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Electric Power Grid Restoration Considering Disaster Economics

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ABSTRACT This paper presents a cost-effective system-level restoration scheme to improve power grids resilience by efficient response to the damages due to natural or manmade disasters. A post-disaster decision making model is developed to find the optimal repair schedule, unit commitment solution, and system configuration in restoration of the damaged power grid. The physical constraints of the power grid, associated with the unit commitment and restoration, are considered in the proposed model. The value of lost load is used as a viable measure to represent the criticality of each load in the power grid. The model is formulated as a mixed-integer program and, then, is decomposed into an integer master problem and a dual linear subproblem to be solved using Benders decomposition algorithm. Different scenarios are developed to analyze the proposed model on the standard IEEE 118-bus test system. This paper provides a prototype and a proof of concept for utility companies to consider economics of disaster and include unit commitment model into the post-disaster restoration process.

INDEX TERMS Disaster management, power grid, restoration, unit commitment.

NOMENCLATURE

Indices:

b	Index for buses.
i	Index for generation units.
l	Index for transmission lines.
t	Index for time.

Parameters:

C_{bt}	Hourly crew cost per person to repair bus b.
C_{lt}	Hourly crew cost per person to repair line l.
C_{it}^{g}	Generation cost of unit i at time t.
C_{it}^{sd}	Shutdown cost parameter of unit i at time t.
C_{it}^{su}	Startup cost parameter of unit i at time t.
D_{bt}	Load demand at bus b at time t.
DR_i	Ramp-down rate limit of unit i.
DT_i	Minimum downtime of generation unit i.
G_i	Primary time periods that unit i is online.
L_i	Primary time periods that unit i is offline.
M	Large positive constant.
P_i^{max}	Maximum generation capacity of unit i .
P_i^{min}	Minimum generation capacity of unit i.
R_t^{max}	Number of available repair crew at time t.
R_b	Crew size to repair bus b at time t.
R_l	Crew size to repair line l at time t.
TTR	Mean time to repair.
UR_i	Ramp-up rate limit of unit i.
UT_i	Minimum uptime of generation unit i.
$VOLL_{bt}$	Value of lost load at bus b at time t.
α_{ib}	Element of unit i and bus b in generation-bus incidence matrix.
β_{lb}	Element of line l and bus b in line-bus incidence matrix.

Variables:

I_{it}	Commitment state of generation unit i at time t; 1 if committed, otherwise 0.
LI_{bt}	Load interruption at bus b at time t.
P_{it}	Real power generation of unit i at time t.
PL_{lt}	Power flow of line l at time t.
SD_{it}	Shutdown cost variable of unit i at time t.
SU_{it}	Startup cost variable of unit i at time t.

u_{bt} Repair state variable of bus b at time t; 1 if on repair, otherwise 0.
v_{lt} Repair state variable of line l at time t; 1 if on repair, otherwise 0.
w_{lt} Outage state of line l at time t; 0 if damaged or under repair, otherwise 1.
y_{it} Outage state of unit i at time t; 0 if damaged or under repair, otherwise 1.
z_{bt} Outage state of bus b at time t; 0 if damaged or under repair, otherwise 1.
δ_{bt} Bus voltage angle.

I. INTRODUCTION

Recent disasters in the United States resulted in significant economic, social, and physical disruptions and caused considerable inconvenience for residents living in disaster areas due to loss of electricity, water, and communications. A resilient power system encounters minimum possible outages and will quickly return to its normal operating state [1]. "*After a storm comes a calm*" is not the case for power systems. The increasing trend of natural disasters (which perceived to be due to climate change) and emerging security threats, call for devising efficient strategies for pre- and post-disaster management of the power infrastructure. Mitigating the aftermath of disasters by improving the power grid resilience, as one of the critical lifeline systems, is of utmost importance for utility companies and governments.

After over a half of a century from publication of one of the earliest studies on efficient response to natural disasters, motivated by Hurricane Carla that slammed into the Gulf Coast and moved onward into the United States and Canada [2], the issue of efficient response to disasters still seems to remain in its immature stage. Grid operators commonly face two challenges in response to the damaged power grid due to disasters: first, in *planning stage* to design more reliable networks, and second, in *operation stage* which they attempt to manage the restoration process in an efficient way [3]. In this paper, the focus will be on *operation stage*. However, the literature in both *planning stage* and *operation stage* are explored in order to provide broader insight for the interested readers.

A. PLANNING STAGE

Various studies have been proposed in the literature in the context of emergency planning for power grids. In [4], the research problems and models for substations and/or distribution feeders planning under normal and emergency conditions were reviewed and discussed. A case study on hurricane planning and rebuilding the electrical infrastructure along the Gulf Coast, for hurricane Katrina was presented in [5]. A risk assessment method for infrastructure technology planning to improve the power supply resiliency to natural disasters was proposed in [6]. Reduced cost as well as power supply availability were considered as two fundamental decision factors in their disaster planning approach. In [7], a stochastic integer program was proposed to find the optimal schedule for inspection, damage evaluation, and repair of electric power grids in post-earthquake restoration with the goal of minimizing the average time that each customer is without power. Bienstock and Mattia [8] proposed two models to solve power grid blackout problems using mixed-integer programming. The optimization problems relevant to the prevention of large-scale blackouts in transmission grids subject to a set of stochastic damage scenarios were considered. The first model makes a decision on which transmission lines to be expanded in capacity in order to guarantee that after damage to transmission lines in different scenarios all power flows are within desired limits. The second model considers the dynamics of cascades in order to find an optimal reinforcement plan that can passively survive a potential cascade. A comprehensive survey of models and algorithms for emergency response logistics in distribution grids, including reliability planning with fault considerations and contingency planning models, were presented in [9] and [10].

