Resilient Post-Disaster Rescue Framework Using Mobile and Connected Electric Vehicles

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***Abstract*—The increasingly frequent occurrence of natural disasters has severely interfered with the operation of fundamental infrastructures such as power, transportation, and communication systems. For these decades-old infrastructures, enhancing the system resilience requires extremely high upgrade expenditure. Therefore, more flexible and cost-efficient solutions are in urgent demand. Equipped with on-broad large-capacity batteries, electric vehicles (EVs) could serve as mobile post-disaster rescue devices, namely mobile energy storage (MES). This paper proposes a flexible post-disaster rescue scheme using mobile and connected EVs as MESs to supply emergency resources before the fundamental infrastructures fully recover. Different from existing literature, this paper uncovers the potential energy supply and communication capabilities of MESs to provide damaged areas with on-demand energy and communication resources. Specifically, the uncertainty of natural disasters of tornadoes and flooding is modelled during different scenario generations. Then, a two-stage stochastic programming problem is formulated to determine the MES deployment location in the pre-disaster stage and the MES service operation in the post-disaster stage. The generated disaster scenarios are integrated into the formulated problem to ensure a statistically optimal result. Simulation results validate the optimality of the proposed scheme compared to benchmark schemes.**

I. Introduction

In recent years, extreme natural disasters have occurred increasingly frequently with catastrophic outcomes, including power outages, disrupted roads, limited communication coverage, and more. On the one hand, these decades-old infrastructures require a high capital expenditure for resilience enhancement. On the other hand, one low-probability yet extreme disaster could cost millions of dollars for post-disaster rescue and recovery. Therefore, the fundamental infrastructures such as power and communication systems urgently need a flexible approach to enhance the system resiliency [1].

With the legislative motivation of zero-emission transportation, electric vehicles (EVs) become increasingly prevalent [2]. In addition to their advancement in clean transportation, EVs can serve as mobile energy storage (MES) with their large battery capacities, mobility, and flexible charging and discharging capability [3]. Existing literature has explored utilizing stationary and mobile EVs for post-disaster rescue [1], [4], [5]. As natural disasters frequently disrupt the power supply and road transportation, the coupled operation of power and transportation systems has been studied in [1], [5]. However, most of the existing works focus on the energy provision capability of MESs while overlooking their communication recovery potential.

MESs have the potential to be mobile base stations with sufficient mounting capability, high battery capacities, and mobility. In literature, UAVs have been extensively explored as disaster recovery devices for building a resilient communication network [6], [7]. The problem is embedded in the limited battery capacities of UAVs to mount a base station while hovering around disaster areas for networking services. As such, MESs become a more realistic solution as mobile base stations to recover the communication network in disaster-damaged areas.

Utilizing the MESs as both energy suppliers and mobile base stations could be cost-efficient due to the geographic overlapping of communication and power outages. The challenges occur in how to optimize the limited MES resource for two rescue services while considering the uncertainty of natural disasters. In this paper, we address these challenges by proposing a resilient post-disaster rescue framework with the following contribution:

- A disaster scenario generation procedure is developed for tornadoes and flooding as the post-disaster rescue operation foundation;
- A two-stage stochastic programming problem is formulated to optimize the pre/post-disaster MES operation to achieve a cost-efficient disaster rescue with the optimal disaster restoration result.

The remainder of the paper is organized as follows. The resilient post-disaster rescue framework is introduced in Section II. Section III presents the disaster scenario generation procedure considering tornadoes and flooding, two commonly occurring disasters in the southeast of the United States. The problem formulation of the two-stage stochastic programming problem is shown in Section IV. Section V provides a case study and finally, Section VI concludes this paper.

II. Resilient Post-Disaster Rescue Framework

The proposed resilient post-diaster rescue framework along with a 9-bus system illustration are shown in Fig. 1. The framework is composed of two-stage operation with the first stage being MES pre-disaster allocation and the second stage being MES post-disaster rescue operation. Before the disaster occurs (stage one), the operator needs to charge the MESs and mount them with base stations. The MESs will then be

