OPTIMAL RESOURCE ALLOCATION TO REDUCE THE DISTRIBUTION SYSTEM RISK INDUCED BY HURRICANES

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ABSTRACT

Preventive measures to reduce the risk of large-scale blackouts caused by natural disasters are necessary. This paper focuses on the resource allocation problem in distribution systems before a coming hurricane. The probability evaluation model of critical load service failure is developed. Emergency resources such as crews, materials, and equipment are considered for allocation, which is essential for the hurricane preparedness and postdisaster repairing in terms of critical loads. An evaluation method of outage risks is introduced considering the intensity and path of the coming hurricane. Due to the uncertainties of system failures, the allocation optimization is formulated into a dynamic Mixed-Integer Nonlinear Programming (MINP). Numerical simulations are performed on the IEEE 33-node feeder with 3 dispatch centers in several scenarios to validate the proposed method. The simulation results show that the risk is largely decreased through the proposed allocation strategy.

1. INTRODUCTION

During extreme events, power networks are seriously affected. Recent hurricanes such as Hurricane Ike (US, 2008), Hurricane Irene (US, 2011), Superstorm Sandy (US, 2011), and Typhoon Soudelor (China, 2015) produced severe damage to the power grid infrastructures and caused widespread power outages [1]-[3].

The research focus mainly concentrates on the risk assessment of basic concepts [4], [5], risk assessment model and calculation method [6], [7], risk assessment index system establishment and improvement based on the risk control decision and risk control system construction, and engineering application. In [8], the researchers develop probabilistic indices of risk to assess the real-time power system security level. The risk captures the event likelihood and the consequence.

For the allocation process, in [9], the ambulance relocation and dispatch policies are studied in dynamic ambulance relocation models to improve the response time of the emergency medical service. This model is based on the modified maximal covering location problem. In [10], truck-mounted mobile emergency generators are used for the resilient emergency response to natural disasters via a scenario-based two-stage stochastic optimization problem. The objective is to minimize the expected outage duration of loads considering their priorities and demand size. [11] presents a method to schedule resources in complex systems that integrate humans with diverse hardware and software components. [12] proposes a proactive resource allocation model for the repair and restoration of potential damages to the power system infrastructure located on the path of an upcoming hurricane.

Considering their complexity, allocating limited resources is a major challenge for decision makers. Our previous work [13] focused on the resource allocation problem in distribution systems ahead of a coming hurricane. Electric buses and generation resources such as diesel oil and batteries are considered for allocation, which can be used to serve the outage critical load in the posthurricane restoration. In this paper, an optimal preparation model is formulated to obtain the optimized allocation of responsive resources to reduce the system-level outage risks caused by hurricanes. Both disruptive impacts and mitigation process of the disaster weather are carefully modeled. The optimal preparation model can be solved by the PSO algorithm, which improves the emergency response resource allocation strategies.

2. PROBLEM FORMULATION

In this section, the optimization of the emergency response resource allocation is formulated as a dynamic programming problem.

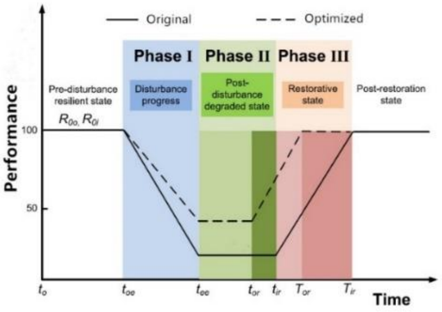

Fig. 1. multiphase system performance trapezoid

This paper adopts the multiphase system performance concept proposed in [14]. Graphically, Fig. 1 shows a quantifiable and time-dependent system performance function with 3 phases.

In Phase I, the performance level drops due to the impacts of the disaster. Specifically, the hurricane causes equipment failure; then, the corresponding power supply path must be disrupted. Critical users along the path are forced to be de-energized.