In context of resource allocation for power grid restoration, [11] presented three mathematical programming models in order to locate the repair units and restore the transmission and distribution lines in an efficient manner. The first model finds the optimal repair-unit dispatch tactical plan with a forecast of adverse weather conditions. The second model derives 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. In [12], 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 [13], the service restoration considering the restrictions on emergency response logistics with the objective of minimizing the customers interruption cost was studied. The reconfiguration and the resource dispatching issues were considered in a systematic way in order to derive the optimal time sequence for every step of the restoration plan. In [14], a decision-making model to manage the required resources for economic power restoration was proposed. The optimal number of depots, the optimal location of depots, and the optimal number of repair crews were determined in their model to minimize the transportation cost associated with restoration operation. In [15], a decision support tool for improvement of information used by electric utilities for managing restoration of distribution grid 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 in a cost-effective manner.

B. OPERATION STAGE

In context of restoration, [3] studied the budgeted and the minimum weighted latency variants of recovery problem of large-scale power outage due to a major disaster. The problems for general case as well as trees and bipartite networks as special cases were studied. Chien [16] formulated a mixed-integer program to model the recovery of the transmission networks damaged due to disasters. The model considers the repair crew constraints as well as the penalty cost of unserved loads to find the recovery schedule which minimizes the cost of power outage. Thibaux *et al.* [17] used a mixed-integer programming framework for modeling the optimal supply restoration of the faulty distribution grids. A two-step decomposition method was developed to derive the optimal configuration as well as the optimal switching sequence of the distribution grid. Hentenryck *et al.* [18] studied three approaches for joint damage assessment and restoration of the power grids after natural disasters. The proposed approaches include an online stochastic combinatorial optimization algorithm which dynamically makes the restoration decisions once each potentially damaged site is visited; a two-stage method that first evaluates the extent of the damage and then restores the system; and 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. Matisziw *et al.* [19] 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 power flow and minimization of the system cost. Nurre *et al.* [20] proposed an integrated network design and scheduling problem for restoration of the interdependent civil infrastructure. The problem was formulated using integer programming, and analyzed on realistic data set 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. [21] 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 grid as quick as possible. The power grid restoration and vehicle routing were decoupled to improve the computational efficiency of the model. The results show 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 [22] by applying randomized adaptive vehicle decomposition technique in order to improve the scalability of the model for large-scale disaster restoration of the power grids with more than 24,000 components. In another work, [23] presented a scalable approach for restoration of the interdependent gas and power infrastructures. Mixed-integer programming was used to obtain minimum restoration set and optimal restoration ordering. Randomized adaptive decomposition was applied in order to improve the solution quality and computational efficiency.

C. CONTRIBUTIONS

In our previous work [24] and [25], we proposed reactive and proactive restoration strategies for power system infrastructure considering natural disaster effects. In [26], we proposed a dynamic maintenance model for power systems subject to failure due to natural disasters. In this paper, we propose a generalized post-disaster restoration scheme for power grids by simultaneously incorporating the physics of the system and the economics of disaster in the restoration process. Intuitively, ignoring the economics of restoration and underlying constraints result in either suboptimal or infeasible restoration plan. In this paper, the unit commitment and optimal power flow problems along with the resource cost and the opportunity cost of load interruption defined by the value of lost load (VOLL), are considered as economic measures in the model. These economic considerations impose additional constraints and redefine the restoration cost function. The restoration problem for a DC power flow model is formulated as a mixed-integer program. By mixed-integer programming approach, different combinations of restoration schedule and operational configuration of the grid are searched in a large solution space to find a cost-effective restoration plan. The model intends to minimize the customer load interruption cost, restoration operation cost, and electricity generation cost without violating the physics of the system. The output of the proposed model includes the post-disaster restoration schedule, generation unit commitment states, power dispatch, and transmission grid configuration. Therefore, the proposed decision making model not only determines the restoration schedule, but also provides a practical and cost-effective operational configuration for major components of the power grid during the restoration time horizon. To the best of our knowledge, this is the first work which considers the unit commitment problem in post-disaster power grid restoration planning.

The rest of this paper is organized as follows: Section II describes the proposed model and Section III presents the problem formulation. Section IV illustrates the numerical results on IEEE 118-bus test system. Finally, Section V provides the concluding remarks.

II. MODEL DESCRIPTION

The major components of power system infrastructure, i.e., generation units, transmission lines, and buses (substations) along with their downstream distribution lines are subject to damage due to a disaster of natural or manmade origin. In our post-disaster restoration model, we propose a decision making tool for a typical vertically integrated utility company to schedule the repair operations of its transmission lines and buses in coordination with operations of its generation units in a cost-effective manner. The proposed model can also be used by Independent System Operator (ISO) in a restructured power market in coordination with associated electric utilities.

Once the disaster strikes, the utility company conducts a damage assessment by an aerial survey of the power network (by using helicopters, drones, or satellite technologies) in affected areas as well as a ground check by inspectors (if the roads are not affected) [29]. Damage assessment determines whether a facility/component has damaged at all, and if damaged, estimates the expected time to repair (TTR) of that component. Each bus along with its downstream distribution lines are consolidated and considered as a single component, hence resulting in a consolidated time to repair. While the generation units are part of the vertically integrated utility company, it is assumed that each generation unit is responsible for repair operations of its damaged facilities. Therefore, each of damaged generation units submit their repair operations schedule to the operations coordinator of the vertically integrated utility company to be used as an input for the restoration scheduling of transmission lines and buses in a coordinated manner. We consider two states for each component: *damaged*, if the component is encountered major damages, thus it is offline and needs to be restored; and *functional*, if it has not been damaged at all, or minor damages has occurred and the component is able to continue its functionality.

