

Edge-Driven Dynamic Two-Tier Blockchain for Energy Trading in Vehicle-To-Grid Networks

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Abstract—Recent developments in vehicle-to-grid (V2G) technology have positioned electric vehicles (EVs) as essential components for increasing the use of renewable energy and managing peak demand. However, while V2G systems utilize blockchain technology for secure energy transactions, they encounter notable inefficiencies due to the high volume of transactions when the number of energy participants increases. The communication overhead associated with processing energy supply and demand is significant. In addition, current energy distribution systems do not fully exploit the potential of EVs. They cannot schedule multiple discharge cycles for a single vehicle over specific periods. Furthermore, existing systems do not provide mechanisms that allow EVs to make smart autonomous decisions about their charging and discharging operations. Instead, they are usually dependent on fixed schedules or manual inputs, which further exacerbates the inefficiency of energy management and market integration. This paper proposes a novel edge-driven two-tier blockchain-based V2G method to optimize the energy management of distributed electric vehicles. The architecture incorporates local dual networks within an electric vehicle blockchain (EVBC) and an energy market blockchain (EMBC), coordinated by a high-level blockchain that manages unfulfilled requests. A dynamic segment-based energy allocation algorithm (DSBEA) is introduced, where the control system allocates energy requests by matching EV offers while continuously updating each EV's remaining energy and available time window after each assignment. The evaluation showed a significant reduction in total time cost compared to baseline methods, with reductions ranging from 42% to 80% in various energy trading scenarios. In addition, the proposed method achieved a 68.6% increase in energy fulfillment compared to the best existing approaches.

Index Terms—Vehicle-to-Grid, Electric Vehicles, Energy Trading, Two-Tier Blockchain, Edge Computing.

I. INTRODUCTION

IN today's energy systems, the rapid integration of renewable energy and the growing demand for sustainable energy solutions highlight the importance of innovative energy management systems. As the world moves towards a lower-carbon future, electric vehicles (EVs) have become key elements in the changing landscape of energy supply and demand. The concept of vehicle-to-grid (V2G) technology has become

popular and offers a promising way to improve the stability of the power grid by allowing EVs to not only consume energy but also feed it back into the grid during peak times [1]–[3]. V2G technology offers more than just individual benefits. The market size for bidirectional chargers has been estimated at \$18 billion in 2023. It is expected to grow to \$32.87 billion by 2031, with a compound annual growth rate of 8.98% from 2024 to 2031 [4].

In V2G systems, electric vehicles act as both energy consumers and suppliers, providing grid stability at peak times and increasing the resilience of the energy system [5], [6]. V2G systems involve many independent and potentially untrusted participants, including electric vehicles and market operators. These systems face several operational challenges, such as managing trust, ensuring verifiable energy transactions, and coordinating activity without centralized control. Blockchain technology can address these issues effectively, recording energy offers and requests as immutable transactions, enabling intelligent contract-based trading automation, and maintaining consistency across participants through distributed consensus. Recent advances in energy trading systems have been significantly driven by the integration of blockchain technology and V2G interactions, which enhance the security, efficiency, and scalability of energy trading [7], [8]. These developments are characterized by decentralized management frameworks that facilitate dynamic resource allocation and improve operational feasibility [9], [10]. In addition, intelligent energy forecasting techniques are becoming increasingly important. They use sophisticated algorithms to accurately predict energy distribution and manage the complexity of real-time data integration [11], [12].

Despite the theoretical potential of V2G systems to enable a smooth flow of energy between EVs and power grids, several practical issues hinder the widespread adoption. In current systems, there is still a need for a robust and efficient solution to support the effective participants of EVs [13]. A state-of-the-art V2G approach, V2GNet [14], is illustrated in Fig. 1(a). It features a blockchain architecture consisting of a semi-decentralized energy market blockchain (semi-EMBC) and an electric vehicle blockchain (EVBC). In this setup, the semi-EMBC processes energy requests from consumers off-chain. In contrast, the EVBC, which is managed by a network of distributed EVs, processes energy offers entirely on-chain. This leaves the integrity of the transaction data unsecured and leads to a significant overhead by processing all information within a single blockchain. As shown in Fig. 1(b), V2GFTN [15] builds on the V2GNet method by interlinking multiple such networks

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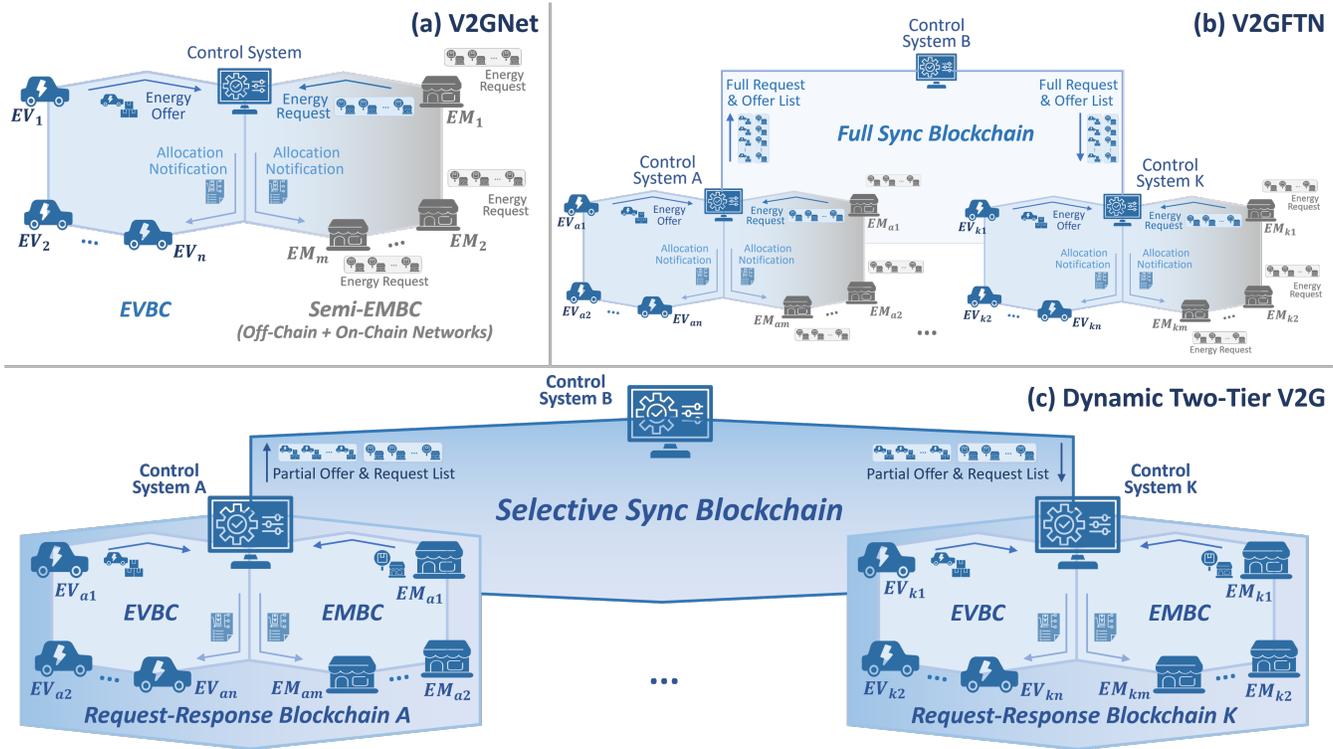


Fig. 1: Overview of V2G Blockchain Architectures for Energy Trading: (a) V2GNet [14] uses a semi-blockchain approach where off-chain energy requests (semi-EMBC) and on-chain EV offers (EVBC). This results in incomplete traceability and requires a single control system to manage all requests and offers. (b) V2GFTN [15] extends V2GNet by dividing the network into multiple subnetworks. However, it requires full synchronization of energy requests and offers across subnetworks. (c) Dynamic Two-Tier V2G (this work) advances to a full blockchain system that fully processes energy offers and requests on-chain within each local EVBC+EMBC pair. Only unfulfilled requests are forwarded to a high-level blockchain, avoiding system-wide synchronization of all energy requests and offers.

together. This extended framework retains the semi-blockchain approach of the semi-EMBC, where energy requests remain off-chain. However, it requires full synchronization of all energy information, including energy offers and requests across the network, which still significantly burdens communication and storage performance.

To our knowledge, integrating electric vehicles into the power grids, mainly distributed edge electric vehicles, faces significant challenges. First, ensuring the security of electric vehicle supply data while maintaining the system's efficiency as the number of EVs increases is still problematic. In addition, effectively utilizing the energy from EVs as suppliers within the grid is a challenge, especially when managing multiple energy requests within specific periods. There is also a lack of intelligent systems for EV charging operations, which should allow vehicles to make wise decisions about charging and discharging autonomously. Instead, systems often rely on predetermined schedules or manual inputs, leading to further inefficiencies in energy supply and market participation.