In Phase II, the system remains at the postdisturbance degraded state for some time before the restoration is initiated. Meanwhile, the amount of required resources for the next phase is also estimated in Phase II.

In Phase III, the optimized solution results in a faster restoration process. The emergency repair resource allocation determines the single recovery time of the critical node; then, the total length of recovery time for the blackout is also calculated.

There is a distinction between the original and the optimal solution because: first, in Phase I, the deployment of emergency resources helps to improve the ability of the critical node to resist disasters and reduce the failure probability; second, the optimal allocation strategy reduces the recovery time of the critical load while improving the system recovery level in Phase III.

2.1 Risk reduction by optimizing the emergency resource allocation

Resource allocation aims to reduce the risk of a distribution system during extreme hurricanes. The risk of a hurricane is affected by the disturbance progress and recovery progress including the postdisturbance degraded state and restorative state, as shown in Fig. 1. This formulation is a two-layer optimization model. In the first layer, a risk evaluation index is proposed to optimize the resource allocation before a disaster. In the second layer, the mathematic model of real-time resource allocation is provided to minimize the time of critical load outage. Therefore, this formulation considers the resource allocation for both Phase I and Phase II.

To quantitatively evaluate the risk of a distribution system, a resilience metric is required. It is evaluated in this paper according to the following equation.

$$\min \Psi = \sum_1^C (P_c \times V_c) = \sum_1^C P_c \times \int_0^t PM_c(t)dt \qquad (1)$$

where Ψ is the overall risk, P_c is the probability of service failure of the critical node c; and V_c is the service value of c weighted by its life-line contributions. $PM_c(t)$ is the recovery status of node c at time t.

2.2 Calculation of the physical mode for each critical node

There are two reasons for the problem formulation in equation (2). On one hand, the load loss is assumed to be equivalent to the loss of physical mode. On the other hand, decision makers must follow an optimal decision support at each time slot, which directs the restoration process to improve the limiting factors in the infrastructure. Thus, the optimal recovery resource allocation can be obtained by solving the following problem.

$$PM_c(t) = PM_{c,max} - (RA_c(t) - W_{s,c,r} \sum_s^S \int_0^t DR_{s,c,r}(t)dt) \qquad (2)$$

$$\text{subject to } \sum_1^D DR_{s,r}(t) \le RC_{s,r} \qquad (3)$$

$$PM_c(t) \le PM_{c,max} \qquad (4)$$

where S is the total number of resource supply points, and C is the total number of damaged critical loads. $PM_c(t)$ indicates the physical mode status at c. $DR_{s,c,r}(t)$ is distributed resource r from s to c, $r \in R, s \in S \text{ and } c \in C$. $RA_c(t)$ is the required repairing amount at c. $W_{s,c,r}$ is the weight of the effectiveness of the distributed resource r from source node s to damaged site c. This weight is affected by the traffic condition, information accuracy, punctuality, etc. $RC_{s,r}$ is the capacity of resource at s.

A candidate solution is the set $DR_{s,c,r}$ over the simulation time and can be written in a sparse matrix form as follows:

$$S_i = \begin{bmatrix} DR_{1,1,1}t_1 & DR_{1,1,1}t_2 & \cdots & DR_{1,1,1}T \\ DR_{2,1,}t_1 & DR_{2,1,1}t_2 & \cdots & DR_{2,1,1}T \\ \vdots & \vdots & \ddots & \vdots \\ DR_{S,C,R}t_1 & DR_{S,C,R}t_2 & \cdots & DR_{S,C,R}T \end{bmatrix} \qquad (5)$$

where $DR_{S,C,R}T$ is the output from the *Sth* dispatch center to the *Cth* load at time *T*, and *T* is the total simulation time. To simplify the model, several reasonable assumptions are made as follows.

a. Only critical loads are considered for allocation after the hurricane.

b. The critical load demands remain the same, since they are only used to satisfy the basic needs of human beings.

c. The transportation cost and delay caused by the real-time traffic condition are not considered in this paper.

