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Power Distribution System Outage Management with Co-Optimization of Repairs, Reconfiguration, and DG Dispatch

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***Abstract*—This paper proposes a two-stage method for the outage management of power distribution systems. The first stage is to cluster repair tasks of damaged power generation and delivery components based on their distances from the depots (central crew stations) and the availability of resources, to improve the computational efficiency in solving outage management problems for large distribution systems. The second stage is to co-optimize the repair, reconfiguration, and DG dispatch to maximize the picked-up loads and minimize the repair time. The distribution system repair and restoration problem (DSRRP) is formulated as a mixed integer linear program (MILP), considering constraints of system operation and routing repair crews (RRC). Crews are dispatched considering equipment resources, traveling time, and repair time. The proposed method is tested on modified IEEE 34 and 123-bus distribution test systems with multiple damages. The results demonstrate the advantages of co-optimizing repair and restoration.**

***Index Terms*—Distributed generation, mixed-integer linear program (MILP), power distribution system, repair crews, service restoration**

NOMENCLATURE

Sets and Indices

m/n	Indices for damaged components and depots
c	Index for crews
i/j	Indices for buses
dp	Return point for the repair crews
k	Index for distribution line connecting i and j
t	Index for time
σ	Index for cluster
BS	Set of buses which are substations
$K(.,i)$	Set of lines with bus i as the to bus
$K(i,.)$	Set of lines with bus i as the from bus
N_σ	Set of damaged components and depots
NG_σ	Set of damaged power generation components
NL_σ	Set of damaged power delivery components
RC_σ	Set of crews in σ
SW	Set of lines with switches
U_c	Set of damaged components crew c cannot repair

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Parameters

α	Weight factor
Cap_c	Resource capacity for crew c
$d(dep_\sigma, m)$	Distance between the depot in cluster σ and damaged component m
H_m	Constant identifying public hazard
nc_σ	Number of crews in the depot for cluster σ
LD	Maximum low-priority load
$p^D_{i,t}/q^D_{i,t}$	Active/reactive demand at bus i and time t
$r_{m,c}$	Expected time needed by crew c to repair damaged component m
R_k/X_k	Resistance/reactance of line k
Res^P_σ	Number of available resources in the depot for cluster σ
Res^N_m	Number of resources required to fix damaged component m
S	Number of clusters or depots
$tr_{m,n,c}$	Traveling time for crew c between m and n
$TD_{\sigma,m}$	Binary parameter equals 1 if the depot in cluster σ has a crew that can repair damaged component m
ω^D_i	Priority weight of load at bus i

Variables

$AT_{m,c}$	Arrival time of crew c at damaged component m
$f_{m,t}$	Binary variable indicating the time damaged component m is repaired
nb_t	Number of buses in a spanning tree at time t
$p^{DG}_{i,t}/q^{DG}_{i,t}$	Active/reactive power generated by DG at bus i
$P_{k,t}/Q_{k,t}$	Active/reactive power flowing on line k
Res^C_c	Number of resources assigned to crew c
$s_{\sigma,m}$	Binary variable indicating whether damaged component m is assigned to cluster σ
$u^G_{i,t}/u^L_{k,t}$	Binary variables indicating the status of the DG/line
$V_{i,t}$	Voltage at bus i and time t
$x^\sigma_{m,n,c}$	Binary variable indicating whether crew c moves from damaged components m to n.
$y^\sigma_{m,c}$	Binary variable indicating whether crew c visited damaged component m
$z_{m,t}$	Binary variable indicating the availability of damaged component m at time t
$\beta_{i,j,t}$	Binary variable equals 1 if i is the parent bus of j and 0 otherwise.
$\rho_{i,t}$	Connection status of the load at bus i

I. INTRODUCTION

NATURAL disasters and extreme weather events happen more frequently in recent years, which highlights the importance of improving outage management and accelerating service restoration in power systems. Outage management system (OMS) is used by utilities to identify locations of damages, prioritize restoration efforts and manage repair crews. An efficient OMS can reduce the durations and sizes of power outages [1].

There has been considerable progress in power system restoration techniques [2], [3]. A variety of algorithms have been proposed for load restoration, including heuristic techniques [4], dynamic programming [5] and multi-agent systems [6]. Network reconfiguration is one of the most commonly used methods to restore a power distribution system. The authors in [7] developed a reconfiguration formulation, using a variation of the fixed charge network problem for service restoration. Recent studies have shown that distributed generators (DGs) and microgrids have the potential to assist outage management. The authors in [8] and [9] investigated the self-healing ability of a power distribution system by sectionalizing the system into multiple networked microgrids. Reference [10] presented a microgrid formation scheme for radial distribution networks to restore critical loads after outages.

Research has been conducted to integrate repair and restoration in power transmission systems. The authors in [11] proposed pre and post-hurricane models for restoring power systems. Repair crews were assigned to specific locations considering the stochasticity of hurricanes. A MILP was developed for post-hurricane system restoration without routing the crews. Routing repair crews (RRC) in transmission systems has been discussed in [12]. A multi-stage approach was employed to decouple the routing and power-flow models. The authors developed two subproblems. The first problem was to find the needed repairs to restore the grid to its full capacity. The second problem was to optimize repair orders to minimize the outage duration. This work was further developed in [13] by using a randomized adaptive vehicle decomposition technique. The authors in [14] used the queuing theory and stochastic point processes to determine the repair schedules. The distribution system was divided into zones or service territories and solved separately. In [15], dynamic programming was used to dispatch repair crews and reconfigure the distribution network. Currently, utilities still rely on their experiences and predefined priorities to dispatch crews. However, these criteria have not been updated for years, which cannot lead to optimal solutions.

It has been shown that the co-optimization of repairs and system restoration is a challenging problem [12]. The routing problem is an NP-hard combinatorial optimization problem that has been studied for a long time in Operations Research [16]. Combining emergent distribution system operation with the routing problem will further increase the complexity. One way to approach the power system operation/restoration and repair crew routing is to consider them as two independent problems. However, DG dispatch, line switching and repair are interdependent in practice. For example, a power system cannot be completely restored without repairing damaged components. On the other hand, the restoration can be accelerated with the help of DGs and automatic line switches. Simply relying on utility operators' experiences to dispatch repair crews during outages cannot lead to an optimal outage management plan. Hence, there is a need to design an integrated framework to optimally coordinate repairs and restoration.

