Leveraging Electric Vehicles to Enhance Resilience of Interconnected Power-Transportation System Under Natural Hazards

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Abstract

The rapid development of transportation electrification brings about the popularity of interconnected power-transportation systems (IPTS). However, the escalating frequency and uncertainty of natural hazards, such as typhoons, pose threats and potential damage to the operation of IPTS. Electric vehicles (EVs) can serve as mobile energy sources, whose proper scheduling in transportation networks can provide power support for the damaged power networks caused by natural hazards, thus enhancing the system’s resilience. This paper proposes a two-stage scenario-based scheduling framework using EVs for the restoration of an IPTS under natural hazard risks. In the first stage, EVs are pre-allocated and pre-charged at the charging stations to maximize their support potential against the predicted hazards; in the second stage, EVs are re-dispatched among different charging stations to help restore the power demands given the damaged IPTS topology. To address the real hazard scenarios and reduce the computational burden, a scenario generation approach indicating the real hazard’s impact on the IPTS is proposed followed by a scenario-reduction algorithm. Numerical experiments are conducted to validate the effectiveness of the proposed method based on the IEEE 33-bus distribution network and the Sioux Falls transportation network.
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Index Terms—Electric vehicles, Interconnected power-transportation system, Resilience, Load Restoration, Hazard

NOMENCLATURE

Sets
\(\mathcal{T}\) Set of all nodes in power network (PN).
\(\mathcal{T}_{CS/G}\) Set of nodes that connect with charging stations (CSs)/distributed generators (DGs) in PN.
\(\mathcal{M}\) Set of roads in transportation network (TN).

Indices
\(i, j, k\) Indice of node used in PN and TN.
\(l(ij)\) Indice of power line \(l\) between grid node \(i\) and \(j\).
\(m\) Indice of road in TN.
\(n\) Indice of electric vehicles (EVs).
\(t\) Indice of time interval.
\(\omega\) Indice of scenario.

Parameters
\(a, b^o\) Model coefficient of power tower in PN.
\(\lambda_c\) Fuel consumption rate of a DG on rated power (g/kWh).
\(c_{i,t}\) Unit charging price of CS connecting to grid node \(i\) during \(t\) (CNY/kWh).
\(c_{Gen}\) Unit fuel cost of a DG (CNY/L).
\(c_{Loss}\) Opportunity cost per vehicle from not participating in transportation tasks (CNY).
\(D_{CS}\) Distance matrix; its element \(d_{ij}\) denotes the distance between CSs connecting to grid node \(i\) and \(j\) (km).
\(D_{Trans}\) Distance vector; its element \(d_{Trans}^i\) denotes the distance between the depot and CS connecting to grid node \(i\) (km).
\(D_{f,t}\) Fatigue damage degree of power tower in grid node \(i\) during \(t\).
\(E_{Cap}\) Battery capacity of a commercial EV (CEV) (kWh).
\(e_{Unit}\) Unit energy consumption of a CEV during trip (kWh/km).
\(I_{max}\) Line current capacity (A).
\(M\) The number of grid nodes in the part to be divided of damaged PN.
\(N_{i,Cap}\) The maximum number of vehicles that CS can accommodate connecting to grid node \(i\).
\(p^\omega\) Probability of scenario \(\omega\).
\(P_{De}\) Active limit of power regulation capacity at grid node \(i\) (kW).
\(P_{EV,\text{rated}},\text{max}\) Maximum charging/discharging power capacity of chargers (kW).
\(P_{Grated}\) Rated power of the DG connecting to grid node \(i\) (kW).
\(r_{Grid}\) Unit energy price for power restoration service at grid node \(i\) during \(t\) (CNY/kWh).
\(r_{ij}\) Line resistance between grid node \(i\) and node \(j\) (Ω).

\(\mathcal{T}_{pre-RS/RS/post-RS} \subset \mathcal{T}\) Set of time period: before hazard happens/during restoration/after restoration service.

\(\mathcal{N}_{i,Cap}\)
**I. Introduction**

The explosive popularity of electric vehicles (EVs) has promoted the deep integration of transportation and power networks, giving rise to the interconnected power-transportation systems (IPTSs) [1], [2]. In this system, EVs are not only essential roles to satisfy transportation demands but also the important load units in the power network (PN) [3]. They can work as mobile energy storage units to both charge from and discharge to the PN through vehicle-to-grid (V2G) service [4].

Simultaneously, extreme weather and natural hazards, notably typhoons, and heavy rainfall events, are becoming more frequent and severe [5], [6], which could damage both the power and transportation networks (TNs) and present serious threats to the operation of IPTS. Their stochastic characteristics and high uncertainties regarding the occurrence and impact underscore the necessity of the resilience enhancement issue, particularly in the restoration service after hazard to mitigate the adverse effects on power users [7]. In alignment with the above background, the resilience of IPTS in this paper focuses on the maximum restoration of the damaged PN while considering the accessibility and topology of the impaired TN [8], [9].