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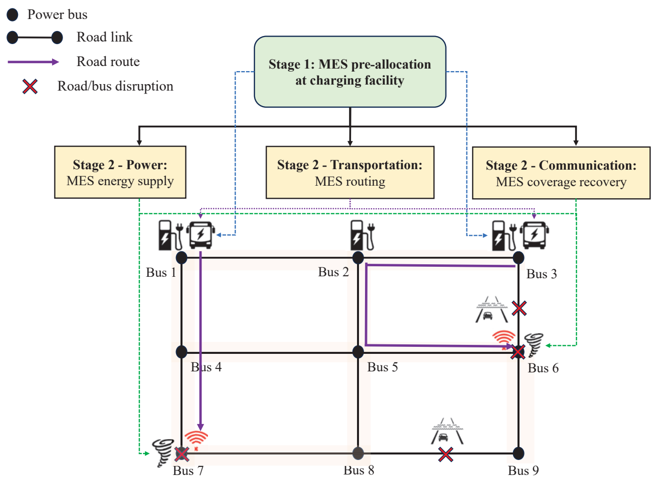

Fig. 1. The operation framework of the resilient post-disaster rescue.

allocated to buses 1, 2, or 3 that have charging facilities for pre-disaster preparation. During the disaster restoration phase (stage two) where the fundamental power infrastructure is under repair, MESs are dispatched to the disaster-damaged areas (buses 4 to 9) for rescue services. In this paper, MESs provide two rescue services: energy supply and communication recovery. Further, the MES routing scheme needs to be optimized in stage 2 as some road links are disrupted due to flooding.

In the following sections, we will introduce how tornadoes and flooding are modelled into different disaster scenarios and how the proposed framework is formulated and solved as a two-stage stochastic programming problem.

III. Disaster Scenario Generation

Before a disaster happens, the power utility operator will obtain the weather forecast data beforehand and the received data will be used to generate the disaster scenario for post-disaster operation analysis. In Tennessee, tornadoes and flooding are the most common disasters which will be considered in the proposed framework.

A. Wind-induced Power Damage Model

Strong winds caused by tornadoes could damage the distribution line poles and therefore, affect the power supply of certain regions. The failure probability of a power line pole can be modelled as an exponential function as [10]:

$$p_{\mathrm{i}}^{D}(v_{\mathrm{t}}) = \min\{w_1 e^{w_2 v_{\mathrm{t}}}, 1\}. \tag{1}$$

The power failure probability at the i-th bus is denoted as $p_{\mathrm{i}}^{D}(v_{\mathrm{t}})$, which is closely related to the wind speed v_{t} at time t. w_1 and w_2 are probability-related parameters for historical wind data regression.

B. Flooding-induced Transportation Damage Model

The heavy rainfalls caused by flooding could result in road disruptions. The disruption probability $p_{\mathrm{j}}^{T}(r_{\mathrm{t}})$ of road link j is closely related to accumulated precipitation r_{t} at time t and can be modelled by a piecewise constant approximation as [11]:

$$p_{\mathrm{j}}^{T}(r_{\mathrm{t}}) = \begin{cases} f_1^T & r_{\mathrm{t}} \in [r_0, r_1] \\ f_2^T & r_{\mathrm{t}} \in [r_1, r_2] \\ \dots & \dots \\ f_{\mathrm{L}}^T & r_{\mathrm{t}} \in [r_{\mathrm{L}-1}, r_{\mathrm{L}}] \end{cases} \tag{2}$$

where f_{j}^{T} denotes the disruption probability of road link j when the rainfall volume is within the range of $[r_{\mathrm{L}-1}, r_{\mathrm{L}}]$.

C. Scenario Generation Procedure

The randomness of tornadoes and flooding could result in different MES rescue dispatch scenarios, which need to be characterized and included in the later problem analysis. In this section, we introduce the scenario generation procedure to iteratively generate a large set of disaster scenarios that can be used for post-disaster operation analysis [1]. Monte Carlo Simulation is used for disaster scenario generation. During each scenario generation process, random variables a/b will be sampled in the range $[0, 1]$. a/b will be compared with the failure/disruption probabilities of power and transportation systems, respectively. If the random variables are greater than the failure/disruption probabilities, the corresponding system will not be affected by the disaster. The disaster impact on the bus i is represented by a binary indicator $u_{\mathrm{i}}^{D,s}$, with 1 indicating an intact bus and 0 denoting a failed bus. Similarly, the disaster impact on road link j is represented by a binary indicator $u_{\mathrm{j}}^{T,s}$, with 1 indicating an intact road link and 0 denoting a failed road link. The whole scenario generation procedure is illustrated in Algorithm 1.