After determining the initial *damaged* or *functional* state of each component, the restoration resources need to be allocated to repair the damaged components. Without loss of generality and for *proof of concept*, we consider the repair crews as the only limited resource that needs to be allocated to the damaged components, while it is assumed that plenty of spare parts and equipment for restoration are available. The resource allocation, however, is subject to the critically of the load to be restored as well as costs associated with seizing the resources in each particular time and location. In this regard, the objective of the problem is defined as to minimize the customer interruption cost, plus the restoration resource cost, and power generation cost. The interruption cost is the amount of the interrupted load multiplied by VOLL. VOLL is an important measure in electricity market's micro- and macroeconomics which represents the willingness of customers to pay for their electricity service to avoid curtailment. Valuation of VOLL, which is usually measured in dollars per MWh, can either be based on the marginal value of the next unit of interrupted electricity load or the average value of interrupted load. However, it varies depending on the type of usage and outage [27]. From economics point of view, the load interruption cost is considered as an opportunity cost.

III. PROBLEM FORMULATION

A. OBJECTIVE FUNCTION

The objective is to minimize the customer load interruption cost, the restoration operation cost, and the power generation cost as follows:

$$\min_{u,v,LI,P,SU,SD} \sum_t \sum_b VOLL_{bt} LI_{bt} + \sum_t \sum_b C_{bt} R_b u_{bt} + \sum_t \sum_l C_{lt} R_l v_{lt} + \sum_t \sum_i \Big(C_{it}^g P_{it} + SU_{it} + SD_{it} \Big), \quad (1)$$

where the first term represents the total opportunity cost of load interruption over the restoration planning horizon, the second term represents the cost of resources allocated to the buses (and their downstream distribution lines), the third term is the cost of resources allocated to transmission lines, and the fourth term indicates the generation cost of all the units feeding the system, including the fuel costs, and the startup/shut down costs. The resource cost is defined as the summation of product of the number of allocated resource(s) to each component and the cost of each unit of resource seized by that component. The binary decision variables u_{bt} and v_{lt} indicate whether or not a unit of crew resources is allocated at each particular time period to each particular bus and line, respectively (1 if allocated, otherwise 0).

B. CONSTRAINTS

1) DAMAGE STATE MODELING

A mechanism is required in the model to allocate the resources only to the damaged components. This mechanism also needs to stop allocation of the resources, and switch the *damaged* state of the components into *functional* state, when the resources were seized for predetermined duration of time to repair. This mechanism for generation units is modeled as follows:

$$y_{it} = 0, \quad \text{if } t \leq TTR_i; \text{ otherwise } y_{it} = 1, \ \forall i, \ \forall t. \quad (2)$$

However, since the *if-then* constraint is not allowed in linear programming, constraint (2) is decomposed and rewritten as follows

$$t - M y_{it} \leq TTR_i, \quad \forall i, \ \forall t, \quad (3)$$

$$M y_{it} \leq TTR_i, \quad \forall i, \ \forall t = 0, 1, \ldots, TTR_i, \quad (4)$$

where binary variable y_{it} represents the *damaged* or *functional* state of generation unit i at time t. Binary variable y_{it} is equal to 0 if generation unit i is damaged due to the disaster and has not been restored until time t; otherwise it is equal to 1. The time that it takes from beginning of planning horizon for a damaged generation unit to be repaired and brought back to the system is represented by TTR_i. If the component has not encountered any damage, the time to repair TTR_i is set to 0.

Constraints (5) and (6) present the relationship between binary state variables w_{lt} and z_{bt} with their corresponding repair decision variables v_{lt} and u_{bt}, respectively:

$$0 \leq w_{l(t+1)} - \Big(\sum_{k=1}^{t} v_{lk} - TTR_l + 0.5 \Big) / M \leq 1 \quad \forall l, \ \forall t, \quad (5)$$

$$0 \leq z_{b(t+1)} - \Big(\sum_{k=1}^{t} u_{bk} - TTR_b + 0.5 \Big) / M \leq 1 \quad \forall b, \ \forall t, \quad (6)$$

where binary variables z_{bt} and w_{lt} are the *damaged* or *functional* state of bus b at time t, and transmission line l at time t, respectively. If the transmission line l at time t is on *damaged* state, the binary variable w_{lt} becomes 0. Once it is repaired, the value of w_{lt} becomes 1 and remains the same up to the end of the restoration planning horizon. Binary variable v_{lt} is the decision variable for repair of line l. When line l is under repair at time t, decision variable v_{lt} takes the value of 1, otherwise 0. Similarly, z_{bt} is equal to 0 when bus b at time t is on *damaged* state; Once it is repaired the value of z_{bt} becomes 1, and remains the same up to the end of the planning horizon. Binary variable u_{bt} is the decision variable for repair of bus b, which takes the value of 1, when the bus b is under repair, otherwise it is equal to 0.

