally, the nodal balances for both electric and gas nodes are updated as (c.15)-(c.16) by incorporating electricity-consumed compressors and gas-fired DG units. These spatial-temporal constraints practically couple the natural gas grid to the power system.

$$g_{mtw}^{DG} = \lambda_i \, p_{itw}^{DG} + \theta_i, \ \forall i \in DG, \forall t, w \tag{c.13}$$

$$p_{jtw}^{comp} = \zeta_z f_{ztw}, \ \forall z \in Z_{act}, \forall t, w \tag{c.14}$$

$$p_{itw}^{DG} - \left( p_{jtw}^{L} + p_{jtw}^{comp} - p_{jtw}^{Shed} \right) = \sum_{l} h_{ltw}, \ \forall j, \forall t, \forall w \tag{c.15}$$

$$g_{mtw}^{G} - \left( g_{mtw}^{L} + g_{mtw}^{DG} - g_{mtw}^{Shed} \right) = \sum_{z} f_{ztw}, \ \forall m, \forall t \tag{c.16}$$

### 3) *Cold load pickup condition*

Following re-energizing the power systems due to occurrence of an extended blackout, a large electric load will be generated more than before the cut-off, because of being thermostatically controlled electrical devices [28]. This overcurrent condition, which is caused by the loss of diversity on the demand side, is known as CLPU. For accurate modeling of load behavior under CLPU condition, a multi-time steps linear model is proposed as shown in Fig. 2 that illustrates a typical delayed exponential curve. As can be deduced from this figure, the fault happens at $t_0$ and subsequently the load is restored at $t_1$ with undiversified loading factor $S_U$. After that, at timeslot $t_2$ the load decreases slowly as the diversity increases until the diversified loading factor $S_D$. Therefore, the consumption at each sampling time ($\Delta t$) can be determined by this curve.

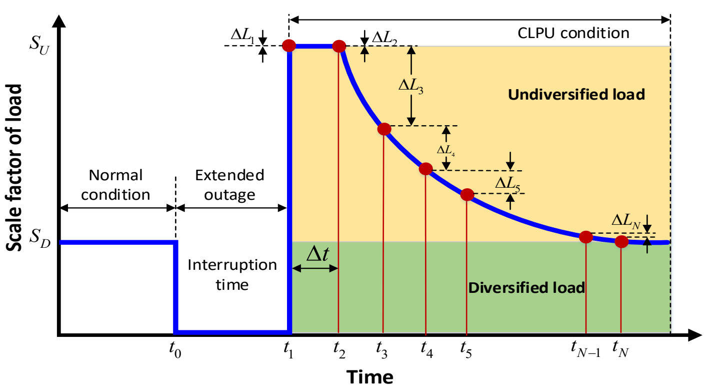



Fig. 2. The load demand under CLPU conditions [21].

In the restoration process, the load changes in two consecutive time intervals are determined by (d.1) and then the actual load demand is calculated in (d.2)-(d.4) by a delayed exponential CLPU curve as shown in Fig. 2. Finally, the CLPU load will be specified in an accumulative manner in equations (d.5)-(d.6).

$$\Delta L_l(k) = \begin{cases} 0, & k = 1 \\ L_l(k) - L_l(k-1), & 1 < k \le N \end{cases} \tag{d.1}$$

$$\begin{aligned} L_l(k) = & \left( S^D + (S_l^U - S_l^D) e^{-\alpha_l * C_{l,k}} \right) u(C_{l,k}) \\ & + S^U \left( 1 - u(C_{lk}) \right), \ 1 < k \le N \end{aligned} \tag{d.2}$$

$$C_{l,k} = (k-1)\Delta t - D_l \tag{d.3}$$

$$u(i) = \{ 1 \rightarrow \ i > 0 \ \ , \ \ 0 \rightarrow i \le 0 \} \tag{d.4}$$

$$p_{lt}^{L} = p_l^{L} \left( S^U x_{lt}^{L} - \sum_{k=1}^{t} \Delta p_l(k) x_{l(t-k+1)}^{L} \right), \forall l, \forall t \tag{d.5}$$

$$q_{lt}^{L} = q_l^{L} \left( S^U x_{lt}^{L} - \sum_{k=1}^{t} \Delta q_l(k) x_{l(t-k+1)}^{L} \right), \ \forall l, \forall t \tag{d.6}$$

