Cluster-Based Blockchain and Dynamic V2V Offloading for Optimized V2G Energy Trading

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***Abstract*—Current vehicle-to-grid (V2G) systems face significant inefficiency challenges, particularly as the number of electric vehicles (EVs) and energy transactions increases. This leads to substantial communication and computational overhead. Additionally, the absence of intelligent, autonomous solutions for energy distribution and task offloading leads to the underutilization of vehicular energy resources. To address these issues, this paper proposes a novel architecture featuring a cluster-based blockchain of electric vehicles and an integrated task offloading framework for vehicle-to-vehicle (V2V) networks. The clustering method organizes EVs utilizing active scores and a heartbeat-based leader selection mechanism, with cluster leaders serving as intermediaries between the control system and the energy distribution. Furthermore, a proximity-bounded task offloading framework facilitates dynamic task transfers among nearby vehicles, intentionally preserving the battery capacity of high-capacity electric vehicles and enhancing overall energy availability. Experimental results demonstrate the advantages of the proposed system. Across different cluster settings, the cluster-based blockchain reduces the communication latency by 15.9%-48.7% and achieves a speedup of approximately 1.9 times at 200 EVs, while maintaining similar communication overhead. Meanwhile, the V2V task offloading framework increases total available grid energy by up to 3.0% and improves the fulfillment rate by up to 3.1%, with higher participation from electric vehicles yielding more significant benefits. These findings highlight the system's effectiveness in enhancing energy trading efficiency and optimizing EV energy utilization within V2G networks.**

***Index Terms*—Energy Trading, Blockchain, Energy Management Methods, Electric Vehicles and Electric Mobility, Vehicular Ad hoc Networks.**

I. INTRODUCTION

IN today's energy systems, the rapid adoption of renewable energy and the growing demand for sustainable energy solutions underscore the need for innovative energy management approaches. As the world transitions toward a lower-carbon future, electric vehicles (EVs) have emerged as pivotal players in reshaping the dynamics of energy supply and demand. Vehicle-to-grid (V2G) technology has gained traction as a promising solution to enhance power grid stability. By enabling EVs to not only consume energy but also feed it back into the grid during peak demand, V2G systems provide a dual benefit. This technology represents more than just individual advantages by playing a key role in strengthening energy resilience. The market for bidirectional electric vehicle chargers exemplifies the growing significance of V2G technology. Valued at USD 1.4 billion in 2023, this market is projected to achieve a compound annual growth rate of over 22.8% between 2024 and 2032 [1]. These figures highlight the expanding opportunities for V2G innovation and adoption in the energy ecosystem [2]–[4].

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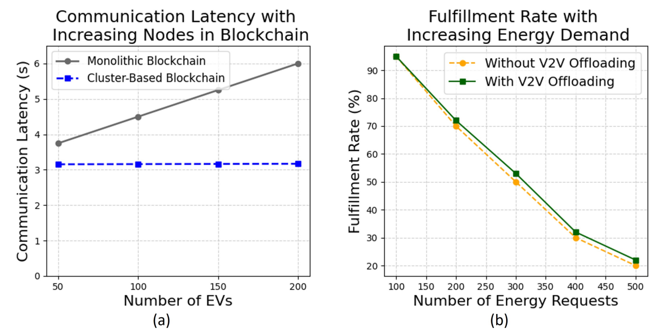
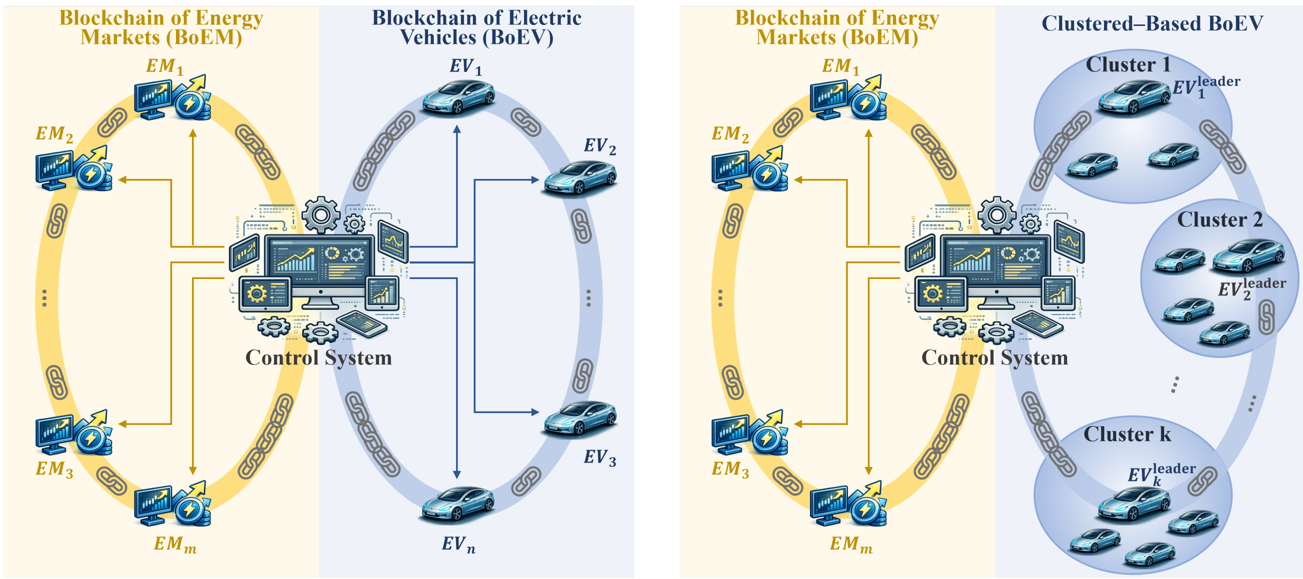


Fig. 1: Illustration of the motivation for the proposed framework: (a) representative comparison of blockchain communication latency between the monolithic and clustered architectures; and (b) conceptual illustration of the decreasing fulfillment rate under increasing task requests and the potential improvement enabled by V2V task offloading.

V2G systems enable EVs to act not only as energy consumers, but also as active energy suppliers, notably contributing to grid stability in times of peak demand and improving the overall resilience of the energy system [6], [7]. The integration of blockchain technology into V2G-based energy trading has emerged as a key development that significantly improves the security, scalability, and operational efficiency of energy transactions [8], [9]. This evolution is characterized by the introduction of decentralized systems that make resource allocation dynamic and thus improve the practicability and responsiveness of energy management systems [10], [11]. At the same time, advances in smart energy forecasting methods are gaining momentum, using advanced computational algorithms to accurately predict energy distribution patterns and effectively manage complex real-time data streams [12], [13].

Despite the potential of V2G systems to support energy exchange between EVs and power grids, two major challenges hinder widespread adoption. First, blockchain-based energy trading architectures face scalability limitations [14]. Fig. 1 (a) presents a representative comparison obtained using the simu-



(a) Baseline V2GNet.

(b) V2GNet with cluster-based BoEV (this work).

Fig. 2: Overview of the baseline vehicle-to-grid network (V2GNet) architecture and the proposed cluster-based framework. (a) The baseline V2GNet architecture presented in the work [5], where each EV acts as an individual node in the flat blockchain of electric vehicles (BoEV) and communicates directly with the control system (CS). (b) The proposed framework retains the blockchain of energy markets (BoEM) and the CS but replaces the flat BoEV with a cluster-based BoEV. EVs are organized into local clusters, and cluster leaders communicate with the CS. The proposed framework also includes V2V task offloading, which is not explicitly shown in the figure.

lation parameters summarized in Table III. The communication latency of the baseline V2GNet architecture [5], as shown in Fig. 2a, increases significantly as more EVs join the network. The reason is propagation and validation delays accumulate for transactions submitted individually to the control system. This limits the practicality of large-scale V2G adoption [15]. Second, EV energy resources may remain underutilized because upcoming driving schedules constrain their participation in energy trading [16]. Consequently, more energy requests may remain unfulfilled as demand increases [17], [18]. Fig. 1 (b) conceptually illustrates this decrease in fulfillment rate and the potential benefit of V2V task offloading. The proposed framework addresses both challenges to support more efficient large-scale V2G energy trading.

To the best of our knowledge, integrating EVs into the power grid, particularly in large-scale decentralized environments, still faces two key challenges. First, as the number of participating EVs increases, communication between each EV and the central control system creates significant communication latency, making it difficult to maintain system efficiency. Second, energy utilization remains limited due to the individual constraints of EVs, such as upcoming driving needs and sporadic availability. This problem becomes even more critical when multiple energy requests must be processed within a narrow timeframe.

This paper presents a scalable and efficient energy trading system for EV networks, incorporating a cluster-based blockchain architecture and a dynamic vehicle-to-vehicle (V2V) task offloading mechanism, as shown in Fig. 2b. The BoEM and the CS are retained from the baseline. The flat BoEV is replaced by a cluster-based BoEV. In this structure, EVs are organized into clusters based on factors such as energy availability, communication reliability, and historical task performance. The proposed clustering approach and leader node selection aim to minimize communication latency while ensuring system responsiveness. The CS facilitates energy trading by communicating exclusively with the cluster leaders. Second, a task offloading framework enables EVs to dynamically assign tasks to nearby nodes based on their current availability. The key contributions of this paper are as follows:

- A dual-network architecture that retains the BoEM and CS of the baseline V2GNet while replacing the flat BoEV with a clustered blockchain and integrating dynamic V2V task offloading.
- An EV coordination framework combining active-score-based clustering, heartbeat-based leader selection, leader rewards, and priority-based matching between energy demands and available supplies.
- A localized V2V task offloading mechanism that identifies nearby vehicles and evaluates their feasibility based on available energy, time windows, and scheduling constraints. It delegates upcoming tasks to suitable peers, preserving more EV energy for the V2G network.
- Evaluation results show that the cluster-based architecture reduces communication latency by 15.9%–48.7% and achieves an approximately 1.9-times speedup at 200 EVs. V2V task offloading increases available grid energy by up to 3.0% and improves the fulfillment rate by up to 3.1%.