In this paper, we propose a two-stage approach for solving the distribution system repair and restoration problem (DSRRP). We consider radial distribution networks with DGs and line switches. The first stage is to cluster the damaged components after an outage, which can reduce the computational complexity of the co-optimization problem in the second stage [12], [17]. Damaged power generation components (e.g., DGs) and power delivery components (e.g., lines, transformers, etc.) are clustered using a proposed integer program, based on their distances to depots and the availability of repair resources. A mixed integer linear program (MILP) is developed in the second stage to co-optimize DG dispatch, system reconfiguration and RRC. The second stage solves the DSRRP based on the clustering results. The proposed MILP aims to maximize the picked-up loads and minimize the repair time. RRC is modelled as a vehicle routing problem (VRP) [18], [19], which is a combinatorial optimization and integer programming problem that aims to find the optimal routes for a fleet of vehicles. We have customized the traditional VRP by considering constraints of repair time, resources and repair crew attributes. The components' repair time and the traveling time between damaged components are considered for each crew. In addition, a crew can carry a limited number of resources once they are dispatched. We consider two types of damages: regular damages that cause loss of energy, and hazardous damages that are potentially dangerous to the public. The crews can handle one or both types of damages depending on their skills. The proposed method is tested on the IEEE 34 and 123 bus systems.

The remainder of this paper is organized as follows. Section II presents the framework of the DSRRP. Routing repair crews is discussed in Section III. The clustering approach is presented in Section IV. Section V details the mathematical formulation. In Section VI, the numerical results and discussion are provided. Section VII concludes the paper with the major findings.

II. DISTRIBUTION SYSTEM REPAIR AND RESTORATION OPERATION FRAMEWORK

Fig. 1 depicts the proposed two-stage framework. After a disastrous event, a utility needs to conduct the damage assessment [20] by sending out field assessors to locate damages as well as estimate the repair time and required resources. Damage assessment can be performed with the help of fault identification algorithms, prediction algorithms, reports from consumers, and aerial survey after extreme conditions. The utility then uses this information to dispatch repair crews. In this paper, we assume this damage assessment information is available and used it as an input for the optimization model [11]. The grid operator receives the locations of damaged

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components, and clusters them using the proposed integer programming model (details are provided in Section III). These clusters are assigned to different depots. After that, the DSRRP model is solved to route repair crews, dispatch DGs, and operate line switches. The available crews receive needed repair resources at depots, and are mobilized to damaged components. Each crew has a specific path starting from a depot and returning to it after finishing all assigned tasks. The main objective is to reduce the outage size and duration.

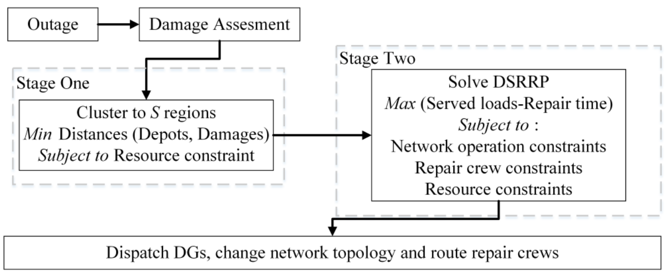

Fig. 1. Overview of DSRRP framework

III. Routing Repair Crews

Dispatching repair crews is an integral part of the proposed co-optimization method. The RRC problem can be defined by an undirected graph with nodes and edges $G(N, E)$. The node set N in the undirected graph contains depots and damaged components, and the edge set E represents the paths connecting each two components. For D damaged components, $N = \{0, 1, ..., D, dp\}$, where 0 and dp are the starting and returning points respectively. The nodes 0 and dp represent the depot, as each crew starts and returns to the depot after finishing the assigned tasks. $N' = N \backslash \{0, dp\}$ is the set of damaged components. Each damaged component $m \in N'$ is characterized by expected repair time $r_{m,c}$ and required repair resources Res_m^N. The depot contains Res^P resources and each crew has a resource capacity of Cap_c. The crews stationed at a depot can access the available resources in the depot. $E = \{(m, n)|m, n \in N; m \neq n\}$ is the edge set containing all possible paths. The traveling time between damaged components m and n for crew c is given by $tr_{m,n,c}$. Define the route assigned to crew c as $Route_c$. The solution to the RRC problem for nc crews includes $Route_1, Route_2, ..., Route_{nc}$, each route has a specific traveling path. A route $Route_c$ is feasible if the total resources required to repair the damaged components do not exceed the capacity of the crew, that is:

$$\sum_{\forall m \in Route_c} Res_m^N \leq Cap_c \tag{1}$$

Fig. 2 shows a possible solution for VRP with two crews and one depot. The routes assigned for crew 1 and 2 are $Route_1 = \{0, a, b, c, dp\}$ and $Route_2 = \{0, d, e, f, g, dp\}$. The capacity of crew 1 must be larger than the total resources required to repair the damages: $Cap_1 \geq Res_a^N + Res_b^N + Res_c^N$. Our purpose is to find the optimal route for each crew to reach the damaged components. Binary variable $x_{m,n,c}$ equals one if a crew c travels the path m to n. Each crew starts from a depot and returns to the same depot after all assigned repair tasks are finished, hence:

$$\sum_{\forall m \in N'} x_{0,m,c} = \sum_{\forall c} \sum_{\forall m \in N'} x_{m,dp,c} = nc, \forall c \tag{2}$$

A damaged component in N' is repaired by one crew only, which means:

$$\sum_{\forall c} \sum_{\forall m \in N \backslash \{n\}} x_{m,n,c} = 1, \forall n \in N' \tag{3}$$

Once the damaged component is repaired, the crew moves on to the next location, i.e.:

$$\sum_{\forall m \in N \backslash \{n\}} x_{m,n,c} = \sum_{\forall m \in N \backslash \{n\}} x_{n,m,c} = 1, \forall c, n \in N' \tag{4}$$