To enhance the resilience of IPTS, the widely distributed EVs, especially commercial EVs (CEVs), can work as mobile energy storage units [10]. First, they have been deployed in urban TNs with a high penetration level [11], eliminating the need for extra energy storage investments. Second, CEVs usually have larger battery capacities than private EVs and are owned by a single entity [12], [13], enabling centralized dispatch and increased power support. In detail, before a hazard happens, CEVs can be placed and charged at charging stations (CSs) (i.e., pre-allocation) as a preparatory measure [14], [15]. After the hazard, CEVs can be spatial-temporally dispatched and increased power support. In detail, before a hazard happens, CEVs can be placed and charged at charging stations (CSs) (i.e., pre-allocation) as a preparatory measure [14], [15]. After the hazard, CEVs can be spatial-temporally dispatched and increased power support. 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size planning and pre-positioning strategy of vehicle-mounted energy storage facilities is proposed in [17] with a mixed-integer second-order cone programming model (MISOCP). Facing hurricane-induced damages, the authors in [18] introduce a pre-allocation and post-disaster restoration strategy for electric buses in the distribution network. Although the three papers above consider the uncertainties from multiple perspectives, their dispatch models of EVs only consider the constraints of PNs, neglecting those from transportation ones. Some researchers consider the EVs’ characteristics both in PNs and TNs. A post-disaster scheduling framework of electric buses for both the power restoration of the distribution network and trip demand is raised in [19]. The authors in [20] propose a coordinated restoration framework through the idle electric buses’ scheduling. A robust restoration model of EVs incorporating an incentive mechanism for the distribution network is proposed in [21] considering uncertainties from renewable generation. Nevertheless, the above three works do not consider the uncertainties from natural hazards, or they heuristically adopt a limited number of hazard scenarios in the model. Besides, they utilize the one-stage model for post-hazard restoration while the pre-hazard preparation process still needs to be addressed.

Based on the aforementioned literature review, this paper introduces a novel two-stage scenario-based scheduling framework for CEVs in an IPTS, which fully considers the uncertainties from natural hazards. In particular, we take the CEVs’ dual characteristics in the power and transportation network into account. In the first stage, CEVs are pre-allocated at charging stations (CSs) and pre-charged to maximize their potential to support against the hazard. In the second stage, CEVs are strategically re-dispatched among different CSs to help restore the power demands. After the restoration, CEVs will return to their origins and recharge to the initial state-of-charge (SOC). We incorporate the real damage model of the hazard to the IPTS into the scenario generation process, which makes the framework more realistic. Then we adopt a scenario reduction algorithm through an unserved energy-based K-means clustering method to mitigate the computational burden. The proposed model largely enhances the system’s resilience by deciding the locations and charging/discharging profiles of the CEVs. Numerical experiments are conducted to validate the effectiveness of the proposed method based on the IEEE 33-bus distribution network and the Sioux Falls network.

The rest of the article is organized as follows. Section II gives a detailed introduction to the IPTS model and the optimization problem methodology. The algorithms for scenario generation and reduction are introduced in Section III. The simulation studies are demonstrated in Section IV with a comprehensive analysis. Conclusions are drawn in Section V.

## II. Problem Formulation

In this paper, we assume typhoon as a typical natural hazard, which attacks the IPTS with its strong winds and heavy rainfalls and cause topology damage. The damage to the PN will result in unstable islanded operation and a lack of load supply. The damage to the TN will break down the connectivity of the road and limit the routing paths of CEVs. Apart from the power generation of the distributed generators (DGs), we schedule the CEVs within the damaged TN to provide restoration service. We assume there are three time periods for the whole restoration service. During the pre-hazard period \( T_{\text{pre-RS}} \), CEVs are pre-allocated at CSs and get charged. During the restoration period \( T_{\text{RS}} \), CEVs are re-dispatched among CSs and discharge power to maximize the power restoration effect. During the post-restoration period \( T_{\text{post-RS}} \), the IPTS will get repaired to its original state, and CEVs will recharge to their initial SOC.

### A. Objective function

From the perspective of a system operator, the overall objective is to maximize the restoration level, specifically by maximizing the restoration revenue while minimizing operational costs. The first stage aims to make the here-and-now decision, and the objective term is the allocation cost of CEVs including opportunity cost and pre-charging cost. The second operating stage aims to make the wait-and-see decision; the
The objective is the expected net revenue, including the restoration revenue and operation cost, as follows:

\[
\max \left[ -C_{\text{Allo}} + \mathbb{E} \left(R_{\text{Oper}} - C_{\text{Oper}}\right) \right],
\]  

\[
C_{\text{Allo}} = C_{\text{Oppe}} + C_{\text{Chg,pre-RS}},
\]  

\[
C_{\text{Oppe}} = c_{\text{Loss}} \sum_{n \in N} \sum_{i \in I^{CS}} s_{n,i,t,0},
\]  

\[
C_{\text{Chg,pre-RS}} = \sum_{t \in T^{pre-RS}} \sum_{i \in I^{CS}} c_{i,t} P_{t,\text{EV,Chg}} \Delta t,
\]  

\[
P_{t,\text{EV,Chg}} = \sum_{n} P_{t,n,\text{EV,Chg}},
\]  

\[
R_{\text{Oper},\omega} = \sum_{n} \sum_{i \in I^{T^{RS}}} i_{i,t,\text{Grid}} P_{t,\text{Base},\omega} \Delta t,
\]  

\[
C_{\text{Oper},\omega} = C_{\text{Gen,\omega}} + C_{\text{Chg,post-RS,\omega}},
\]  

\[
C_{\text{Gen,\omega}} = c_{\text{Gen}} \sum_{t \in T^{RS}} \sum_{i \in I^{G}} P_{t,i,\omega} \Delta t,
\]  

\[
C_{\text{Chg,post-RS,\omega}} = \sum_{t \in T^{post-RS}} \sum_{i \in I^{CS}} c_{i,t} P_{t,\text{EV,Chg,\omega}} \Delta t.
\]  

