

# **Blockchain and Vehicle-to-Grid Collaborative Scheduling for Post-Disaster Resilience**

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**Abstract:** Extreme natural disasters pose severe threats to power distribution networks, making the efficient dispatch of distributed resources critical for post-disaster resilience. While electric vehicles (EVs) exhibit significant potential as mobile energy storage, traditional dispatch faces bottlenecks such as information asymmetry, lack of trust, and low efficiency. This paper proposes a collaborative post-disaster recovery model synergizing blockchain, Vehicle-to-Grid (V2G) technology, and differential pricing. To eliminate trust friction, a blockchain framework is deployed for transparent data sharing, while a consumer psychology-based mechanism determines EV response rates under nodal differential pricing reflecting resource scarcity. Furthermore, complex physical network constraints are transformed into a Mixed-Integer Second-Order Cone Programming (MISOCP) model via Second-Order Cone Relaxation (SOCR) to uniformly optimize V2G dispatch and network reconfiguration. Simulation results demonstrate that the proposed strategy substantially reduces the comprehensive system recovery cost and decreases load shedding penalties, achieving a multi-party economic win-win for both the grid and EV users.

**Keywords:** Blockchain; Vehicle-to-Grid; Post-disaster power supply; Differential pricing

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## **I. INTRODUCTION**

With the escalation of global climate change, natural disasters present unprecedented challenges to power systems, causing large-scale outages that severely disrupt socio-economic activities[1]. Traditional post-disaster restoration strategies primarily rely on the reconfiguration of distribution network tie-lines[2][3][4]. However, these topological adjustment approaches often struggle to achieve rapid and efficient power recovery due to inherent issues such as low dispatching efficiency and inequitable resource allocation[5].

In recent years, Vehicle-to-Grid (V2G) technology has offered novel perspectives by transforming EVs from simple loads into flexible distributed energy storage resources capable of supplying power to damaged grid nodes [6][7]. Recent studies have developed robust load restoration methods accommodating EV availability[8]and agile decision support systems using EVs as mobile energy sources [9].

Nevertheless, effectively incentivizing EV users to participate in post-disaster recovery and achieving precise supply-demand matching for grid nodes remain critical unresolved issues. In this context, blockchain technology, with its decentralized and transparent characteristics, offers robust technical support by enabling real-time information sharing and trusted smart contract transactions [10][11].

To address these challenges, this paper proposes a coordinated blockchain-V2G optimization framework. First, relying on the decentralized architecture of the blockchain, a trusted information interaction mechanism is constructed to achieve the transparent sharing of affected node statuses and available vehicle resources. Second, a differential pricing mechanism reflecting resource scarcity is innovatively designed, which accurately depicts the

V2G participation threshold from a micro-behavioral perspective using consumer psychology theories. Second, a source-load optimization model is developed to minimize the recovery cost of the entire system. Complex nonlinear physical constraints, such as Alternating Current Optimal Power Flow (ACOPF), are convexified and transformed into a MISOCP problem via the SOCR technique to ensure efficient and accurate solutions.

## II. V2G RESPONSE AND DIFFERENTIAL PRICING MECHANISM

To ensure the efficient and trusted execution of post-disaster recovery, this paper leverages a complete-information platform built upon blockchain technology. Relying on its decentralized architecture, the blockchain establishes a trusted information interaction mechanism between grid nodes and EV users, achieving the transparent real-time sharing of affected node statuses and available vehicle resources. This transparent data layer effectively eliminates information asymmetry, providing the foundational support for the subsequent nodal differential pricing and smart contract-enabled dispatching.