Constraints (7) and (8) further guarantee that enough time and resources are allocated to restore each damaged component:

$$\sum_{k=t}^{t+TTR_l-1} v_{lk} \geq TTR_l(v_{lt} - v_{l(t-1)}), \quad \forall l, \forall t, \tag{7}$$

$$\sum_{k=t}^{t+TTR_b-1} u_{bk} \geq TTR_b(u_{bt} - u_{b(t-1)}), \quad \forall b, \forall t. \tag{8}$$

We assume that once the restoration operation on a particular component is started, it should continue at least for the estimated time to repair (TTR) duration. Addition of these constraints eliminates partial repair on damaged components. Finally, constraints (9)-(11) narrow down the solution space and eliminate unnecessary allocation of resources to repaired components:

$$y_{i(t+1)} \geq y_{it}, \quad \forall i, \forall t, \tag{9}$$

$$w_{l(t+1)} \geq w_{lt}, \quad \forall l, \forall t, \tag{10}$$

$$z_{b(t+1)} \geq z_{bt}, \quad \forall b, \forall t. \tag{11}$$

2) RESOURCE CONSTRAINT

The objective function of the model is constrained by limited restoration resources, as follows:

$$\sum_l R_l v_{lt} + \sum_b R_b u_{bt} \leq R_t^{max}, \quad \forall t. \tag{12}$$

Constraint (12) represents the maximum amount of resources that can be allocated to the entire system in each unit of time.

3) LOAD BALANCE CONSTRAINT

The physics of the grid imposes another constraint, i.e. the bus load balance constraint, to the objective function of the post-disaster model, as follows:

$$\sum_{i \in N_b} P_{it} + \sum_{l \in N_b} PL_{lt} + LI_{bt} = D_{bt}, \quad \forall b, \forall t, \tag{13}$$

where N_b is the set of components connected to bus b. The bus load balance constraint (13) ensures that the injected power to a bus from connected transmission lines and generation units is fully supplying the bus load; however, if the injected power is not sufficient, the load is interrupted (modeled by a load interruption variable LI_{bt}). The load interruption variable is nonnegative and smaller than the load at its associated bus.

4) REAL POWER GENERATION CONSTRAINTS

The real power generation in each unit i is bounded with its damage state, unit commitment state, and minimum and maximum generation capacity, as follows:

$$P_i^{min} y_{it} I_{it} \leq P_{it} \leq P_i^{max} y_{it} I_{it}, \quad \forall i, \forall t. \tag{14}$$

The real power generation constraint (14) is nonlinear. We linearize this constraint by defining a new variable $n_{it} = y_{it} I_{it}$ and using the following set of equations:

$$P_i^{min} n_{it} \leq P_{it} \leq P_i^{max} n_{it}, \quad \forall i, \forall t, \tag{15}$$

$$n_{it} - y_{it} \leq 0, \quad \forall i, \forall t, \tag{16}$$

$$n_{it} - I_{it} \leq 0, \quad \forall i, \forall t, \tag{17}$$

$$-n_{it} + y_{it} + I_{it} \leq 1, \quad \forall i, \forall t, \tag{18}$$

$$n_{it} \geq 0, \quad \forall i, \forall t. \tag{19}$$

It is important to notice that if a generation unit is not in the *functional* state, it cannot be committed for generation. Therefore, the coupling constraint of unit commitment and damage state holds all the time, i.e.,

$$I_{it} \leq y_{it}, \quad \forall i, \forall t. \tag{20}$$

The damage state of bus(es) connected to each generation unit constrains the real power generation, as follows

$$-M \sum_b \alpha_{ib} z_{bt} \leq P_{it} \leq M \sum_b \alpha_{ib} z_{bt}, \quad \forall i, \forall t, \tag{21}$$

where α_{ib} is the element of generation-bus incidence matrix that takes the value of 1, if generation unit i is connected to bus b; otherwise 0. If a connected bus to a generation unit is damaged, the associated generation unit becomes offline.

5) POWER FLOW CONSTRAINTS

Incorporating the physics of the grid, the damage state of each transmission line along with associated bus(es) and their impacts on power flow are modeled as follows:

$$-PL_l^{max} w_{lt} \leq PL_{lt} \leq PL_l^{max} w_{lt}, \quad \forall l, \forall t, \tag{22}$$

$$-M \sum_b \beta_{lb}^{from} z_{bt} \leq PL_{lt} \leq M \sum_b \beta_{lb}^{from} z_{bt}, \quad \forall l, \forall t, \tag{23}$$

$$-M \sum_b |\beta_{lb}^{to}| z_{bt} \leq PL_{lt} \leq M \sum_b |\beta_{lb}^{to}| z_{bt}, \quad \forall l, \forall t, \tag{24}$$

$$\begin{aligned} -M(1-w_{lt}) - M(1 - \sum_b |\beta_{lb}| z_{bt}) &\leq PL_{lt} - \frac{\sum_b \beta_{lb}\delta_{bt}}{x_l} \\ &\leq M(1-w_{lt}) + M(1 - \sum_b |\beta_{lb}| z_{bt}), \\ &\forall l, \forall b, \forall t, \end{aligned} \tag{25}$$

where β_{lb}^{from} represents the positive elements of the bus-line incidence matrix and β_{lb}^{to} represents the negative elements of the bus-line incidence matrix. As shown in (22), if the line l at time t is in the *functional* state, the line can transfer power, but is limited to its power flow capacity. However, if the line is damaged, the power flow will be equal to 0. In addition, as long as any of the buses connected to each particular transmission line is in a *damaged* state, the power cannot flow in that particular line as shown in (23)-(25).