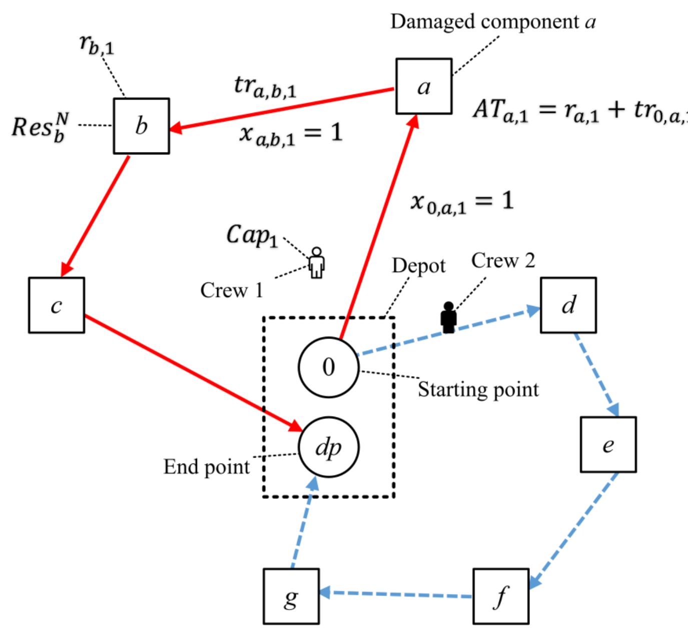

Fig. 2. Illustration of the crew routing problem

Since crew 1 is assigned with $Route_1$ in the example shown in Fig. 2, then $x_{0,a,1}$=$x_{a,b,1}$=$x_{b,c,1}$=$x_{c,dp,1}$=1, and 0 for all other paths. The total time to complete all repairs is the sum of the traveling and repair times for each crew, thus all repairs are finished after: $\sum_{\forall m} \sum_{\forall n} \sum_{\forall c} (r_{m,c} + tr_{m,n,c}) x_{m,n,c}$. If crew c travels from m to n, then the arrival time at the damaged component n is:

$$AT_{n,c} = AT_{m,c} + r_{m,c} + tr_{m,n,c} \tag{5}$$

Therefore, a damaged component m is repaired after $AT_{m,c} + r_{m,c}$. In Fig.2, the time to arrive to a for crew 1 is $AT_{a,1} = tr_{0,a,1}$, and the time to arrive to b is $AT_{b,1} = AT_{a,1} + r_{a,1} + tr_{a,b,1}$.

The objective of a regular routing problem is to minimize the total traveling time. However, for the problem of repair and restoration, the objective is to dispatch crews to maximize restored loads in a fast way. The crew routing formulation is detailed Section V.

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IV. Clustering of Damaged Components

To reduce the computational complexity of the co-optimization problem, we propose a clustering method to assign damaged components to depots. The damaged components are clustered before RRC by dividing them into S clusters, which is determined by the number of depots [21]. Clusters are denoted by the index σ, where $\sigma = 1, 2, ..., S$. By performing the pre-routing clustering, the RRC problem is decomposed from a single large VRP problem to S small VRP problems. Each depot has a set of crews and resources. Resources that may be required by repair tasks include vehicles, equipment, crews, etc. After damages are clustered, the information is sent to the second stage to solve the DSRRP. We formulate the clustering problem as an integer linear program. The input data of the optimization problem includes distances between depots and damaged components $d(dep_\sigma, m)$, resources available at depots Res_σ^P and resources required to fix damages Res_m^N. A binary variable $s_{\sigma,m}$ is used to decide which cluster a component m is assigned to.

$$s_{\sigma,m} = \begin{cases} 1\,, m \ is\ clustered\ to\ \sigma \\ 0\,, \quad o.w. \end{cases} \quad \forall \sigma, m \tag{6}$$

Fig. 3 illustrates the clustering approach. Consider a damaged component *m*, the component is clustered based on the shortest distance to a depot, i.e., $min\{d(1,m), d(2,m), d(3,m)\}$. If the depot does not have enough resources, the damaged component is clustered to the next closest depot.

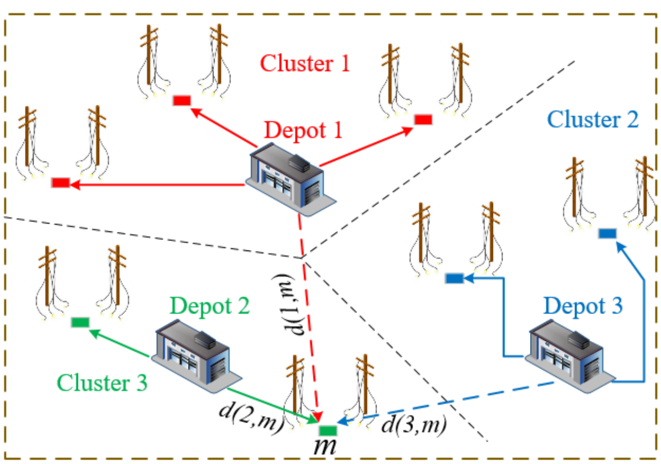

Fig. 3. Illustration of the clustering method

The clustering problem is modeled as follows.

$$\min_s \sum_{\forall \sigma} \sum_{\forall m} d\,(dep_\sigma, m)\ s_{\sigma,m} \tag{7}$$

$$\sum_{\forall \sigma} s_{\sigma,m} = 1\ ,\ \forall m \tag{8}$$

$$Res_\sigma^P \geq \sum_{\forall m} Res_m^N\ s_{\sigma,m}\ ,\ \forall \sigma \tag{9}$$

$$TD_{\sigma,m} \geq s_{\sigma,m}\ \forall \sigma, m \tag{10}$$

$$s_{\sigma,m} \in \{0,1\}\ ,\ \forall \sigma, m \tag{11}$$

The objective (7) is to assign the damaged components to their closest depots. Constraint (8) ensures that a damaged component is assigned to a single depot. The assignment is performed while considering the resource availability constraint in (9). The resource constraint ensures that depots have enough resources to handle the assigned damages. These resources are then assigned to the crews in the repair and restoration problem in the next section. Furthermore, each damage should be assigned to a depot that has a crew capable of repairing the damage, which is represented by constraint (10), where $TD_{\sigma,m}$ equals 1 if depot σ can handle damage m, and 0 otherwise.