Eq. (1) calculates the total restoration service revenue for the IPTS, where $C_{\text{Allo}}$ denotes the allocation cost of CEVs during the pre-hazard period. The expected revenue of the second stage is calculated through $\mathbb{E} \left(R_{\text{Oper}} - C_{\text{Oper}}\right) = \sum_{\omega=1}^{\Omega} \rho^{\omega} \cdot (R_{\text{Oper},\omega} - C_{\text{Oper,\omega}})$, where $\rho^{\omega}$ denotes the probability of scenario $\omega$; $R_{\text{Oper},\omega}$ and $C_{\text{Oper,\omega}}$ denote the operation revenue and cost, respectively. As shown in Eq. (2), $C_{\text{Allo}}$ denotes the allocation cost, which is consistent with the opportunity cost of CEVs arising from not participating in transportation tasks, $C_{\text{Allo}}$, and the charging energy cost of CEVs during the pre-hazard period, $C_{\text{Chg,pre-RS}}$. They are expressed in Eqs. (3) and (4), respectively. Symbol $c_{\text{Loss}}$ denotes the unit opportunity cost per vehicle; symbol $s_{n,i,t,0}$ is a binary indicator denoting the location of CEV $n$ during starting time of pre-hazard period $t_0$. $s_{n,i,t,0} = 1$ if CEV $n$ is located at CS connecting to grid node $i$ during $t_0$; $s_{n,i,t,0} = 0$, otherwise. In Eq. (4), $c_{i,t} \beta_{\text{Chg}}$ denotes the unit charging price of CS connecting to grid node $i$ during $t$; $P_{t,\text{EV,Chg}}$ denotes the accumulated charging power during $t$. In Eq. (5), $P_{t,\text{EV,Chg},\omega}$ denotes the charging power of CEV $n$ during $t$ in scenario $\omega$. We also introduce $P_{t,\text{EV,Dis}}$ to denote the discharging power of CEV $n$ during $t$. The CEVs get charged during $T^{pre-RS}$ and $T^{post-RS}$, when $P_{t,\text{EV,Chg}} \geq 0, P_{t,\text{EV,Dis}} = 0$; during $T^{RS}$, CEVs discharge power to grid and $P_{t,\text{EV,Dis}} \geq 0, P_{t,\text{EV,Chg}} = 0$. In Eq. (6), $i_{i,t,\text{Grid}}$ denotes the unit restoration revenue at grid node $i$ during $t$, which depends on the importance of nodes in the PN. The term $P_{t,\text{Base},\omega}$ denotes the active base load power at grid node $i$ during $t$ in scenario $\omega$. As shown in Eq. (7), the operation cost consists of generation cost of DGs, $C_{\text{Gen,\omega}}$, and energy cost for CEVs’ re-charging to their initial SOC after restoration service, $C_{\text{Chg,post-RS,\omega}}$. They are calculated through Eq. (8) and Eq. (9), respectively. We assume the DG is powered by fuel. $c_{\text{Gen}}$ denotes the unit fuel cost, $\beta_{\text{Gen}}$ denotes the fuel density, and $\delta_{\text{Gen}}$ denotes the effective specific fuel consumption rate. Symbol $P_{t,i,\omega}$ denotes the active power generation of DG connecting to grid node $i$ during $t$ in scenario $\omega$.

B. First-stage optimization: Pre-hazard CEV allocation

In the first-stage optimization, CEVs move out from the depot, which are pre-allocated at CSs and get charged to the required SOC level. At one time, CEV can be located in only one CS, which is expressed as follows:

\[
\sum_{i \in I^{CS}} s_{n,i,t} \leq 1, \quad \forall n, \forall t \in T^{pre-RS}.
\]  

During one period, the total number of CEVs located in CS connecting to grid node $i$ cannot exceed its capacity, $N_{i,\text{Cap}}$, as follows:

\[
\sum_{n \in N} s_{n,i,t} \leq N_{i,\text{Cap}}, \quad \forall i \in I^{CS}, \forall t \in T^{pre-RS}.
\]  

We assume that once they are pre-allocated, they will be located in the corresponding CS until the hazard happens, as follows:

\[
s_{n,i,t} = s_{n,i,t,0}, \quad \forall i \in I^{CS}, \forall n, \forall t \in T^{pre-RS}/\{t_0\}.
\]  

At the start of the restoration service period $t^{RS}$, CEVs’ SOC level, $S_{n,i,\text{RS}}$, should reach the required level, as follows:

\[
S_{n,i,\text{RS}} = S_{n,i,\text{post-RS}} + \sum_{t_0}^{t^{RS}} P_{n,i,t} \Delta t - e_{n,t_0}, \quad \forall n, \forall t_0.
\]  

\[
\sum_{i \in I^{CS}} P_{n,i,t} \Delta t \leq E_{\text{Cap}}, \quad \forall n, \forall t_0.
\]  

\[
0 \leq P_{n,i,t} \leq P_{\text{Rated}}, \quad \forall i \in I^{CS}, \forall t, \forall n,
\]  

where $S_{n,i,\text{RS}}$ denotes the SOC of CEV $n$ at the initial time; $e_{n,t_0}$ denotes the energy consumption of CEV $n$ from the depot to the corresponding CS; $E_{\text{Cap}}$ denotes the battery capacity of a CEV. In Eq. (15), $e_{\text{Unit}}$ denotes the unit energy consumption rate; $D_{\text{Trans}} = (d_{i,\text{trans}}^{\text{CS}}) \in R_{1 \times N^{CS}}$ denotes the distance vector from the depot to CSs where $N^{CS}$ is the number of CSs, and its element $d_{i,\text{trans}}^{\text{CS}}$ denotes the shortest distance from the depot to CS $i$. Symbol $s_{n,i,t_0} = (s_{n,i,t_0}) \in R_{1 \times N^{CS}}$ denotes the binary vector for CEV $n$ during $t_0$. For example, $s_{n,i,t_0} = [0 \ 1 \ \ldots \ 0]$ means CEV $n$ is moves from depot to CS 2 during $t_0$. Eq. (16) means that charging/discharging power of CEVs is bounded by the rated power capacity, $P_{\text{Rated}}$.

C. Second-stage optimization: PN restoration and CEVs’ re-dispatch

The second stage optimization works during the restoration and the post-restoration period when the PN topology is re-configured, and CEVs are re-dispatched among CSs to provide power support.