### 4) *Service restoration index*

The proposed service restoration strategy must satisfy the required resilience metrics. For this reason, we have to propose effective metrics to correctly measure the resilience of the power systems. The proposed metrics can be either *attribute*-based or *performance*-based [29]. The attribute-based approaches mainly focus on providing a baseline understanding of the resilience level, while the performance-based methods are indeed quantitative metrics that measure the potential benefits and costs related to the resilience enhancement efforts. The performance of power systems from different points of view can be roughly regarded as a quantifiable nonnegative index (e.g., generation adequacy, operation security, frequency stability, and economic activities). So, the performance-based methods have more priority for cost-benefit analysis. To develop a meaningful performance-based index, we should create a tradeoff between four distinct properties: first of all its computation should be simple; it is able to provide *retrospective* and *forward-looking* analysis; it would be highly *informative*; and finally should be sorely consistent for any contingency.

Keeping these in mind, we have proposed a *time-dependent* performance-based index to measure the effectiveness of the proposed plan on the resilience and restoration of interdependent system in a rational manner. The proposed service restoration index (SRI) is on the basis of trapezoid curve of power system resilience [30]. After the incident, the system with initial performance $Q_0$ will be damaged at time $t_d$ and the severity of the damage is increased until the event is over at $t_{pe}$ (the system performance at this stage is $Q_{pe}$). Thereupon, the system prepares from $t_{pe}$ to $t_r$ in order to commence its restoration process. From time $t_r$ to $t_{pr}$, the system enters the restoration stage and employs its capabilities to recover the network as soon as possible to the acceptable state $Q_{pr}$. The proficiency of the proposed method on this system restoration cycle is measured by (e.1), which should not be less than the desired value $\Gamma^*$. The presented index is normalized for more meaningful comparison and its value can vary from 1 to 0 (i.e., 1 for maximum restoration capacity and 0 for lowest state).

$$SRI = \int_{t_d}^{t_{pr}} \frac{\left( Q(t) - Q_{pe} \right) dt}{\left( Q_0 - Q_{pe} \right) \left( t_{pr} - t_r \right)} \le \Gamma^* \tag{e.1}$$

### *B.3. Third Stage: Uncertainty Hedging*

To consider the unpredicted uncertainties that may happen during the restoration process, we proposed a hybrid stochastic/IGDT technique. This method not only reduces the computational burden of the pure scenario-based modeling, but also takes the pessimistic condition into account and tries to hedge the system against the worst possible scenario. In the presented problem, it is assumed that the start-time and end-time of the approaching storm are subject to uncertainty $\xi_t \in \{\xi_t^{srt}, \xi_t^{end}\}$, therefore the stochastic programming models the start-time deviations of the storm by constructing scenarios and the IGDT method handles its end-time variability (as presented in Fig. 1).

It is worth stating that 10-year hourly wind profiles, achieved from MERRA re-analysis [31], is used in this paper to generate the scenarios and then hourly wind profile is randomly selected for each sequential Monte Carlo simulation trial. These wind profiles are generated at different locations within each region, and then the wind profile with the maximum wind speeds that would cause the largest damage is chosen as representative for each region in order to model the "*worst-case*" scenarios that can hit the network.

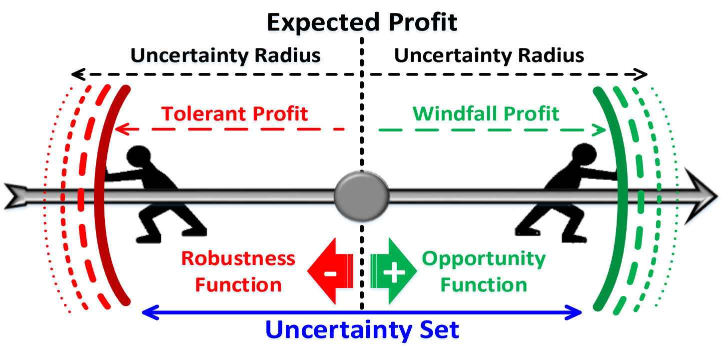



Fig. 3. The mechanism of IGDT in facing severe uncertainty [33].