V. DSRRP Mathematical Formulation

This section provides the optimization formulation for the DSRRP. Our model solves two main problems in DSRRP. The first problem is distribution system restoration using DGs and reconfiguration,with variables $\{p^{DG}, u^G, u^L, P, Q, \beta, \rho, V\} \in \Gamma$. The second is the routing problem characterized by depots, repair crews, resources, damaged components and paths between the damaged components, with variables $\{x, y, AT, f, z\} \in Y$. In practice, these two problems are interdependent. Therefore, we propose a single MILP formulation that integrates the two problems for distribution system repair and restoration. The objective of the proposed model is given as follows.

$$\begin{aligned} \max_{\Gamma, Y}\ \alpha_1 \sum_{\forall t} \sum_{\forall i} \omega_i^D \rho_{i,t} p_{i,t}^D \\ - \alpha_2 \sum_{\forall t} \sum_{\forall m} H_m t\ f_{m,t} \end{aligned} \tag{12}$$

The objective (12) is to maximize the picked-up loads and minimize the repair time of the damaged components, each assigned with weight α. The main objective of the repair and restoration problem is to maximize the served loads (i.e. the first term in the proposed objective function). However, there are two main issues if we only consider this objective: 1) If all loads are served before the repairs are finished, there is no incentive for the crews to finish the remaining repairs as fast as possible, and 2) multiple restoration strategies may be selected as they can achieve the same total served loads. Therefore, we need the second term in the objective function to ensure that the fastest strategy is selected. Since the main goal is to maximize the restored loads, the weights are set such that $\alpha_1 \gg \alpha_2$. The binary variable $\rho_{i,t}$ indicates whether a de-energized load is restored, i.e., $\rho_{i,t}$ = 1 means the load is picked-up. The load priorities are taken into account by ω_i. In this paper, we consider high and low priority loads. The weight ω_i equals 1 for low-priority loads, while the weight for the high-priority loads is given by the following equation [22].

$$\omega_i = LD/p_i^D + 1 \tag{13}$$

where LD is the maximum low-priority load. These weights ensure that high-priority loads are prioritized. Note that the weights of loads are parameters in the proposed model, and can be changed by utility operators. $f_{m,t}$ is a binary variable

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indicating when a damaged component is restored. For example, if component $m = 1$ is repaired at $t = 5$, then $f_{1,5} = 1$ and $\sum_{\forall t} t\ f_{1,t} = 5$. In case the damaged component is a public hazard, the constant H_m takes a large value and one otherwise. Repair crews must first deal with public safety-related hazards and repair damages that are connected to high-priority loads, such as hospitals or fire stations.

A. Distribution System Modeling

$$0 \le p_{i,t}^{DG} \le p_i^{DGmax} u_{i,t}^G\ ,\ \forall i,t \tag{14}$$

$$0 \le q_{i,t}^{DG} \le q_i^{DGmax} u_{i,t}^G\ ,\ \forall i,t \tag{15}$$

$$-\,u_{k,t}^L P_k^{max} \le P_{k,t} \le u_{k,t}^L P_k^{max}\ ,\ \forall k,t \tag{16}$$

$$-\,u_{k,t}^L Q_k^{max} \le Q_{k,t} \le u_{k,t}^L Q_k^{max}\ ,\ \forall k,t \tag{17}$$

$$u_{k,t}^L = 1, \forall k \notin \{SW \cup NL\} \tag{18}$$

$$\beta_{i,j,t} + \beta_{j,i,t} = u_{k,t}^L,\ \forall k,t \tag{19}$$

$$\beta_{i,j,t} = 0,\ \forall i,j \in BS, t \tag{20}$$

$$\sum_{\forall i} \beta_{i,j,t} \le 1,\ \forall j,t \tag{21}$$

$$\sum_{\forall k \in K(.,i)} P_{k,t} + p_{i,t}^{DG} = \sum_{\forall k \in K(i,.)} P_{k,t} + \rho_{i,t} p_{i,t}^D\ , \forall i,t \tag{22}$$

$$\sum_{\forall k \in K(.,i)} Q_{k,t} + q_{i,t}^{DG} = \sum_{\forall k \in K(i,.)} Q_{k,t} + \rho_{i,t} q_{i,t}^D\ , \forall i,t \tag{23}$$

$$V_{j,t} - V_{i,t} + \frac{R_k P_{k,t} + X_k Q_{k,t}}{V_1} \le (1 - u_{k,t}^L) M,\ \forall k,t \tag{24}$$

$$-(1-u_{k,t}^L)M \ \le\ V_{j,t} - V_{i,t} + \frac{R_k P_{k,t} + X_k Q_{k,t}}{V_1},\ \forall k,t \tag{25}$$

$$1 - \varepsilon \le V_{i,t} \le 1 + \varepsilon\ ,\ \forall i,t \tag{26}$$

$$\rho_{i,t+1} \ge \rho_{i,t}\ ,\ \forall i,t \tag{27}$$

The distribution network operation constraints are represented by (14)-(27). In this paper, we consider dispatchable DGs for supplying loads in the distribution network. Constraints (14) and (15) define the active and reactive power output limits for DGs, respectively. Constraints (16) and (17) indicate that the power flow through a damaged line should be zero, which is achieved by multiplying the line limits by a binary variable $u_{k,t}^L$. Line switches can be switched ON/OFF by $u_{k,t}^L$ to reconfigure the network. Constraint (18) maintains the switching status of a line $u_{k,t}^L$ to be 1 when it is neither damaged nor a switch.

The distribution network is reconfigured dynamically using switches to maintain the radial configuration. The radiality constraints are represented by (19)-(21) based on the spanning tree approach in [23]. The authors in [23] showed that it is possible to maintain a radial configuration regardless of the direction of power flow. Two binary variables $\beta_{i,j,t}$ and $\beta_{j,i,t}$ are defined to model the spanning tree. $\beta_{i,j,t}$ equals 1 if bus i is the parent bus to child bus j. For a radial network, each bus cannot be connected to more than one parent bus and the number of lines equals the number of buses other than the root bus. Constraint (19) presents the relation between the connection status of the line and the spanning tree variables $\beta_{i,j,t}$ and $\beta_{j,i,t}$. If the distribution line is connected, then either $\beta_{i,j,t}$ or $\beta_{j,i,t}$ must be one. Constraint (20) indicates that the substation does not have a parent bus and designates it as a root bus. Constraints (21) requires that every bus has one or less parent bus. The spanning tree constraints guarantee that the number of buses in a spanning tree, other than the root, equals the number of lines. By taking the sum of (19) for all lines, we can find the following.

$$\sum_{\forall i} \sum_{\forall j} \beta_{i,j,t} = \sum_{\forall k} u_{k,t}^L, \forall t \tag{28}$$

Considering that each bus has at most one parent bus, then the number of lines equals the number of buses (nb_t) besides the root bus.

$$nb_t - 1 = \sum_{\forall i} \sum_{\forall j} \beta_{i,j,t} = \sum_{\forall k} u_{k,t}^L, \forall t \tag{29}$$

DistFlow [24] equations are used to represent power flows in distribution networks. Linearized Distflow equations have been extensively used and verified in literature [24], [25], [26], [27]. Constraints (22) and (23) represent the active and reactive power balance constraints respectively. The total real and reactive power flow into a bus should equal the flow out of the bus. The voltage at each bus is expressed in constraints (24) and (25), where V_1 is the reference voltage. A *big M* method is used to ensure the voltage levels of two disconnected buses (i.e., when $u_{k,t}^L$ equals zero) are decoupled. The combination of constraints (16)-(25) represents the network connectivity which is affected by damaged components and line switches. Constraint (26) defines the allowable range of voltage deviations, where ϵ is set to be 5%. Once a load is picked-up, it should remain energized, which is enforced by constraint (27).