The remainder of this paper is organized as follows. Sec-

TABLE I: Nomenclature Table

Symbol	Definition
α	Parameter for EV experience
$\beta_1, \beta_2, \beta_3$	Weights for active score
$\gamma_1, \gamma_2, \gamma_3$	Normalized weights for request priority
κ	Consistency factor
λ	Decay parameter for communication attempts
μ	Fraction of the total profit
μ^w	Recency-weighted mean (communication)
$\sigma^{\max}$	Maximum possible weighted standard deviation
σ^w	Recency-weighted std. dev. (communication)
$\Pi(t)$	Total profit during round t
$B(t)$	A baseline reward pool during round t
C	Total number of attempts
C^{success}	Number of successful attempts
E^{baseline}	Maximum battery capacity among all EVs
E^{current}	EV's current remaining energy
E^{future}	Predicted energy consumption for future task
E^{offer}	Amount of energy an EV can offer
E^{prov}	Cumulative energy supplied by the EV
E_i^{req}	Required energy by request R_i
E^{reserve}	Minimum energy reserve for essential EV driving
E^{total}	Total energy supplied by the entire fleet
Exp	Experience metric of an EV
g	A cluster
$\mathcal{G}$	Set of clusters
$\mathcal{G}^{\text{sel}}$	Subset of selected clusters
K	Number of clusters
L_g	Leader node of a cluster
Lv^{act}	Activity level of an EV
n^{lv}	Number of activity levels
N	Number of EV nodes
$\mathcal{N}$	Set of EV nodes
$\mathcal{O}$	Set of energy offers
P	Priority score of an energy request
P^I	Request criticality
P^T	Tolerance for partial fulfillment of the request
P^U	Urgency of energy need
Q^{comp}	Number of tasks completed by the EV
Q^{total}	Total number of tasks
R^{baseline}	Baseline value for the reward
R^{comm}	Communication reliability
$R_{L_g}(t)$	Reward to a leader node during round t
$\mathcal{R}$	List of energy requests
S^{act}	Active score of an EV
S^{block}	Block size
S^{tx}	Transaction size
t	Energy trading round
T^{agg}	Processing time for aggregating one EV offer
T^{create}	Block creation time
T^{prop}	Transaction propagation time
T^{validate}	Transaction validation time
T^{verify}	Block verification time
w_i	Weight of outcome x_i
$x_1, x_2, \ldots, x_C$	Outcomes of the last C communication attempts
X	Number of energy requests for energy distribution
Y	Number of energy offers for energy distribution

tion II reviews related work on V2G energy trading, V2V task offloading, and blockchain-based energy systems. Section III presents the proposed framework, including EV clustering, leader selection, energy distribution, and V2V task offloading. Section IV evaluates its performance in terms of communication latency, energy utilization, and task fulfillment. Section V discusses the remaining challenges and future research directions. Finally, Section VI concludes the paper by summarizing the key findings and contributions and outlining future research directions.

II. Related Work

This section reviews the body of research on energy trading systems, focusing on advancements in V2G energy trading, methodologies for V2V task offloading, and the application of blockchain technologies. V2G energy trading systems are examined for their role in optimizing energy transfer between electric vehicles and the grid, enhancing energy distribution, and supporting sustainable energy practices. V2V offloading mechanisms are explored for their ability to enable collaborative task execution among EVs, improving resource utilization and network efficiency. Additionally, blockchain solutions are analyzed for their contributions to secure, decentralized coordination in energy trading, ensuring transparency and robustness in managing transactions within distributed networks. Together, these technologies form the foundation of innovative frameworks aimed at addressing the challenges of energy trading and management in EV networks.

A. V2G Energy Trading

V2G energy trading has emerged as a critical area of research, enabling EVs to interact dynamically with the power grid. Recent advancements in blockchain technology have significantly enhanced the security, efficiency, and scalability of V2G systems. Guo et al. [8] introduced a Byzantine-based consensus mechanism to improve transaction throughput and reduce latency, particularly relevant for real-time V2G interactions. Similarly, Abegaz et al. [19] proposed a multi-agent framework integrating deep reinforcement learning and game theory, enabling dynamic resource trading in industrial IoT environments, a concept that can be extended to V2G networks.

Blockchain-based solutions have also been employed to secure regional and peer-to-peer electricity trading. Zhao et al. [20] and Hua et al. [9] addressed the protection of transaction data in energy markets, while Liang et al. [5] presented V2GNet, a semi-blockchain architecture that improves the integration of energy markets into the power grid. This work was further extended in vehicle-to-grid forecasting and trading network (V2GFTN), which connects multiple local networks to enhance scalability and resource allocation [21]. In addition, decentralized approaches and consortium blockchains have been explored to optimize energy balancing in highly mobile scenarios and manage demand response in smart grids [10], [22], [23].

Recent research has also focused on the real-time dynamics and operational challenges of V2G systems. Gümrükcü et al. [24] introduced a decentralized management system for urban charging stations, addressing the rigid scheduling of EVs. Liu et al. [25] utilized 6G technology to enable intelligent distributed cooperation among EVs. In contrast, Huang et al. [26] and Tao et al. [27] deployed simulation-based primal-dual approaches and deep reinforcement learning for energy trading, albeit on a limited scale. Hossain et al. [28] propose a genetic algorithm-based reinforcement learning framework for efficient scheduling and cost-friendly data privacy. Similarly, Shen et al. [29] introduced a privacy-preserving authentication

TABLE II: Comparison of Existing Literature and the Proposed Framework

Reference	Key Approaches	Scalability & Low Latency	Future Resource Awareness	Incentive Mechanism
Guo et al. [8]	Byzantine consensus	×	×	✓
Zhao et al. [20]	Smart contracts	×	×	✓
Liang et al. [5]	Semi-blockchain architecture	∼	×	✓
Liang et al. [21]	Multi-local networks	∼	×	✓
Kheradmand et al. [30]	Meta-heuristic clustering	✓	×	×
Kheradmand et al. [31]	Meta-heuristic clustering	✓	×	×
Wang et al. [32]	Resource expansion	✓	×	✓
Zhang et al. [33]	Distributed heuristics	✓	×	✓
Shi et al. [34]	Deep reinforcement learning	∼	×	✓
Moghaddasi et al. [35]	Deep reinforcement learning	∼	×	✓
Rahmani et al. [36]	Deep reinforcement learning	∼	×	✓
Moghaddasi et al. [37]	Deep reinforcement learning	∼	×	✓
Chen et al. [38]	Distributed scheduling	×	∼	×
Fan et al. [39]	Trajectory modeling	×	∼	×
This Work	**Cluster-based blockchain, Dynamic V2V matching**	✓	✓	✓

method that enhances security without the complexity of traditional crypto-based methods.

Despite these advances, challenges such as scalability, high operational costs, and difficulties adapting to real-time dynamics remain. These hinder the practical implementation of V2G technologies in larger and more dynamic environments. Addressing these challenges remains a key focus for future research in V2G energy trading.

B. V2V Offloading and Blockchain Solutions

Blockchain technologies have been widely deployed to mitigate security and trust issues in V2V networks by providing decentralized authentication, privacy protection, and robust key sharing. Several works focus on lightweight mechanisms and smart contracts to authenticate vehicles and detect adversaries with minimal overhead [40], [41]. In contrast, others incorporate more advanced strategies such as multi-domain key management and dual-signature protocols to facilitate cross-domain trust [42]. The risk of single points of failure is often addressed by decentralized or certificateless architectures, where the blockchain serves as a distributed trusted third party [43]. Researchers have proposed consortium-based or hybrid blockchain frameworks to promote trustworthy interactions, especially in resource trading or cooperative tasks. These frameworks often include improved consensus algorithms, pricing schemes, or physically unclonable functions to protect nodes from malicious attacks [44], [45]. In parallel, techniques such as distributed storage of dashcam data utilize multi-signature access control to ensure tamper-proof sharing, demonstrating the potential of blockchain for processing large-scale requests in real-time [46].

Meanwhile, the growing complexity of vehicular systems has driven research into V2V offloading, where vehicles can share computing or communication resources to improve performance under different mobility conditions. Some approaches address the challenges of a dynamic environment by using advanced modeling of service paths, vehicle trajectories, or software-defined networks, reducing task completion time and out-of-service periods [47], [48]. Additionally, to manage high vehicular mobility and dynamic network topologies, cluster-based routing schemes employing meta-heuristic algorithms, such as Harris Hawks and Gray Wolf Optimization, have been introduced to optimize cluster head selection and enhance overall network throughput [30], [31]. Others propose edge- or cloud-assisted solutions [49], [50] that jointly optimize parameters like spectrum sharing or power control, often formulated through coalition games or distributed heuristics. In the broader context of collaborative edge-cloud computing, efficient computation management and resource expansion schemes have been proposed to optimize server configurations. These approaches ensure that stringent quality-of-service and latency constraints are met while maximizing the long-term profitability and resource utilization of edge servers [32], [33]. Deep reinforcement learning and blockchain-based incentives also enable secure, efficient offloading between unknown vehicles and ensure reliability and privacy in resource allocation [34]. Double deep Q-networks and asynchronous advantage actor-critic frameworks, have been successfully implemented in 5G-enabled and blockchain-secured vehicular edge computing environments. These models effectively manage the complex trade-offs between energy consumption, processing latency, and system operational costs [35]–[37]. Furthermore, purely V2V-focused methods explore opportunistic gatherings (e.g., stops at traffic lights) to exploit idle vehicular resources for cooperative task execution [38], while advanced scheduling and classification mechanisms improve system-wide performance by adaptively dispatching tasks to roadside units or nearby peers [39].

Nevertheless, many existing V2V offloading solutions still lack future resource awareness or robust incentive mechanisms. These capabilities are important for motivating vehicles to share surplus resources while preserving their operational needs. In addition, existing solutions often depend on network-wide or broadcast-based management. This can become inefficient and cause excessive overhead in large, rapidly changing vehicular environments. Consequently, these methods struggle to balance scalability, responsiveness, and fair resource allocation in dynamic V2V networks.

To clarify the research gap and highlight the contributions of this paper, Table II provides a comprehensive comparison of the reviewed literature against our proposed framework. The comparison considers scalability and low latency, future resource awareness, and incentive mechanisms. As shown in Table II, existing studies generally support only some of the three considered capabilities. Several methods improve scalability or provide incentive mechanisms, but future resource awareness is largely absent. The few methods that consider future resources provide only partial support and do not simultaneously offer scalability and incentive mechanisms. Therefore, none of the reviewed studies supports all three capabilities. In contrast, the proposed framework combines a cluster-based blockchain architecture for scalability and low latency, future-resource-aware V2V task offloading, and a leader reward mechanism. It therefore addresses these limitations within a unified framework.