3. PROBABILISTIC PREDICTION OF SERVICE FAILURE OF CRITICAL LOADS

3.1 Device failure events caused by a hurricane

It is assumed that the path and intensity of the hurricane are predicted; thus, the affected devices can be identified. The probability of service failure of a critical node is affected by the intensity of the hurricane, topologies of the distribution network and resource allocation.

The failure probability of the devices in the distribution network increases with the intensity of a hurricane. However, the failure probability is difficult to obtain and can only be roughly evaluated by history data and experience equation [15]. The failure probability of overhead distribution lines in a hurricane can be evaluated by equation (6)

$$P_l = \begin{cases} 0 & , \quad v \le V \\ \exp[\dfrac{0.6931(v-V)}{2V}]-1, & V < v < 2V \\ 1 & , \quad v \ge 2V \end{cases} \qquad (6)$$

where P_l is the failure probability of the distribution line; v is the wind speed, which can be obtained by short-time forecast or experienced equations; and V is the acceptable maximum wind speed for the distribution lines.

3.2 Device protection from the emergency resource

The optimal allocations of emergency resources before the hurricane can improve the service failure of a critical node. A linear relationship between the service failure of the critical load and the resource allocation is assumed as shown in equation (7) to describe the improvement.

$$[\lambda_{1i}, \lambda_{2i}, \cdots \lambda_{nc}] \cdot \begin{bmatrix} \Delta R_1 \\ \Delta R_2 \\ \vdots \\ \Delta R_n \end{bmatrix} = \Delta \phi_c \qquad (7)$$

where R_n is the prehurricane resource allocations and power line hardening at node *n*, such as energy storage systems, distributed generations, crews, materials and equipment; and λ_{nc} is the influence factor of resource allocations at node n on critical load c, which is obtained by experience analysis.

Therefore, the comprehensive probability of service failure of critical node c can be obtained by equation (8) considering the effects of both hurricane and prehurricane resource allocations.

$$P_c = \phi_c + \Delta\phi_c \tag{8}$$

3.3 Probability of critical load outages

The failure probability of the critical load can be obtained by network topologies that search from the critical loads to the emergency resources, which can be calculated by equation (9).

$$\begin{cases} \phi_c = 1 - \overline{\phi}_c \\ \overline{\phi}_c = \prod_{l=1}^{m} (1 - P_l) \end{cases} \tag{9}$$

where ϕ_c is the service failure of critical node c, which can be obtained by the failure probability of the devices that cause the service failure of node c; and $\overline{\phi}_c$ is the probability that service failure does not occur.

4. RECONFIGURATION AND RESTORATION TIME ESTIMATION

4.1 Repair Path and Amount Calculation

Spanning Trees search is used in this section for topological reconfiguration and repair amount calculation. Previous research [16] indicates that the Spanning Tree Search algorithm requires less computing time and fewer operations of the reconfiguration switches than the mixed integer nonlinear programming and heuristic searches.

Using graph theory, we can map each bus and each branch in the EDS to a vertex and an edge, respectively. Then, this system can be represented as a graph $G(V, E)$ using a sparse adjacency matrix. To easily understand, the reconfiguration of the distribution system is essentially the reconnection of the graph $G(V, E)$.

The shortest-path problem aims at finding a path between two nodes (or vertices) in a graph such that the summation of the weights of its candidate path is minimized. A Shortest-Path Tree (SPT), which is rooted at a specific vertex, is a spanning tree T of G. This tree ensures that the path distance from the root to any other vertex in T is the shortest.

In this paper, instead of searching for all equally weighted vertices in the shortest fashion, the SPT searches for the critical nodes at the beginning. This presents two advantages: it prevents the supply of the critical loads from being shed and simultaneously reduces the computational time.

Finally, the minimum repairing path is calculated according to the optimal reconfiguration; then, the repair amount is estimated by investigating the faulted components along the path.