B. RRC

$$\sum_{\forall n \in N_\sigma \backslash \{m\}} x_{m,n,c}^\sigma - \sum_{\forall n \in N_\sigma \backslash \{m\}} x_{n,m,c}^\sigma = 0\ , \quad \forall \sigma, c \in RC_\sigma,\ m \in N_\sigma \backslash \{0, dp\} \tag{30}$$

$$\sum_{\forall m \in N_\sigma \backslash \{0\}} x_{0,m,c}^\sigma - \sum_{\forall m \in N_\sigma \backslash \{0\}} x_{m,0,c}^\sigma = 1\ ,\ \forall \sigma, c \in RC_\sigma \tag{31}$$

$$\sum_{\forall m \in N_\sigma \backslash \{dp\}, c \in RC_\sigma} x_{m,dp,c}^\sigma = nc_\sigma\ ,\ \forall \sigma \tag{32}$$

$$\sum_{\forall c \in RC_\sigma} y_{m,c}^\sigma = 1\ ,\ \forall \sigma, m \in N_\sigma \backslash \{0, dp\} \tag{33}$$

$$y_{m,c}^\sigma = \sum_{\forall n \in N_\sigma \backslash \{0,m\}} x_{m,n,c}^\sigma\ ,\ \forall \sigma, c \in RC_\sigma, \quad m \in N_\sigma \backslash \{dp\} \tag{34}$$

$$y_{m,c}^\sigma = 0\ ,\ \forall \sigma, c, m \in U_c \tag{35}$$

This subsection presents constraints (30)-(35) for the routing problem. The damaged components in each cluster are defined in set $N_\sigma = \{0, 1, ..., dp\}$. The set N_σ can be further

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divided into the subsets NG_σ and NL_σ, which represent the damaged DGs and power delivery components, respectively. RC_σ represents the set of crews in each cluster. The path-flow conservation constraint (30) ensures that a crew arriving at a damaged component leaves it after finishing the repair, which can be derived from (4). Constraint (31) ensures that the crews start from depots and constraint (32) indicates that all crews return to the depots, where nc_σ is the number of crews in the cluster. If a crew c visits a damaged component m, then $y^\sigma_{m,c}$ equals 1. Constraint (33) indicates that a damaged component is fixed by only one crew to ensure that no crew visits a repaired component. Constraint (34) couples the binary variables $y^\sigma_{m,c}$ and $x^\sigma_{m,n,c}$, i.e., if a crew c takes the traveling path $x_{m,n}$, then $y_{m,c} = 1$. Constraint (35) indicates that a crew will not travel to a damaged component that he cannot repair. For instance, some crews are able to repair damages to transformers and DGs, while others can handle overhead distribution lines.

C. Resource Availability

$$Res^C_c \geq \sum_{\forall m \in N_\sigma} Res^N_m \, y^\sigma_{m,c} \ , \ \forall \sigma, c \tag{36}$$

$$\sum_{\forall c} Res^C_c \leq Res^P_\sigma, \ \forall \sigma \tag{37}$$

$$Res^C_c \ \leq \ Cap_c \ , \ \forall c \tag{38}$$

In the clustering stage, we have ensured that depots have sufficient resources to repair the damages. Each crew receives Res^C_c resources to complete the assigned repair tasks. Constraint (36) ensures that crews have enough resources to complete all of their repair tasks. Constraint (37) indicates that the total resources assigned to the crews are less than or equal to the resources available at the depot for each cluster. Constraint (38) sets the limit on crews' resources.

D. Repair of Damaged Components

$$\begin{gathered} AT_{m,c} + r_{m,c} + tr_{m,n,c} - AT_{n,c} \leq \left(1 - x^\sigma_{m,n,c}\right) M \ , \\ \forall \sigma, m \in N_\sigma \backslash \left\{dp\right\}, n \in N_\sigma, c \in RC_\sigma \end{gathered} \tag{39}$$

$$\sum_{\forall t} f_{m,t} = 1 \ , \ \forall \sigma, m \in N_\sigma \tag{40}$$

$$\begin{gathered} \sum_{\forall t} t f_{m,t} \geq \sum_{\forall c \in RC_\sigma} \left(AT_{m,c} + r_{m,c} y^\sigma_{m,c}\right), \\ \forall \sigma, \ m \in N_\sigma \end{gathered} \tag{41}$$

$$\begin{gathered} \sum_{\forall t} t f_{m,t} \leq \sum_{\forall c \in RC_\sigma} \left(AT_{m,c} + r_{m,c} y^\sigma_{m,c}\right) + 1 - \ \varepsilon, \\ \forall \sigma, m \in N_\sigma \end{gathered} \tag{42}$$

$$0 \leq AT_{m,c} \leq y^\sigma_{m,c} M \ , \ \forall \sigma, m \in N_\sigma, \ c \in RC_\sigma \tag{43}$$

$$z_{m,t} \leq \sum_{\tau=1}^{t-1} f_{m,\tau} \ , \ \forall \sigma, m \in N_\sigma, t \tag{44}$$