1) Original power flow: The operation of the PN needs to follow the constraints of power flow during the whole scheduling period. In this paper, we assume the PN to be
a radial structure [22]. We establish the original power flow model based on the DistFlow model [23], as follows:

\[ P_{k,i,t} = \sum_{j \in I_i^c} \left( P_{i,j,t} + I_{i,j,t}^2 r_{ij} \right) + P_{i,t}, \quad \forall k \in I_i^c, \forall i \in I, \forall t, \]  

(17)

\[ Q_{k,i,t} = \sum_{j \in I_i^c} \left( Q_{i,j,t} + I_{i,j,t}^2 x_{ij} \right) + Q_{i,t}, \quad \forall k \in I_i^c, \forall i \in I, \forall t, \]  

(18)

\[ f_{i,t} \leq P_{i,t} \leq f_{i,t}^B, \quad \forall i \in I, \forall n, \forall t, \]  

(19)

\[ Q_{i,t} \leq Q_{i,t}^B, \quad \forall i \in I, \forall t, \]  

(20)

\[ f_{i,t} T_i \leq P_{i,t} \leq f_{i,t}^B T_i, \quad \forall i \in I, \forall t, \]  

(21)

\[ P_{k,i,t} = f_{i,t}^B \left( P_{i,t} - P_{i,t}^C - P_{i,t}^G \right), \quad \forall i \in I, \forall n, \forall t, \]  

(22)

\[ Q_{k,i,t} = Q_{i,t}^B - Q_{i,t}^G, \quad \forall i \in I, \forall t, \]  

(23)

\[ P_{k,i,t} = \sum_{i \in I} \left( \eta p_{n,i,t}^{E,ch} - \eta p_{n,i,t}^{E,ch} \right), \quad \forall i \in I^c, \forall n, \forall t, \]  

(24)

\[ V_{i,t}^2 + \left( x_{i} G_{i,t}^G + x_{i} F_{i,t}^G \right) V_{i,t} = V_{i,t}^2 + 2 \left( r_{i,t} P_{i,t} + x_{i} Q_{i,t} \right), \quad \forall i \in I, \forall j \in I_i, \forall t, \]  

(25)

\[ f_{i,t} \leq V_{i,t} \leq f_{i,t}^\text{max}, \quad \forall i \in I, \forall t, \]  

(26)

\[ |I_{i,j,t}| \leq s_{i,j,t}^\text{max}, \quad \forall i \in I, \forall j \in I_i, \forall t, \]  

(27)

\[ P_{i,t}^G + Q_{i,t}^G \leq f_{i,t}^G V_{i,t}^2, \quad \forall i \in I, \forall j \in I_i, \forall t, \]  

(28)

\[ (P_{i,t}^G)^2 + (Q_{i,t}^G)^2 \leq \left( S_{i,t}^G \right)^2, \quad \forall i \in I, \forall t. \]  

(29)

Constraints (17) and (18) denote that the total active/reactive injection power from the parent node(s) is equal to the sum of the outflow active/reactive power to the child node(s), the line loss and nodal active/reactive power, respectively. Constraints (19) and (20) denote that the nodal active/reactive power consists of the active/reactive base load demand, the accumulated power injection/outflow from the CS, and the active/reactive power generation of the DG during t. Constraint (21) denotes that the nodal power is constrained by the node power state \( f_{i,t} \) and the active power capacity \( P_{i,t} \). Symbol \( f_{i,t} = 1 \) if node i is powered, \( f_{i,t} = 0 \), otherwise. Constraint (22) denotes that before the hazard happens and after the restoration period, the active base load equals the load demand in node i, \( P_{DB} \); during the restoration period, the base load will be powered by discharging power from the CEVs and the DGs to reach the load demand. Constraint (23) indicates the relationship between active and reactive base load. Constraint (24) calculates the net power injection/outflow of the CS from CEVs in node i during t. Without CS in node i, this term equals zero. Constraint (25) is the branch equality on voltage and current. Constraint (26) and (27) limit the security ranges of voltage and current subject to \( f_{i,t} \) and line power state, \( s_{ij,t} \). Symbol \( s_{ij,t} = 1 \) if the power line between node i and j is powered; \( s_{ij,t} = 0 \) otherwise. Constraint (28) is a relaxed second-order cone form of the line current calculation. Constraint (29) limits the DG’s active and reactive power capacity. Without DG in node i, \( P_{i,t}^G \) and \( Q_{i,t}^G \) equal zero.

2) Virtual power network integration: During the restoration period, the topology of the PN is damaged by the typhoon. It needs reconfiguration to keep the connectivity with a general radial structure of the islanded parts of the PN [24], which also satisfies the reliability and protection requirements of the power supply. Following the reference [25], we adopt a rooted graph model with virtual nodes and lines to establish a virtual PN. The virtual root node, \( 0^V \), connects to the nodes with power resources (CSs and DGs) through virtual lines but does not consume or transmit actual power. The constraints based on the virtual PN structure are described as follows:

\[ f_{i,t} = 1, \quad \forall i \in I^C \cup I^G, \forall t, \]  

(30)

\[ f_{i,t} \leq 1, \quad \forall i \in I \setminus (I^C \cup I^G), \forall t, \]  

(31)

\[ \sum_{k \in I_i^c} s_{ki,t} + \sum_{j \in I_i^c} s_{ji,t} \leq 1, \quad \forall i \in I, \forall t, \]  

(32)

\[ \sum_{k \in I_i^c} s_{ki,t} + \sum_{j \in I_i^c} s_{ji,t} \geq f_{i,t}, \quad i \neq 0, \forall i \in I, \forall t, \]  