In response to these challenges, this paper proposes an edge-driven dynamic two-tier blockchain architecture designed explicitly for distributed electric vehicles to optimize energy management and allocation, as illustrated in Fig. 1(c). The proposed method uses a network of local dual blockchains

for electric vehicles (EVBC) and energy markets (EMBC). Control systems (CS) from each dual network coordinate to form a high-level blockchain.

This architecture ensures the integrity of energy information by enabling on-chain transmission of energy supply and demand at the local level. Only unfulfilled requests are transferred to the higher-level blockchain to reduce network load after local allocation. The proposed dynamic segment-based energy allocation algorithm considers the dynamic and decentralized nature of energy resources in electric vehicles. In addition, integrating innovative charging management and scheduling for electric vehicles and energy consumption prediction methods contributes to a more accurate and efficient energy distribution. The main contributions of this paper are summarized as follows:

- Edge-driven dynamic two-tier blockchain architecture: We propose a dynamic two-tier V2G, a blockchain-based framework where the first tier consists of multiple dual-networks, each containing an electric vehicle blockchain (EVBC), an energy market blockchain (EMBC), and a control system. The second tier is formed by control systems that share and process extra energy offers and requests for efficient energy management.
- Dynamic segment-based algorithm for energy allocation:

The energy supply from electric vehicles is strategically planned to maximize their availability, allowing a single EV to fulfill multiple requests with minimal residual energy.

- Smart management of EV charging operations: We integrate smart charging management and scheduling strategies for EVs with advanced energy consumption prediction methods.

The rest of this paper is organized as follows. Section II discusses the related works on energy trading systems based on blockchain networks, vehicle-to-grid energy trading, and innovative energy forecasting approaches. Section III introduces the proposed edge-driven dynamic two-tier V2G method, including the energy trading process, intelligent management of EV charging operations, and a dynamic energy allocation algorithm. Section IV provides the performance evaluation of the proposed method. Section V highlights and discusses issues that also require attention, and section VI presents a conclusion of the paper.

II. RELATED WORK

This section presents the related works on energy trading systems based on blockchain networks, vehicle-to-grid energy trading, and innovative energy forecasting approaches.

A. Energy Trading Systems Based on Blockchain Networks

Integrating blockchain technology into energy trading systems has been extensively researched to enhance security, efficiency, and scalability. Guo et al. [7] introduced a Byzantine-based consensus mechanism to improve transaction throughput and reduce latency. In contrast, Abegaz et al. [16] proposed a multi-agent framework with deep reinforcement learning and game theory for dynamic resource trading in the industrial internet of things. Zhao et al. [17] and Hua et al. [8] utilized blockchain to secure regional and peer-to-peer electricity trading, specifically addressing transaction data protection. The work in [9], [18], [19] explored decentralized approaches and consortium blockchains to optimize matching in high mobility scenarios and manage demand-side management in smart grids. Lin et al. [20] and Hassija et al. [21] investigated the scalability of blockchain in managing decentralized energy transactions in smart grids and vehicle-to-everything platforms, focusing on real-time demand imbalances and system capacity challenges. The authors in [22]–[24] enhanced security protocols, proposed robust scheduling frameworks, and developed privacy-preserving mechanisms, including extended blockchains and smart contracts, to protect user privacy in V2G networks. Liang et al. [14] presented V2GNet, which contains a semi-blockchain architecture that improves the integration of energy markets into the power grid. This was extended in the work V2GFTN, which connects multiple local networks, each consisting of a blockchain for energy vehicles and a semi-blockchain for energy markets, to further improve scalability and resource allocation [15]. While these methods enable secure or efficient transactions within blockchain configurations, challenges remain in optimizing electric vehicle energy use within energy trading systems.

B. Vehicle-to-Grid Energy Trading

Recent researches in the field of V2G interactions includes Gümürkü et al. [25], who introduced a decentralized management system for urban charging stations that struggle with the real-time dynamics of electric vehicles due to rigid scheduling, and Liu et al. [26], who used 6G technology to enable intelligent distributed cooperation among EVs. Huang et al. [27] and Tao et al. [28] deployed simulation-based primal-dual approaches and deep reinforcement learning for vehicle-to-vehicle energy trading, although on a limited scale. Research by Ahmed et al. [29] focused on optimizing grid interactions and reducing emissions through evolutionary computing. In contrast, Cheng et al. [30] explored business models for car-sharing services using EV fleets for dual-service provision. Regarding privacy enhancements, Hossain et al. [31] presented a reinforcement learning framework based on genetic algorithms aiming at efficient scheduling and cost-friendly data privacy, Pokhrel et al. [32] introduced a federated reinforcement learning framework tailored for practical privacy preservation in EV-Smart Grid interactions, and Shen et al. [33] proposed a privacy-preserving authentication scheme that enhances security in V2G networks without the complexity of traditional crypto-based schemes. Despite these advances, these studies highlight common challenges in V2G technologies, including scalability issues, high operational costs, and difficulties in adapting to real-time dynamics, which continue to hinder their practical implementation in larger and dynamic environments. Moreover, while some works apply complex optimization models or static matching strategies, there remains a need for energy allocation methods that are both computationally efficient and capable of adapting dynamically to evolving EV and request conditions.

C. Smart Energy Forecasting Approaches

Significant progress has been made in energy management systems by adopting hybrid deep learning algorithms and reinforcement learning, significantly improving prediction accuracy and operational efficiency. To effectively manage and predict energy distributions, Fang et al. [11] and Meng et al. [34] introduced forecasting models that utilize a combination of Hankel matrices, Copula functions, and nonparametric multivariate density forecasts. Hong et al. [12] developed a robust system that aims to minimize energy costs and maintain the reliability of supply through safe reinforcement learning algorithms. In the field of renewable energy forecasting, Liang et al. [35] and Li et al. [36] improved ultra-short-term prediction using attention-driven temporal convolutional networks that integrate physical and data-driven models for better accuracy. However, most approaches still do not fully account for rapid market changes in V2G networks, nor do they address the uncertainties associated with EVs, highlighting the urgent need for models that can anticipate and adapt to fluctuations in energy trading.

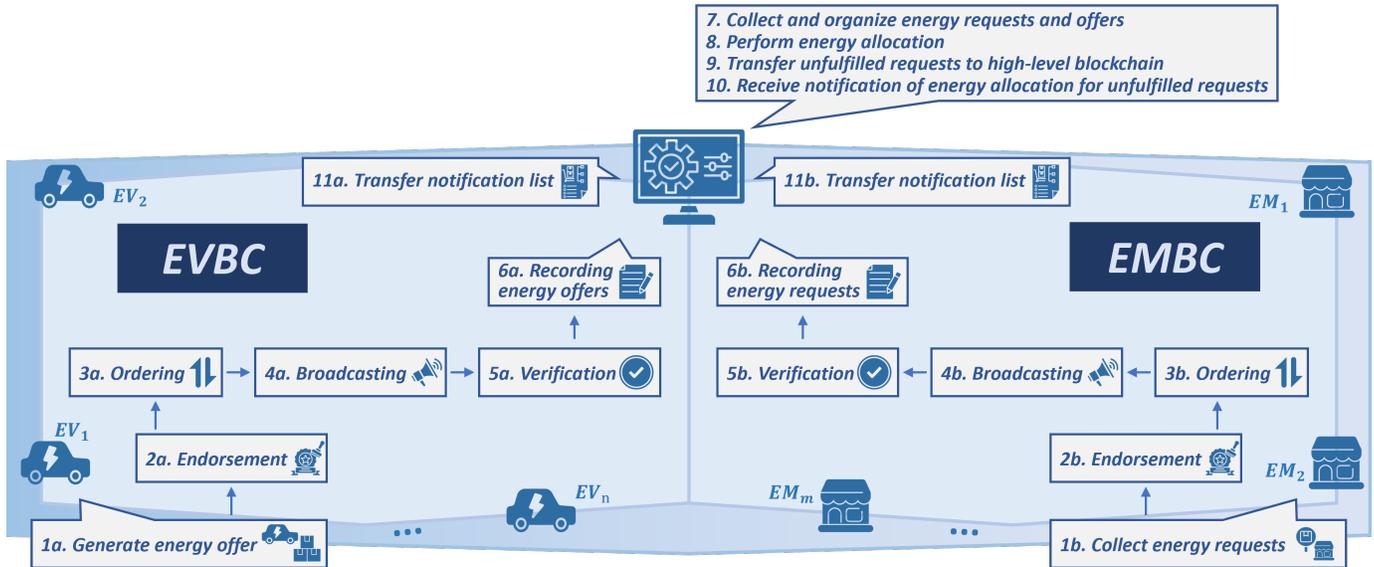


Fig. 2: A request-response blockchain in edge-driven dynamic two-tier V2G, comprising the electric vehicles blockchain (EVBC) and the energy market blockchain (EMBC). The workflow details the process from generating energy offers and collecting energy requests to completing energy allocation and transferring notifications.