First, the scenarios are generated by Monte Carlo simulation and then their number is reduced by SCENRED2 toolkit [32] in GAMS to lessen the execution time of the problem. After that, the restoration plan is run for each scenario (f.1) and the results are revised by the proposed *risk-averse* IGDT technique by means of *robustness function* (f.2). The mechanism of IGDT in facing uncertainty is depicted in Fig. 3 [33]. As can be seen, the uncertain parameter can fluctuate between two marginal values (f.3)-(f.4) with uncertainty radius $\alpha$ and this technique tends to find the maximum amount of the uncertainty radius in such a way that the minimum amount of the objective function is not less than a specified value ($F_{w}^{RA}$). It should be mentioned that the tolerant value of the objective function will be determined by operator (f.5).

$$F_{w}^{base} = \max\ F\left(\mathbf{U}, \xi_{t}^{srt}\right),\ \ \forall w \in \{1,2,...,N_{w}\} \tag{f.1}$$

$$\tilde{\alpha}\left(\mathbf{U}, F_{w}^{T}\right) = \max_{F}\left\{\alpha : \min_{\xi\in\mathbf{U}}\ F\left(\mathbf{U}, \xi_{t}^{end}\right) \geq F_{w}^{RA}\right\} \tag{f.2}$$

$$\forall \alpha \in U\left(\tilde{\xi}_{t}^{end}, \alpha\right) = \left\{\xi_{t}^{end} : \left|\frac{\xi_{t}^{end} - \tilde{\xi}_{t}^{end}}{\tilde{\xi}_{t}^{end}}\right| \leq \alpha\right\},\ \alpha \geq 0 \tag{f.3}$$

$$\tilde{\xi}_{t}^{end}\left(1-\alpha\right) \leq \xi_{t}^{end} \leq \left(1+\alpha\right)\tilde{\xi}_{t}^{end} \tag{f.4}$$

$$F_{w}^{RA} = \left(1-\beta^{RA}\right)F_{w}^{Base} \tag{f.5}$$

## III. Case Study and Numerical Results

### A. Data and Case Studies

In this section, the proposed fast-track build-upward restoration planning strategy is implemented on a modified 33 bus distribution system [34] equipped with a 12 node natural gas grid (as presented in Fig. 4) and the results are numerically verified by executing numerous case studies. The storm fragility curve of distribution lines is borrowed from [35]. The computational tasks are performed under GAMS environment, on an Intel Core i7-7200U, 2.4 GHz CPU, 12 GB RAM laptop.

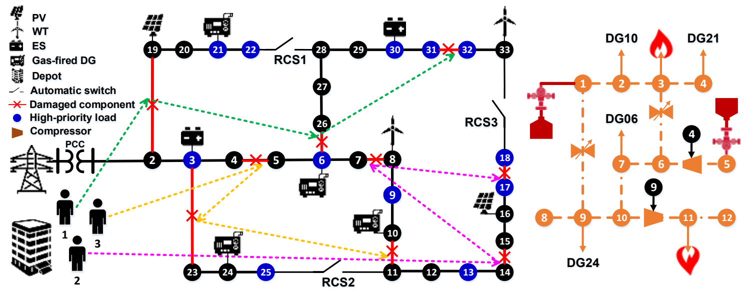



Fig. 4. Repair routing for 33-bus power system coupled with a 12-node gas grid.

In the applied 33-bus distribution system, several DERs are installed that are including four dispatchable gas-fired DG units with a maximum capacity of 300 kW for each unit, two energy storages with a maximum capacity of 250 kW for each device, two wind turbines with a capacity of 200 kW, as well as two photovoltaic modules each with a capacity of 150 kW. The technical data related to these generation units (i.e., min/max limits, ramp-up and -down constraints and minimum-up and -down time, etc.,) is taken from [36]. Moreover, three normally-open tie-switches are already allocated between the system feeders in order to change the topology of system. The priority of demands for load restoration is chosen arbitrarily. Three repair crews and one depot are available, where the travel time between damaged components ranges from 5 to 10 minutes, and the time step used in the restoration process is considered to be 10 minutes. Besides, it is assumed that the event occurs at 4 AM, whereas its start-time and end-time uncertainties are modeled by the scenarios and IGDT, respectively. The scenarios are generated through MCS process and then reduced by SCENRED2 toolkit so that 1000 random scenarios with unequal probability have been reduced to 30 most possible scenarios with higher probability.

To convincingly verify the abilities and performance of the proposed plan, we executed two distinct case studies each of which consists of two parts as follows.