Algorithm 1 Iterative Topological Reconfiguration Scheme

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Input: Reconfigured $G$, closed tie lines, disconnected nodes $V_d$ and broken edges $E_b$
while electrical violation exists do
    while non-critical leaf node exists do
        Prune leaf node with satisfying pruning condition;
        Update $G$
    if all the leaf nodes are critical then
        Curtail the other non-critical nodes with satisfying load curtailment condition;
        Update $G$
    else
        Find best candidate reconfiguration;
        Find the minimum repairing path
        Update $G$
```

4.2 Estimated Restoration Time

The impact from a hurricane may involve multiple devices and infrastructures. For simplicity, we only focus on the overhead line failure in this paper. Therefore, the required repair time for a single critical node is proportional to the number of faulted lines along the minimum repairing path plus the travelling time, which is calculated in section 4.1 and mathematically expressed as follows:

$$\mathrm{T}_{\mathrm{c,required}} = \frac{\mathrm{RA_c}}{\mathrm{RR_c}} + \mathrm{T}_{\mathrm{c,travel}} \tag{10}$$

where $T_{c,travel}$ is the travelling time of the dispatched resource. Since the traffic condition is not considered, $T_{c,travel}$ is purely determined by the distance from s to c. RR_c is the repair rate at c, and RR_c is determined by the least available distributed resources r, i.e.,

$$\mathrm{RR_c} = \min(\mathrm{r_{c,crews}}, \mathrm{r_{c,materials}}, \dots, \mathrm{r_{c,electricity}}) \tag{11}$$

where r is the allocated resource.

However, due to the limitation and delay of allocation, the actual recovery time for node c differs from $\mathrm{T_{c,required}}$ and can be expressed as follows.

$$\mathrm{T_{c,actual}} = \mathrm{t} \mid \mathrm{PM_c(t)} = \mathrm{PM_{c,max}} \tag{12}$$

where $T_{c,rec}$ is the actual recovery time at node c, and $T_{c,rec}$ is equal to t when the physical mode reaches its maximum status.

5. SOLUTION ALGORITHM

5.1 Overall workflow for an incoming hurricane

With the prediction of the path and intensity of the hurricane, the affected devices can be identified. Then, probabilities of device failure are evaluated. Moreover, by optimizing the recovery resource dispatches, the failed device and power supply paths can be quickly restored. After solving this optimal restoration plan, the minimum outage duration can be estimated. Finally, the system-level outage risk can be evaluated by accounting for all power losses and their occurrence probabilities. This risk can be minimized by optimizing the allocation of recovery resources.

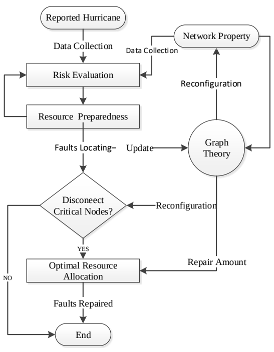

Fig. 4. Flow chart of proposed method

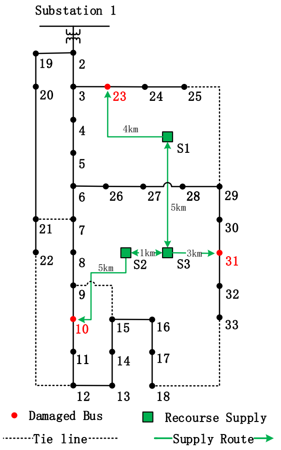

Fig. 5. The topological configuration of disaster response

The specific restoration steps are as follows:

Step 1 To evaluate the risk of a reported hurricane, related data are collected. The input data include the following: 1) the intensity of the hurricane to each line of the distribution system; 2) the line fragility property; 3) the initial amount and location of each available resource; 4) the electrical property of the distribution system; 5) traffic information among the nodes;

Step 2 Emergency resources are prepared in different dispatch centers prior to this hurricane;

Step 3 After the hurricane strikes, if there is a disconnected critical node after the reconfiguration, the optimal resource allocation strategy is implemented using MINP from the Yalmip package. This strategy ensures a global optimum by simultaneously considering the repair time and repair level following the minimization problem (1).

Step 4 After all critical nodes have been restored, the system returns to its normal operational state.