III. V2G Energy Distribution and V2V Task Offloading

In our system, energy trading is coordinated between two blockchain networks: one for energy markets and one for EVs. The energy markets submit energy requests to the control system, which then broadcasts these requests to the EV network. EVs that are willing and capable of participating respond with acknowledgements, including their available energy offers. The CS collects these offers and performs energy matching to determine which EVs will fulfill which requests, a process commonly referred to as demand-response matching. We present a dual-strategy approach by leveraging V2G and V2V capabilities. First, we propose an energy distribution mechanism within the V2G system, where EVs are grouped based on readiness and reliability, and a CS manages energy trading to ensure efficiency and scalability. Second, we introduce a task offloading framework in the V2V system, allowing EVs to transfer tasks to nearby vehicles. Crucially, these two networks are highly integrated. The functional role of the localized V2V network is to act as a resource-optimization layer designed to directly enhance the broader V2G system's capacity. When an EV successfully offloads an upcoming task to a neighbouring vehicle with just enough available energy to complete it, the sending EV is relieved of its future energy commitment. This mechanism intentionally preserves the battery capacity of higher-capacity EVs specifically for energy trading. Consequently, this localized offloading aims to increase the total volume of surplus energy available for the V2G network, thereby optimizing the system's overall potential to fulfill grid energy demands.

A. Energy Distribution Mechanism in V2G Network

1) EV Clustering: First, we perform EV clustering to organize many EVs into manageable groups. Our approach assigns an active score to each vehicle based on factors such as current state of charge, communication reliability, and historical performance (e.g., task completion rate). This score is then mapped to an activity level, a discrete indicator of the EV's readiness to participate in the V2G network. Fig. 3 illustrates this process of clustering, where EVs' capabilities are assessed, assigned an activity level, and then placed in clusters according to their activity levels.

To initiate clustering, each EV calculates the amount of energy it can potentially offer for distribution. We denote this amount as E^{offer}, calculated by:

$$E^{\text{offer}} = \max(0, E^{\text{current}} - E^{\text{future}} - E^{\text{reserve}}), \tag{1}$$

where E^{current} is the current remaining energy, E^{future} is the predicted energy consumption for future tasks, and E^{reserve} represents the minimum energy reserved to sustain the EV's essential driving needs. The use of the maximum function explicitly prevents edge cases where an EV might calculate a negative energy offer. Using this metric, the EV can determine how much surplus energy it can contribute during a trading round.

Another decisive factor is the communication reliability of the EV, which is denoted by R^{comm}. It measures how successfully an EV has carried out communication or transaction attempts in the recent past:

$$R^{\text{comm}} = \frac{C^{\text{success}}}{C}, \tag{2}$$

where C^{success} is the number of successful attempts and C is the total number of attempts. A high R^{comm} indicates that the EV is generally responsive and reliable in the network.

We use a recency-weighted approach to capture the quality and consistency of recent communications more accurately. Let $x_1, x_2, \ldots, x_C (x_i \in \{0, 1\})$ be the outcomes of the last C communication attempts, where $x_i = 1$ for a success and $x_i = 0$ otherwise. More recent events are given a higher weighting:

$$w_i = e^{-\lambda(C-i)}, \tag{3}$$

where $\lambda > 0$ is a decay parameter that controls how quickly historical data loses relevance. The recency-weighted mean is defined as:

$$\mu^w = \frac{\sum_{i=1}^{C} w_i x_i}{\sum_{i=1}^{C} w_i}, \tag{4}$$

and the recency-weighted variance is:

$$(\sigma^w)^2 = \frac{\sum_{i=1}^{C} w_i \big(x_i - \mu^w\big)^2}{\sum_{i=1}^{C} w_i}, \tag{5}$$

leading to the weighted standard deviation σ^w. Finally, we define the consistency metric:

$$\kappa = 1 - \frac{\sigma^w}{\sigma^{\max}}, \tag{6}$$

where κ is the consistency factor and σ^w represents the recency-weighted standard deviation of recent communication attempts. The parameter $\sigma^{\max}$ denotes the maximum possible weighted standard deviation. Normalizing by $\sigma^{\max}$ ensures that κ ranges from 0 (low consistency) to 1 (high consistency).

In addition to real-time energy and communication metrics, historical experience also informs how active and reliable an EV is within the network. Unlike the communication reliability metric (Eq. 2), which evaluates network stability, the experience factor (Exp) measures the EV's actual physical contributions to the system. Exp reflects both the number of

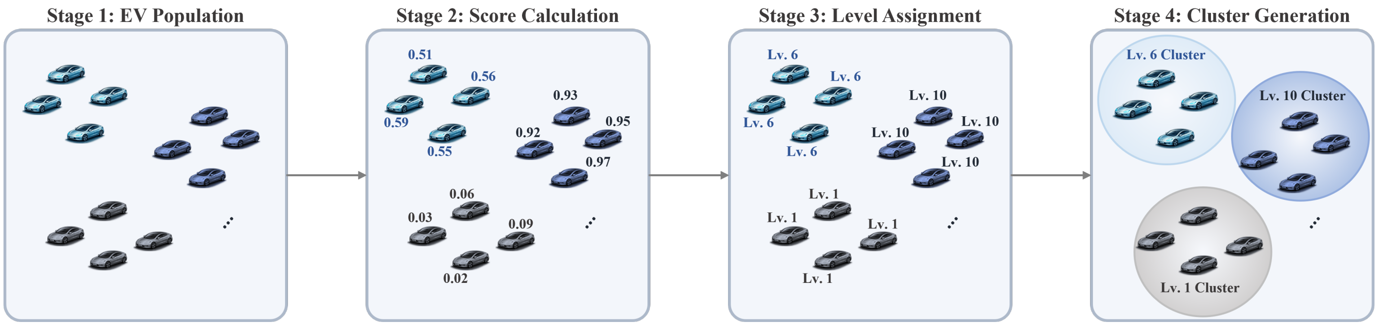


Fig. 3: The detailed process of EV clustering. The framework consists of four stages: (1) initialization of the EV population; (2) calculation of individual evaluation scores; (3) assignment of discrete levels (e.g., Lv. 1, Lv. 6, Lv. 10) based on those scores; and (4) generation of final clusters grouping EVs with identical assigned levels.

tasks completed and the total energy provided. The experience factor is formulated as:

$$Exp = \alpha \frac{Q^{\text{comp}}}{Q^{\text{total}}} + \big(1-\alpha\big) \frac{E^{\text{prov}}}{E^{\text{total}}}, \tag{7}$$

where Q^{comp} is the total number of tasks completed by the EV in a given time period, Q^{total} is the total number of tasks, E^{prov} is the cumulative energy supplied by an EV, and E^{total} is the total energy supplied by the entire EV fleet. The parameter α balances the relative importance of task frequency and energy contribution.

These factors are combined into a single active score, S^{act}, defined by:

$$S^{\text{act}} = \frac{E^{\text{offer}}}{E^{\text{baseline}}} \times (\beta_1 R^{\text{comm}} + \beta_2 \kappa + \beta_3 Exp), \tag{8}$$

where E^{baseline} denotes the maximum battery capacity among all EVs, and $\beta_1, \beta_2, \beta_3$ are non-negative weighting parameters constrained by $\beta_1 + \beta_2 + \beta_3 = 1$. Physically, S^{act} represents an EV's overall readiness to participate in energy trading and cluster coordination. Its components capture current tradable energy, communication reliability, communication consistency, and historical contribution. The term $E^{\text{offer}}/E^{\text{baseline}}$ normalizes the available energy and acts as an energy-availability factor. Meanwhile, R^{comm}, κ, and Exp are bounded within $[0, 1]$ through their respective ratio, normalization, and weighted-combination definitions. Consequently, S^{act} is also bounded within $[0, 1]$, preventing differences in numerical scale from disproportionately affecting the score. The parameters β_1, β_2, and β_3 control the relative importance of the three components and can be adjusted for different operating requirements.

Furthermore, for the activity level Lv^{act} calculation in Eq. 9, we set the total number of activity levels n^{lv} to 10, mapping the continuous score into discrete operational tiers. We define the activity level Lv^{act} of an EV as:

$$Lv^{\text{act}} = \min\big(\lfloor n^{\text{lv}} \cdot S^{\text{act}} \rfloor + 1,\, n^{\text{lv}}\big), \tag{9}$$

where n^{lv} is the total number of activity levels. After determining the activity level of each EV, we propose a clustering algorithm (Alg. 1) to form clusters of EVs with similar activity level. In each cluster, the EV with the highest active score automatically serves as the leader node to communicate with the control system. In the event of a tie in active scores during leader selection, the system defaults to the EV with the lowest unique network identifier. Furthermore, to handle network churn as EVs dynamically join or leave, and to prevent structural oscillations, the clustering algorithm and leader selection are strictly recomputed only at the beginning of each discrete energy trading round t. To keep cluster leaders motivated and ensure long-term stability, we propose a reward mechanism presented in Section III-A2.

Algorithm 1 Activity score-based clustering algorithm

Require: A list $\mathcal{N}$ of N nodes, where each node i has an associated level n_i^{lv}, and a predefined group size s.
Ensure: A list $\mathcal{G}$ of K groups such that each group contains up to s nodes, with nodes sorted in descending order by n_i^{lv}.

```
Sort nodes in descending order based on n_i^lv
Set i ← 1
while i ≤ N do
    Initialize empty list
    Let g ← N[i : min(i + s − 1, N)]
    Append g to G
    i ← i + s
end while
return G
```

2) Reward Mechanism for Leader Nodes: In the blockchain-based V2G network, each cluster of EVs selects a leader who collects status information from the member EVs and communicates with the control system. Although some clusters are chosen more frequently for energy trading (due to higher activity levels), all leaders devote resources to monitoring and organization. To ensure that both active and less active clusters remain engaged, we propose a reward system consisting of two components: a base monetary reward for each leader proportional to the overall profit, and a discharge priority for leaders in selected clusters.

Let $\Pi(t)$ denote the total profit generated by all energy transactions during round t. We allocate a fraction $\mu (0 < \mu \leq 1)$ of $\Pi(t)$ to form a base reward pool $B(t) = \mu \cdot \Pi(t)$. Suppose there are K clusters, and the pool $B(t)$ is divided among the

K leaders. Each leader L_g receives an equal share:

$$R_{L_g}(t) = \frac{B(t)}{K} \tag{10}$$

After assigning the base reward, we determine which clusters will actively participate in the energy distribution this round. Let $\mathcal{G}^{\text{sel}}$ be the subset of selected clusters. For each leader whose cluster g belongs to $\mathcal{G}^{\text{sel}}$, the system grants a privilege for the first discharge and no additional bonus. This means that in each selected cluster, if multiple EVs are eligible for discharge, the leading EV is prioritized and chosen first.