$$u^G_{m,t} \leq z_{m,t} \ , \ \forall \sigma, m \in NG_\sigma, t \tag{45}$$

$$u^L_{m,t} \leq z_{m,t} \ , \ \forall \sigma, m \in NL_\sigma, t \tag{46}$$

This subsection explains constraints (39)-(46). Constraint (39) represents the arrival time. From (5), once a crew arrives at a damaged component m at time $AT_{m,c}$, he/she spends a time $r_{m,c}$ to repair the damaged component, and then takes $tr_{m,n,c}$ time to arrive at the next damaged component n. The *big M* method is used to decouple the times to arrive at components m and n if the crew does not travel through the path $x_{m,n,c}$. The binary variable $f_{m,t}$ equals 1 once a damaged component m is repaired at time t. Constraint (40) indicates that the damaged component is repaired once, i.e., crews do not travel to damaged components that are already repaired. The time to repair a damaged component is determined by the arrival time and the required repair time. Consider an example in which a crew $c = 1$ arrives at a damaged component $m = 1$ at time $AT_{1,1} = 1$, and the crew needs $r_{1,1} = 3.5$ to fix the component. Therefore, the damaged component is repaired at $AT_{1,1}+r_{1,1} = 4.5$. Constraints (41) and (42) define $\lceil tf_{i,t} \rceil$ which is the time a damaged component is repaired. The damaged component $m = 1$ in the example is repaired at $tf_{i,t} = 5$. If the damaged component is not repaired by a crew c then the arrival time and repair time for this crew should not affect constraints (41) and (42), which is realized by using constraint (43) to set $AT_{m,c} = 0$. Constraint (44) indicates that the restored component becomes available in all subsequent time periods. For example, if $t = 1..5$ and $f = [0, 0, 1, 0, 0]$ then $z = [0, 0, 0, 1, 1]$, thus the component is available at $t = [4, 5]$. Constraints (45) and (46) connect RRC with the distribution network operation constraints by forcing $u^G_{i,t}$ and $u^L_{i,t}$ to zero if the damage is not fixed. Finally, the proposed DSRRP model is formulated as follows:

DSRRP Model	
Objective:	(12)
Constraints:	(14)-(27), (30)-(46)
	$f_{m,t}, u^G_{i,t}, u^L_{k,t}, x^\sigma_{m,n,c}, y^\sigma_{m,c},$
	$z_{m,t}, \beta_{i,j,t}, \rho_{i,t} \in \{0, 1\}$

VI. Simulation and Results

The proposed method is tested on two IEEE distribution test systems, IEEE 34-bus network [28] and IEEE 123-bus network [29]. The problems are modeled in AMPL and solved using CPLEX 12.6.0.0 on a PC with Intel Core i7-4790 3.6 GHz CPU and 16 GB RAM. In both cases, we consider dispatchable DGs and assume that the locations of damages are known. We assume crews have different skills, e.g., some crews are unable to fix DGs or hazards, and the needed repair time varies from one crew to another.

A. Case I: IEEE 34-Bus Network

For illustration, we assume the network has 6 damaged lines, and one damaged DG, as shown in Fig. 4. In addition, there are two depots, each has 15 units of available resources and two crews. DGs 1, 2, 3, and 4 are rated at 100, 150, 200 and 250 kW respectivly. Detailed load demand information can be found in [28]. Table I lists the damaged components with the amount of required repair resources and the time each crew needs to fix the damages.

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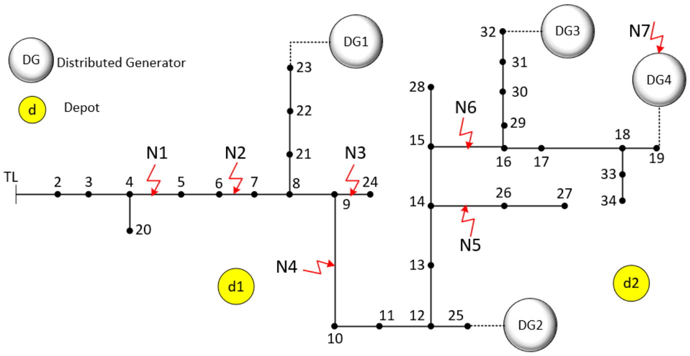

Fig. 4. IEEE 34-bus network with damages

TABLE I
REPAIR TIME AND REQUIRED RESOURCES FOR THE DAMAGES IN CASE I

Damage	Repair time (30 minutes step)				Required Resources
	Crew 1	Crew 2	Crew 3	Crew 4	
N1	2	3	2	3	2
N2	2	2	2	2	2
N3	2	3	2	2	2
N4	6	5	6	5	4
N5	4	3	3	3	2
N6	3	4	3	3	2
N7	4	NA	4	4	4

For illustration, we choose the number of clusters to be one since it is a small network. The repair and restoration problem is solved using the model presented in Section V. The MILP model is solved in 15 seconds, and the resulting routes are shown in Fig. 5, where each color represents one crew. Table II depicts the sequence of repair tasks. Damages $N1, N2$ and $N4$ are prioritized as they are on the main distribution line connecting to the substation. $N7$ is prioritized so that DG 4 and DG 3 supply the loads on the right side of the network. Therefore, $N6$ is not prioritized since DG 3 and DG 4 are supplying the important loads in the network. A single low priority load is connected to bus 24, hence Line 9-24 is repaired last.

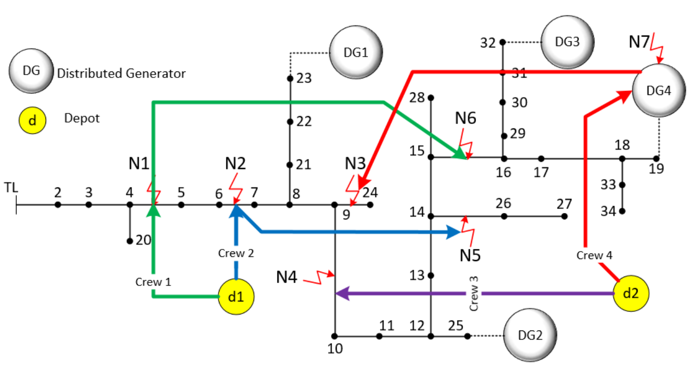

Fig. 5. IEEE 34-bus DSRRP routing schedule

To demonstrate the improvement of the proposed co-optimization model, we compare it with a benchmark model which treats the co-optimization as two independent problems, i.e., an optimal repair crew dispatching problem and a network reconfiguration/DG dispatching problem. Therefore, we consider solving two separate optimization problems. The first problem is to find the optimal routes that minimize the

TABLE II
TIME SEQUENCE OF THE REPAIRS IN CASE I

Time Step (30 minutes step)	Repaired Components
1	
2	
3	N1, N2
4	
5	N7
6	
7	N4, N5
8	N6
9	N3

time to repair all components without considering operation constraints. After obtaining the route and the expected time when each damaged component is restored, we solve the network reconfiguration and DG dispatch problem with operation constraints. RRC is formulated as follows:

$$\min_{Y} \sum_{\forall t} \sum_{\forall m} H_m t \, f_{m,t} \tag{47}$$

Constraints (30)-(44)

$$f_{m,t}, x^{\sigma}_{m,n,c}, y^{\sigma}_{m,c}, z_{m,t} \in \{0,1\}\,,$$
$$\forall \sigma, c, t, (m,n) \in N_{\sigma}$$

The objective of the first problem is to minimize the repair time of the damaged components as given in (47). The values of binary variable $z_{i,t}$ are used as inputs for the following power operation problem:

$$\max_{\Gamma} \sum_{\forall t} \sum_{\forall i} \omega^{D}_{i} \rho_{i,t} p^{D}_{i,t} \tag{48}$$

Constraints (14)-(27), (45)-(46)

$$u^{G}_{i,t},\ u^{L}_{k,t},\ \rho_{i,t} \in \{0,1\}\,,\ \forall i,k,c,t$$

We name this approach the Route First method. The routing schedule is optimized independently from the power system operation/restoration, which results in the solutions shown in Fig. 6.