### 2.1 Nodal Differential Pricing

Following a disaster, the node importance is defined as a composite metric that integrates both the social value of the load and its topological value within the grid network. The pricing strategy not only considers the real-time power gap of the node itself but also accounts for the attributes of associated nodes connected via power lines or tie-lines[12]. The basic electricity price  $\pi_{j,base}$  for target node  $j$  is formulated as follows:

$$\pi_{j,base} = C_{base} \cdot (\alpha_p \cdot \omega_j + \beta_p \cdot \omega_{\Omega_j}) \quad (1)$$

where  $\omega_j$  represents the node importance weight,  $C_{base}$  is the base electricity price coefficient reflecting the fundamental cost of power supply, and  $\alpha_p$  and  $\beta_p$  are weight adjustment coefficients utilized to allocate the proportion of "self-value" and "network value".  $\omega_{\Omega_j}$  represents the average importance of the power supply domain  $\Omega_j$ . This power supply domain  $\Omega_j$  is defined as a specific set of nodes that can be supplied with power via functional grid lines and tie-lines connected to node  $j$ . It is collectively calculated as  $\omega_{\Omega_j} = \frac{1}{N_{\Omega_j}} \sum_{s \in \Omega_j} \omega_s$ , where  $N_{\Omega_j}$  is the total number of nodes within this domain, thereby comprehensively reflecting the regional scarcity of power resources.

### 2.2 Consumer Psychology-Based User Screening

User participation decisions are regulated by a perceived threshold mechanism based on consumer psychological decision-making theories [13]. EV users evaluate the costs and revenues incurred during V2G activities. The net profit  $U_m^{EV}$  for EV user  $m$  is formulated as follows:

$$U_m^{EV} = \mu_q \cdot R_{dis,m} - C_{move,m} - C_{rent} - C_{loss,m} \quad (2)$$

Each component of the net profit is strictly defined by the following mathematical expressions:

- **Discharging Revenue ( $R_{dis,m}$ ):** Calculated by the unit electricity price compensation and the actual amount of power supplied, expressed as  $R_{dis,m} = \sum_{j \in BV2G} y_{m,j} \cdot \pi_{j,base} \cdot E_{dis,m}$ , where  $E_{dis,m}$  denotes the actual energy discharged by the user.
- **Travel Cost ( $C_{move,m}$ ):** Determined by the unit distance cost and the actual driving distance, expressed as  $C_{move,m} = c_{km} d_{m,j}$ , where  $c_{km}$  represents the unit distance cost and  $d_{m,j}$  denotes the driving distance from the user's current location to the target power supply node  $j$ .
- **Battery Degradation Cost ( $C_{loss,m}$ ):** Precisely quantified by incorporating the total battery procurement cost  $C_{battery}$ , cycle life  $N_{cycle}$ , depth of discharge  $DoD_m$ , and a non-linear degradation coefficient  $\gamma$ . It

is calculated as  $C_{loss,m} = \frac{C_{battery}}{N_{cycle}(DoD_m)^\gamma}$ .

- **Rental Fee ( $C_{rent}$ ):** Indicates the unified rental fee generated when the user utilizes the charging pile for power supply.
- **Trust Coefficient ( $\mu_q$ ):** A dynamic trust fulfillment coefficient that captures the impact of information asymmetry and settlement risks inherent in traditional centralized dispatching. Relying on the complete-information platform built via blockchain, it establishes an endogenous mechanism between the macroscopic blockchain data on-chain rate  $q \in [0,1]$  and the microscopic user expected revenue. The coefficient is formulated as  $\mu_q = \mu_{min} + (1 - \mu_{min}) \cdot q$ . By utilizing smart contracts within a trusted environment, the blockchain platform effectively mitigates the "trust friction" caused by opaque information, thereby enhancing users' perceived net profit.

To accurately depict the V2G participation threshold from a micro-behavioral perspective, an Individual Rationality Constraint is established. EV users will exhibit a genuine willingness to respond only when the economic compensation is sufficient to cover their implicit costs. With  $y_{m,j}$  defined as a binary variable indicating whether user  $m$  is assigned to grid node  $j$  for discharging, the constraint is expressed as:

$$y_{m,j} \cdot U_m^{EV} \geq 0 \quad (3)$$

### III. POST-DISASTER RECOVERY MISOCPP OPTIMIZATION MODEL

#### 3.1 Physical and Topological Constraints

The post-disaster recovery model is established based on the alternating current optimal power flow (ACOPF) framework [14][15]. The active and reactive power balance at each node  $j \in B$  must be strictly maintained:

$$\begin{cases} \sum_{i:i \rightarrow j} (P_{ij} - r_{ij} I_{ij}^2) + P_j^g + P_j^{V2G} = \sum_{k:j \rightarrow k} P_{jk} + P_j^d \\ \sum_{i:i \rightarrow j} (Q_{ij} - x_{ij} I_{ij}^2) + Q_j^g = \sum_{k:j \rightarrow k} Q_{jk} + Q_j^d \end{cases} \quad (4)$$

where  $P_{ij}$  and  $Q_{ij}$  are the active and reactive power flowing from upstream node  $i$  into node  $j$ ,  $P_j^g$  and  $Q_j^g$  represent the power supplied by the main grid, and  $P_j^{V2G}$  represents the total active power injected from V2G stations.  $P_j^d$  and  $Q_j^d$  denote the actual load demands, while  $r_{ij}$  and  $x_{ij}$  are the resistance and reactance of branch  $ij$ .

To accommodate the post-disaster network reconfiguration and isolate faulty lines, a binary branch state variable  $z_{ij}$  is introduced, where  $z_{ij} = 1$  indicates a closed branch[16]. The Big-M method is applied to decouple the voltage relationship for open branches:

$$-M(1 - z_{ij}) \leq V_i^2 - V_j^2 - 2(r_{ij}P_{ij} + x_{ij}Q_{ij}) + (r_{ij}^2 + x_{ij}^2)I_{ij}^2 \leq M(1 - z_{ij}) \quad (5)$$

where  $V_i$  and  $V_j$  are the voltage magnitudes at nodes  $i$  and  $j$ , and  $M$  is a sufficiently large positive constant.

#### 3.2 Second-Order Cone Relaxation Constraints

To guarantee computational tractability and convexity, the non-linear relationship of the power flow is transformed using the standard Second-Order Cone Relaxation (SOCR) technique:

$$\left\| \begin{bmatrix} 2P_{ij} \\ 2Q_{ij} \\ I_{ij}^2 - V_i^2 \end{bmatrix} \right\|_2 \leq I_{ij}^2 + V_i^2 \quad ij \in E_b \quad (6)$$

where  $\|\cdot\|_2$  denotes the 2-norm. This transformation successfully converts the constraints into convex forms suitable for efficient calculation.

#### 3.3 Overall Optimization Objective

Following an extreme disaster, the overall optimization objective aims to minimize the comprehensive global system recovery cost, which consists strictly of the economic loss penalty caused by load shedding and the V2G compensation paid to EV users. The overall Mixed-Integer Second-Order Cone Programming (MISOCPP) problem is formulated as follows, and its globally optimal collaborative scheme is automatically calculated and executed via smart contracts to ensure transparent resource sharing and multi-party mutual trust:

$$\min F = \sum_{j \in B} l_{LS,j} P_j^{LS} (T_{save} - T_{V2G}) + \sum_m \sum_{j \in BV2G} \gamma_{m,j} \pi_{j,base} E_{dis,m} \quad (7)$$

s. t. (3) – (6)

where  $l_{LS,j}$  represents the economic loss penalty per unit of shed load at node  $j$ , and  $P_j^{LS}$  is the amount of active load shed.  $T_{save}$  denotes the total emergency repair time,  $T_{V2G}$  denotes the response time required for EVs to participate in V2G, and  $E_{dis,m}$  is the actual energy discharged by user  $m$ .