- **Case I:** Standalone power system
  - A: Without sectionalization [8], [9]
  - B: With sectionalization [12], [13]
- **Case II:** Interdependent power and gas systems
  - A: Without sectionalization [20]
  - B: With sectionalization (the proposed plan)

### B. Simulation Results

To implement the proposed build-up restoration plan, three main steps are performed consecutively. The first step is to recognize the post-disaster status of system through identifying lines damaged by the storm, which is determined based on wind-affected fragility curves. If the failure probability of line exceeds its tolerance threshold, that line will be considered vulnerable against storm. The next step is to optimally determine the repair sequence of damaged lines by the repair crew. Finally, the last step will be to recover the system and loads according to their priorities.

Fig. 5 depicts the temporary response of the system to the hurricane in different cases. As can be deduced from this figure, the performance of the system when the event happens (hour 4) will be significantly reduced, so that the amount of damage depends on its robustness and redundancy. For example, the performance level in the Case II-B is 15.48% while in the Case I-A it is 58.66% which shows that the proposed method improves the network performance level by 73.61%. This increase in the performance level of the system is mainly due to the network sectioning and utilization of the gas network potentials, which raises power system flexibility.

In addition, restricting the event amplitude by sectionalization and utilization of gas network as a complementary source not only increases the response speed of power system, but also reduces its load shedding. These claims can be clearly interpreted from Table I by comparing the results of Cases I-A and II-B as two boundary cases. As can be seen, the amount of load shedding in Case I-A is 8268.75 kWh, which in Case II-B is reduced to 2580.12 kWh (a decrease of about 68.79%) while the system recovery speed was improved by 64.34% due to parallel restoration. Note that the results of Cases I-B and II-A are intermediate between these two boundary cases, so that the best case occurs when both the network sectioning and gas grid utilization are considered simultaneously.

Another important feature of the proposed build-up restoration strategy is a noticeable reduction in the execution time of the algorithm (as shown in the last column of Table I), which significantly increases the recovery speed of the distribution network. The reason for this is the use of parallel retrieval by network partitioning as well as the computational and modeling techniques such as the application of linearization methods, improved optimization algorithms and accelerated uncertainty modeling methods like hybrid stochastic/IGDT.

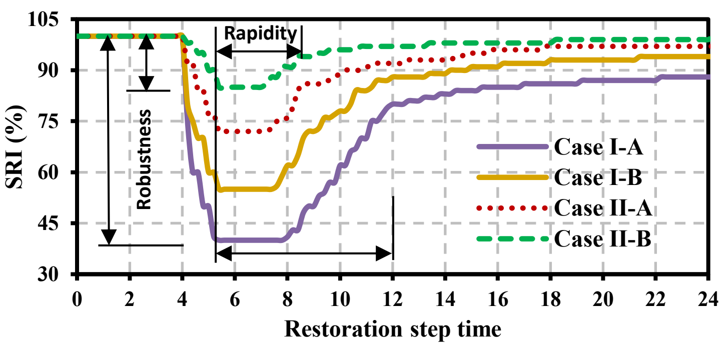


Fig. 5. Resilience trapezoid for all cases.

TABLE I
INDICES OF THE PROBLEM IN DIFFERENT CASES

| | Load shedding [kWh] | SRI value [%] | Critical load pickup [kW] | Restoration time [h] |
|---|---|---|---|---|
| Case I-A | 8268.75 | 41.337 | 375.20 | 6.45 |
| Case I-B | 6552.34 | 55.791 | 491.23 | 5.18 |
| Case II-A | 4278.91 | 71.685 | 685.04 | 4.02 |
| Case II-B | 2580.12 | 84.523 | 821.66 | 2.31 |

We should also mention that in order to improve the flexibility and network layout for load recovery, three automatic RCS are embedded between different feeders to modify network topology in the post-disaster situations. The optimal switching sequence of RCS is shown in Fig. 6. Reconfiguration by these switches in combination with network partitioning can help us find the proper network layout for fast and reliable remedial actions. Specifically, Fig. 7 shows a state of network configuration for aftermath of event, in which the network is divided into seven microgrids and the switches are closed to provide the passes to energize other feeders and transfer the cranking power to non-black-start (NBS) resources. After energizing other feeders and enabling Cranking power to NBS resources, the loads can be retrieved in their order of priority (i.e., I, II, III, and IV). The temporal and spatial sequence of load recovery is shown in Fig. 8, which is obtained based on the importance of each load point and CLPU condition.