(33)

\[ s_{i,j,t} = s_{ij,t}^V + s_{ji,t}^V \leq u_{i,j,t}, \forall i \in I, \forall j \in I_i, \forall t, \]  

(34)

\[ s_{ij,t} - 1 \leq f_{i,t} - f_{j,t} \leq 1 - s_{ij,t}, \forall i \in I, \forall j \in I_i, \forall t, \]  

(35)

\[ P_{i,t}^V = P_{i,t}^V + \sum_{j \in I_i^c} P_{i,t}^V, \quad \forall i \in I, \forall t, \]  

(36)

\[ P_{i,t}^V = P_{i,t}^V \times 1, \quad \forall i \in I, \forall t, \]  

(37)

\[ -s_{i,j,t} M \leq P_{i,t}^V \leq s_{i,j,t} M, \quad \forall i \in I, \forall j \in I_i, \forall t, \]  

(38)

\[ s_{0,i,t}^V = 1, \quad \forall j \in I^C \cup I^G, \forall t, \]  

(39)

\[ s_{0,i,t}^V = 0, \quad \forall j \in I \setminus (I^C \cup I^G), \forall t, \]  

(40)

\[ s_{j,0,t}^V = 0, \quad \forall j \in I, \forall t, \]  

(41)

Constraints (30) and (31) denote that the nodes connecting with CSs and DGs will keep being powered during \( T^R \) while the power states of the other nodes are subjected to the scheduling results; Constraints (32) and (33) denote the power state of node i is dependent on the flow-in and flow-out states of the power lines connecting with node i during t; Constraint (34) denotes the power state of a line is dependent on two binary variables, the forward and reverse power flow, \( s_{ij,t}^V \) and \( s_{ji,t}^V \). This constraint ensures power flow of the line \( ij \) has a single direction during t, which is restricted by the binary line state parameter \( u_{i,j,t} \). Constraint (35) indicates the consistency relationship between the power states of node i and j, and the power state of line \( ij \) during t. Constraints (36) – (38) denotes the conservation of virtual power flow \( P_{i,t}^V \), where the virtual load at node \( i \), \( P_{i,t}^V \), is uniformly set to 1. Constraint (39) indicates that virtual forward current exists from the virtual root node to the power source nodes. Constraint (40) indicates that no virtual forward current will flow out to non-source nodes from the virtual root node. Constraint (41) indicates that the current cannot flow back into the root node. The above three constraints denote the virtual root node \( 0^V \) will only connect to the nodes with CSs or DGs, which ensure the radial structure of the reconfigured PN.

3) CEV re-dispatch: To provide power support for the critical loads as much as possible, it is essential to re-dispatch the pre-allocated CEVs among different CSs. It should be
noted that the topology of the damaged IPTS will influence the reconfiguration and power flow in the PN and the spatial-temporal re-dispatch of CEVs in the TN. In detail, the accessibility of the roads will change the shortest trip distances of CEVs among CSs, which further influences the arrival SOC of CEVs at CSs and their charging/discharging profiles. Thus, the available discharging energy to PN and the power flow will be affected, leading to different restoration effects on the IPTS. During $T_{RS}$ and $T_{post-RS}$, the constraints of CEVs’ re-dispatch process are shown as follows:

$$\sum_{n \in N} s_{n,t}^N \leq 1, \quad \forall n, \forall t \in T_{RS},$$

(42)

$$\sum_{n \in N} s_{n,t}^N \leq \lambda_i^\text{Cap}, \quad \forall i \in T_{CS}, \forall t \in T_{RS},$$

(43)

$$SOC_{\text{min}} \leq SOC_{n,t} \leq SOC_{\text{max}}, \quad \forall n, \forall t,$$

(44)

$$SOC_{n,t} = SOC_{n,t,\text{RS}} - \frac{e_{n,t}^\text{PN} + e_{n,t}^\text{TN}}{E_i^\text{Cap}} \text{,} \quad \forall n, \forall t \in T_{RS} \cup T_{post-RS},$$

(45)

Constraints (42) and (43) denote the plugging-in and capacity constraints, which are the same as Eq. (10) and (11) in the first stage. Constraint (44) restrains the upper limit and lower requirement of real-time SOC during $t$, which is obtained through Eq. (45). Constraint (46) calculates the net discharging energy to the PN of CEV $n$ during $t$, $e_{n,t}^\text{PN}$. Constraints (47) and (48) calculate the trip energy consumption of CEV $n$ during $t$, $e_{n,t}^\text{TN}$. The different topologies of the damaged TNs will result in different values of $D_{ij}$. The term $s_{n,t}^N \cdot D_{ij}^N$ will select the element $d_{ij}$ with the perspective row and column, which indicates the trip distance of CEV $n$ between the CS during $t - 1$ and the one during $t$ in km. Due to the bi-linear term multiplication, we transform the polynomial constraints equivalently through $D_{n,t}^\text{CS,trip} = s_{n,t}^N (D_{ij})^T$. Here, we introduce $s_{n,t}^N \in \mathbb{R}_{1 \times (N^{CS})^2}$ to represent the motion process of CEVs among CSs, and $D_{ij}^N \in \mathbb{R}_{1 \times (N^{CS})^2}$ to reshape $D_{ij}$ from the $N^{CS} \times N^{CS}$ matrix to a $1 \times (N^{CS})^2$ vector, which can deal with the unsolvable issue. During the post restoration period, CEVs will recharge to their initial SOC and return to the depot, as follows:

$$SOC_{n,t,0} \leq SOC_{n,t,\text{end}}, \quad \forall n, \forall t,$$

(49)

$$SOC_{n,t,\text{end}} = SOC_{n,t,\text{end}} + (e_{n,t,\text{end}} - e_{n,t}^\text{TN}) / E_i^\text{Cap}, \quad \forall n,$$