III. EDGE-DRIVEN DYNAMIC TWO-TIER BLOCKCHAIN ARCHITECTURE AND ENERGY TRADING METHODS IN V2G NETWORKS

The proposed system features a two-tier blockchain architecture that improves communication and efficiency of energy allocation between electric vehicles and energy markets. This structure integrates multiple request-response blockchains, consisting of an electric vehicle blockchain (EVBC) and an energy market blockchain (EMBC), which are connected through multiple control systems (CS). These dual blockchains enable direct interactions and monitor the distribution and allocation of energy.

An illustration of the request-response blockchain is shown in Figure 2. Electric vehicles are equipped with sophisticated energy management methods, including an innovative EV charging algorithm and a method for accurately predicting energy consumption. Each EV generates energy offers based on surplus capacity, which are then endorsed by the network nodes. Similarly, energy markets collect and confirm consumer requests. Once confirmed, both the offers and requests are ordered and broadcast across the network to ensure that all nodes receive the latest status of the ledger. The nodes then verify each transaction to maintain the integrity of the blockchain. The control systems then allocate energy based on optimized matching algorithms, considering energy quantity and period factors. Unfulfilled requests are forwarded to a high-level, selective sync blockchain, which enables collaborative problem solving and resource sharing among the different control systems within the network. Each control system then receives notification of energy allocation for unfulfilled requests. Finally, the results of the energy allocation are reported back to the respective participants in the EVBC and EMBC via allocation notifications.

A. Distributed Energy Trading Mechanism in Dual Blockchain Systems

We then present the distributed energy trading mechanism in a request-response blockchain, a dual-blockchain network. As shown in Figure 3, the process of energy trading is initiated from three different points: START EV, START CS, and START EM, which represent the entry of electric vehicles, control systems, and energy markets, respectively. In this dual blockchain system, the CS orchestrates the communication with the EVs within the electric vehicle blockchain and the exchanges within the energy market blockchain. On the EV side, each vehicle assesses its current state, i.e., connection to the grid and ability to return within a specific time frame. Connected EVs determine availability based on existing or future tasks and forecast end times and residual energy levels. They then submit offers to the CS, which include important data such as vehicle ID, state, activity details, remaining energy, and available time spans. At the same time, the energy markets compile the consumers' energy requests in a list that is forwarded to the CS. After receiving both offer and request lists, the CS applies the dynamic segment-based energy allocation algorithm (DSBEA) to allocate energy resources effectively. This allocation process results in two notification lists: one for the EVs to discharge and one for the markets to inform consumers. While the EVs discharge the energy according to the allocated instructions, the exchanges notify the consumers to execute the payments and prepare for the incoming energy supply, ensuring a smooth energy distribution cycle.

B. Dynamic Segment-Based Energy Allocation

This section presents the dynamic segment-based energy allocation algorithm between energy requests and EVs. The energy allocation method between EVs and energy requests

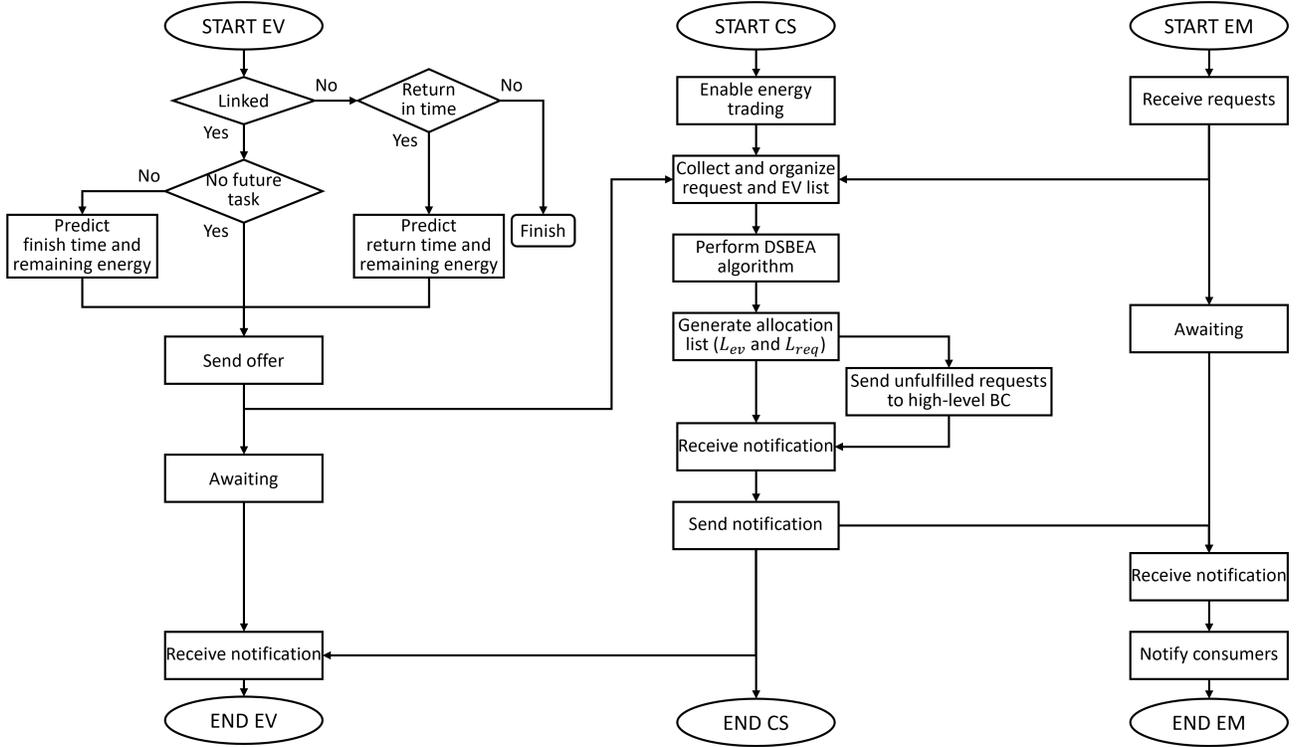


Fig. 3: Flowchart depicting the operational procedure of energy allocation between electric vehicles and energy markets through the control system in a dual blockchain architecture.

operates through a systematic process designed to maximize efficiency and fulfill energy demands effectively.

In the proposed energy allocation method, we consider an "hour-ahead" case where all consumers request energy within one hour. Each request in the list includes specific attributes such as the start and end time of energy usage and the input power, which determines the limit of energy usage per request. Each request, denoted as Req_i , is characterized by the start time of energy usage $T_i^{usage,s}$, the end time $T_i^{usage,e}$, and the power of energy usage P_i^{req} . The total energy demand for each request E_i^{dem} is calculated as follows:

$$E_i^{dem} = (T_i^{usage,e} - T_i^{usage,s}) \times P_i^{req} \quad (1)$$

This equation calculates a consumer's total energy over the requested time window, assuming a constant power draw. The process begins by organizing the list of energy requests according to their profit potential, denoted by PP , in descending order. This ensures that not only a high rate is achieved, but also benefits from longer durations, which accumulate more profit. The profit potential of request i is calculated as follows:

$$PP_i = E_i^{dem} \times B_i \quad (2)$$

The profit potential reflects the quantity of energy requested and the consumer's willingness to pay (bid price), guiding the allocation priority, where B_i denotes the bid price of the request. Its remaining energy and discharge power characterize each electric vehicle in the system. Given the constraints of hour-ahead energy requests, each EV can discharge at its specified power level for one hour, determining the maximum energy it can supply in that period. Requests are then organized

based on the unit bid tariff offered by each consumer, with the list ranked in descending order to prioritize higher bids. The request with the highest bid price is first selected when starting energy allocation. For each energy request, Req_i , the trading potential of an EV, EV_j , reflects the amount of energy it can supply during a specified request window from $T_i^{usage,s}$ to $T_i^{usage,e}$, and is calculated based solely on this capability. It does not take into account the remaining energy of the EV after the request has been fulfilled. For allocation and operational planning, while trading potential helps decide which EVs can fulfill a request, the remaining energy of each EV is also evaluated independently to determine the order of use. This approach ensures that while all selected EVs can fulfill a request, the EVs with higher remaining energy after discharge are prioritized for allocation. This prioritization is critical to maintaining fleet functionality and readiness for future requests, making it a separate but parallel consideration for calculating trading potential.

For a given energy request, Req_i , which is characterized by a start time $T_i^{usage,s}$ and an end time $T_i^{usage,e}$, the discharge potential $PT_{i,j}$ of EV_j is calculated based on the state of the EV and its discharge power P_j^{dis} . The evaluation of the discharge potential is different for each state of the vehicle.

- State 1: EV is idle and linked to the grid. The calculation is straightforward:

$$PT_{i,j} = (T_i^{usage,e} - T_i^{usage,s}) \times P_j^{dis} \quad (3)$$

This applies to idle EVs and fully available to discharge during the entire request window. It represents the maximum energy the EV can provide during the request

window without any operational constraints. When an EV is classified as idle, it could either be doing nothing or charging. If it is charging, we assume that the charging can continue until the start of the energy trading window.