6) STARTUP AND SHUTDOWN COSTS CONSTRAINTS

The startup and shutdown costs have been defined in the objective function as positive variables to avoid using additional extra binary state variables to improve the computational efficiency of the program. Based on [28] and [30], the startup and shutdown cost variables are bounded to constraints (26)-(29), as follows:

$$SU_{it} \geq C^{su}_{i\tau}\left(I_{it} - \sum_{k=1}^{\tau} I_{i(t-k)}\right), \quad \forall i,\ \forall t,\ \forall \tau = 1, \ldots, ND_i, \tag{26}$$

$$SU_{it} \geq 0, \quad \forall i,\ \forall t, \tag{27}$$

$$SD_{it} \geq C^{sd}_{it}\left(I_{i(t-1)} - I_{it}\right), \quad \forall i,\ \forall t, \tag{28}$$

$$SD_{it} \geq 0, \quad \forall i,\ \forall t, \tag{29}$$

where ND_i is the number of time intervals of the startup cost function for generation unit i.

7) RAMP-UP AND RAMP-DOWN CONSTRAINTS

The mechanical and thermal inertia that should be overtaken to decrease (ramp-down) or increase (ramp-up) the real power generation of a thermal generation units poses variety of constraints to the system [31]. The related constrains can be found in Appendix.

8) MINIMUM UP TIME AND DOWNTIME CONSTRAINTS

In thermal generation units, the temperature change can only occur gradually. Thus, when a generation unit is operating, it cannot be decommitted immediately (minimum up time); and once the unit is offline, it requires some time before it can be committed again (minimum downtime) [32]. The related constrains can be found in Appendix.

9) FULL RESTORATION CONSTRAINT

There is a possibility for circumstances that the system load is fully recovered, while some generation units, transmission lines, or buses still have not been repaired. The reason is that the functional generation units, transmission lines, and buses are temporarily compensating for the outage of redundant damaged components. Therefore, due to economic dynamics of the system, the restoration process can be terminated by partial restoration. However, due to potential load increments, the system may not be able to fully and economically supply loads beyond the restoration horizon. To ensure that all damaged components are repaired by the end of the restoration horizon, the following constraint is added:

$$\sum_i y_{i(NT)} + \sum_b z_{b(NT)} + \sum_l w_{l(NT)} = NG + NB + NL, \tag{30}$$

Algorithm 1 Benders Decomposition for Mixed-Integer Program

{initialization}
Lower bound (LB):= $-\infty$, Upper bound (UB):= $+\infty$
while UB $-$ LB $> \varepsilon$ **do**
{solve dual LP subproblem}
$\max_U \{\sum_t \sum_b C_{bt}R_b\bar{u}_{bt} + \sum_t \sum_l C_{lt}R_l\bar{v}_{lt} + (H - B\bar{Y})^T U \mid A^T U \leq C, U \geq 0\}$
  if unbounded **then**
  Get unbounded ray $\bar{U}$
  Add cut $(H - BY)^T \bar{U} \leq 0$ to IP master problem
  else
  Get extreme point $\bar{U}$
  Add cut $\theta \geq \sum_t \sum_b C_{bt}R_b u_{bt} + \sum_t \sum_l C_{lt}R_l v_{lt} + (H - BY)^T \bar{U}$ to master problem
  UB := min {UB, $\sum_t \sum_b C_{bt}R_b\bar{u}_{bt} + \sum_t \sum_l C_{lt}R_l\bar{v}_{lt} + (H - B\bar{Y})^T \bar{U}$}
  end if
{solve IP master problem}
$\min_Y \{\theta \mid cuts, Y \in \{0, 1\}\}$
LB := $\bar{\theta}$
end while

where NT is the length of restoration planning horizon, and NG, NB, and NL are the number of generation units, buses, and transmission lines, respectively.

C. DECOMPOSITION STRATEGY

Benders decomposition has been widely used in the power system literature [33]. Benders decomposition for mixed-integer programming is an efficient strategy when the original problem is large-scale and difficult to solve. In order to employ the decomposition strategy for the proposed problem, we consider the continuous variable vector as $\mathbf{X} = [LI^T_{bt}, P^T_{it}, PL^T_{lt}, SU^T_{it}, SD^T_{it}]^T$, the binary variable vector as $\mathbf{Y} = [u^T_{bt}, v^T_{lt}, y^T_{it}, z^T_{bt}, w^T_{lt}, I^T_{it}]^T$, the cost coefficient matrix of the integer variables in the objective function as $\mathbf{C^T}$ composed of $C_{bt}R_b$ and $C_{lt}R_l$, and the cost coefficient matrix of the continuous variables in the objective function as $\mathbf{D^T}$ composed of $VOLL_{bt}$ and $\mathbf{1}$. We also assume that $\mathbf{A}$ and $\mathbf{B}$ represent the coefficient matrices of $\mathbf{X}$ and $\mathbf{Y}$ in the constraints, respectively. Finally, $\mathbf{H}$ is assumed to represent the right-hand-side matrix of constraints. Now we can rewrite the proposed mixed-integer programming model in the following abstract form:

$$\min_{X,Y} \ \mathbf{C^T X} + \mathbf{D^T Y} \tag{31}$$

$$\text{s.t. } \mathbf{AX} + \mathbf{BY} \geq \mathbf{H},$$
$$\mathbf{Y} \in \{0, 1\}, \quad \mathbf{X} \geq 0. \tag{32}$$

The proposed problem is decomposed into an integer program (IP) master problem and a dual linear program (LP) subproblem. Considering $\mathbf{U}$ as the dual variable vector for the subproblem, the Benders decomposition algorithm for the proposed model is shown in Algorithm 1 [34]. In each iteration, after solving the master problem, the subproblem evaluates the obtained solution for feasibility. If the dual LP subproblem found to be unbounded, the feasibility cuts are generated and added to the IP master problem; otherwise the optimality cuts are generated to be added to the master problem to form a new objective function for the master problem (the constraints with θ represent the optimality cuts). The iterative process will continue until an acceptable relative gap (ε) between current upper and lower bounds is obtained. The value of ε is considered to be 0.05 for this study.