3) Energy Distribution Algorithm on CS: Before the available energy from the EVs is allocated to the requests, it is necessary to determine which energy requests should be served first, especially in scenarios where the total supply is insufficient to fulfill all requests. Therefore, each request is assigned a priority score based on importance, tolerance for partial fulfillment, and time urgency. The CS then performs a heuristic algorithm for energy distribution that processes higher-priority requests before lower-priority ones, ensuring that critical or time-sensitive needs are satisfied first.

a) Priority for Energy Requests: Each energy request is assigned a priority score P. The score is derived from three factors:

- Importance (P^I): Represents the criticality of the request (e.g., hospitals or banks have higher importance). P^I is normalized between 0 and 1, with 1 indicating the highest importance.
- Tolerance (P^T): Reflects how tolerant the request is to partial fulfillment.
- Urgency (P^U): Captures how urgently the energy is needed. A highest urgency value indicates that the energy is needed immediately, while a lower value indicates a more flexible time window. P^U is normalized between 0 and 1, where 1 represents the maximum urgency.

These factors are then combined using a weighted sum. Let $\gamma_1, \gamma_2, \gamma_3$ be non-negative weights with $\gamma_1 + \gamma_2 + \gamma_3 = 1$. The priority score P is given by:

$$P = \gamma_1 P^I + \gamma_2 (1 - P^T) + \gamma_3 P^U \tag{11}$$

ensures that requests from critical facilities with low tolerance for partial fulfillment and tight deadlines are given the highest priority.

b) Heuristic Energy Matching Algorithm: After prioritizing the requests, the CS performs a heuristic algorithm for energy distribution. The EVs are grouped into subnetworks, and the CS contacts these groups sequentially, starting with the highest-level group. Within each group, the leader node collects offers from its EVs and forwards them to the CS. Once enough offers have been collected to meet the demand, or when the last group is reached, the CS sorts the request list in descending order of priority and the offer list in descending order of available energy. Each request is then run through in sequence, allocating energy from the most significant offers until the request is fully satisfied or the available supply is exhausted. All requests are fully satisfied in scenarios where the total EV supply exceeds the total demand. When supply is limited, higher-priority requests are given priority in energy allocation. This approach balances simplicity and effectiveness, allowing critical tasks to be completed before less critical ones while efficiently utilizing available EV energy resources. The algorithm is presented in Alg. 2.

Algorithm 2 Heuristic Priority-Based Energy Matching

Require: A list $\mathcal{R}$ of X requests, where each request R_i has a priority P_i and required energy E_i^{req}. A list $\mathcal{O}$ of Y energy offers where each offer O_j has an offered energy E_j^{offer}.
Ensure: Matching result between energy requests and offers.
Sort request list $\mathcal{R}$ in descending order based on P_i
Sort offer list $\mathcal{O}$ in descending order based on E_j^{offer}
for $i = 1$ to R **do**
  $r \leftarrow E_i^{\text{req}}$
  for each $O_j \in \mathcal{O}$ **do**
    if $r \leq 0$ **then**
      break
    end if
    if $E_j^{\text{offer}} \geq r$ **then**
      Assign r from O_j to R_i
      $E_j^{\text{offer}} \leftarrow E_j^{\text{offer}} - r$
      $r \leftarrow 0$
      if $E_j^{\text{offer}} = 0$ **then**
        Remove O_j from $\mathcal{O}$
      end if
    else
      Assign E_j^{offer} from O_j to R_i
      $r \leftarrow r - E_j^{\text{offer}}$
      Remove O_j from O
    end if
  end for
end for
return Matching result

The time complexity of the proposed heuristic matching algorithm is primarily determined by the sorting and matching steps. Given a request list of size X and an offer list of size Y, the algorithm first sorts the requests by priority and the offers by available energy, which takes $\mathcal{O}(X \log X)$ and $\mathcal{O}(Y \log Y)$ time, respectively. The algorithm then attempts to fulfill each request by iterating over the available offers. In the worst case, if each request requires offers from multiple EVs, the matching takes $\mathcal{O}(X \cdot Y)$ time. Therefore, the total time complexity is $\mathcal{O}(X \log X + Y \log Y + X \cdot Y)$.

4) Leader Node Selection: In a distributed blockchain configuration, it is essential to designate a leader node to streamline the process of block production and efficiently manage the transactions on the chain. However, if this leader node becomes unresponsive or loses communication, the protocol must detect the problem and promote a new leader without affecting the system's consistency. We propose a heartbeat-based mechanism, as shown in Fig. 4, to monitor the liveness of the leader node and replace the leader node when it is offline. The detailed steps of this mechanism are as follows.

- Step 1: The protocol selects a node with the highest active score. This node becomes the leader node responsible for coordinating the block creation.

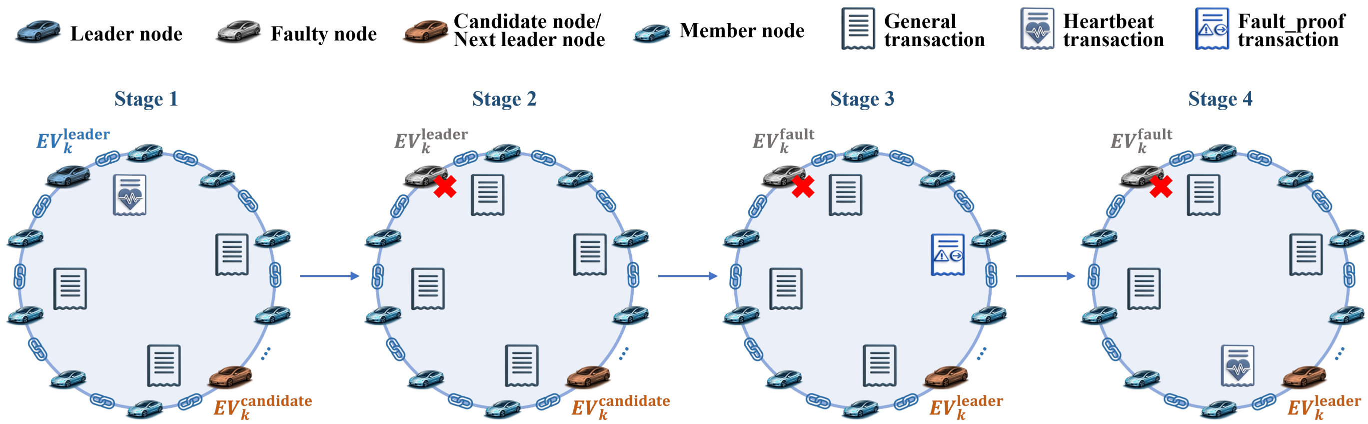


Fig. 4: An illustration of the proposed leader node selection process. The four stages depict normal operation with an active leader, the occurrence of a leader fault, fault detection, and the subsequent promotion of a candidate node to become the new leader.

- Step 2: To confirm its continued liveness, the leader node must publish a *heartbeat* transaction at fixed intervals. Specifically, the leader adds a special transaction of the form Heartbeat (leader_node_id, timestamp, signature) to the blockchain every fixed number of blocks. This transaction proves that the leader is online and actively participating in block production.
- Step 3: Each node in the network tracks the most recent *heartbeat*. The network initiates a fault confirmation process if no *heartbeat* is observed within the expected interval.
- Step 4: If the leader node fails to publish a *heartbeat*, the group can confirm the fault by creating a Fault_Proof transaction. The format of the Fault_Proof is as follows:
  - Faulty_node_id: The ID of the leader node suspected of being offline.
  - Evidence: References to blocks (or a block range) where a *heartbeat* should have appeared but did not.
  - Signatures: Signatures from a threshold of the group or validators confirming the absence of a valid *heartbeat*.
  - Next_leader_node_id: The ID of the node to become the new leader.
- Step 5: When a valid Fault_Proof is processed, the chain performs two actions:
  - Marks Faulty_node_id as offline.
  - Selects the node with the next highest active score as the new leader node. The on-chain logic directly updates the status of the leader node.

B. Task Offloading Mechanism in V2V Network

1) Proximity-Bounded Neighbour Detection: In a blockchain-enabled V2V network, the first step in enabling task offloading is to determine which vehicles are close enough to each other to communicate efficiently, as shown in Fig. 5. To achieve this, each EV periodically broadcasts its current location via short-range wireless communication protocols (e.g., IEEE 802.11p or Cellular V2X). The location data, which is usually obtained via the onboard GPS or inertial navigation systems, is signed or otherwise secured to preserve data integrity and prevent spoofing. Crucially, this location message is restricted to a local broadcast area to ensure it does not propagate to the entire blockchain network.

If an EV, say EV A, broadcasts its location, other EVs within range can receive this message. However, not all receivers are automatically considered neighbours. Upon receiving EV A's location, each potential neighbour applies a distance calculation (e.g., Euclidean formula) to determine whether EV A is within a predefined proximity threshold. If the calculated distance is less than or equal to this threshold, the receiving EV adds EV A to its internal neighbour list; otherwise, the broadcast is ignored.

Since vehicles in a road environment can quickly enter or leave communication range, neighbours are detected at regular intervals. Each vehicle sends regular updates to ensure that newly arrived cars can be detected, while vehicles that exceed the threshold are removed from the neighbour lists after a timeout period. As described in the following section, EVs can then reliably identify suitable neighbours for task offloading.

2) Task Offloading Algorithm: Before detailing the algorithmic workflow, it is necessary to establish an explicit operational definition of the offloaded tasks. In this framework, the offloaded object is strictly defined as a physical driving or energy service obligation assigned to a vehicle, rather than a mere computational process or an abstract load balancing variable. The state of each task is rigorously delineated by its required service duration, exact energy demand, start and finish time window, strict deadline, and feasibility conditions. To guarantee that transferring this task maintains physical feasibility under urban mobility and charging constraints, the offloading algorithm enforces multiple system level validation checks. A task transfer is only finalized if the receiving vehicle satisfies all relevant constraints, including spatial reachability and proximity under mobility conditions, sufficient available battery energy, compatibility with charging requirements, and the absence of scheduling conflicts with its currently assigned tasks. These constraints make it clear that the proposed