- State 2: EV is linked to the grid but has a future task. The discharge potential depends on the overlap with the EV's task schedule. We denote the overlap time between Req_i and EV_j as $T_{i,j}^{overlap}$. This overlap time indicates the duration the consumer needs energy and the EV is simultaneously available. The corresponding discharge potential can then be formulated as:

$$PT_{i,j} = (T_{i,j}^{ov}) \times P_j^{dis} \quad (4)$$

Based on different EV states, we calculate $T_{i,j}^{ov}$ as follows:

- If the EV's task starts before the request:

$$T_{i,j}^{ov} = \max(T_i^{usage,e} - \max(T_j^{task,s}, T_i^{usage,s}), 0) \quad (5)$$

- If the EV's task ends after the request:

$$T_{i,j}^{ov} = \max(T_i^{usage,e} - \max(T_j^{task,s}, T_i^{usage,s}), 0) \quad (6)$$

- If the EV's task envelops the request's start and end times:

$$T_{i,j}^{ov} = (T_j^{task,s} - T_i^{usage,s}) + (T_i^{usage,e} - T_j^{task,e}) \quad (7)$$

The above equations capture different overlap scenarios between the consumer's request window and the EV's task schedule. Eq. 5 applies when the EV's task ends before or during the request window, so the EV can discharge only after its task ends. Eq. 6 covers cases where the EV's task starts after the request begins, limiting the EV's ability to discharge to the period before its task. Eq. 7 is for the case where the EV's task entirely overlaps the request, except for brief periods at the beginning and end, resulting in two short discharge segments. These formulations ensure that discharge potential is accurately bounded by the EV's availability and task constraints.

- State 3: EV is not linked to the grid but will return in time. The calculation considers the EV's return time:

$$PT_{i,j} = \max(T_i^{usage,e} - \max(T_j^c, T_i^{usage,s}), 0) \times P_j^{dis} \quad (8)$$

This equation calculates the discharge potential of EVs that are not currently connected but will return during the request window. The available duration is the remaining time from the EV's return until the end of the request, ensuring that only feasible discharge periods are considered. If the EV returns after the request ends, the overlap is zero. These calculated potentials guide the decision-making process in selecting the most suitable EVs to fulfill the requirements. After calculating the discharge potentials, the EVs are ranked first according to their potential to meet the energy demand and then according to their current remaining energy. The process strategically manages the fleet to maintain functionality and prepare for subsequent demands by prioritizing EVs with higher potential and greater remaining energy.

TABLE I: Notation Reference for DSBEA Algorithm

Symbol	Description
$\mathbf{R} = \{Req_i\}$	Set of energy requests
Req_i	Energy request i
E_i^{dem}	Total energy demand of request i
$T_i^{usage,s}, T_i^{usage,e}$	Start and end time of request usage
P_i^{req}	Required input power for request i
B_i	Unit bid price for request i
$\mathbf{EV} = \{EV_j\}$	Set of electric vehicles
EV_j	Electric vehicle j
P_j^{dis}	Discharge power of EV j
$State_j$	Current operational state of EV j
E_j^{rem}	Remaining battery energy of EV j
$T_j^{task,s}, T_j^{task,e}$	Start and end time of future task of EV j
T_j^{back}	Expected return time of EV j
L^{dis}	Output discharge allocation list
$PT_{i,j}$	Discharge potential of EV j for request i
$SumPT$	Accumulated discharge potential
$EligibleEV$	List of EVs eligible for a given request

When determining which EV to allocate for a specific request, the algorithm first checks whether the combined discharge potential of all available EVs can cover the energy demand of the request. Suppose the cumulative potential from all EVs cannot cover the energy demand of the request. In that case, the request is considered unfulfillable and discarded, allowing the process to move on to the subsequent request. However, if the sum of the potentials can potentially satisfy the request, the summation is stopped as soon as the accumulated potential exceeds the demand. Once it has been determined that the request can be fulfilled, the system checks whether a single EV can fulfill the request independently. The potentials are checked in descending order, starting with the highest. As this EV alone exceeds the demand, it is immediately selected for allocation.

A combination of EVs is considered if no single EV can fully meet the request on its own. The strategy starts by allocating the EV with the highest available potential, subtracting its contribution from the total demand. This process continues by successively deploying the EVs with the next highest potential until the total energy demand of the request is met. Once an EV has been assigned to a request, its remaining energy is adjusted to account for discharge. This change is recorded in a discharge list, which records details such as the request ID, the EV ID, the start and end times of the energy service, and the amount of energy delivered. Updating the status of a vehicle after discharging involves following four steps:

(a) Immediate updates: If an EV's remaining energy is exhausted (reaches zero) after fulfilling a request, it will no longer be considered for future allocations.

(b) Updates for partial energy use: For EVs that still have energy after a discharge, their operational availability must be reassessed. This includes updating their energy levels and possibly adjusting their availability periods:

- Before request time $T_i^{usage,s}$: Segment the availability of EVs before the request start time.
- During request time $T_i^{usage,s}$ to $T_i^{usage,e}$: During this period, the EV is occupied and not considered for other allocations.
- After request time $T_i^{usage,e}$: Segment the availability of

Algorithm 1 Dynamic Segment-Based Energy Allocation (DSBEA) Between EVs and Energy Requests

<p>1: Input: Request list \mathbf{R}, EV list \mathbf{EV}</p> <p>2: Output: Discharge allocation list L^{dis}</p> <p>3: Step 1: Preprocessing</p> <p>4: Calculate energy demand for all Req_i in \mathbf{R}</p> <p>5: Calculate profit potential for all Req_i in \mathbf{R}</p> <p>6: Sort \mathbf{R} by profit potential in descending order</p> <p>7: Step 2: EV selection and potential calculation</p> <p>8: For each Req_i in \mathbf{R} do</p> <p>9: Step 2.1: Initialization</p> <p>10: $EligibleEV$: Temporary list of available EVs</p> <p>11: $SumPT$: Temporary summation of trading potentials</p> <p>12: Step 2.2: Calculate single EV's trading potential</p> <p>13: For each EV_j in \mathbf{EV} do</p> <p>14: If $State_j$ allows and E_j^{rem} is sufficient</p> <p>15: Calculate trading potential $PT_{i,j}$</p> <p>16: Append EV_j and $PT_{i,j}$ to $EligibleEV$</p> <p>17: Step 2.3: Calculate EV's total trading potential</p>	<p>18: For each $(EV_j, PT_{i,j})$ in $EligibleEV$ do</p> <p>19: $SumPT \leftarrow SumPT + PT_{i,j}$</p> <p>20: Step 2.4: Decide EV allocation and update list</p> <p>21: If $SumPT \geq E_i^{dem}$ then</p> <p>22: Break from the loop</p> <p>23: If $SumPT < E_i^{dem}$ then</p> <p>24: Move on to next request</p> <p>25: Else</p> <p>26: If $PT_{i,j} \geq E_i^{dem}$ then</p> <p>27: Allocate EV_j to Req_i</p> <p>28: Update E_j^{rem} and $State_j$</p> <p>29: Add entry to discharge list</p> <p>30: If no single EV_j can meet Req_i then</p> <p>31: Use multiple EV_j to fulfill Req_i</p> <p>32: Update discharge list and EV_j status accordingly</p> <p>33: If Req_i cannot be met, add to unmet requests list</p> <p>34: Return discharge list</p>
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EVs after the request end time.

In this work, only the segments 'before' and 'after' are actively considered for future allocations.

(c) Management of the list: Depending on the EV's availability about the request, different segments are created:

- If available before and after the request, replace the original entry with two new entries corresponding to these periods.
- If only available before or after the request, replace the original entry with a new one for the respective period.

This segmentation ensures that the EV list can be dynamically expanded to reflect changes in individual EVs' availability and energy status. Each EV can be represented by multiple entries in the updated list, each corresponding to different availability periods. As a result, future allocations involving an EV will require synchronous updates of all entries that have the same EV ID to maintain consistent energy status data.

(d) Completion of the allocation process: The process continues until all requests have been processed or there are no more available EVs in the list to fulfill further demands. Algorithm 1 summarizes the entire procedure, and the notations used are listed in Table I for clarity. To mitigate the impact of attackers, we apply a robust mechanism proposed in a previous work [14], where consumer behavior is monitored across multiple rounds of trading. The core idea is to reduce the energy allocation to suspicious consumers by applying a cumulative penalty — if a request is identified as an attacker, its energy demand is reduced in subsequent rounds. In extreme cases, the repeated behavior of an attacker may result in the request being filtered out completely. This mechanism allows the system to suppress malicious influences while gradually maintaining overall trading performance.

C. Smart Management of EV Charging Operations

Intelligent management of EV charging operations is essential for optimizing EV fleet functionality. This section introduces a comprehensive system that starts with a prediction method to determine the energy consumption of EVs for current or upcoming tasks. These predictions' results serve as the basis for deciding whether an EV should charge or discharge depending on its expected energy requirements. Figure 4 illustrates how predicting energy consumption feeds into innovative charging management and scheduling.