## IV. SIMULATION AND CONCLUSION

### 4.1 Simulation Setup

To verify the effectiveness of the proposed strategy, a modified IEEE 33-bus distribution network coupled with a 30-node road network system is employed as the test system, as illustrated in Fig. 1

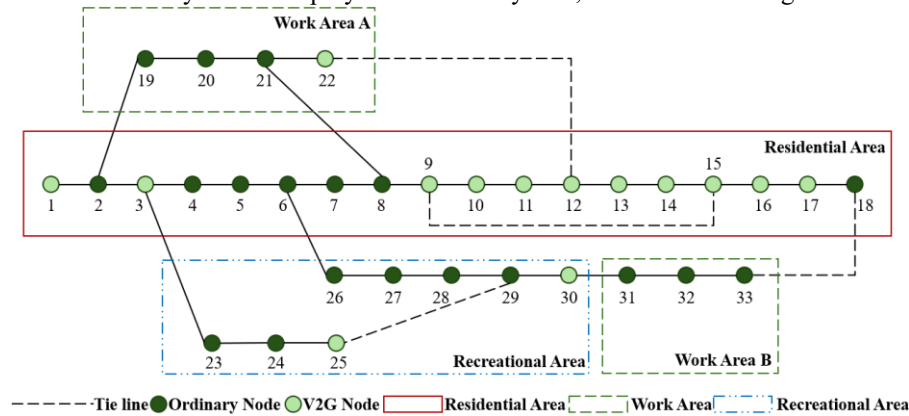


Fig. 1. Topology of the modified IEEE 33-bus distribution network

The simulation was conducted under 100 random fault scenarios using the MATLAB 2024a software and the CPLEX solver. Three comparative case studies are conducted:

- Case 1 considers only distribution network tie-line reconfiguration.
- Case 2 considers both reconfiguration and traditional V2G participation.
- Case 3 represents the proposed blockchain-V2G collaborative model under complete information.

### 4.2 Result Analysis

Under 100 random scenarios, the scatter distribution of the total system cost comprehensively demonstrates the robustness of the proposed collaborative model. As shown in Fig. 2, the scatter points representing Case 3 are positioned at the lowest level in the vast majority of scenarios.

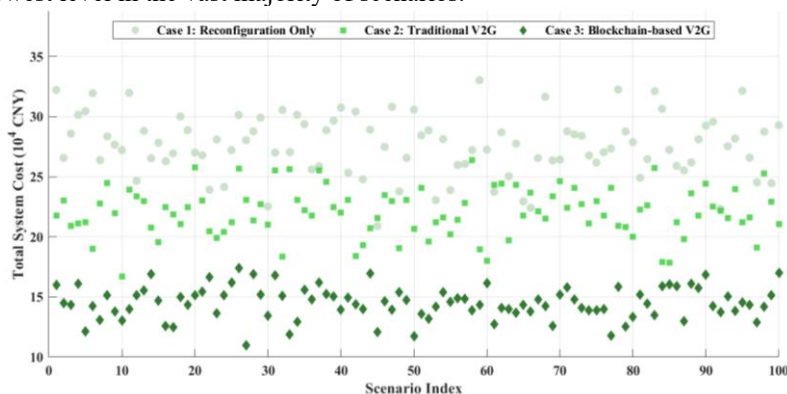


Fig. 2. System Cost Comparison Among Three Cases Under 100 Scenarios

Regarding specific data points presented in Fig. 3, the proposed collaborative model (Case 3) substantially minimizes both economic costs and physical grid losses. Compared with Case 1 and Case 2, Case 3 reduces the average system cost from 275,771 CNY and 220,302 CNY to 145,141 CNY, achieving a significant cost reduction rate of 47.4% compared to the baseline. Similarly, the average amount of load shedding plummets from 1,532 kW (Case 1) and 1,240 kW (Case 2) to 1,045 kW (Case 3), yielding a reduction of 31.8%.