(50)

$$e_{n,t}^\text{TN} = e_{n,t}^\text{Unit} D_{n,t}^\text{Trans} = e_{n,t}^\text{Unit} D_{n,t}^\text{Trans} (s_{n,t}^N)^T, \quad \forall n.$$

(51)

Constraints (49) denotes that at the end of the scheduling period $t_{\text{End}}$, the SOC of CEVs can not be lower than that at the initial time, which is realized through Eq. (50). Eq. (51) denotes the trip energy consumption from CSs to the depot during the final period. To summarize, the whole problem is an MISOCP problem, that can be solved through off-the-shelf commercial solvers. After solving the optimization problem, we reshape the dimension of the term $s_{n,t}^N \in \mathbb{R}_{1 \times (N^{CS})^2}$ through a new symbol $s_{n,t}^N \in \mathbb{R}_{N^{CS} \times N^{CS}}$. Their dimensions are reshaped sequentially. Then, the binary location signals of the two intervals during $T_{RS}$ can be obtained as follows:

$$s_{n,t-1}^N = (I_{1 \times N^{CS}}) (s_{n,t}^N)^T, \quad \forall n, \forall t \in T_{RS},$$

(52)

$$s_{n,t}^N = (I_{1 \times N^{CS}}) s_{n,t+1}^N, \quad \forall n, \forall t \in T_{RS},$$

(53)

where $I_{1 \times N^{CS}}$ denotes the vector that all elements are 1.

III. SCENARIO GENERATION FOR THE DAMAGED IPTS TOPOLOGY

1) IPTS model under typhoon hazard: Typhoon hazards are low probability-high impact events. Within the time range of one day ahead or several hours ahead, the predicted happening time can be relatively precise [26]. However, due to the high uncertainty of the typhoon track, the real-time wind, and rainstorm levels, the damaged nodes in the IPTS are difficult to predict. Referring to [27], we generate the cumulative damage model of grid towers in the IPTS under typhoon hazard. Here, we assume there is one grid tower in each grid node. The typhoon model is established based on the Rankine vortex model [28], and the failure rate of the grid tower follows the Palmgren-miner linear cumulative damage law [29]. The fatigue damage model of the tower in node $i$ during $t$ is shown as follows [30]:

$$D_{i,t} = \begin{cases} 0, & v_{i,t} \in [0, v_0), \\ ae^{bt}, & v_{i,t} \in [v_0, v_{\text{max}}), \\ 1, & v_{i,t} \in [v_{\text{max}}, +\infty], \end{cases}$$

(54)

where $D_{i,t}$ denotes the fatigue damage value of the tower in node $i$ during $t$; $a$ and $b$ are the model coefficients relevant to the material strength of the tower. There are three typhoon speeds: $v_0$ as the critical value when a typhoon begins to cause tower fatigue, $v_{\text{max}}$ as the real-time speed value at grid node $i$ during $t$, $v_{\text{max}}$ as the ultimate value when typhoon certainly destroys the tower and causes tower’s collapse. Based on Poisson model [31], the probability of tower’s not-collapsing of node $i$ at time $t$ is described as follows:

$$\lambda_{i,t}^{\text{To,not}} = e^{-\left[\sum_{t_i \in \mathbb{R}_t} \left(\frac{D_{i,t}}{E_i} \Delta t\right)\right]},$$

(55)

Thus, the failure probability of the power line between node $i$ and $j$ during $t$ is as follows:

$$\lambda_{ij,t}^{\text{To,not}} = 1 - \lambda_{i,t}^{\text{To,not}} \lambda_{j,t}^{\text{To,not}}.$$

(56)

For the transportation network part, the damage probability of road $m$ is closely related to the road altitude and the accumulated precipitation induced by the typhoon [32]. Assuming the road altitude is known, the probability of the damaged road depends only on the precipitation $h^\text{r}$ based on historical data. Based on [33], the piece-wise probability of road $m$ is
Algorithm 1 Procedure for scenario generation

**Input:** Sampling number \( N_\omega \), model coefficient \( a \) and \( b \), wind speed \( v_{t,i} \) and critical wind speed \( v_0 \) and ultimate value \( v_{\text{max}} \).

**Output:** Power line status and road status during \( t \), using \( u_{ij,t,\omega}^{\text{PN}} \).

1. Calculate \( \lambda_{ij,t}^{\text{TN}} \) with Eq. (54) – (56);
2. Calculate \( \lambda_{m,t}^{\text{TN}} \) with Eq. (57);
3. Set \( \omega = 0 \);
4. while \( \omega < N_\omega \) do
5. \( \text{PN:} \)
6. while \( l(ij) \in L \) do
7. Generate random number \( y \) in \([0,1]\);
8. If \( y \leq \lambda_{ij,t}^{\text{TN}} \), \( u_{ij,t,\omega}^{\text{PN}} = 1 \); vice versa;
9. end while
10. If \( \sum_{ij} u_{ij,t,\omega}^{\text{PN}} > 3 \), go to step \( \text{PN:} \);
11. \( \text{TN:} \)
12. while \( m \in M \) do
13. Generate random number \( z \) in \([0,1]\);
14. If \( z \leq \lambda_{m,t}^{\text{TN}} \), \( u_{m,t,\omega}^{\text{PN}} = 1 \); vice versa;
15. end while
16. If \( i \) is connecting \( m \), \( u_{m,t,\omega}^{\text{TN}} \) is replaced by \( u_{ij,t,\omega}^{\text{PN}} \);
17. \( \text{return} \) \( u_{ij,t,\omega}^{\text{PN}}, \omega \);
18. \( \omega = \omega + 1 \);
19. end while

Algorithm 2 Procedure for scenario reduction

**Scenario selection:**

1. Select and cluster the scenarios that no transportation or grid nodes are damaged, the corresponding number is recorded as \( N_{\omega}^{\text{norm}} \) and the probability without damages is \( p_{\text{norm}} = N_{\omega}^{\text{norm}} / N_\omega \);

2. Obtain the set of scenarios with damages, \( \Phi_i \), and record the scenario number, \( N_{\omega}' = N_\omega - N_{\omega}^{\text{norm}} \).