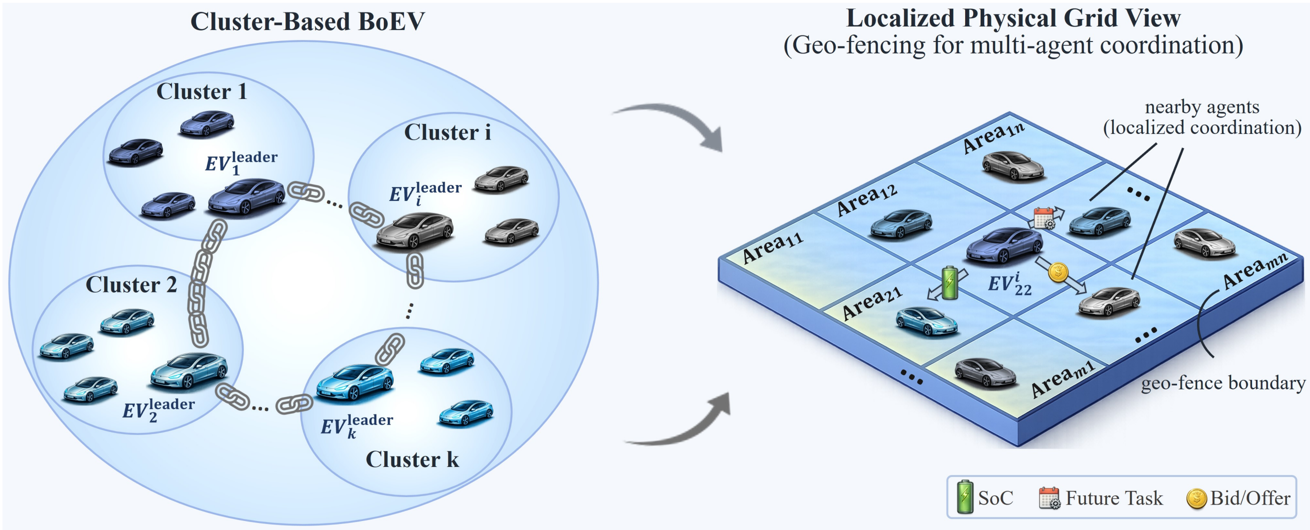


Fig. 5: An illustration of proximity bounded neighbour detection within the proposed cluster-based BoEV. The left part depicts the logical network architecture, where EVs are grouped into clusters managed by interconnected leader nodes. The right part illustrates the corresponding localized physical grid, demonstrating how geofencing enables an individual vehicle to perform multi-agent coordination, such as negotiating bids and sharing state of charge (SoC) and future tasks, exclusively with physically adjacent neighbours.

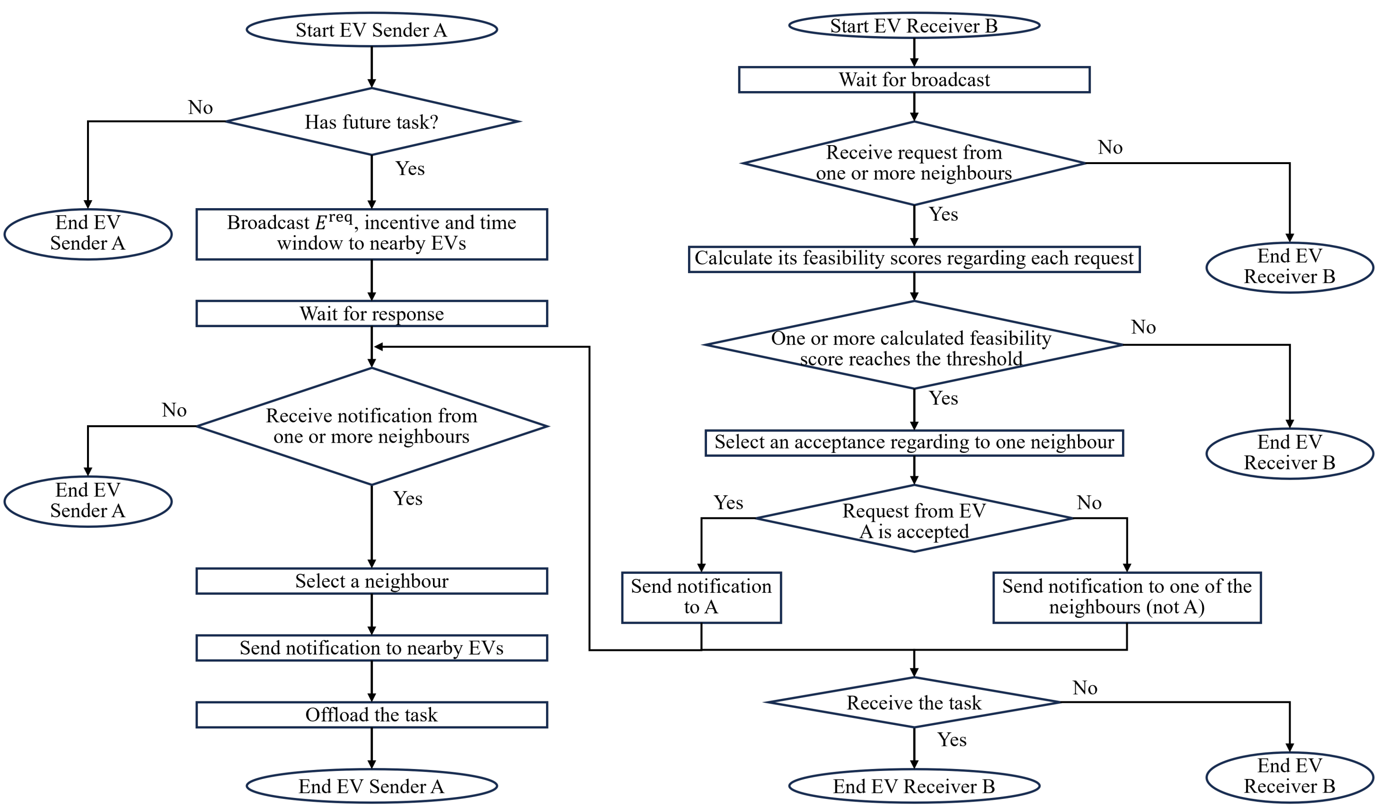


Fig. 6: A flowchart illustrating the V2V task offloading process. The diagram depicts the parallel decision making workflows. The left side outlines how EV Sender A broadcasts a task requirement and selects a neighbour. The right side details how EV Receiver B evaluates incoming requests using feasibility scores to accept the task.

offloading mechanism functions as a physically constrained intelligent transportation system operation grounded in vehicle mobility, battery, and time window limitations.

A detailed flow of the proposed task offloading algorithm is illustrated in Fig. 6. An EV with a future task broadcasts information about the task, including the required energy and the allowed time window, to all reachable neighbours via V2V communication. After receiving the broadcast, each neighbouring vehicle checks whether it can take over the task by checking two conditions: (1) it has sufficient remaining energy to complete the task, and (2) doing so would not conflict with its own planned activities.

If several neighbours meet these criteria, the sender selects the one with the least energy surplus after completing the task. This approach ensures efficient energy utilization across the network, as EVs with only a tiny amount of extra capacity are prioritized for task dispatch. Once a suitable neighbour is selected, the sender finalizes the task transfer, and the receiving EV updates its operational plan accordingly. By assigning tasks to EVs with just enough available energy, the mechanism helps preserve the availability of higher-capacity EVs for other purposes, such as energy trading.

C. Threat Model and Trust Assumptions

In this framework, the CS serves as the fully trusted authority responsible for authenticating electric vehicles and assigning unique cryptographic network identifiers upon registration. Conversely, individual vehicles are treated as untrusted entities capable of malicious behavior. To mitigate Sybil identities and false energy offers, the system relies on the active score mechanism. Because a high active score requires a sustained history of successful task completions and reliable communication, newly fabricated identities inherently receive low scores and are prevented from assuming leadership roles. Furthermore, the system actively defends against malicious or colluding cluster leaders through the continuous heartbeat protocol and fault proof transactions. If a leader acts maliciously or goes offline, the network detects the missing heartbeat, generates a fault proof, and instantly demotes the compromised node. Finally, large scale denial of service attacks and single point failures are mitigated by the fundamental cluster-based architecture. By organizing vehicles into manageable localized groups, the framework decentralizes communication and restricts the impact of any localized flooding attack to a single cluster, thereby preserving the stability of the broader macro grid.

IV. Evaluation

A. Evaluation Methodology

1) Evaluation of Cluster-Based Blockchain Architecture: Communication Overhead and Latency: This section describes the approach used to evaluate the proposed cluster-based blockchain architecture for energy trading in terms of communication overhead and latency. The evaluation is conducted under controlled experimental settings.

All simulations were executed in a Python 3.10 environment on a computing system equipped with 16 GB of RAM and an NVIDIA RTX 3060 GPU. The experimental setup consists of an energy trading system where EVs transmit energy offers to the blockchain. The system parameters are set as follows: EV number of 50, 100, 150, and 200, multiple cluster configurations ranging from 2 to 5 clusters, a transaction size of 500 bytes, a block size of 1 MB, a transaction propagation time of 10 ms, a transaction validation time of 5 ms, a block creation time of 2 seconds, and a block verification time of 1 second. The block size, transaction propagation and validation time, block creation time, and block verification time refer to the Blocksim simulator [51]. In addition, a per-EV aggregation delay of 0.1 ms was introduced to model the processing required by a cluster leader to aggregate the offers received from its members. A detailed description can be found in Table III.

The number of clusters contacted in the cluster-based system varies depending on whether the early clusters cover the total energy demand. In the best case, only one cluster is contacted, while in the worst case, all clusters are contacted sequentially before the total demand is covered. The communication overhead is calculated as the total data exchanged, which results from the number of transactions multiplied by the transaction size. The communication latency is calculated as the sum of transaction propagation, transaction validation, cluster aggregation, block creation, and block verification times. For each contacted cluster, the propagation and validation delays are included for both the EV-to-leader and leader-to-CS communication stages. Under the evaluated settings, the total transaction payload in each trading round remains below 1 MB; therefore, one block is generated in all cases.

2) Evaluation of V2V Task Offloading in V2G Energy Trading: Fulfillment Rate and Energy Contribution: In addition to evaluating the communication overhead and latency, we also assess the fulfillment rate of the energy trading system with and without V2V task offloading. The fulfillment rate is defined as the percentage of the total energy demand that is successfully matched with the energy supplied by EVs. The objective is to determine whether allowing EVs to transfer their future driving tasks to nearby EVs increases the total energy available for trading and improves the fulfillment rate of the system.

The evaluation uses various combinations of the number of EVs and the number of requests. Specifically, the number of EVs is set to 50, 100, 150 and 200, while the number of energy requests is set to 100, 200, 300, 400 and 500. For each combination, 100 trials are performed to obtain statistically significant results. To adequately capture spatial variability, the physical location of each electric vehicle was randomly initialized within the predefined geographic boundaries at the start of each independent trial.