1) *Smart EV Charging Algorithm:* Electric vehicles utilize an innovative EV charging algorithm based on a neural network. This approach manages charging and discharging operations for a single car and the entire fleet, considering comprehensive real-time data from all connected vehicles. Key inputs include each vehicle's state of charge (SoC), energy price fluctuations, expected grid demand, grid stability requirements, renewable energy availability, weather conditions, and the operating schedules of all EVs in the fleet. The neural network processes these inputs to continuously update the charging recommendations based on current energy supply scenarios and expected fluctuations in demand. The configuration of the charging schedules and the energy distribution in the electric car fleet is adjusted accordingly in response to the inputs processed by the neural network. The model adopted in this work was developed in our previous study [37], where the network architecture, training method, and dataset are fully described.

2) *Energy Consumption Prediction Method:* We deploy the energy consumption prediction method, a multi-stage approach to manage the energy resources of EVs, as detailed in [38]. This method is particularly effective for long trips, where the journey is segmented into shorter intervals, and energy consumption is predicted for each segment using a neural network. This segmentation allows for more accurate and tailored

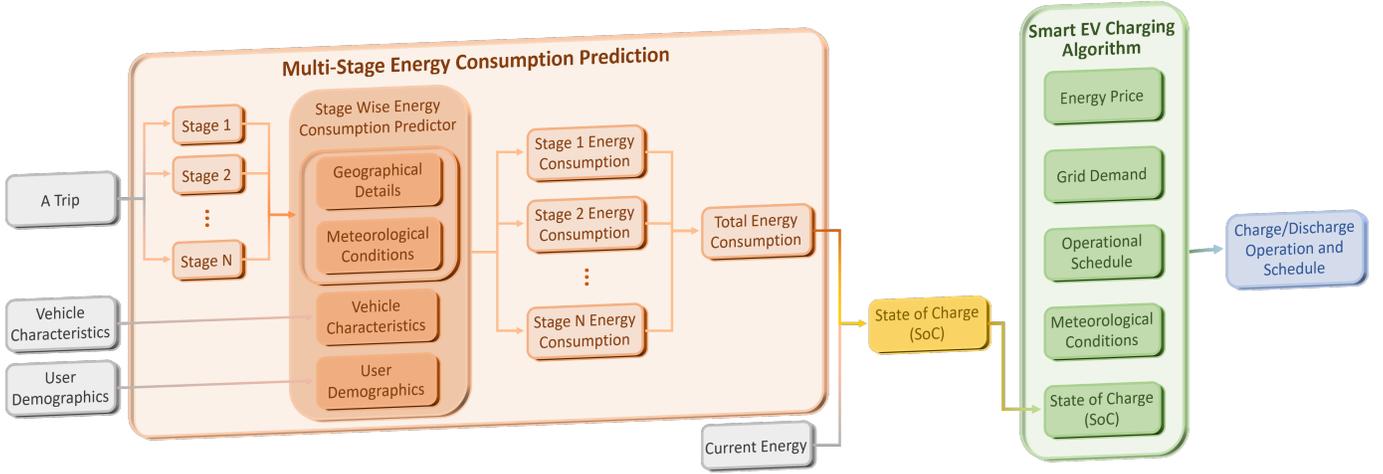


Fig. 4: Smart EV Charging Management and Scheduling with an Energy Consumption Prediction Method.

predictions, adapting the analysis to the specific characteristics of each part of the trip. For shorter trips that do not require segmentation, the neural network directly predicts energy consumption without further division, demonstrating the method's flexibility to accommodate various trip ranges. Inputs for this predictive model include geographical details such as latitude and longitude, weather conditions like wind, precipitation, and sunshine, EV specifics such as age and model type, and user demographics such as age. Additionally, the method estimates residual energy levels for EVs returning to charging stations to ensure vehicles are adequately charged and prepared for subsequent tasks. This sophisticated predictive capability is essential for effectively planning and managing the energy demands of electric vehicles, ensuring optimal readiness and efficiency.

D. Time Analysis of A Local Dual Blockchain

We theoretically analyze the time costs associated with a single round of trading within a local dual blockchain architecture, specifically examining the EVBC and EMBC. The goal is to identify and quantify the temporal dynamics and inefficiencies that may affect the overall responsiveness and efficiency of the system.

1) *Request Collection in EMBC*: In each EMBC, we consider a cluster of energy markets $\{EM_i\}$, $i \in N_{em}$, N_{em} is the number of markets. In each energy market, the request list has N_i^{req} requests, each with size s^{req} . The maximum storage capacity of a single transaction is denoted by s^{tx} . Therefore, the number of transactions is formulated as

$$N_i^{tx} = \lceil \frac{N_i^{req} \times s^{req}}{s^{tx}} \rceil \quad (9)$$

The total time for endorsing all transactions is formulated by

$$T_i^{rc,endo} = N_i^{tx} \times t_i^{rc,endo} \quad (10)$$

Where $t_i^{rc,endo}$ is the average time for endorsing a single transaction in EMBC during request collection. Since the ordering, broadcasting, and verification happen once per block, we denote them by $T_i^{rc,order}$, $T_i^{rc,best}$, and $T_i^{rc,ver}$, respectively. The time to record the blockchain on the public ledger

is denoted by $T_i^{rc,rec}$. Therefore, the time cost from when the energy market begins processing transactions to when the block is fully recorded is formulated by:

$$T_i^{rc,total} = T_i^{rc,endo} + T_i^{rc,order} + T_i^{rc,best} + T_i^{rc,ver} + T_i^{rc,rec} \quad (11)$$

The control systems then need to process the request list, the processing time is denoted by $T_i^{rc,proc}$. Therefore, the total time for request collection in EMBC can be formulated as:

$$T^{rc,EM} = \max(T_1^{rc,total} + T_1^{rc,proc}, T_2^{rc,total} + T_2^{rc,proc}, \dots, T_{N_{em}}^{rc,total} + T_{N_{em}}^{rc,proc}) \quad (12)$$

2) *Offer Collection in EVBC*: In each EVBC, we consider an EV fleet $\{EV_j\}$, $j \in N_{ev}$, N_{ev} is the number of EVs that are willing to join the next trading round. In each vehicular network, we consider the total number of N_j^{offer} offers, each with size s^{offer} . Therefore, the number of transactions is formulated as

$$N_j^{tx} = \lceil \frac{N_j^{offer} \times s^{offer}}{s^{tx}} \rceil \quad (13)$$

The total time for endorsing all transactions is formulated by

$$T_j^{oc,endo} = N_j^{tx} \times t_j^{oc,endo} \quad (14)$$

Where $t_j^{oc,endo}$ is the average time for endorsing a single transaction in EVBC during offer collection. Since the ordering, broadcasting, and verification happen once per block, we denote them by $T_j^{oc,order}$, $T_j^{oc,best}$, and $T_j^{oc,ver}$, respectively. The time to record the blockchain on the public ledger is denoted by $T_j^{oc,rec}$. Therefore, the time cost when the a single EV begins processing transactions to when the block is fully recorded is formulated by:

$$T_j^{oc,total} = T_j^{oc,endo} + T_j^{oc,order} + T_j^{oc,best} + T_j^{oc,ver} + T_j^{oc,rec} \quad (15)$$

The control systems need to process each energy offer; the processing time is denoted by $T_j^{oc,proc}$. After obtaining

all energy offers, the CS must organize them into an offer list. The time cost for this operation is denoted by $T^{oc,org}$. Therefore, the total time for request collection in EVBC can be formulated as:

$$T^{oc,EV} = \max(T_1^{oc,total} + T_1^{oc,proc}, T_2^{oc,total} + T_2^{oc,proc}, \dots, T_{N_{ev}}^{oc,total} + T_{N_{ev}}^{oc,proc}) + T^{oc,org} \quad (16)$$

3) *Transmission of Unfulfilled Requests and Unallocated Offers in the Selective Sync Blockchain*: After energy requests have been matched with available offers through the allocation algorithm, the unfulfilled requests and unallocated offers are transferred to the high-level selective sync blockchain. Let N_{un}^{req} denote the number of energy requests that have not been fulfilled yet. Similarly, we indicate the number of unallocated offers by N_{un}^{offer} . The total size of the list for unfulfilled requests and unallocated offers can be formulated as:

$$S_{un} = N_{un}^{req} \times s^{req} + N_{un}^{offer} \times s^{offer} \quad (17)$$

The number of transactions is formulated as:

$$N_{un}^{tx} = \lceil S_{un}/s_{tx} \rceil \quad (18)$$

The total time for endorsing all transactions is formulated by:

$$T_{un}^{endo} = N_{un}^{tx} \times t_{un}^{endo} \quad (19)$$

We denote the time for order, broadcasting, verification, and record by T_{un}^{bcst} , and T_{un}^{ver} , T_{un}^{rec} . Therefore, the time cost for transmission of unfulfilled requests is formulated by:

$$T_{un}^{total} = T_{un}^{endo} + T_{un}^{order} + T_{un}^{bcst} + T_{un}^{ver} + T_{un}^{rec} \quad (20)$$