IV. Problem Formulation

A. Stage I - MES Pre-disaster Allocation

In the proposed framework, the power utility operator is the MES owner and can allocate and dispatch MESs as needed. In the pre-disaster phase, the operator needs to decide the number of MESs x_{z} allocated to charging facility z so that the overall allocation cost $\sum_z a_{\mathrm{z}} x_{\mathrm{z}}$ can be minimized while the expected post-disaster rescue reward $E_{\mathrm{s}\in\mathrm{S}}[Q(x, u)]$ in stage two can be maximized:

$$\max_{x_{\mathrm{z}}} \quad -\sum_z a_{\mathrm{z}} x_{\mathrm{z}} + E_{\mathrm{s}}[Q(x, s)] \tag{3}$$

$$\text{s.t.} \quad 0 \le x_{\mathrm{z}} \le N_{\mathrm{z}}, \forall z \tag{3. a}$$

$$0 \le \sum_z x_{\mathrm{z}} \le N, \tag{3. b}$$

where a_{z} denotes the MES allocation cost at charging facility z. s denotes the s-th disaster scenario to consider in stage two for MES dispatching. $Q(x, s)$ represent the MES rescue reward under s-th scenario. Constraint (3.a) ensures the number

Algorithm 1: Disaster Scenario Generation Procedure

Input: Sampling number N_s, forecasted wind speed v_t, and forecasted precipitation r_t

Output: Power and transportation disruption indicators $u_i^{D,s}$, $u_j^{T,s}$

Calculate p_i^D for power bus i with v_t using Eq. (1) ;
Calculate p_j^T for road link j with r_t using Eq. (2)
while $s < N_s$ **do**
  for *each power bus* i **do**
    Generate random variable a in [0, 1] ;
    if $a > p_i^D$ **then** $u_i^{D,s} = 1$;
    else $u_i^{D,s} = 0$;
  end
  for *each road link* j **do**
    Generate random variable b in [0, 1] ;
    if $b > p_j^T$ **then** $u_j^{T,s} = 1$;
    else $u_j^{T,s} = 0$;
  end
end

of MES allocated to each charging facility can be charged on time. Constraint (3.b) ensures the number of allocated MESs is less than the operator's MES fleet size.

B. Stage II - Scenario-Based Post-Disaster Rescue

Once the MESs are allocated to the charging facilities and all disaster scenarios have been generated, we can start to analyze the MES dispatching scheme for rescue services. The formulated stage-two problem aims to maximize the expected rescue reward under various disaster scenarios, as follows:

$$E_s[Q(x,s)] = \max_{y_{z,i}^{k,s}, P_i^s} \sum_s p(s) \cdot (R_E - C_T + R_{Com}), \quad (4)$$

Under the s-th scenario, the operator decides the number of MESs dispatched from charging facility z to bus i through the k-th route (denoted as $y_{z,i}^{k,s}$) and the assigned power P_i^s for communication task at bus i. The rescue reward is composed of the energy supply reward R_E, the MES routing cost C_T, and the communication recovery reward R_{Com}.

1) MES Energy Supply Reward: After tornadoes, the damaged power poles cannot provide service and correspondingly, MESs are dispatched to these damaged areas for rescue service. The more urgent and sufficient energy is supplied in the damaged area, the higher the rescue reward. Therefore, the MES energy supply reward R_E is calculated as the summation of compensated energy:

$$R_E = \alpha_E \sum_i E_i^s, \quad (5)$$

where α_E denotes the reward coefficient and E_i^s denotes the overall MES supplied energy at the bus i. The amount of energy to be supplied at each bus is closely related to the MES routing choice $y_{z,i}^{k,s}$ and the MES energy supply capacity B, following constraints below:

$$E_i^s + P_i^s \Delta t = \sum_z \sum_{k\in(z,i)} y_{z,i}^{k,s} \cdot B, \quad \forall i \quad (6)$$

$$\sum_i \sum_{k\in(z,i)} y_{z,i}^{k,s} \le x_z, \quad \forall z, \quad (7)$$

$$0.9(1-u_i^{D,s})D_i \le E_i^s \le 1.1(1-u_i^{D,s})D_i, \quad \forall i \quad (8)$$

Constraint (6) explains the coupling relation between power, transportation, and communication system, where MES traffic flowing to bus i through different routes will supply energy at bus i. The supplied energy are load supply, denoted as E_i^s and communication recovery supply, denoted as $P_i^s \Delta t$. Constraint (7) ensures that the upper bounds of MES charging facilities are met. Constraint (8) guarantees that the MES energy provision is within the range of required energy at the damaged bus.