**K-means clustering:**

3. Obtain \( \Delta e_{i,\omega} \) for each scenario in \( \Phi_i \) through Eqs. (58) – (59);

4. Partition the unserved energy vectors with total number of \( N_{\omega}' \) in to \( k \) \( (k < N_{\omega}') \) sets, \( \Phi_1, \Phi_2, ..., \Phi_k \).

5. Randomly select one representative scenario among \( \Phi_i \) and the corresponding probability is calculated as \( \sum_{\omega \in \Phi_i} p_{\omega} = \sum_{\omega \in \Phi_i} (1/N_\omega) \).

2) Scenario generation: We first produce a total of \( N_\omega \) scenarios of IPTS topology to simulate the typhoon’s effect through Monte Carlo simulation. Considering the system reliability theory and practical situations [35], the probability of the cases where the number of damaged grid nodes are larger than three in the meantime is extremely small. Therefore, in this work, we take the scenarios where no more than three grid nodes are damaged into the model simulation. Based on [33], a modified algorithm of scenario generation for the damaged IPTS is given in Algorithm 1.

3) Scenario reduction: To cover all the possible scenarios, the \( N_\omega \) needs to be set as large as possible, which will bring in heavy computational burden. We introduce a scenario reduction method including scenario selection and a modified K-means clustering method based on [36]. The algorithm is shown in Algorithm 2. For the K-means clustering process, a new \( \mathcal{I} \)-dimension vector indicating the distribution of unserved energy of the PN is introduced as below:

\[
\Delta e_{i,\omega} = (\Delta e_{1,\omega}^1, \Delta e_{2,\omega}^2, ..., \Delta e_{\mathcal{I},\omega}^\mathcal{I}), \quad \forall i \in \mathcal{I},
\]

where \( \Delta e_{i,\omega}^i \) is the accumulated unserved energy of grid node \( i \) during the period \( t \) for scenario \( \omega \), as follows,

\[
\Delta e_{i,\omega}^i = \sum_{t \in T} (p_{i,t}^{\text{De}} - F_{i,t}^{\text{Base},\omega}) \Delta t, \quad \forall i \in \mathcal{I}.
\]

Figure 1: An IPTS based on IEEE-33 bus distribution network and Sioux-falls network under scenario 30

Table II: Scenario statistics

<table>
<thead>
<tr>
<th>IPTS Damage type</th>
<th>Scenario ID</th>
<th>Total number</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 PN node damage</td>
<td>1-12</td>
<td>106</td>
</tr>
<tr>
<td>2 PN nodes damage</td>
<td>13-20</td>
<td>112</td>
</tr>
<tr>
<td>3 PN nodes damage</td>
<td>21-40</td>
<td>498</td>
</tr>
<tr>
<td>No damage</td>
<td>41</td>
<td>284</td>
</tr>
</tbody>
</table>
Table III: System critical parameter setting

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a$</td>
<td>$1.9249 \times 10^{-7}$</td>
<td>$P_{EV, \text{rated}}$</td>
<td>$180$ kW</td>
</tr>
<tr>
<td>$b^m$</td>
<td>$0.0055$</td>
<td>$SOC_{\text{max}}$</td>
<td>$98%$</td>
</tr>
<tr>
<td>$b^G$</td>
<td>$200$ g/kWh</td>
<td>$SOC_{\text{min}}$</td>
<td>$18%$</td>
</tr>
<tr>
<td>$c^m$</td>
<td>$6.0$ CNY/L</td>
<td>$SOC_{\text{Re}}$</td>
<td>$90%$</td>
</tr>
<tr>
<td>$c^L$</td>
<td>$200$ CNY</td>
<td>$SOC_{\text{n,t}}$</td>
<td>$50%$</td>
</tr>
<tr>
<td>$E_{\text{cap}}$</td>
<td>$300$ kWh</td>
<td>$v_0$</td>
<td>$20$ m/s</td>
</tr>
<tr>
<td>$N_{\text{cap}}$</td>
<td>$[20 10 10 15 5]$</td>
<td>$v_{\text{max}}$</td>
<td>$53$ m/s</td>
</tr>
<tr>
<td>$N_{\text{CS}}$</td>
<td>$4$</td>
<td>$\eta$</td>
<td>$90%$</td>
</tr>
<tr>
<td>$N_{\text{EV}}$</td>
<td>$30$</td>
<td>$\rho^m$</td>
<td>$0.8$ kg/L</td>
</tr>
</tbody>
</table>

Table IV: TOU and restoration price settings of CSs

<table>
<thead>
<tr>
<th>Index</th>
<th>CS area</th>
<th>TOU price (CNY/kWh)</th>
<th>Restoration price (CNY/kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CS1</td>
<td>Central commercial area</td>
<td>0-7, 23-0: 1.1342; 7-10, 15-18, 21-23: 1.4346; 10-15, 18-21: 1.7440</td>
<td>TOU * 10</td>
</tr>
<tr>
<td>CS2</td>
<td>Central residential area</td>
<td>0-8: 1.0500; 8-14, 17-19, 22-0: 1.2500; 14-17, 19-22: 1.4500</td>
<td>TOU * 15</td>
</tr>
<tr>
<td>CS3</td>
<td>Non-central commercial area</td>
<td>Same as CS1</td>
<td>TOU * 5</td>
</tr>
<tr>
<td>CS4</td>
<td>Non-central residential area</td>
<td>Same as CS2</td>
<td>TOU * 10</td>
</tr>
<tr>
<td>CS5</td>
<td>Suburb area</td>
<td>0-8: 0.7300; 8-14, 17-19: 0.9800; 14-17, 19-0: 1.1900</td>
<td>TOU * 5</td>
</tr>
</tbody>
</table>