4) *Notification of Energy Allocation Results for Unfulfilled Requests*: The allocation algorithm is then applied to the unfulfilled requests and unallocated offers. Subsequently, the results are received by each control system. Let N_{mat} denote the number of supply-demand matches. We also denote the size of each supply-demand match by s_{mat} . The total size of the list can be formulated as:

$$S_{mat} = N_{mat} \times s_{mat} \quad (21)$$

The number of transactions is formulated as:

$$N_{mat}^{tx} = \lceil S_{mat}/s_{tx} \rceil \quad (22)$$

The total time for endorsing all transactions is formulated by:

$$T_{mat}^{endo} = N_{mat}^{tx} \times t_{mat}^{endo} \quad (23)$$

We denote the time for order, broadcasting, verification, and record by T_{mat}^{bcst} , and T_{mat}^{ver} , T_{mat}^{rec} . Therefore, the time cost for transmission of unfulfilled requests is formulated by:

$$T_{mat}^{total} = T_{mat}^{endo} + T_{mat}^{order} + T_{mat}^{bcst} + T_{mat}^{ver} + T_{mat}^{rec} \quad (24)$$

5) *Post-Allocation Notification in EMBC*: The next step is notifying the energy markets about the outcomes. Let N_{sel}^{req} denote the number of energy requests selected for notification after the allocation process. Let s_{sel}^{req} represent the average size of a single record in the allocation list. The total size of the notification list for energy markets can be formulated as:

$$S_{sel}^{req} = N_{sel}^{req} \times s_{sel}^{req} \quad (25)$$

The number of transactions is formulated as:

$$N_{sel}^{req,tx} = \lceil S_{sel}^{req}/s_{tx} \rceil \quad (26)$$

The total time for endorsing all transactions is formulated by:

$$T_{sel}^{req,endo} = N_{sel}^{req,tx} \times t_{sel}^{req,endo} \quad (27)$$

We denote the time for order, broadcasting, verification, and record by $T_{sel,req,bcst}$, and $T_{sel,req,ver}$, $T_{sel,req,rec}$. Therefore, the time cost when the control system begins processing transactions until the block is fully recorded is formulated by:

$$T_{sel}^{req,total} = T_{sel}^{req,endo} + T_{sel}^{req,order} + T_{sel}^{req,bcst} + T_{sel}^{req,ver} + T_{sel}^{req,rec} \quad (28)$$

6) *Post-Allocation Notification in EVBC*: After energy requests have been matched with available offers through the allocation algorithm, the next step is notifying the EV fleet about the discharging tasks. Let N_{sel}^{ev} denote the number of energy requests selected for notification after the allocation process. Let s_{sel}^{ev} represent the average size of a single record in the allocation list. The total size of the notification list for energy markets can be formulated as:

$$S_{sel}^{ev} = N_{sel}^{ev} \times s_{sel}^{ev} \quad (29)$$

The number of transactions is formulated as:

$$N_{sel}^{ev,tx} = \lceil S_{sel}^{ev}/s_{tx} \rceil \quad (30)$$

The total time for endorsing all transactions is formulated by:

$$T_{sel}^{ev,endo} = N_{sel}^{ev,tx} \times t_{sel}^{ev,endo} \quad (31)$$

We denote the time for order, broadcasting, verification, and record by $T_{sel}^{ev,bcst}$, and $T_{sel}^{ev,ver}$, $T_{sel}^{ev,rec}$. Therefore, the time cost when the control system begins processing transactions until the block is fully recorded is formulated by:

$$T_{sel}^{ev,total} = T_{sel}^{ev,endo} + T_{sel}^{ev,order} + T_{sel}^{ev,bcst} + T_{sel}^{ev,ver} + T_{sel}^{ev,rec} \quad (32)$$

IV. EVALUATION

A. Evaluation Methodology

We first evaluate the time cost of a single trading round under different blockchain architectures, including V2GNet [14], V2GFTN [15], and the proposed dynamic two-tier V2G. To enhance the clarity of architectural differences and allocation strategies, Table II summarizes the key characteristics of these approaches, including their architecture design, request

TABLE II: Comparison of Energy Trading Architectures and Their Allocation Strategies

Approach	Architecture Design	Request Processing	Allocation Strategy
V2GNet	EVBC + Semi-EMBC	Requests processed off-chain, offers processed on-chain	Static one-shot matching
V2GFTN	Multiple subnetworks for EVBC and Semi-EMBC	Full synchronization of offers and requests across subnetworks	Static one-shot matching
Two-Tier V2G + DSBEA (This Work)	Local dual networks (EVBC + EMBC) with high-level blockchain for unfulfilled requests	Local on-chain processing; only unfulfilled requests transferred to high-level blockchain	Dynamic segment-based allocation with EV status update

TABLE III: Configuration for the Blockchain Simulation on the Request-Response Blockchain.

Request Collection in EMBC		Offer Collection in EVBC		Post-Allocation Notification in EMBC		Post-Allocation Notification in EVBC	
Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
No. of markets	3	No. of EVs	15, 75	No. of selected requests	0-180	No. of selected EVs	0-75
No. of requests	60, 180	Offer size	0.5KB	Request notification size	0.3KB	EV notification size	0.3KB
Request size	0.4KB	Endorsement time	10-200ms	Endorsement time	10-200ms	Endorsement time	10-200ms
Transaction size	1MB	Ordering time	750ms	Ordering time	50-600ms	Ordering time	50-750ms
Endorsement time	10-200ms	Broadcasting time	150ms	Broadcasting time	100-120ms	Broadcasting time	100-150ms
Ordering time	600ms	Verification time	250ms	Verification time	100-200ms	Verification time	100-250ms
Broadcasting time	120ms	Recording time	150ms	Recording time	50-150ms	Recording time	50-150ms
Verification time	200ms						
Recording time	120ms						

processing methods, allocation strategies, and scalability considerations. Here, DSBEA refers to the allocation algorithm used within our proposed two-tier V2G architecture, while V2GNet and V2GFTN adopt their matching methods. This comparison highlights that both V2GNet and V2GFTN rely on static one-shot matching strategies, with V2GFTN additionally requiring global synchronization across subnetworks, which increases communication overhead. In contrast, the proposed two-tier V2G architecture combined with DSBEA enables localized energy allocation with dynamic EV status updates, reducing communication overhead and improving scalability. The following evaluation results demonstrate the impact of these differences on system time cost, energy fulfillment, and profit performance.

We also evaluate the time cost associated with different blockchain operations within EMBC and EVBC. Specific parameters were defined to represent the number of energy markets, the volume of requests and EVs, the transaction sizes, and the sizes of requests, offers, and notifications. In addition, detailed processing times were defined for the different blockchain phases, including endorsement, ordering, broadcasting, verification, and recording. The simulation was implemented using Python, following a structure inspired by the Blocksim simulator [39]. Modeling parameters were configured by Blocksim's design guidelines and performance assumptions, and adapted to the phases of the proposed dual-blockchain system. Table III and Table IV provide a comprehensive configuration for these parameters.

In addition, we assess the performance of the proposed DSBEA algorithm by comparing it with state-of-the-art methods in V2G systems. The evaluation focuses on three key performance metrics:

- **Total Energy Fulfillment:** This quantifies the total energy provided by the EVs, assessing the efficiency of energy distribution.
- **Total Profit:** This measures the overall economic benefits.

TABLE IV: Configuration for the Blockchain Simulation on the High-Level Blockchain.

Transmission of Requests and Offers		Notification	
Parameter	Value	Parameter	Value
No. of subnetworks	3	Notification size	0.9 KB
Endorsement time	10-200ms	Endorsement time	10-200ms
Ordering time	900ms	Ordering time	900ms
Broadcasting time	200ms	Broadcasting time	200ms
Verification time	300ms	Verification time	300ms
Recording time	200ms	Recording time	200ms

TABLE V: Configuration for Energy Distribution Based on Request and EV Characteristics.

Input Feature	Value
No. of Consumers	60, 90, 120, 150, 180
No. of EVs	45, 60, 75
EV State	Idle, Charging, Driving
Future Task	Yes, No
Battery Capacity	60 kWh
Max Request Time Slot	1 hour
Input Power	3 to 10 kW
Discharge Power	10 kW
Requests Capacity	0 to 10 kWh
Bid Price	29.62 to 40.32 JPY

- **Number of Fulfilled Requests:** This counts how many energy requests have been successfully met, indicating the method's effectiveness in meeting consumer demand.

The dataset for this evaluation consists of lists of EVs and energy requests, generated based on the configurations detailed in Table V. In my blockchain configuration, various factors such as transaction size, endorsement time, ordering time, etc., are considered. These parameters follow the modeling assumptions previously described to simulate realistic scenarios that reflect the different capacities and demands typical of V2G systems.