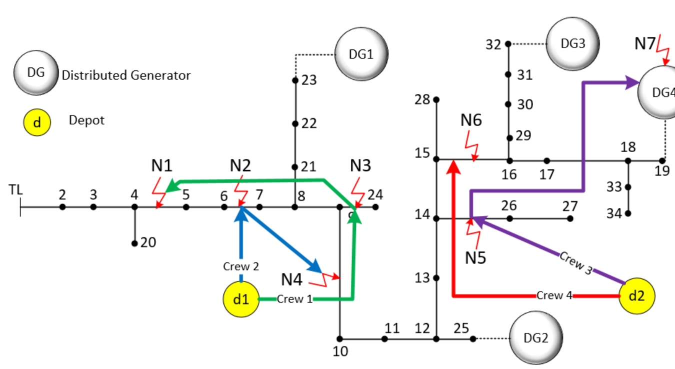

Fig. 6. IEEE 34-bus optimized routing schedule without considering power system operation

After finding the routing schedule, the power restoration problem is solved. The final solution is obtained after 6 seconds (5.8 seconds for the routing problem and 0.16 seconds for power operation). The total served loads at each time

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step is compared in Fig. 7. By co-optimizing the repair and restoration, a total of 6,399 kWh is served in 15 time periods, which is 16.5% higher than the loads served using the Route First approach, which serves only 5,493 kWh.

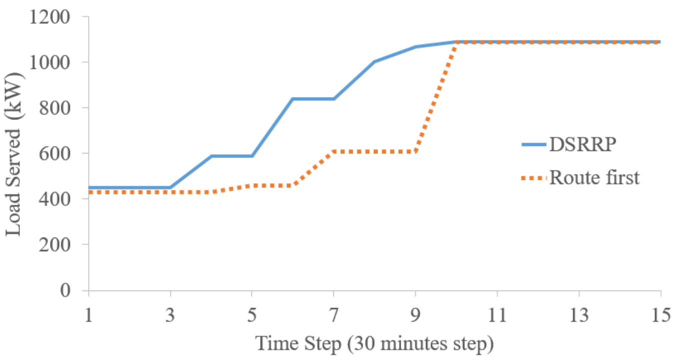

Fig. 7. Total demand served with and without co-optimization for Case I

B. *Case II: IEEE 123-Bus Network*

Fig. 8 shows the IEEE 123-bus network with four dispatchable DGs and six line switches. The capacities of DGs at buses 11 and 450 are 150 kW and 200 kW respectivley. DGs at buses 28 and 85 have capacities of 250 kW. The data for the demand can be found in [29]. There are seventeen damaged lines, three damages are public hazards and one damaged DG located at bus 11, their required repair resources range from two to five units. The clustering model, presented in Section IV, is used to assign the damaged components to depots. After clustering, the problem becomes a VRP problem with three depots, which reduces the number of variables. For illustration, we assume depot 1 has 20 units of available repair resources and three crews, depot 2 has 15 units of resources and 2 crews, and depot 3 has 24 units of resources and 2 crews. The traveling times between damaged components ranges from 15 minutes to 2 hours, where the traveling time between two farthest damaged components is 2 hours.

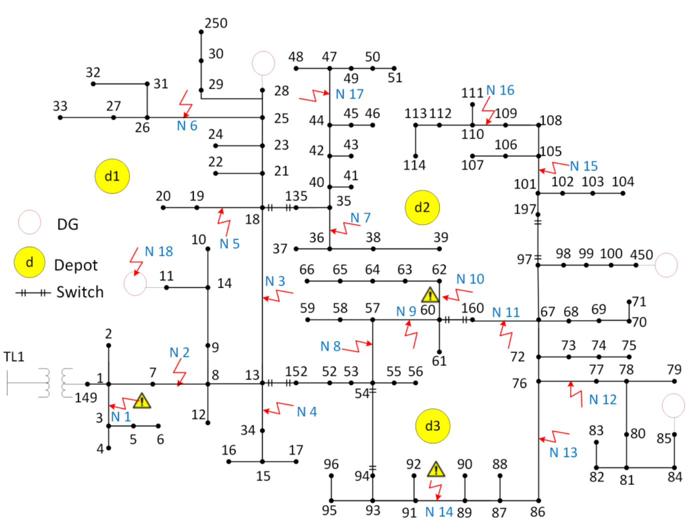

Fig. 8. IEEE 123-bus network with damages

To demonstrate the usefulness of the proposed clustering method, the co-optimized model is used to solve the problem without clustering. A limit of 2 hours is set for the computation time. The program converges to a feasible solution with an optimality gap of 42.86%. This highlights the computational challenge without clustering. Table III shows the clustering results and the time needed to fix each damaged component. The clustering solution is obtained in less than a second.

TABLE III
CLUSTERS AND NEEDED REPAIR TIMES OF THE DAMAGED COMPONENTS IN CASE II

Clusters	Damage	Required Repair Time		
		Crew 1	Crew 2	Crew 3
Depot 1	N1	3	1	NA
	N2	4	3	4
	N3	4	5	6
	N4	3	2	3
	N5	2	3	4
	N6	3	3	2
	N18	5	NA	4
Depot 2	N7	2	2	-
	N10	NA	2	-
	N15	2	2	-
	N16	1	1	-
	N17	3	2	-
Depot 3	N8	4	3	-
	N9	2	2	-
	N11	3	3	-
	N12	1	1	-
	N13	4	3	-
	N14	1.5	NA	-

After clustering, the DSRRP model is solved in 400 seconds. Table IV shows the reconfiguration results. Fig. 9 shows the routing schedules of repair crews, and Table V depicts the sequence of repair tasks.