2) MES Routing Cost: The travelling time of MES dispatching from the charging facility to the designated rescue location will affect the service quality. Therefore, it is quantified as the routing cost that should be minimized. Under each disaster scenario, the MES routing cost is calculated as:

$$C_T = \alpha_T \sum_k u_{z,i}^{k,s} T_{z,i}^{k,s} y_{z,i}^{k,s}, \quad (9)$$

where α_T denotes the routing cost coefficient. $T_{z,i}^{k,s}$ denotes the travelling time on the k-th route from charging facility z to rescue location i in s-th scenario. $u_{z,i}^{k,s}$ is the damage indicator of the k-th route, which can be calculated using the scenario generated road link indicator $u_j^{T,s}$ as:

$$u_{z,i}^{k,s} = \prod_{j\in k} u_j^{T,s}. \quad (10)$$

Constraint (10) states that if a road link is damaged due to flooding, any route including the damaged road link will be considered infeasible to travel and the travelling cost will not be counted. The MES routing is also subject to the road condition (damaged or not) and road capacity $C_{z,i}^k$ as:

$$0 \le y_{z,i}^{k,s} \le u_{z,i}^{k,s} \cdot C_{z,i}^k. \quad (11)$$

3) MES Communication Recovery Reward: During the post-disaster rescue, one of the MESs dispatched to each damaged area will mount and power the base station to recover the communication coverage. The communication recovery reward is quantified by the recovered coverage area as:

$$R_{Com} = \alpha_C \sum_i (1-u_i^{D,s}) \frac{(d_i)^2}{4} \lambda_i, \quad (12)$$

where α_C denotes the communication reward coefficient. d_i denotes the maximum coverage diameter at bus i and λ_i denotes the user density near bus i. The reward calculates the

TABLE I
SIMULATION PARAMETERS

Parameter	Value	Parameter	Value
w_1	5×10^{-5}	w_2	4.2×10^{-2}
N	70	B	5 kWh
SNR_{m}	20 dB	I_{i}	100 mW
h_{i}	2.718	K_{i}	0.37
α_{i}	2	α_{E}	15
α_{T}	2	α_{C}	30
m	22.9	n	0

summation of recovered communication coverage of damaged power buses. MESs adjust their communication power P_{i}^s to maximize the communication coverage for the damaged area. The allocated communication power has a linear relationship with the MES transmission power P_{i}^c due to the RF amplifier loss [12]:

$$P_{\mathrm{i}}^s = mP_{\mathrm{i}}^c + n. \tag{13}$$

The MES transmission power in area i has a direct impact on the communication power P_{i}^l received by user l at bus i, which is calculated as [13]:

$$P_{\mathrm{i}}^l = P_{\mathrm{i}}^c h_{\mathrm{i}} K_{\mathrm{i}} (d_{\mathrm{i}}^l)^{-\alpha_{\mathrm{i}}}. \tag{14}$$

h_{i} denotes the fading channel parameter. K_{i} and α_{i} represent the path loss parameters. d_{i}^l denotes the distance between user l and the MES at bus i. The signal-to-noise ratio for user l served by the MES at bus i is calculated by:

$$SNR_{\mathrm{i}}^l = \frac{P_{\mathrm{i}}^l}{I_{\mathrm{l}} + \sigma^2}, \tag{15}$$

where I_{l} denotes the interference of user l. In the post-disaster scenario, users will not have other communication methods and this item can be ignored. σ^2 denotes the white noise. If the user's SNR is higher than a predefined threshold SNR_{m}, the user can successfully receive the signal from MES. Therefore, the furthest user the MES can reach is at the exact SNR threshold [12]:

$$d_{\mathbf{i}} = \max d_{\mathrm{i}}^l \quad (s.t. \quad SNR_{\mathrm{i}}^l \geq SNR_{\mathrm{m}}). \tag{16}$$

The formulated problem is a mixed integer linear problem in nature and can be efficiently solved by off-the-shelf solver such as CPLEX.

V. CASE STUDY

A. Simulation Setting

The case study is conducted on the 9-bus power/transportation system, as shown in Fig. 1. Disaster-related weather data could be obtained from the Meteorological Bureau in real life. During the simulation, we utilize historic weather data. The wind speeds at different levels of tornadoes are referred to [14] and the rainfall level of flooding along with its piecewise probability are referred to [15]. The load demand at each bus is sampled between 30 and 100 kWh. All related simulation parameters are presented in Table I. The communication channel parameters are referred to [7]. Based on the data, the scenario generation has been performed 20 times. The optimization model of the proposed scheme along with two benchmark schemes are implemented on GAMS using an MIP solver.