TABLE 1. Damaged buses and time to repairs.

Bus #	Time to Repair (Hours)	Load Type
$B1$	24	Commercial
$B2$	11	Residential
$B3$	18	Residential
$B4$	15	Critical
$B5$	5	N/A
$B8$	4	Residential
$B11$	22	Industrial

TABLE 2. Damaged transmission lines and time to repairs.

Line #	Time to Repair (Hours)
$L1$	20
$L2$	18
$L10$	16
$L14$	10
$L16$	22

TABLE 3. Damaged generation units and time to repairs.

Unit #	Time to Repair (Hours)
$G1$	17
$G2$	12
$G3$	24
$G5$	8

IV. NUMERICAL RESULTS

The IEEE 118-bus system is used to analyze the proposed post-disaster restoration model. The system has 118 buses, 54 generation units, 186 branches, and 91 load sides. The system setup is shown in Tables 1–3. Among damaged buses, B1, B2, B3, B4, B8, and B11 are load buses, feeding their downstream distribution lines, while B5 is not a load bus. From [27], the value of lost load is considered to be \$3.706/kWh for industrial loads, \$6.979/kWh for commercial loads, and \$0.110/kWh for residential areas. The value of lost load for critical loads, e.g., medical centers and water treatment plants are misstated in micro and macro economic approach. However, due to the crucial importance of these critical loads, the value of lost load in an *ad hoc* manner is considered to be \$10/kWh to impose higher priority to these areas. In this analysis, as shown in Table 1, bus B1 is considered as commercial load, bus B11 as industrial load, bus B4 as critical load, and the rest of the load buses in the system are considered as residential loads. The time to repair in Tables 1 and 2 indicate the estimated duration of the repair for buses and transmission lines, respectively; while the time to repair in Table 3 shows the time it takes from the beginning of the restoration planning horizon to repair and restore each damaged generation unit.

The repair crew is considered to be the only limited resource that is allocated to repair the damaged components. It is assumed that each damaged bus requires 12 repair crews/hour, while for each damaged transmission line 18 repair crews/hour are required. Although depending on skill levels different crew costs can be considered, we assume that all repair crews have equal skill levels; hence, they are equally paid (we could think of it as a bundle of resources which their average wage is used as an input into our model). The hourly wages for repair crews varies based on the working shift and types of repair. For repairing the buses and downstream distribution lines, the average wages are assumed to be \$60/hour at shift 1 (8:00 A.M.–4:00 P.M.), \$70/hour at shift 2 (4:00 P.M.–12:00 A.M.), and \$80/hour at shift 3 (12:00 A.M.–8:00 A.M.); for repairing the transmission lines, the average wages are assumed to be \$65/hour at shift 1, \$75/hour at shift 2, and \$85/hour at shift 3. Without loss of generality, it is assumed that all generation units are incurred identical generation, startup, and shutdown costs. From [35], the generation cost is considered to be \$0.3509/kWh. The shutdown cost is assumed to be \$250 per shutdown for each generation unit. The startup cost is assumed to be \$150 within the first hour after last shutdown. For each additional hour (up to eight hours), an incremental cost of \$25 would be added to the startup cost. Restoration planning horizon starts at 8:00 AM. The length of restoration planning horizon is set to be $NT = 120$ hours.

The following scenarios are considered to analyze the model and the impacts of economic considerations in post-disaster restoration:

Scenario I: The problem is solved without considering the economics of disaster; only load interruption is minimized.

Scenario II: The problem is solved with consideration of the VOLL and repair cost; However, the generation cost is not considered.

Scenario III: The problem is solved with full economic consideration, i.e., VOLL, repair cost, and generation cost.

Scenario IV: The economic impact of maximum number of available resources (repair crews) on restoration is analyzed for five different cases. The number of crews ranges from 50 in Case 1, with an increment of 25 in other cases, up to 150 for Case 5.

The proposed model implemented on the IEEE 118-bus system setup is composed of 162,481 decision variables, in which 22,308 of them are integer variables. The model also is constrained with 352,514 linear equations. The model

TABLE 4. Optimal repair schedule for buses in Scenarios I-III.

Bus #	Scenario I	Scenario II	Scenario III
$B1$	1-24	1-24	1-24
$B2$	1-11	1-11	1-11
$B3$	1-18	1-18	1-18
$B4$	1-15	1-15	1-15
$B5$	1-5	3-7	1-5
$B8$	1-4	1-4	6-9
$B11$	1-22	1-22	1-22

TABLE 5. Optimal repair schedule for transmission lines in Scenarios I-III.

Line #	Scenario I	Scenario II	Scenario III
$L1$	5-24	84-103	92-111
$L2$	7-24	1-18	1-18
$L10$	6-21	19-34	95-100
$L14$	5-14	74-83	71-80
$L16$	1-22	28-49	48-69

TABLE 6. Economic indices for Scenarios I-III (costs $\times 10^3$).

Economic Index	Scenario I	Scenario II	Scenario III
Total Cost	\$30,188	\$30,261	\$28,764
Lost Load Cost	\$17,893	\$18,000	\$15,929
Generation Cost	\$12,099	\$12,067	\$12,640
Resource Cost	\$196.92	\$194.76	\$193.62
Lost Load (MWh)	2174	2,275	3,902

TABLE 7. Optimal repair schedule for buses in Scenario IV.