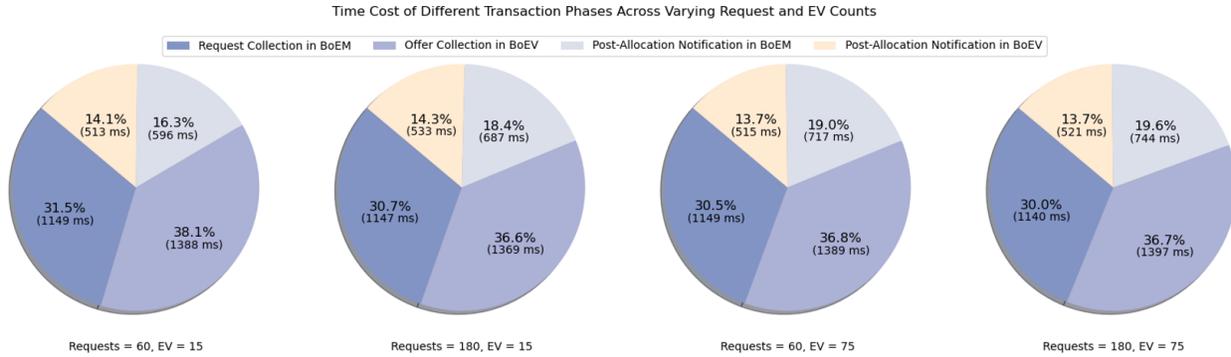


Fig. 5: Evaluation of the time cost distribution of transaction phases in different scenarios, illustrated by pie charts. These charts compare systems with different volumes of requests (60 or 180) and electric vehicles (15 or 75). The sequence illustrates the increasing complexity and responsiveness of the system under different operating loads.

The experimental framework tests the DSBEA method under various EV numbers and request volume combinations. Additionally, we evaluate the robustness of the algorithm with 180 energy requests and 75 electric vehicles (EVs). Among the 180 requests, 20% are designated as fake consumers (attackers). These fake requests fully participate in the matching process but do not result in actual energy transmission, thereby causing wasted energy from the EVs that are assigned to them.

B. Evaluation Results

TABLE VI: Evaluation of the total time cost during an energy trading round across three blockchain-based methods.

No. of Requests	No. of EVs	V2GNet [14]	V2GFTN [15]	Dynamic Two-Tier V2G (This Work)
60	45	15.71	19.16	8.68
	60	19.33	22.59	9.09
	75	22.56	25.79	9.48
90	45	24.64	28.11	9.82
	60	29.67	33.15	10.29
	75	34.23	37.59	10.79
120	45	34.35	37.87	11.75
	60	40.78	44.25	11.69
	75	46.21	49.66	12.35
150	45	38.14	41.74	16.84
	60	52.77	56.34	13.89
	75	60.08	63.59	14.05
180	45	44.01	47.55	25.11
	60	70.90	74.46	17.55
	75	80.50	84.10	16.28

We first evaluate the distribution of transaction phases within a blockchain system for different configurations of requests and EVs. Figure 5 illustrates how the time distribution between the various phases responds to the number of requests and EVs changes. For instance, the time cost share for request collection in BoEM remains constant between 30.0% and 31.5% across all scenarios, with a maximum deviation of only 1.5%. This indicates a stable performance in the processing of requests and the operation of EVs, regardless of the number of requests or EVs involved. Similarly, the time cost share for offer collection in BoEV remains almost constant and

varies between 36.6% and 38.1%. In addition, the time cost shares for the two notification phases after allocation vary only minimally by 3.3% and 0.4%, respectively. Furthermore, the absolute time costs for the different phases are stable, with the most significant variation being only 148 ms. This proves the system's scalability when the number of requests or EVs increases. Table VI highlights the efficiency of the dynamic two-tier V2G method compared to V2GNet and V2GFTN regarding the total time costs of a single energy trading round. For a combination of 60 requests and 45 EVs, dynamic two-tier V2G has a time cost of 8.68 seconds—42% and 55% faster than V2GNet and V2GFTN, respectively. For 180 requests and 75 EVs, the time cost of the proposed method is 16.28 seconds, which is nearly 80% faster than the 80.50 seconds of V2GNet and the 84.10 seconds of V2GFTN. In contrast to V2GNet and V2GFTN, where all requests and offers need to be exchanged across the entire system, dynamic two-tier V2G benefits from the distribution operations performed in the sub-networks, leaving only minor tasks for the high-level blockchain, resulting in a significant reduction in time costs.

In the evaluation, the proposed DSBEA exhibited superior performance across various configurations, consistently outperforming other algorithms in V2G systems. As evidenced in Figure 6, DSBEA's sum fulfillment dramatically improved as the number of EVs increased, especially evident in scenarios with 180 requests where DSBEA reached up to 400 kWh of fulfillment with 75 EVs, compared to the action-based incentive scheme and double auction mechanism which achieved less than 200 kWh, respectively. Furthermore, V2GNet and V2GFTN algorithms showed moderate scalability but still fell short, with V2GFTN achieving a maximum of around 250 units under similar conditions. Like the sum fulfillment metrics, the DSBEA demonstrates a significant advantage in total profit generation, as shown in Figure 7. For instance, with 75 EVs handling 180 requests, the DSBEA achieves an average profit of 14,300 JPY, which is 67% higher compared to the 8,540 JPY generated by the V2GFTN. Additionally, as illustrated in Figure 8, DSBEA shows a pronounced edge in the number of requests fulfilled, particularly when few EVs are available to manage many requests. In the most favorable

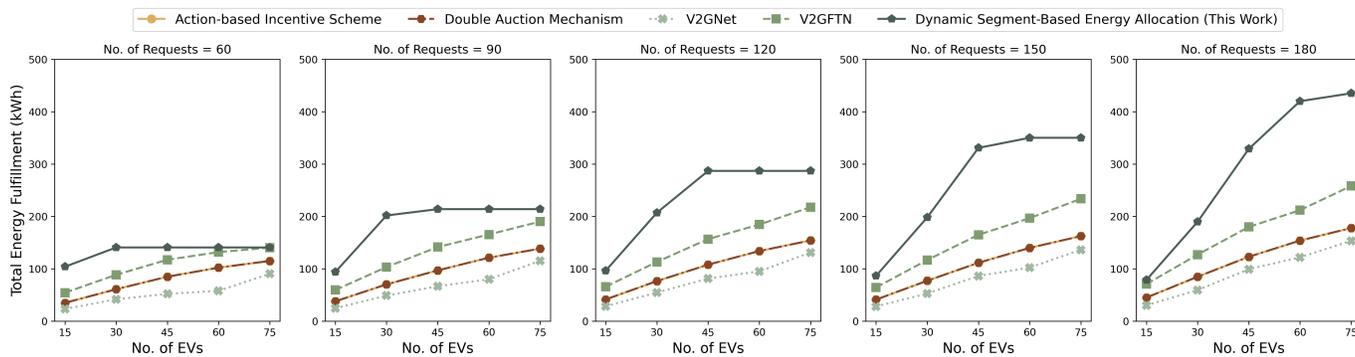


Fig. 6: Evaluation of trading strategies of action-based incentive scheme [40], double auction mechanism [41], V2GNet [14], V2GFTN [15], and the proposed work on sum fulfillment. Different combinations of EVs and request amounts were investigated.

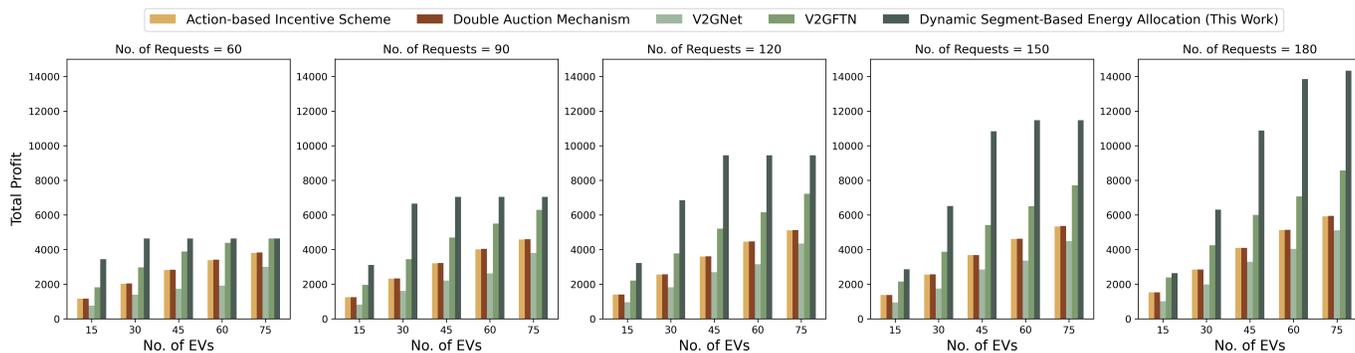


Fig. 7: Evaluation of trading strategies of action-based incentive scheme, double auction mechanism, V2GNet, V2GFTN, and the proposed work on total profit. Different combinations of EVs and request amounts were investigated.