The required energy demand for each request was generated using a uniform random distribution ranging from 1 to 20 kWh. This specific range was selected based on practical experience, as it accurately reflects a typical vehicle energy consumption profile over a period of several hours. Furthermore, each request is assigned three priority factors: Importance (P^I), Tolerance (P^T), and Urgency (P^U). While

TABLE III: Configuration of parameters for cluster-based blockchain evaluation

Parameter	Symbol	Value	Description
Number of EVs	N	50, 100, 150, 200	Total number of electric vehicles in the system
Number of Clusters	K	2, 3, 4, 5	Total number of EV clusters in the system
Active-Score Weights	$\beta_1, \beta_2, \beta_3$	$1/3, 1/3, 1/3$	Weights for communication reliability, consistency, and experience
Experience Balance	α	0.5	Balance between task completion and energy contribution
Recency Decay	λ	1	Decay rate for recent communication outcomes
Communication History Length	C	10	Number of recent communication attempts considered
Baseline Energy	E^{baseline}	60 kWh	Maximum EV battery capacity used for normalization
Maximum Standard Deviation	$\sigma^{\max}$	0.5	Theoretical maximum for binary communication outcomes
Number of Activity Levels	n^{lv}	10	Number of discrete activity levels used for clustering
Transaction Size	S^{tx}	500 bytes	Size of a single transaction in the blockchain
Block Size	S^{block}	1 MB	Maximum block size in the blockchain
Transaction Propagation Time	T^{prop}	10 milliseconds	Time required to propagate a transaction through the network
Transaction Validation Time	T^{validate}	5 milliseconds	Time required to validate a transaction
Block Creation Time	T^{create}	2 seconds	Time required to create a blockchain block
Block Verification Time	T^{verify}	1 second	Time required to verify a block before adding it to the chain
Per-EV Aggregation Delay	T^{agg}	0.1 milliseconds	Processing time for aggregating one EV offer

TABLE IV: Configuration of EV parameters for V2V task offloading evaluation

Parameter	Range / Values	Description
E^{current}	0 to 60 kWh	Current remaining energy before future task
E^{reserve}	3 kWh	Minimum required reserved energy
E^{future}	$(0, E^{\text{current}} - E^{\text{reserve}})$	Energy consumption for the future task
State	{0, 1, 2, 3}	0: idle, 1: charge, 2: discharge, 3: driving (can return in time)
Future Task	{0, 1}	0: has a future task, 1: no future task
Latitude	39 to 40	EV's latitude coordinate
Longitude	139 to 141	EV's longitude coordinate
Neighbour Range (Latitude)	±0.09	Latitude range to define nearby EVs
Neighbour Range (Longitude)	±0.12	Longitude range to define nearby EVs

the final priority score of each request is deterministically calculated, these underlying variables for importance, tolerance, and urgency were uniformly generated to simulate a diverse array of real world trading scenarios. The weight fractions of these factors are set as $\gamma_1 = \gamma_2 = \gamma_3 = 1/3$. Similarly, the active score weights are set to $\beta_1 = \beta_2 = \beta_3 = 1/3$. The active-score parameter settings are summarized in Table III, while a comprehensive description of the EV parameters is provided in Table IV. The value $\alpha = 0.5$ gives equal importance to task completion and energy contribution in the experience factor. The settings $\lambda = 1$ and $C = 10$ emphasize recent communication behavior over a history of ten attempts. The baseline active-score weights were deliberately balanced to establish a neutral performance benchmark that does not artificially favor any single metric.

To examine weight sensitivity, consider transferring an amount δ from β_j to β_i while maintaining $\beta_1+\beta_2+\beta_3 = 1$. Let $x_1 = R^{\text{comm}}$, $x_2 = \kappa$, and $x_3 = Exp$. The resulting change in the active score is $\Delta S^{\text{act}} = (E^{\text{offer}}/E^{\text{baseline}})\delta(x_i - x_j)$. Since all components are bounded within $[0, 1]$, the score change satisfies $|\Delta S^{\text{act}}| \leq |\delta|$. Thus, small changes in the weights produce bounded changes in the active score, although they may alter the ordering of EVs with similar scores. Increasing β_1 favors EVs with higher communication success rates, increasing β_2 favors EVs with more consistent communication, and increasing β_3 favors EVs with stronger historical contributions. Similarly, increasing α gives more importance to task completion, while decreasing it gives more importance to energy contribution. Therefore, although the evaluation uses balanced weights, these parameters can be configured for different deployment requirements.

B. Evaluation Results

TABLE V: Evaluation results of communication overhead in different blockchain architectures

Number of EVs	Monolithic (bytes)	Clustered (bytes)
50	25000	25000
100	50000	50000
150	75000	75000
200	100000	100000

1) Evaluation of Cluster-Based Blockchain Architecture: Communication Overhead and Latency: This section presents the evaluation results of the proposed cluster-based blockchain architecture in terms of communication overhead and latency. The comparison is performed between the baseline V2GNet architecture, where all EVs communicate directly with the control system, and the cluster-based architecture, where only cluster leaders communicate with the control system. Additionally, we account for intra-cluster communication, where EV members communicate with their respective cluster leader before the leader transmits to the control system.

Table V presents the total data exchanged in one trading round for different EV numbers. Every EV directly communicates with the control system in the monolithic system, resulting in high communication overhead. In the cluster-based system, while leaders communicate with the control system, intra-cluster communication remains a factor, ensuring that the total data exchanged remains the same. The results indicate that the total data exchanged remains the same in both architectures. Fig. 7 presents the communication latency in seconds for different numbers of EVs under various cluster configurations. The original system experiences high latency

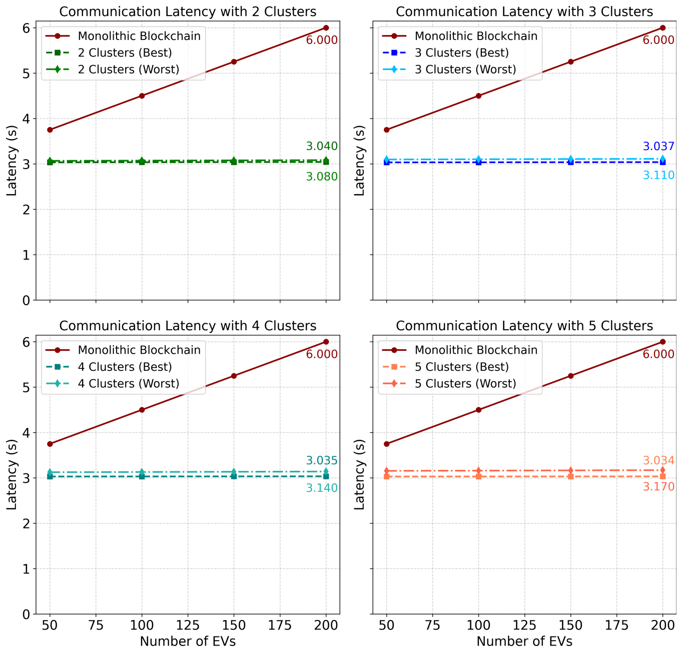


Fig. 7: Evaluation results of communication latency in different blockchain architectures.

due to the many direct transactions to the control system. In the cluster-based system, only the leaders send transactions to the control system, which reduces latency, although communication within the cluster requires a certain amount of processing time. Compared with the monolithic system, the cluster-based system reduces the latency by 15.9%-48.7%. At 200 EVs, the worst-case latency reduction ranges from 47.2% to 48.7%, corresponding to a speedup of approximately 1.9 times. Specifically, the monolithic approach exhibits a steep linear increase in latency because the control system must process transactions from every single EV, creating a severe bottleneck. In contrast, the cluster-based curves remain remarkably flat regardless of the fleet size. This is because the number of on-chain transactions processed by the control system is capped by the number of clusters rather than the total number of EVs, thereby reducing the control system's transaction-processing burden.

The results show that the cluster-based system significantly reduces latency by minimizing the number of transactions sent to the control system. Even when communication within the cluster is taken into account, the latency remains significantly lower than that of the original system. Further analysis of Fig. 7 reveals the role of the clustering mechanism in driving the observed latency reductions. The structural advantage of the clustering mechanism is the primary driver of the quantitative drop in latency. By organizing EVs into manageable groups, clustering transforms the network topology from a flat structure into a hierarchical one, drastically reducing the volume of concurrent transactions that the control system must process. Although it is not evaluated separately in Fig. 7, the leader node selection mechanism is designed to support reliable cluster operation by selecting the EV with the highest active score and monitoring its availability through the heartbeat protocol. Finally, the core advantage of this clustering framework lies in its ability to localize communication, thereby mitigating the scalability bottlenecks inherent in large-scale V2G networks.

2) Evaluation of V2V Task Offloading in V2G Energy Trading: Fulfillment Rate and Energy Contribution: This section presents the evaluation results of the impact of V2V task offloading on the fulfillment rate and the additional energy contribution in the energy trading system. The comparison is made between two versions of the system: one with V2V task offloading enabled and one without. The goal is to evaluate the extent to which V2V communication helps to increase the energy available for trading and improve the system's ability to meet energy demands.

Fig. 8 presents the fulfillment rate achieved by the two methods across different combinations of EV count and request volume. The results show that the benefit of the V2V offloading becomes more pronounced as the number of EVs increases, especially when the demand is higher. When the number of requests is low, the system maintains a high fulfillment rate, limiting the improvement. However, in high-demand scenarios, the proposed V2V offloading method achieves an increase in fulfillment rate of up to 3.1% compared to the baseline V2GNet without offloading. This widening performance gap can be attributed to network density and energy hoarding. When energy demand is low, the baseline system possesses sufficient reserves, leaving little room for improvement. However, as demand intensifies, the baseline system rapidly depletes its available energy. Under these high demand conditions, the V2V offloading mechanism thrives because a larger EV population translates to a higher probability of discovering a suitable neighbour for task transfer. This dynamically prevents the sharp drop off in fulfillment observed in the baseline system.

Fig. 9 illustrates the average additional energy contributed through V2V task offloading. The larger the number of vehicles, the more energy is available for trading as tasks are offloaded between EVs. The results show that the proposed mechanism increases the total available energy by up to 3.0%, confirming its effectiveness in improving energy utilization. These results suggest that local cooperation among EVs through V2V communication can significantly improve the efficiency of the system and its ability to fulfill a greater energy demand. This upward trend occurs because a denser network provides more opportunistic V2V matching possibilities. By allowing high capacity EVs to delegate their future driving tasks to lower capacity peers, the system unlocks large energy reserves that would otherwise be held in reserve. Consequently, as the EV fleet grows, the synergistic effect of these localized V2V transfers increases the aggregate surplus energy injected into the macro grid market.