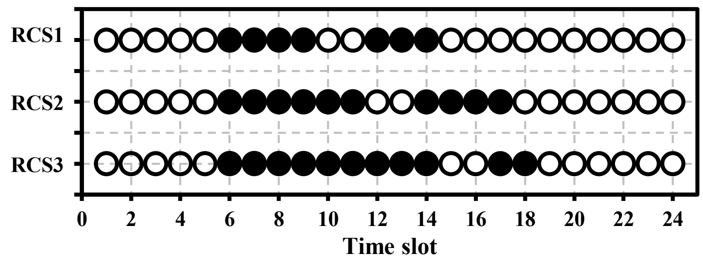


Fig. 6. ON/OFF status of RCS in the restoration process.

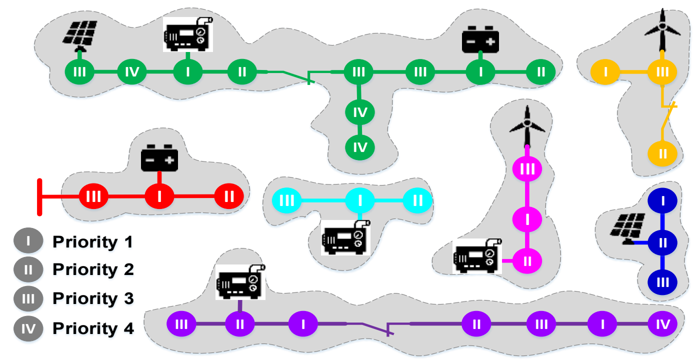


Fig. 7. Post-disaster configuration and load pickup sequence.

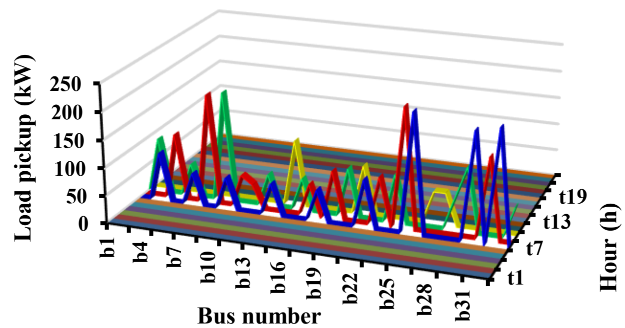


Fig. 8. Spatial and temporal sequence of load pickup in Case II-B.

The set of Figs. 9 to 11 visually illustrate the conservative production scheduling of DGs and ESS units. In particular, Fig. 9 shows the resilience-oriented unit commitment of black-start DGs, in which a part of their production is spent on energizing feeders and restarting NBS resources. Furthermore, during islanding mode these dispatchable resources are responsible for ensuring power balance and voltage control in each section. Fig. 10 displays the proactive charging/discharging schedule of ESS. As can be seen, the proposed strategy tries to maximize the amount of energy stored in the ESS units in order to increase the preparedness of the system when hurricane landfalls (i.e., hours 2 to 5). In the end, the generation of renewables is given in Fig. 11, which should be planned in such a way as to have minimum power spillage.

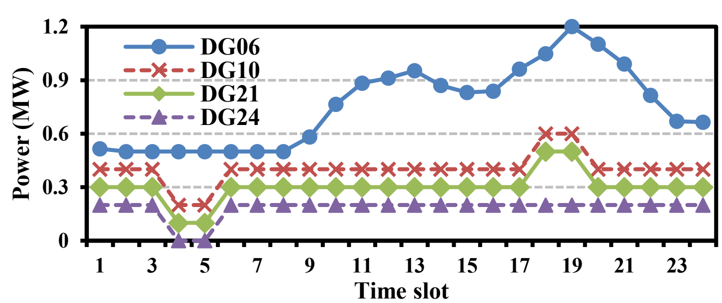
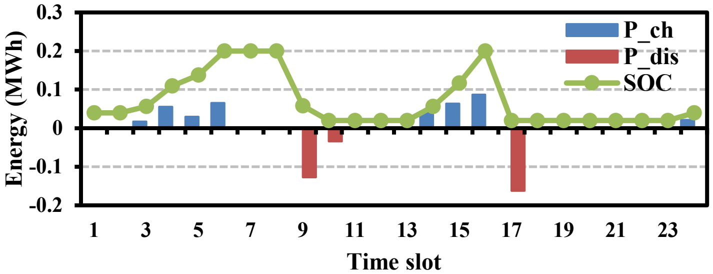
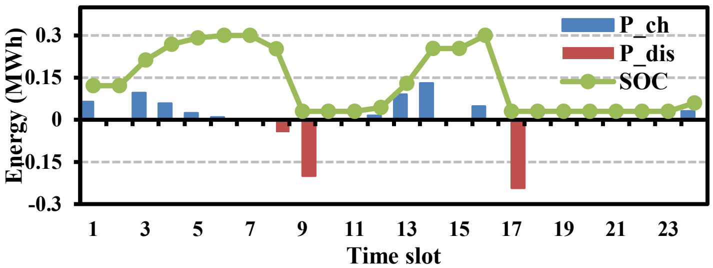