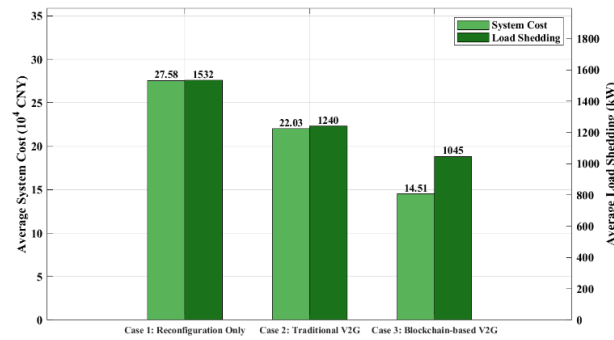


Fig. 3. Average System Cost and Load Shedding

To further illustrate the dynamic recovery process, Fig. 4 presents the real-time load shedding profiles under a specific random scenario. Owing to the complete-information platform and rapid dispatching method, Case 3 demonstrates superior EV response speeds and more rapid load recovery compared to traditional strategies.

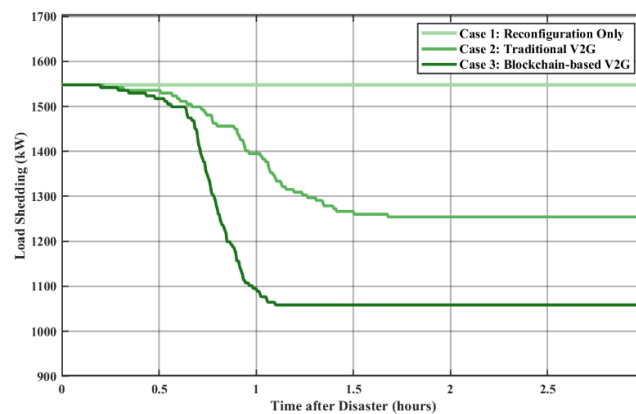


Fig. 4. Dynamic Load Shedding Profiles under Different V2G Strategies

Furthermore, subject to the individual rationality constraints, the transparent pricing mechanism effectively stimulates the discharge potential on the user side. As depicted in Fig. 5, the average total V2G injection power surges from 326 kW in Case 2 to 541 kW in Case 3, marking an increase of over 60%. Concurrently, the average total revenue of participating EV users skyrockets from 2,540 CNY to 6,375 CNY.

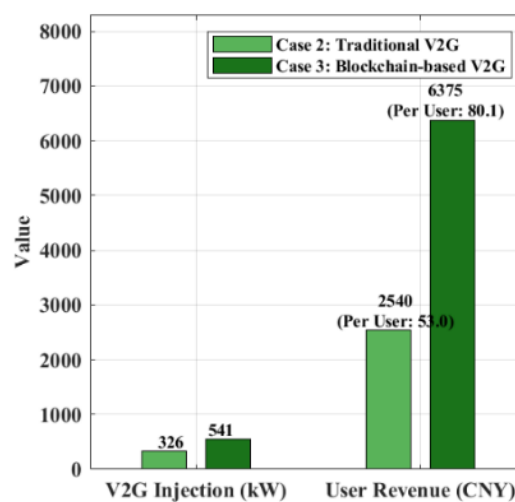


Fig. 5. Comparison of V2G Effectiveness

This strategic economic incentive drastically slashes the heavy penalties associated with load shedding, robustly demonstrating that the proposed framework profoundly exploits the physical potential of idle EVs to support the grid.

### 4.3 Conclusion

This paper proposes a blockchain and Vehicle-to-Grid (V2G) optimization framework tailored for distribution network restoration after extreme disasters. To address the inherent information asymmetry and low dispatch efficiency present in traditional schemes, this framework leverages a transparent blockchain platform and utilizes smart contracts for unified dispatch. By integrating consumer psychology principles, implicit costs such as travel energy consumption and battery degradation are quantified into individual rationality constraints to accurately characterize EV discharge response thresholds under a differential pricing mechanism. Furthermore, complex Alternating Current Optimal Power Flow (ACOPF) constraints are transformed into a Mixed-Integer Second-Order Cone Programming (MISOCP) problem via second-order cone relaxation, ensuring that radial topology reconfiguration and V2G dispatch obtain highly efficient and accurate solutions. The proposed model successfully actualizes a multi-party economic win-win scenario, minimizing comprehensive system recovery costs while maximizing user net revenues, thereby providing a viable new paradigm for post-disaster resilient recovery.

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