Bus #	R_t=50	R_t=75	R_t=100	R_t=125	R_t=150
$B1$	27-50	1-24	1-24	1-24	1-24
$B2$	16-26	16-26	17-27	1-11	1-11
$B3$	28-45	25-42	1-18	1-18	1-18
$B4$	1-15	1-15	1-15	1-15	1-15
$B5$	1-5	1-5	1-5	1-5	4-8
$B8$	49-52	27-30	27-30	6-9	6-9
$B11$	6-27	1-22	1-22	1-22	1-22

TABLE 8. Optimal repair schedule for transmission lines in Scenario IV.

Line #	R_t=50	R_t=75	R_t=100	R_t=125	R_t=150
$L1$	17-36	7-26	95-114	92-111	93-112
$L2$	59-76	47-64	6-23	1-18	1-18
$L10$	53-68	96-111	89-104	95-100	92-107
$L14$	1-10	25-34	71-80	71-80	71-80
$L16$	45-66	23-44	46-67	48-69	35-56

TABLE 9. Economic indices for different cases in Scenario IV (costs $\times 10^3$).

Economic Index	R_t=50	R_t=75	R_t=100	R_t=125	R_t=150
Total Cost	\$37,713	\$29,377	\$28,798	\$28,764	\$28,762
Lost Load Cost	\$24,952	\$16,562	\$15,966	\$15,929	\$15,926
Generation Cost	\$12,547	\$12,598	\$12,629	\$12,640	\$12,641
Resource Cost	\$213.24	\$216.00	\$203.46	\$193.62	\$194.10
Lost Load (MWh)	6,544	5,098	4,232	3,902	3,875
Interruption Time	50 h	42 h	27 h	24 h	24 h

is decomposed into an IP master problem and a dual linear subproblem, and is solved using Benders decomposition method. The optimal restoration schedule for buses and transmission lines of Scenarios I to III are shown in Tables 4 and 5, respectively. The costs of implementing Scenarios I and II, as well as the optimal restoration cost of system with full consideration of economics of disaster (Scenario III) are shown in Table 6. As shown, implementation of Scenario I which only minimizes the load interruption regardless of economic issues in grid restoration process results in 12.3% increase in cost of lost load as an index to measure the social welfare. The overall restoration cost in this scenario increases by about 5% compared to Scenario III. In Scenario II, even though the objective function minimizes both lost load cost and repair crew cost, the induced impairment in the objective function results in even higher cost of lost load and total restoration cost. Scenario III as a comprehensive economic restoration model, which is used as a benchmark for Scenarios I and II, provides the most economic restoration scheme and establishes an equilibrium between generation cost, lost load cost, and repair cost.

In Scenario IV the economics of resources is analyzed. The optimal schedules for Cases 1 to 5 of Scenario IV's buses and lines are shown in Tables 7 and 8, respectively. As expected, the load on B4 which as a critical load is restored as quick as possible in all scenarios. Due to their VOLLs, the repair operations on commercial and industrial loads are initiated from early stage of the planning horizon to restore these costly interruptions. On the other hand, the restoration of the transmission lines in vast majority of the cases are postponed to the middle or late stage of the planning horizon.

Table 9 summarizes the total restoration cost, opportunity cost of the lost load, generation cost, resource cost, the amount of lost load, and the last time span that system still experiences partial load interruption in Scenario IV. Due to the physics and economics of the problem, the restoration operations will continue for a longer period than required time to eliminate partial load interruption in the system for each case, as shown in Fig. 1. The higher level of restoration resources results in shorter interruption time in the system. Thus, the load interruption and operations duration diagram diverges by increasing the resource level, as illustrated in Fig. 1. On the other hand, the higher resource level will extend the restoration planning horizon to complete the remaining operations in a cost-effective manner, i.e. by allocating less expensive resources, and configuring a more economic generation unit commitment.

As shown in Table 9 and in Fig. 2, higher resource level results in lower amount of total lost load in the system. The higher level of restoration resources results in lower total restoration cost. This cost dynamics is significantly due to impact of resource level on cost of load interruption. Interestingly, by securing higher level of restoration resources, the trend of the total resource cost shows a descending pattern. However, the total restoration resource

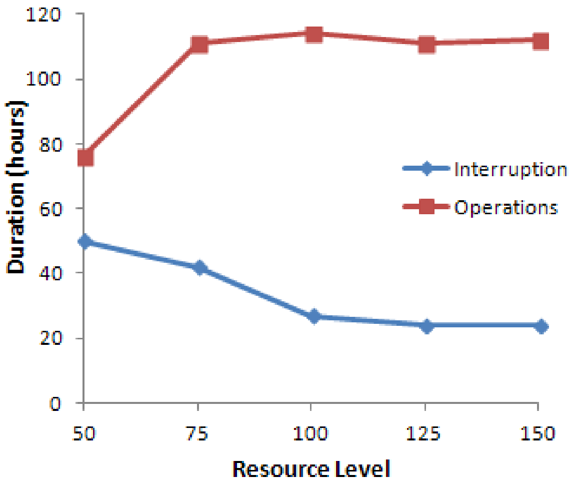

FIGURE 1. Interruption vs. operations duration for different cases in Scenario IV.