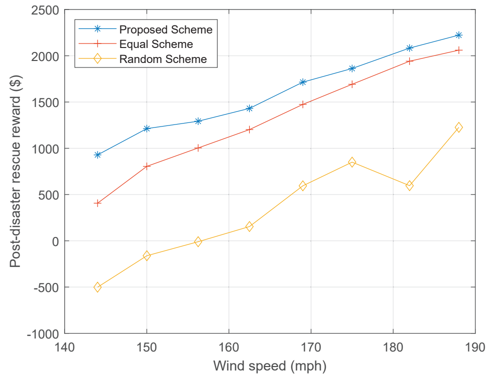

Fig. 2. Operation cost comparison under different wind speeds.

B. Simulation Results

1) Rescue Performance in Tornado Scenario: The post-disaster rescue performance of the proposed scheme and two benchmark schemes under different wind speeds (i.e., different tornado levels) are shown in Fig. 2. The first benchmark scheme, the equal scheme, assigns most MESs to the charging facilities with the lowest allocation cost. The second benchmark, the random scheme, randomly assigns MESs to three charging facilities without considering the allocation cost. It is shown that the proposed scheme has the best performance as the wind speed increases from tornado level 2 to level 4. The equal scheme has a better performance compared to the random scheme as it greedily chooses the facilities with the lowest allocation cost, which results in a lower allocation cost compared to the random scheme.

2) Cost Analysis in Flooding Scenario: We also analyze the impact of flooding severity on the MES dispatch and rescue service, quantified by different service revenue/cost, as shown in Fig. 3. It can be observed that as rainfall increases, the overall revenue decreases. This is due to the increasing tendency of road disruption, which can be reflected in the transportation cost. With flooding, some regular chosen routes that are faster may not be available and MESs need to route on longer routes. The energy supply revenue (power revenue) also decreases as MESs may not travel to some of the damaged areas due to severe road disruption. Correspondingly, the communication revenue also decreases as MESs cannot provide the optimal coverage for all damaged areas.

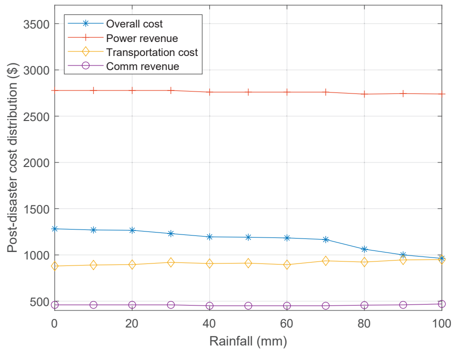

Fig. 3. Operation cost comparison under different rainfall scenarios.

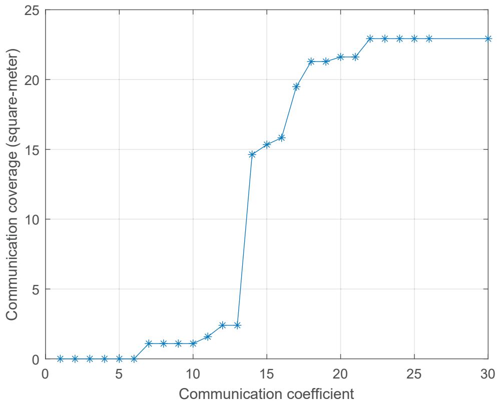

Fig. 4. Communication coverage under different service coefficients.

3) Communication Coverage Analysis: Considering the rescue operation competes for resources for multiple systems. We further study the communication coverage performance with respect to its service coefficient, which is shown in Fig. 4. When the coefficient is low (less than 6), there is no communication coverage, as its revenue is much smaller than providing load energy. When the coefficient is high (higher than 22), the MES communication coverage reaches its maximum due to the MES battery limit. In between the coefficient range of 6 and 22, the communication coverage increases as MESs allocate more energy for mobile base stations.

VI. Conclusion

In this paper, we propose to use mobile EVs as dual-functional rescue devices after natural disasters occur to provide energy supply and communication coverage services. First, a resilient post-disaster rescue framework has been proposed for efficient usage of mobile and connected EVs as MESs. To characterize features of different disasters, a scenario generation procedure has been developed to model the disaster impact on power, transportation, and communication systems. Then, a two-stage stochastic programming problem has been formulated to optimize the pre-disaster MES allocation and post-disaster MES rescue service operation. The simulation results have validated the effectiveness of the proposed scheme while also discussing the impact of different disasters on MES dispatch. In our future work, we will consider the cooperation between MESs and UAVs for a more effective communication coverage recovery.

VII. Acknowledgement

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