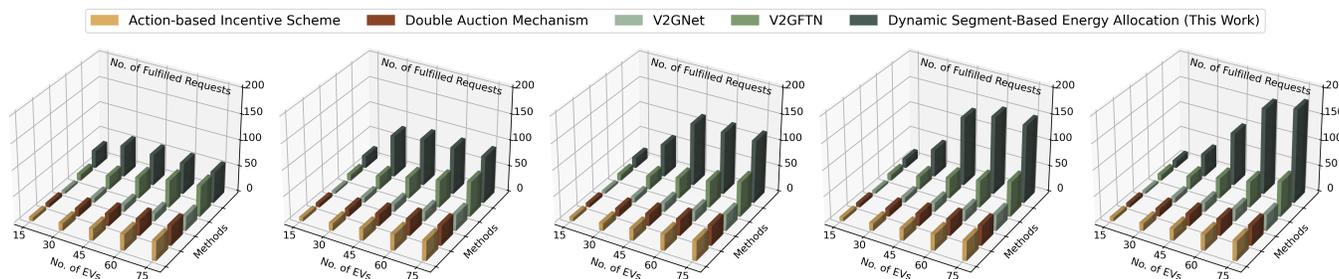


Fig. 8: Evaluation of trading strategies of action-based incentive scheme, double auction mechanism, V2GNet, V2GFTN, and the proposed work on the number of fulfilled energy requests. Different combinations of EVs and request amounts were investigated.

scenarios, DSBEA can fulfill three times as many requests as other approaches, attributed to its efficient utilization of EV capacity. Key advantages of the proposed approach are summarized as follows:

- Time Cost: Reduced by up to 80%, significantly enhancing real-time responsiveness.
- Energy Fulfillment: Improved by up to 5.4%, demonstrating better utilization of available EV resources.
- Total Profit: Increased by up to 6.7%, indicating improved economic efficiency.

To evaluate the robustness of the proposed algorithm, we simulated a scenario in which 20% of the energy requests come from attacker consumers that participate in the allocation

process but do not perform actual energy transactions. Figure 9 compares a non-resilient configuration with an attack-resilient configuration that progressively penalizes such requests. Both configurations achieve a similar level of effective energy fulfillment, on average about 348 kWh per round. However, the attack-resistant configuration reduces the energy loss from an average of 90 kWh to 46 kWh per round, a reduction of 49%. Remarkably, in the resistant configuration, the energy loss decreases by over 90% from the first to the last round, demonstrating the method's effectiveness in suppressing the attackers over time.

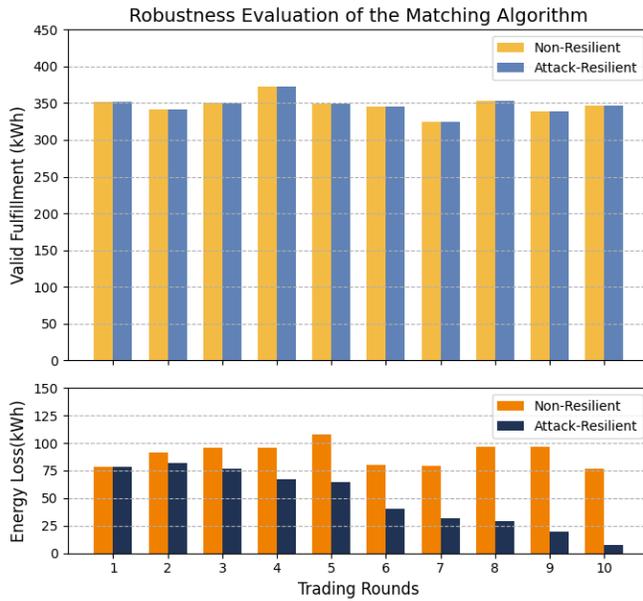


Fig. 9: Evaluation of the proposed algorithm regarding robustness against consumer attackers. The top plot shows the valid energy fulfillment delivered to legitimate consumers under non-resilient and attack-resilient configurations. The bottom plot illustrates the corresponding energy loss due to attacker requests.

V. DISCUSSION

The introduction of a dynamic segment-based algorithm for energy allocation within a novel two-tier blockchain framework represents a significant improvement in the management of EV energy resources. This approach enables dynamic adaptation of energy management and effectively addresses the limitations of conventional systems that often struggle with the sporadic nature of energy demand. Compared to traditional static one-shot allocation methods, the proposed DSBEA algorithm enables more flexible matching by incrementally updating EV status during allocation, allowing the system to respond to dynamic and diverse demand conditions. In addition, the algorithm accounts for practical parameters such as charging/discharging power, energy request time windows, and bid prices, ensuring more realistic and feasible matching outcomes. The evaluation also shows that the algorithm remains effective in the presence of attacker requests, with the energy loss decreasing significantly over time as these requests are gradually penalized. The evaluation further shows that the algorithm remains effective under adversarial conditions, with energy loss decreasing considerably over time as attacker requests are progressively penalized. Despite considering planning, urgency, and renewable energy sources, there are still challenges on both the request and EV side. In our current work, we consider requests with at least one hour of advance notice; changes in requests or urgent cases may require energy in extremely short time frames, complicating logistics. On the EV side, immediate tasks or vehicle issues could disrupt planned operations. In addition, consumers could

potentially bid for energy in multiple markets, making demand management even more complex. Furthermore, communication between EVs is not yet sufficiently explored. Effective interaction could determine whether an EV should charge or discharge, influencing operational decisions based on the availability of other EVs.

In addition to the operational dynamics of EVs and requests, economic mechanisms also require careful consideration. The trading price should dynamically adjust to real-time offers and requests from EVs and consumers. Currently, the control system performs a single allocation round, which limits the ability of end nodes to adjust prices intelligently. Tackling this complexity could lead to a more adaptable and responsive system, but could also mean increased overhead for the blockchain network. Thus, there is an urgent need to explore more efficient blockchain solutions that can handle the increased load without sacrificing performance. The results show that blockchain technology facilitates the interaction between energy markets and EVs, leading to noticeable energy fulfillment and economic efficiency. However, the scalability of this system still needs to be thoroughly investigated, especially in large-scale scenarios where the time cost of energy allocation becomes critical when demand is urgent. While this study focused on EVs as energy suppliers, exploring scenarios where EVs act as both consumers and suppliers introduces further complexity and requires new solutions for real-time energy trading and communication strategies among EVs. In addition to our architectural-level design based on a two-tier blockchain to reduce communication overhead, emerging consensus-level enhancements such as sharding, proof-of-stake (PoS), or delegated PoS (DPoS) are conceptually complementary and could be integrated in future implementations to improve scalability and transaction throughput further. These techniques are exemplified in public blockchain platforms such as Ethereum 2.0 [42] and Polkadot [43]. Furthermore, while our simulation captures key blockchain processes such as endorsement and ordering delays, it does not explicitly model network congestion or dynamic computation loads on blockchain nodes. These factors could affect real-world latency and throughput, particularly under heavy transaction volumes. Mitigating such issues may require performance-aware scheduling or adaptive consensus configurations, which should be explored in future system extensions.

Another critical aspect in real-time energy trading systems is the reliability of data transmission. While our tiered blockchain structure reduces overall communication delay by distributing transaction processing across subnetworks, practical deployment may require additional safeguards to handle transient latency or data loss. Depending on the networking infrastructure used, these may include fault-tolerant communication mechanisms such as error correction or message acknowledgment protocols.

Security is another crucial concern in blockchain-based systems. While blockchain ensures data integrity and secure energy transactions, vulnerabilities such as 51% attacks and double-spending may arise in general blockchain deployments. Our system substantially reduces these risks by adopting a permissioned blockchain architecture, where participant ac-

cess and consensus policies are controlled. In addition, advanced mechanisms such as multi-signature schemes and zero-knowledge proofs offer further avenues to enhance transaction security and privacy.

Looking toward practical applications, the proposed system is well-positioned for deployment in real-world scenarios such as smart cities, where electric vehicles interact with localized energy markets and renewable energy sources. For instance, environments with solar-powered charging stations, community-based peer-to-peer energy trading, or decentralized microgrids can benefit from dynamic energy matching and reduced communication overhead. The system's distributed design also enables flexible integration with diverse urban energy infrastructures, making it well-suited for deployment in future sustainable mobility and energy ecosystems.

VI. CONCLUSION

This paper proposes an edge-driven dynamic two-tier blockchain method for energy trading for V2G, which optimizes energy management and transaction efficiency between electric vehicles and energy markets. The architecture processes most energy requests and offers within local dual networks, while the higher-level blockchain handles a minor portion of energy distribution tasks. This reduces the communication overhead in the blockchain by up to 80% and improves EV energy utilization. The novel DSBEA algorithm significantly enhances energy fulfillment by 68.6% and overall profit by 67.5% compared to existing methods. Evaluation results have demonstrated the superior performance of DSBEA, especially in vehicle-to-grid systems, in high-demand and limited-resource scenarios. These contributions mark a significant advance in applying blockchain technologies for innovative grid management. The results also indicate that the algorithm maintains robust performance under adversarial conditions and effectively minimizes the energy loss due to attackers' requests over time through adaptive penalization. Future work will include developing strategies for dealing with unfulfilled requests, focusing on enabling the system to adapt dynamically and in real time to urgent energy needs. An important area for further research is the approach to dealing with instantaneous requests that occur at short notice and must be fulfilled within minutes to ensure that the system can adapt dynamically and in real time to urgent energy needs.

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