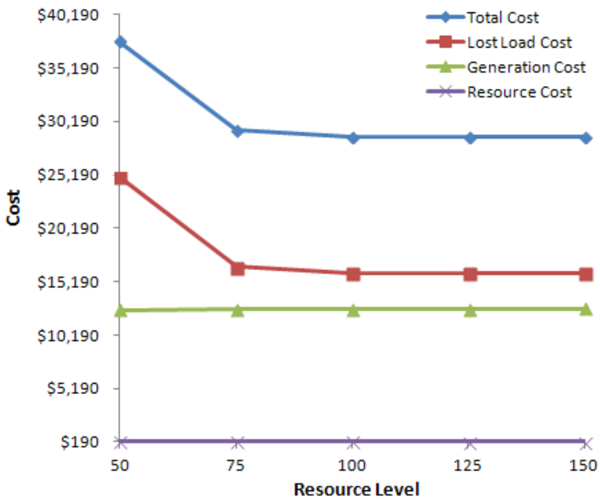

FIGURE 2. Optimal restoration cost breakdown for different cases in Scenario IV (costs $\times 10^3$).

cost is significantly lower than other cost components. In the first glance, the generation cost is perceived to have low sensitivity to the resource level. However, considering different time-to-restoration length for different cases in Scenario IV, the average power generation per kWh for Cases 1 to 5 are \$0.5663, \$0.3848, \$0.3721, \$0.3847, and \$0.3762, respectively. Therefore, the average generation cost can significantly be affected by number of available restoration resources.

V. CONCLUSION

An efficient model was proposed to support the post-disaster decision making process for power grid restoration. The results demonstrate that the proposed model is able to find the optimal restoration schedule of damaged components in a cost-effective manner. The opportunity cost of lost loads, the repair cost, and the generation costs were considered as economic indices. It was demonstrated that economy of disaster needs to be an important part of the restoration plan. Moreover, the numerical results showed that the restoration resource level significantly impacts the total incurred cost of restoration. The results suggested that investing on restoration resources would be paid off in a sense that by securing enough restoration resources, a considerable restoration cost saving could be realized. In addition, the higher level of resources can significantly shorten the partial grid restoration. It was shown that the number of available resources has a significant impact on the average cost of power generation. This study suggests that incorporation of the unit commitment problem, value of lost load, and repair crew cost into the restoration decision making model can result in significant cost-saving in economic restoration of the grid.

APPENDIX

A computationally efficient mixed-integer linear formulation for the ramp-up rate, shutdown ramp, ramp-down rate, minimum uptime, and minimum downtime as shown in (33)-(41) was proposed by [28]. Our post-disaster restoration model is restricted to these constraints, as follows:

$$P_{it} - P_{i(t-1)} \leq UR_i \cdot I_{i(t-1)} + UR_i^{su} \cdot \Big(I_{it} - I_{i(t-1)}\Big) + P_i^{max} \cdot \Big(1 - I_{it}\Big), \quad \forall i,\ \forall t, \tag{33}$$

$$P_{it} \leq P_i^{max} \cdot I_{i(t+1)} + DR_i^{sd} \cdot \Big(I_{it} - I_{i(t-1)}\Big), \quad \forall i,\ \forall t, \tag{34}$$

$$P_{i(t-1)} - P_{it} \leq DR_i \cdot I_{it} + DR_i^{sd} \cdot \Big(I_{i(t-1)} - I_{it}\Big) + P_i^{max} \cdot \Big(1 - I_{i(t-1)}\Big), \quad \forall i,\ \forall t, \tag{35}$$

where the ramp-up rate is modeled in (33), the shutdown ramp rate is shown in (34), and ramp-down rate is represented by (35) in the model. The minimum up time constraint is as follows

$$\sum_{t=1}^{G_i} \Big(1 - I_{it}\Big) = 0, \quad \forall i, \tag{36}$$

$$\sum_{k=t}^{t+UT_i-1} I_{ik} \geq UT_i \cdot \Big(I_{it} - I_{i(t-1)}\Big), \quad \forall i, \quad \forall t = G_i + 1, \ldots, NT - UT_i + 1, \tag{37}$$

$$\sum_{k=t}^{NT} \Big(I_{ik} - (I_{it} - I_{i(t-1)})\Big) \geq 0, \quad \forall i,\ \forall t = NT - UT_i + 2, \ldots, NT, \tag{38}$$

where $G_i = \min\{NT, (UT_i - U_i^0) I_i^0\}$ is the number of primary time periods that generation unit i is online, U_i^0 is the number of time periods up to the beginning of the planning horizon before generation unit i becomes online, and I_i^0 is the primary commitment state of generation unit i. The minimum downtime constraint is shown as follows

$$\sum_{t=1}^{L_i} I_{it} = 0, \quad \forall i, \tag{39}$$

$$\sum_{k=t}^{t+DT_i-1} \left(1 - I_{ik}\right) \geq DT_i \cdot \left(I_{i(t-1)} - I_{it}\right), \quad \forall i, \quad \forall t = L_i + 1, \ldots, NT - DT_i + 1, \tag{40}$$

$$\sum_{k=t}^{NT} \left(1 - I_{ik} - (I_{i(t-1)} - I_{it})\right) \geq 0, \quad \forall i, \ \forall t = NT - DT_i + 2, \ldots, NT, \tag{41}$$

where $L_i = \min\{NT, (DT_i - S_i^0)(1 - I_i^0)\}$ is the number of primary time periods that generation unit i is offline, and S_i^0 is the number of periods up to the beginning of planning horizon that generation unit i has been offline.

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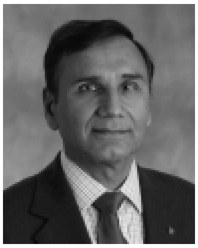

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