IV. SIMULATION AND RESULT ANALYSIS

A. Simulation setup

The simulation model is based on the standard IEEE 33-bus distribution network and the Sioux Falls Network [37]. We initially generated 1000 scenarios, which were finally reduced to 40 after the process in Section III. The number of damaged grid nodes ranges from one to three while the one of damaged roads is from three to six. For the convenience of display, we list the general scenario statistics from the view of the damaged grid node in Table II. We select the scenario 30 with the largest probability for illustration, and the topology figure is shown in Fig. 1. The damaged power lines are 2–3, 3–4, and 6–26 in the PN; the damaged roads are 3–4, 3–9, 9–10, and 4–11 in the TN. The IPTS has five CSs, thirty CEVs, and two diesel-fueled DGs. The setting of critical parameters is represented in Table III. The parameters of CEVs refer to the configuration of a popular bus model, BYD K9M [38]. The time-of-use (TOU) price of electricity refers to the tariff table of Guangdong Province issued in 2021 [39]. The time-of-use charging prices, including electricity and service fees, are based on the real data in typical CSs of Shenzhen, China [40]. The restoration prices are based on geographic locations, load importance levels, land usage types, and time-of-use electricity prices [41]. We define five types of CSs in this work. Their unit charging and restoration price setting is shown in Table IV. The operation cost of the DGs refers to [42]. During the pre-hazard period, the CEVs move from the original depot at the TN node 6 to different CSs. We set up three cases for the control experiment. Case 1 adopts the proposed method; Case 2 utilizes the CEVs’ battery without considering their mobility, which means they can provide power support only at pre-allocated CSs. Case 3 only uses DGs for power restoration without CEVs’ integration as the benchmark case.

Figure 2: Accumulated power profiles of CSs of case 1 under scenario 30

Figure 3: CEVs’ spatial scheduling results of case 1 under scenario 30

Figure 4: Power and SOC profiles of CEV 1 of case 1 under scenario 30

B. Result analysis

1) CEV dispatch strategy: Fig. 2 shows the accumulated charging and discharging power profiles of five CSs during
the whole day. From 6:00 – 10:00, CEVs are charging before the hazard happens; from 15:00 – 18:00, CEVs are discharging for load restoration; from 21:00 – 24:00, CEVs recharge to their initial SOC. Fig. 3 shows the spatial-temporal scheduling results of the CEVs. Taking CEV 1 as an example, Fig. 4 shows the charging/discharging and SOC profiles of CEV 1 under scenario 30. The dispatch strategy of CEV 1 is as follows: During 0:00 – 6:00, it stays idle in the depot, and the initial SOC keeps at 50%; from 6:00 – 6:30, it moves from depot to CS 5, the SOC reduces to 41.7%; from 6:30 – 8:00, it gets charged and the SOC rises to 90.0%; from 8:00 – 15:00, it is located at CS 5 for preparation; from 15:00 – 17:00, it moves to CS 2 to provide power support for grid node 25, and the SOC reduces to 18% which is the minimum requirement; from 18:00 – 23:00, it moves to CS 5 and get recharged due to the lowest charging price, and the SOC reaches to 53.5%; from 23:00 – 24:00, it moves back to the depot at CS 1 with trip energy consumption, and the SOC reduces to 50%.

Figure 5: Restored PN’s topology of case 1 and 3 under scenario 30

Figure 6: Power profiles at node 23 and 30 under scenario 30

2) Benefits of restoration service by CEVs: Fig. 5 shows the PN’s topology through restoration service of case 1 and case 3 under scenario 30. The orange area denotes the common nodes that get restored and the green area denotes the extra restored nodes in case 1. Compared with case 3 where 16 grid nodes get powered, 30 nodes in case 1 get power support from CSs and DGs. The participation of the CEVs will enlarge the restored area of the damaged PN. Fig. 6 compares the power profiles of grid nodes 23 and 30 of the three cases. During 15:00 – 18:00, it can be seen that case 1 can restore the maximum power for the two nodes among the three cases. Node 30 connecting to CS 4 gets more power support than node 23, which does not directly connect the CSs or DGs. The spatial-temporal scheduling of the CEVs will also maximize the power support of the damaged PN. Thus, the benefits of the restoration service by the CEVs are verified.

3) Necessity of spatial re-dispatching process: In Fig. 6, we can see that if CEVs cannot be re-dispatched geographically in case 2, the restored power of nodes 23 and 30 is much lower than those in case 1. This is because CEVs’ pre-allocated locations are away from these two nodes and cannot provide enough power support. Besides, in table V, the total revenue of case 2 is 45.5% lower than that of case 1. This is because in case 2 CEVs cannot be dispatched to the CSs with higher restoration prices. Thus, we can see that considering the spatial re-dispatch process of CEVs in the TN is necessary, which can lead to a better restoration effect.

V. CONCLUSION

A two-stage scenario-based pre-allocation and re-dispatch framework of CEVs is proposed to enhance the resilience of IPTS under hazard attack. The scenarios are generated using a modified generation algorithm and K-means reduction algorithm based on real hazard damage model. The damaged PN is reconfigured based on a virtual PN model. The results show CEVs’ spatial-temporal scheduling largely enhances the PN’s restoration effect and the IPTS’s resilience. In the future, a compact ancillary service framework including reserve supply in normal operation and restoration service in emergent situations will be investigated, which is more promising to fully utilize the CEVs’ V2G potential.

REFERENCES