TABLE IV
LINE SWITCHING STATUS

Time	Switches				
	13-152	18-135	60-160	97-197	54-94
1-9	1	1	1	1	1
10-15	1	1	0	1	1

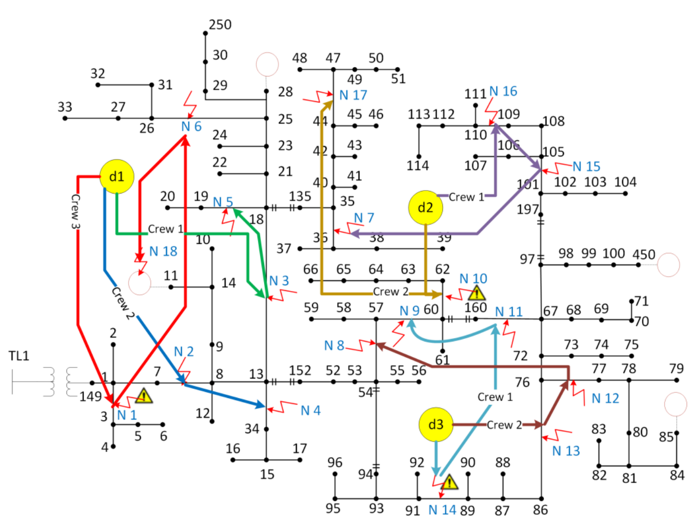

Fig. 9. IEEE 123-bus co-optimized DSRRP routing schedule

Damaged components $N1$, $N10$, and $N14$ are prioritized, as they are public hazards. Similarly to Case I, the main

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TABLE V
TIME SEQUENCE OF THE REPAIRS IN CASE II

Time Step (30 minutes step)	Repaired Components
1	
2	N14, N16
3	N10
4	N1, N13, N15
5	N2, N12
6	N3, N11, N17
7	N4, N6, N7
8	N5
9	N8, N9
10	
11	
12	N18

distribution lines, such as $N2$ and $N3$, are prioritized. $Crew$ 3 from depot 1 chooses to repair the damaged DG lastly, since the power can be supplied by the main substation by repairing $N2$ firstly. $N8$ and $N9$ isolate buses 59, 58 and 57, the two damaged lines can be repaired later since these buses are connected to low-priority loads. All switches are ON until $N8$ and $N9$ are fixed in period $T = 9$, 60-160 is switched OFF so that the network remains radial. The routing schedule is optimized independently using the Route First method, and the solution is obtained in 11 seconds (8 seconds for the routing problem and 3 seconds for power operation) with clustering. The total demand served using the proposed formulation is compared to the Route First approach in Fig. 10. The co-optimized approach serves 14,962.5 kWh, while the Route First method with clustering can only restores 13,412.5 kWh. The results show the need for a co-optimized approach and the effectiveness of the proposed method in improving service restoration.

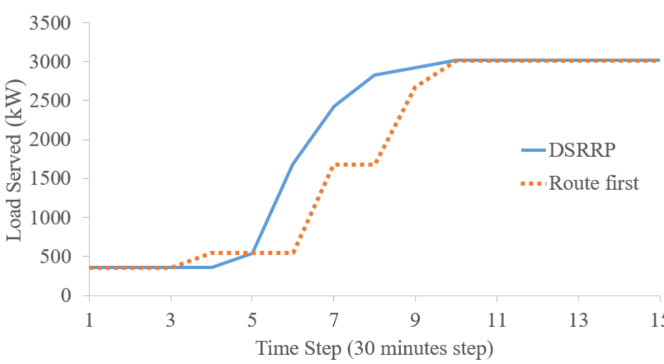

Fig. 10. Total demand served with and without co-optimization for Case II

In the simulation, the weights in the objective function are set to be α_1 = 100 and α_2 = 1 to prioritize the first objective. A sensitivity analysis on α_1 and α_2 is performed, and the results are shown in Table VI. Table VII shows a detailed comparison between the results obtained from (α_1, α_2) = (100,1) and (1,100). If only the first objective is used (i.e. α_2 = 0), the repair crews take a longer time to finish the repairs, as there is no incentive for them to be faster. If we select α_1 = 1 and α_2 = 100, the repairs become faster, but the overall served load is lower as shown in Table VII. The reason is that the crew routing strategy and the repair sequence are not optimized to maximize the total served load. For example, with α_1 = 100 and α_2 = 1, 56% of the loads after 3 hours, while 18% are restored with α_1 = 1 and α_2 = 100.

TABLE VI
SENSITIVITY ANALYSIS FOR CASE II

α_1	α_2	Total served loads (kWh)	Time to finish all repairs
1	0	14,962.5	7.5 hrs
1	1	14,962.5	6 hrs
10	1	14,962.5	6 hrs
100	1	14,962.5	6 hrs
1	100	14,315.5	5 hrs

TABLE VII
TIME SEQUENCE OF THE REPAIRS AND THE PERCENTAGE OF PICKED-UP LOADS, FOR (α_1, α_2) = (100,1) AND (1,100)

Time Step	Repaired Component		% Picked-up Loads	
	$\alpha_1 = 100$ $\alpha_2 = 1$	$\alpha_1 = 1$ $\alpha_2 = 100$	$\alpha_1 = 100$ $\alpha_2 = 1$	$\alpha_1 = 1$ $\alpha_2 = 100$
1	-	-	12%	12%
2	N14, N16	N14, N16	12%	12%
3	N10	N1, N6, N9, N10	12%	12%
4	N1, N13, N15	N15	12%	18%
5	N2, N12	-	18%	18%
6	N3, N11, N17	N2, N3, N5, N8, N11, N17	56%	18%
7	N4, N6, N7	N7	80%	77%
8	N5	N4, N12	94%	83%
9	N8, N9	-	97%	100%
10	-	N13, N18	100%	100%
11	-	-	100%	100%
12	N18	-	100%	100%
13	-	-	100%	100%
14	-	-	100%	100%
15	-	-	100%	100%

VII. CONCLUSION

In this paper, we proposed a two-stage co-optimization approach for the repair and restoration of distribution networks. The paper developed a MILP model to coordinate DGs, switches and repair crews to minimize the sizes and durations of outages. Repair crews' attributes are taken into consideration by resource, traveling time, repair time, and skill set constraints. To reduce the computational complexity of the model, we have proposed a new integer program to cluster damaged components considering their distances to depots and required repair resources. The proposed co-optimization model is compared with existing methods where the repair crew routing and service restoration are treated as two independent problems. The results confirm the advantages of co-optimizing crew routing, DG dispatch, and network reconfiguration in improving the outage management under severe weather events.

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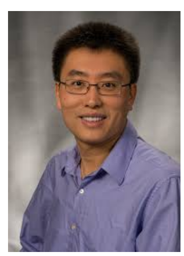

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