Fig. 9. Resilience-oriented gas-fired DGs unit commitment.




(a) *ES unit located at bus 3*




(b) *ES unit located at bus 30*

Fig. 10. Pre- and post-hurricane charging/discharging scheduling ES units.

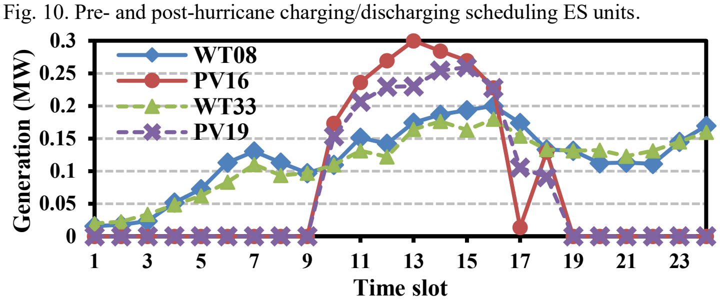



Fig. 11. Renewable generation during scheduling horizon time.

## C. Discussion

To further investigate the effect of uncertainties subject to hurricane land-falling and completion on the restoration decisions, two sensitivity analyzes were performed according to Table II and Fig. 12, which are only obtained for Case II-B. As can be deduced from Table II, the amount of load pickup in the worst-case scenario decreased by 19.93% compared to the expected value, while in the best-case scenario it shows an increase of 28.13%. Beyond that, the restoration index depicts a 15.72% drop in the pessimistic scenario compared to the expected value. These results confirm that if the occurrence time of the storm would be shorter than the predicted time, the recovery performance of the system will be decreased due to reduced readiness and the system operator will not have enough time to fully implement its preventive programs.

In order to clarify the importance of uncertainty and the effect of the proposed stochastic method on the usefulness of network retrieval, two indicators namely *expected value of perfect information* (EVPI) and *value of the stochastic solution* (VSS) have been used [37]. In this problem, the amount EVPI is 12897.66$ which roughly shows the importance of uncertainty for network operators. Further, the value of VSS is 1950.44$ which indicates the additional cost imposed to immunize and hedge the system against severe uncertainty. In other words, this additional cost is due to the violation from deterministic state to deal effectively with unforeseen circumstances. On the other hand, Fig. 12 depicts changes in the robustness function relative to changes in the uncertainty radius ($\alpha$) and tolerant parameter ($\beta$). As can be seen, by reducing the uncertainty radius, the robustness function increases accordingly, which in turn raises the system costs to deal with unpredicted risk. It should be stated this in this work the maximum value of uncertainty radius is 0.468 that guaranties the minimum tolerable value for objective function.

TABLE I
STATISTICAL ANALSYSIS OF OBJECTIVES

| Variables | Expected value | Standard deviation | Worst-case scenario | Best-case scenario |
|---|---|---|---|---|
| Critical load pickup | 821.66(kW) | 261.84(kW) | 658.01(kW) | 1052.364 |
| Load curtailment | 2580.1(kWh) | 1260.4(kWh) | 3840.3(kWh) | 1436.775 |
| Restoration index | 84.52 (%) | 13.45 (%) | 71.23 (%) | 92.61 (%) |

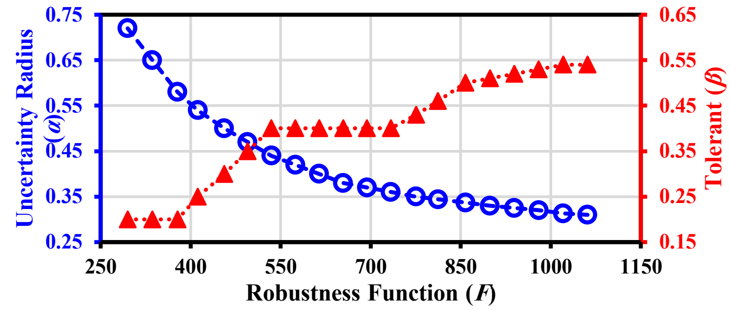



Fig. 12. Variation of robustness function against uncertainty radius and tolerant.