V. Discussion

The evaluation results demonstrate that the proposed methods significantly enhance V2G energy trading. The cluster-based blockchain architecture effectively reduces latency by minimizing direct communication with the control system

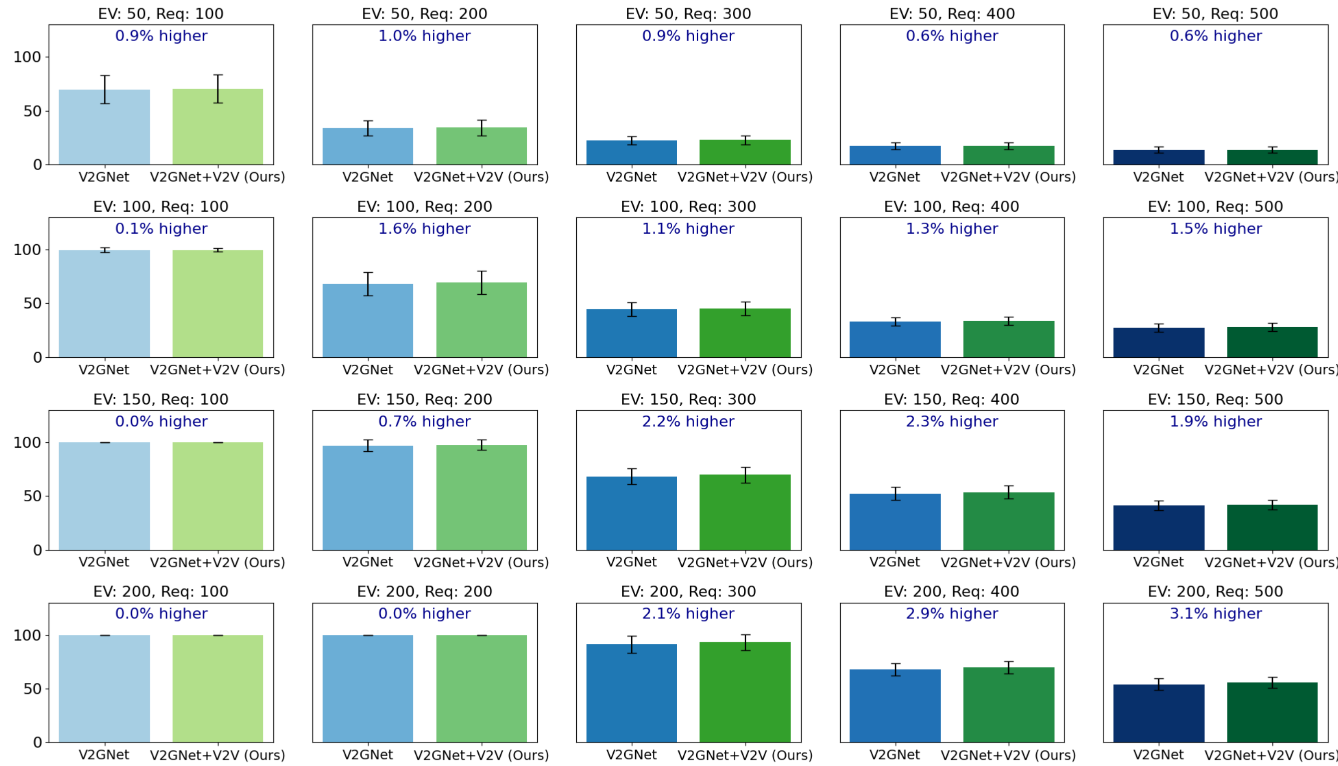


Fig. 8: Evaluation results of V2G energy trading methods with and without V2V task offloading in terms of fulfillment rate.

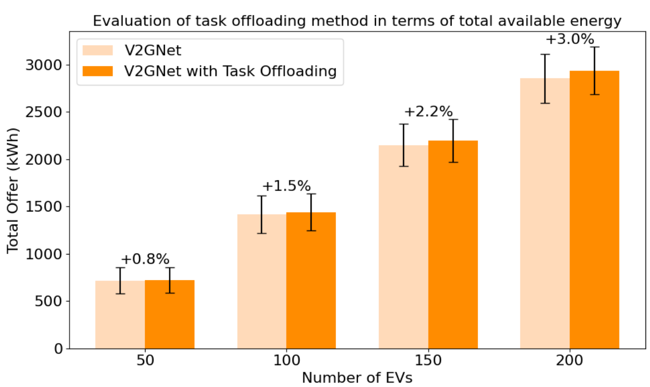


Fig. 9: Evaluation results of contribution from V2V task offloading in total energy offer.

while maintaining the overall communication overhead. This improvement is particularly impactful in large-scale networks, where direct transactions from all EVs could become a bottleneck. Even under best and worst scenarios, the cluster-based approach consistently outperforms the monolithic blockchain in terms of communication latency. Additionally, the V2V task offloading mechanism improves energy availability by enabling EVs with upcoming tasks to transfer their commitments to nearby vehicles, thereby increasing the fulfillment rate. The benefits of this mechanism are particularly evident under high energy demand conditions, reinforcing its suitability for integration into V2G trading frameworks. Unlike baseline V2G systems, the proposed method dynamically enables EVs to offload tasks to nearby vehicles, resulting in higher energy utilization and providing greater flexibility for EVs to manage their tasks and operational status.

The proposed methods have practical real-world applications for enhancing energy utilization and trading efficiency. The cluster-based blockchain model has the potential to extend beyond energy trading to other decentralized systems requiring hierarchical coordination. However, for widespread deployment, technical challenges such as charging infrastructure limitations and policy considerations must be addressed, including regulatory variations between private and shared EV ownership. Future research should explore incorporating time constraints for energy matching and EV availability, as well as developing more precise models for predicting future energy consumption and task durations. Additionally, efficiency losses during charge and discharge cycles need to be taken into account. The scalability of the cluster-based blockchain in large-scale implementations should also be examined. For the V2V task offloading mechanism, potential overhead from minor task transfers may affect overall efficiency, which warrants further investigation in future work.

VI. Conclusion and Future Work

This paper introduces an innovative V2G energy trading framework that incorporates a cluster-based blockchain architecture and a V2V task offloading mechanism. Specifically, the main contributions include a robust EV clustering algorithm utilizing active scores and a heartbeat-based leader selection mechanism. The cluster-based blockchain network enhances communication efficiency by minimizing direct interactions between EVs and the control system. Simultaneously, the V2V task offloading mechanism enables EVs to delegate upcoming tasks to nearby EVs, intentionally preserving the battery capacity of high-capacity EVs and thereby increasing the energy available for trading. Together, these strategies significantly enhance the efficiency and effectiveness of energy trading within V2G networks. Evaluation results show that the cluster-based blockchain architecture reduces the communication latency by 15.9%-48.7% and achieves a speedup of approximately 1.9 times at 200 EVs, while the V2V task offloading mechanism increases the total available grid energy by up to 3.0% and boosts the fulfillment rate by up to 3.1%, optimizing the utilization of EV energy resources. This work addresses challenges related to communication overhead and energy utilization, contributing to the advancement of more efficient and effective V2G energy trading systems. Future research could explore adaptive clustering techniques and advanced decision-making models for task offloading to further enhance the responsiveness and adaptability of V2G networks. Future research will focus on evaluating the framework in more complicated and dynamic real world scenarios. This includes investigating highly chaotic urban mobility patterns, such as sudden traffic fluctuations and unpredictable driver behaviors, that can abruptly impact cluster stability and V2V communication. Furthermore, we plan to explore the physical constraints of heterogeneous EV fleets, specifically analyzing how efficiency losses during frequent charge and discharge cycles affect long term energy trading and task offloading performance under these complex conditions.

REFERENCES

[1] Bi-directional Electric Vehicle Charger Market. https://www.gminsights.com/industry-analysis/bi-directional-electric-vehicle-charger-market/. Accessed: April 5, 2026.

[2] Ping Chen, Lu Han, Guoyu Xin, Aiwei Zhang, Hui Ren, and Fei Wang. Game theory based optimal pricing strategy for V2G participating in demand response. *IEEE Trans. Ind. Appl.*, 59(4):4673–4683, 2023.

[3] Shiyao Zhang and Ka-Cheong Leung. Joint optimal power flow routing and vehicle-to-grid scheduling: Theory and algorithms. *IEEE Trans. Intell. Transp. Syst.*, 23(1):499–512, 2022.

[4] Dhaou Said and Hussein T. Mouftah. A novel electric vehicles charging/discharging management protocol based on queuing model. *IEEE Trans. Intell. Veh.*, 5(1):100–111, 2020.

[5] Yuxiao Liang, Zhishang Wang, and Abderazek Ben Abdallah. V2GNet: Robust blockchain-based energy trading method and implementation in vehicle-to-grid network. *IEEE Access*, 10:131442–131455, 2022.

[6] Arnob Ghosh and Vaneet Aggarwal. Menu-based pricing for charging of electric vehicles with vehicle-to-grid service. *IEEE Trans. Veh. Technol.*, 67(11):10268–10280, 2018.

[7] Huijun Liang, Yungang Liu, Fengzhong Li, and Yanjun Shen. Dynamic economic/emission dispatch including PEVs for peak shaving and valley filling. *IEEE Trans. Ind. Electron.*, 66(4):2880–2890, 2019.

[8] Jianxiong Guo, Xingjian Ding, and Weili Wu. An architecture for distributed energies trading in byzantine-based blockchains. *IEEE Trans. Green Commun. Netw.*, 6(2):1216–1230, 2022.

[9] Weiqi Hua, Yue Zhou, Meysam Qadrdan, Jianzhong Wu, and Nick Jenkins. Blockchain enabled decentralized local electricity markets with flexibility from heating sources. *IEEE Trans. Smart Grid*, 14(2):1607–1620, 2023.

[10] Arzoo Miglani and Neeraj Kumar. A blockchain based matching game for content sharing in content-centric vehicle-to-grid network scenarios. *IEEE Trans. Intell. Transp. Syst.*, 25(5):4032–4048, 2024.

[11] Zhiguo Wan, Tong Zhang, Weizhuang Liu, Mingqiang Wang, and Liehuang Zhu. Decentralized privacy-preserving fair exchange scheme for V2G based on blockchain. *IEEE Trans. Dependable Secur. Comput.*, 19(4):2442–2456, 2022.

[12] Xia Fang, Wei Zhang, Yuhao Guo, Jie Wang, Mei Wang, and Shunlei Li. A novel reinforced deep RNN–LSTM algorithm: Energy management forecasting case study. *IEEE Trans Ind. Informat.*, 18(8):5698–5704, 2022.

[13] Seong-Hyun Hong and Hyun-Suk Lee. Robust energy management system with safe reinforcement learning using short-horizon forecasts. *IEEE Trans. Smart Grid*, 14(3):2485–2488, 2023.

[14] Lei Zhang, Long Cheng, Fahad Alsokhiry, and Mohamed A. Mohamed. A novel stochastic blockchain-based energy management in smart cities using V2S and V2G. *IEEE Trans. Intell. Transp. Syst.*, 24(1):915–922, 2023.