5.2 Solve the proposed optimization by GA

The objective of the proposed optimization model in this paper is the minimum risk of a distribution network during extreme hurricanes. The variables are the locations of resources, amounts of resources including crews, materials and equipment, and their recourse supply. The developed optimization model is a two-stage problem, and the variables are also affected by the optimization procedure through (6)-(9). The GA is suitable for solving such optimal problems, and the elitist strategy is used in this paper to improve the convergence [17].

6. TEST CASE AND SIMULATION RESULTS

The IEEE 33-node feeder is used to test the proposed method, as shown in Fig. 4. The loads at nodes 10, 23 and 31 are faulted critical loads with equal priorities. To restore them, three emergency resources are required: crews, materials and equipment. These resources are available at three different dispatch centers: S1, S2 and S3. The amount of available resources in each center is shown in Table I, and the demand of resources is shown in Table II.

A single load may be restored by several sources and vice versa. In Table III, the 6-unit and 4-unit crews from S1 are allocated to CL-23 and CL-30, respectively. Meanwhile, their summation reaches the maximum storage capacities of S1. Since the total demand from faulted load is much higher than the total capacity of storage, all resources are allocated before the completion of the restoration. According to the allocation plan, one thousand scenarios are generated, and the comparison of risks from the base case and the expected optimized case is provided in Table IV.

TABLE I
INITIAL RESOURCE

Location	Crews (Number)	Materials (Units)	Equipment (Units)
10	10	5	2
23	5	5	2
31	2	10	1
Total	17	20	5

TABLE II
DEMAND OF RESOURCES

Location	Crews (Number)	Materials (Units)	Equipment (Units)
10	10	10	4
23	15	15	5
31	30	35	10
Total	55	60	19

TABLE III
ALLOCATION MATRIX AT TIME SLOT 2

	CL-10	CL-23	CL-30
Crews_S1	0	6	4
Crews_S2	1	4	0
Crews_S3	2	0	0
Materials_S1	0	0	5
Materials_S2	0	5	0
Materials_S3	10	0	0
Equipment_S1	0	2	0
Equipment_S1	2	0	0
Equipment_S1	1	0	0

With the application of the mixed-integer nonlinear programming described in section II, the physic mode of the destroyed critical load is largely recovered within 24 hours. Fig. 6 shows the timely results following the allocation strategy for the entire repairing process to prioritize the postcontingency response when emergency resources are limited.

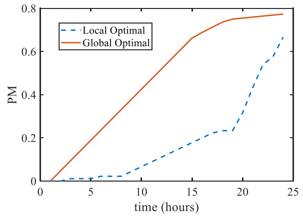

Fig. 6. Comparison of PM minimization using greedy and global optimization

TABLE IV
COMPARISON OF RESULTS

Scenario	Ψ
Base Case	0.8348
Optimized Case	0.5298

For comparison, the greedy algorithm is implemented as a control group to find the local optimal solution. The control group witnesses a constant lower value than the global optimized allocation, which validates our proposed strategy.

7. CONCLUSION

This paper focuses on the disaster preparedness before and after a hurricane in the electrical distribution system. An evaluation method of outage risks with an optimal resource allocation strategy is proposed, which allocates the number of crews, materials and equipment for repairing the faulted critical loads. The optimal weights of the preventive resource allocation can be used as a reference for utilities to increase the emergency resources in the prehurricane preparation stage.

Numerical simulation results based on the IEEE-33 node show that the risk of the system is significantly reduced, which validates the effectiveness of the proposed method. This proposed framework can be applied for both long-term planning and optimal fast response during extreme contingencies.

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