## D. Validation

To validate the applicability and generality of the proposed model on the restoration of real-scale distribution systems, we have applied it on a large-scale 123-bus distribution system [37] equipped with 16-node natural gas network as presented in Fig. 13. As can be seen, the proposed algorithm divides the network into 9 zones, each of which can be retrieved independently and in parallel, and finally the whole set can be connected together. Briefly, the results of the main objectives are given in Table II. It can be seen that the Case II-B has the better performance compared to others from both restoration index and load shedding. This is because of potential flexibilities of natural gas grid that enables additional routes to supply the cranking power of nonblack-start generation resources, and energize the feeders to restore the critical loads of the system.

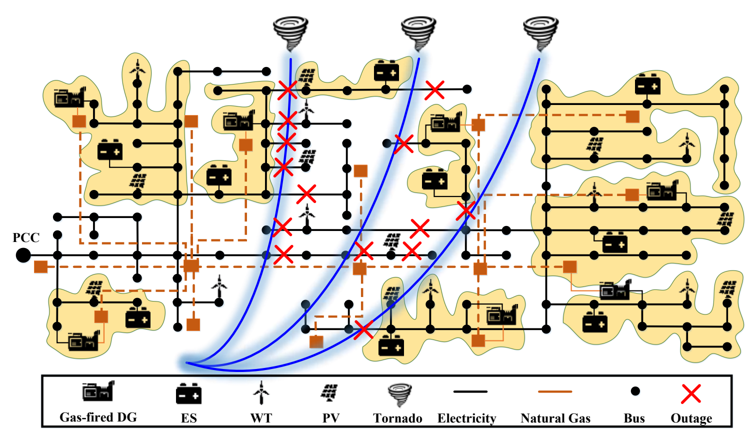



Fig. 13. Splitting of 123-node system after hurricane land falling.

TABLE II
RESULTS OF 123-BUS SYSTEM IN DIFFERENT CASES

| Objective | Case I-A | Case I-B | Case II-A | Case II-B |
|---|---|---|---|---|
| Restoration index (pu) | 0.345 | 0.386 | 0.548 | 0.789 |
| Generation offline (pu) | 0.583 | 0.532 | 0.491 | 0.395 |
| Feeder offline (pu) | 0.692 | 0.654 | 0.518 | 0.404 |
| Load Curtailment (pu) | 0.796 | 0.612 | 0.395 | 0.296 |

## IV. Conclusion

Resilience is an overarching concept that requires combined efforts from interdependent critical infrastructures to achieve. In this paper, an interactive repair crew dispatch and remedial actions strategy was developed for interdependent electric and natural gas systems to enhance the resilience of the system against weather-related events. The proposed model was an *out-of-market* one that fully considers whole cycle of operation states like preparedness, proactive management and restoration. In the propounded model, after the detection of damaged lines by fragility curves, the repair crew routing is scheduled to repair the damaged components in the shortest possible time. The distribution network is then divided into small autonomous areas and each part performs its load recovery in parallel. In the system restoration stage, different operational actions such as energy storages, network reconfiguration, and conservative DER scheduling are performed.

Based on the results achieved from simulations, the following practical hits are derived:

- *Splitting distribution networks* into a set of small-scale zones not only reduces load shedding, but also dramatically reduces the *recovery time* due to the possibility of *parallel restoration*.
- *Merging different energy systems* increases the *robustness* and *flexibility* of the entire complex, which mainly comes from their unique spatial and temporal characteristics.
- *Preventive measures* increase network *preparedness* for an impending incident that may play an undeniable role in improving the *rapidity* of recovery strategies.
- Existing *severe* uncertainty in the decision-making process leads to inefficient decisions that must be offset by additional costs to reduce system risks. The additional costs that decision maker is willing to pay for obtaining perfect information about approaching event can be easily calculated by *EVPI*. Besides, the profit obtained by implementing stochastic programming instead of deterministic one can be computed by *VSS*.

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