[15] Dimitra Apostolopoulou, Rahmat Poudineh, and Anupama Sen. Distributed vehicle to grid integration over communication and physical networks with uncertainty effects. *IEEE Trans. Smart Grid*, 13(1):626–640, 2022.

[16] Mohammed Shurrab, Shakti Singh, Hadi Otrok, Rabeb Mizouni, Vinod Khadkikar, and Hatem Zeineldin. A stable matching game for V2V energy sharing–a user satisfaction framework. *IEEE Trans. Intell. Transp. Syst.*, 23(7):7601–7613, 2022.

[17] Mohammed Shurrab, Shakti Singh, Hadi Otrok, Rabeb Mizouni, Vinod Khadkikar, and Hatem Zeineldin. An efficient vehicle-to-vehicle (V2V) energy sharing framework. *IEEE Internet Things J.*, 9(7):5315–5328, 2022.

[18] Azizulrahman Shafiqurrahman, Vinod Khadkikar, and Akshay Kumar Rathore. Electric vehicle-to-vehicle (V2V) power transfer: Electrical and communication developments. *IEEE T. Transp. Electrific.*, 10(3):6258–6284, 2024.

[19] Mohammed Seid Abegaz, Hayla Nahom Abishu, Yasin Habtamu Yacob, Tewodros Alemu Ayall, Aiman Erbad, and Mohsen Guizani. Blockchain-based resource trading in multi-UAV-assisted industrial IoT networks: A multi-agent DRL approach. *IEEE Trans. Netw. Service Manag.*, 20(1):166–181, 2023.

[20] Kairan Zhao, Meng Zhang, Rongxing Lu, and Chao Shen. A secure intra-regional-inter-regional peer-to-peer electricity trading system for electric vehicles. *IEEE Trans. Veh. Technol.*, 71(12):12576–12587, 2022.

[21] Yuxiao Liang, Zhishang Wang, and Abderazek Ben Abdallah. Robust vehicle-to-grid energy trading method based on smart forecast and multi-blockchain network. *IEEE Access*, 12:8135–8153, 2024.

[22] Zhenyu Zhou, Bingchen Wang, Mianxiong Dong, and Kaoru Ota. Secure and efficient vehicle-to-grid energy trading in cyber physical systems: Integration of blockchain and edge computing. *IEEE Trans. Syst., Man, Cybern., Syst.*, 50(1):43–57, 2020.

[23] Ahmed Barnawi, Shubhani Aggarwal, Neeraj Kumar, Daniyal M. Alghazzawi, Bander Alzahrani, and Mehrez Boulares. Path planning for energy management of smart maritime electric vehicles: A blockchain-based solution. *IEEE Trans. Intell. Transp. Syst.*, 24(2):2282–2295, 2023.

[24] Erdem Gümrükcü, Jonatan Ralf Axel Klemets, Jon Are Suul, Ferdinanda Ponci, and Antonello Monti. Decentralized energy management concept for urban charging hubs with multiple V2G aggregators. *IEEE Trans. Transp. Electrific.*, 9(2):2367–2381, 2023.

[25] Peng Liu, Zhe Liu, Ning Zhang, and Fei Lin. Cooperative game-based charging-discharging efficiency optimization of electric vehicles in 6G-enabled V2G. *IEEE Trans. Green Commun. Netw.*, 7(2):1078–1089, 2023.

[26] Qilong Huang, Li Yang, Qing-Shan Jia, Yaowen Qi, Cangqi Zhou, and Xiaohong Guan. A simulation-based primal-dual approach for constrained V2G scheduling in a microgrid of building. *IEEE Trans. Autom. Sci. Eng.*, 20(3):1851–1863, 2023.

[27] Yuechuan Tao, Jing Qiu, Shuying Lai, Xianzhuo Sun, Yunqi Wang, and Junhua Zhao. Data-driven matching protocol for vehicle-to-vehicle energy management considering privacy preservation. *IEEE Trans. Transp. Electrific.*, 9(1):968–980, 2023.

[28] Mohammad Belayet Hossain, Shiva Raj Pokhrel, and Hai L. Vu. Efficient and private scheduling of wireless electric vehicles charging using reinforcement learning. *IEEE Trans. Intell. Transp. Syst.*, 24(4):4089–4102, 2023.

[29] Gang Shen, Chengliangyi Xia, Yumei Li, Hua Shen, Weizhi Meng, and Mingwu Zhang. Traceable and privacy-preserving authentication scheme for energy trading in V2G networks. *IEEE Internet Things J.*, 11(4):6664–6676, 2024.

[30] Behbod Kheradmand, Ali Ghaffari, Farhad Soleimanian Gharehchopogh, and Mohammad Masdari. Cluster-based routing schema using harris

hawks optimization in the vehicular ad hoc networks. *Wirel. Commun. Mob. Comput.*, 2022(1):1606317, 2022.

[31] Behbod Kheradmand, Ali Ghaffari, Farhad Soleimanian Gharehchopogh, and Mohammad Masdari. Clustering-based routing protocol using gray wolf optimization and technique for order of preference by similarity to ideal solution algorithms in the vehicular ad hoc networks. *Concurr. Comput. Pract. Exp.*, 34(23):e7209, 2022.

[32] Wei Wang, Yongmin Zhang, Rui Huang, Ju Ren, Feng Lyu, and Yaoxue Zhang. Efficient resource management and expansion scheme for collaborative edge-cloud computing. *IEEE Trans. Mobile Comput.*, 23(4):2731–2747, 2024.

[33] Yongmin Zhang, Wei Wang, Rui Huang, Junfan Zhou, Yang Xu, Ju Ren, and Yaoxue Zhang. Collaborative edge and cloud computing: Optimal configuration and computation management. *IEEE Trans. Mobile Comput.*, 24(11):11641–11656, 2025.

[34] Jinming Shi, Jun Du, Yuan Shen, Jian Wang, Jian Yuan, and Zhu Han. DRL-based V2V computation offloading for blockchain-enabled vehicular networks. *IEEE Trans. Mobile Comput.*, 22(7):3882–3897, 2023.

[35] Komeil Moghaddasi, Shakiba Rajabi, and Farhad Soleimanian Gharehchopogh. Multi-objective secure task offloading strategy for blockchain-enabled IoV-MEC systems: A double deep Q-network approach. *IEEE Access*, 12:3437–3463, 2024.

[36] Amir Masoud Rahmani, Jawad Tanveer, Farhad Soleimanian Gharehchopogh, Shakiba Rajabi, and Mehdi Hosseinzadeh. A novel offloading strategy for multi-user optimization in blockchain-enabled mobile edge computing networks for improved internet of things performance. *Comput. Electr. Eng.*, 119:109514, 2024.

[37] Komeil Moghaddasi, Shakiba Rajabi, Farhad Soleimanian Gharehchopogh, and Mehdi Hosseinzadeh. An energy-efficient data offloading strategy for 5G-enabled vehicular edge computing networks using double deep Q-network. *Wirel. Pers. Commun.*, 133(3):2019–2064, December 2023.

[38] Chen Chen, Lanlan Chen, Lei Liu, Shunfan He, Xiaoming Yuan, Dapeng Lan, and Zhuang Chen. Delay-optimized V2V-based computation offloading in urban vehicular edge computing and networks. *IEEE Access*, 8:18863–18873, 2020.

[39] Wenhao Fan, Yi Su, Jie Liu, Shenmeng Li, Wei Huang, Fan Wu, and Yuan'an Liu. Joint task offloading and resource allocation for vehicular edge computing based on V2I and V2V modes. *IEEE Trans. Intell. Transp. Syst.*, 24(4):4277–4292, 2023.

[40] Debashis Das, Sourav Banerjee, Pushpita Chatterjee, Uttam Ghosh, and Utpal Biswas. A secure blockchain enabled V2V communication system using smart contracts. *IEEE Trans. Intell. Transp. Syst.*, 24(4):4651–4660, 2023.

[41] Mohsin Kamal, Gautam Srivastava, and Muhammad Tariq. Blockchain-based lightweight and secured V2V communication in the internet of vehicles. *IEEE Trans. Intell. Transp. Syst.*, 22(7):3997–4004, 2021.

[42] Dariush Abbasinezhad-Mood and Hadi Ghaemi. Dual-signature blockchain-based key sharing protocol for secure V2V communications in multi-domain IoV environments. *IEEE Trans. Intell. Transp. Syst.*, 25(10):13407–13416, 2024.

[43] Hui-Tang Lin and Wei-Li Jhuang. Blockchain-based lightweight certificateless authenticated key agreement protocol for V2V communications in IoV. *IEEE Internet Things J.*, 11(16):27744–27759, 2024.

[44] Peng Liu, Weipeng Jing, Xinyu Fu, Yang Xiao, and Lili Jia. Consortium blockchain-based security and efficient resource trading in V2V-assisted intelligent transport systems. *IEEE Trans. Intell. Transp. Syst.*, 24(11):13436–13447, 2023.

[45] Qi Xie, Zixuan Ding, Wen Tang, Debiao He, and Xiao Tan. Provable secure and lightweight blockchain-based V2I handover authentication and V2V broadcast protocol for VANETs. *IEEE Trans. Veh. Technol.*, 72(12):15200–15212, 2023.

[46] Dongjun Na and Sejin Park. Blockchain-based dashcam video management method for data sharing and integrity in V2V network. *IEEE Access*, 10:3307–3319, 2022.

[47] Fangming Liu, Jian Chen, Qixia Zhang, and Bo Li. Online MEC offloading for V2V networks. *IEEE Trans. Mobile Comput*, 22(10):6097–6109, 2023.

[48] Hui Guo, Lan-lan Rui, and Zhi-peng Gao. V2V task offloading algorithm with LSTM-based spatiotemporal trajectory prediction model in SVCNs. *IEEE Trans. Veh. Technol.*, 71(10):11017–11032, 2022.

[49] Chung-Ming Huang, Meng-Shu Chiang, Duy-Tuan Dao, Wei-Long Su, Shouzhi Xu, and Huan Zhou. V2V data offloading for cellular network based on the software defined network (SDN) inside mobile edge computing (MEC) architecture. *IEEE Access*, 6:17741–17755, 2018.

[50] Mengting Huang, Zhirong Shen, and Guanglin Zhang. Joint spectrum sharing and V2V/V2I task offloading for vehicular edge computing networks based on coalition formation game. *IEEE Trans. Intell. Transp. Syst.*, 25(9):11918–11934, 2024.

[51] Maher Alharby and Aad van Moorsel. Blocksim: An extensible simulation tool for blockchain systems. *Front. Blockchain*, 3, June 2020.

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