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

Zhishang Wang[1], *Member, IEEE*, Yuxiao Liang[2], *Member, IEEE*, Achraf Ben Ahmed[3], *Member, IEEE*, Khanh N. Dang[1], *Member, IEEE*, and Abderazek Ben Abdallah[1], *Senior Member, IEEE*

***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

This work was supported by The University of Aizu, CRF-P7-2024.

[1]Zhishang Wang, Khanh N. Dang, and Abderazek Ben Abdallah are with the Advanced Computing Systems Laboratory, School of Computer Science and Engineering, The University of Aizu, Aizu-Wakamatsu, Fukushima, 965-8580, Japan. (e-mail: zwang@u-aizu.ac.jp, khanh@u-aizu.ac.jp, benab@u-aizu.ac.jp)

[2]Yuxiao Liang is with School of Management Science & Engineering, Shanxi University of Finance and Economics, Taiyuan, Shanxi, 030006, China. (e-mail: ts17030023a3@cumt.edu.cn)

[3]Achraf Ben Ahmed is with Centan Inc., Minato-ku, Tokyo, 108-0075, Japan. (e-mail: achraf26@gmail.com)

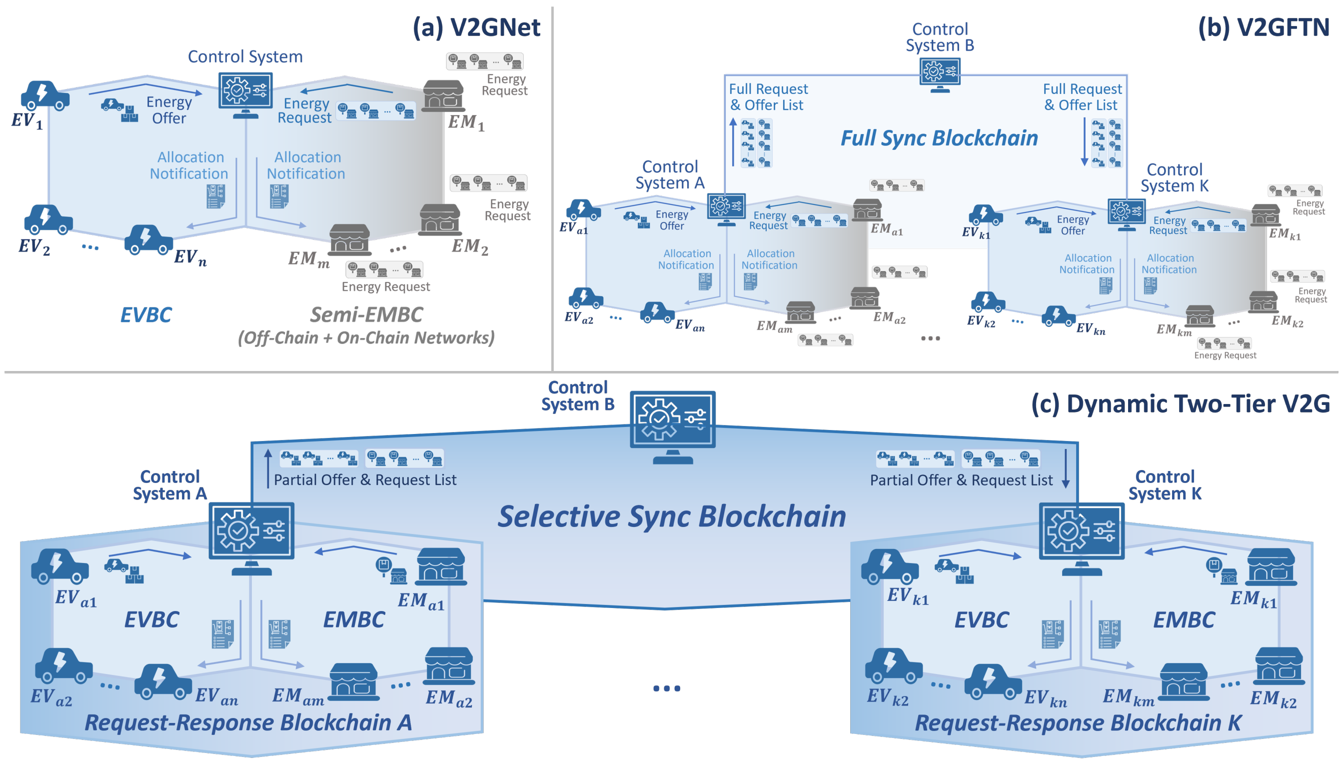

Fig. 1: Overview of V2G Blockchain Architectures for Energy Trading: (a) V2GNet [14] uses a semi-blockchain approach where off-chain energy requests (semi-EMBC) and on-chain EV offers (EVBC). This results in incomplete traceability and requires a single control system to manage all requests and offers. (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

Blockchain-based energy trading systems have been widely studied for improving security, scalability, and efficiency. Guo et al. [7] introduced a Byzantine consensus mechanism to increase transaction throughput and reduce latency, while Abegaz et al. [16] proposed a multi-agent framework combining deep reinforcement learning and game theory for dynamic resource trading in industrial IoT. Several studies [8], [17] focused on securing regional and peer-to-peer electricity trading through blockchain-enabled transaction protection. Decentralized and consortium blockchain models have also been explored for demand-side management and high-mobility scenarios [9], [18], [19]. To address scalability, Lin et al. [20] and Hassija et al. [21] investigated decentralized scheduling for smart grids and vehicle-to-everything systems under real-time demand. Other efforts enhanced security and privacy through extended blockchain structures, robust scheduling, and smart contracts [22]–[24]. Liang et al. [14] introduced V2GNet, a semi-blockchain architecture for integrating energy markets with the power grid. This was later extended to V2GFTN [15], which connects multiple local networks with separate blockchains for vehicles and energy markets to improve scalability and resource allocation. While these approaches enable secure and decentralized transactions, optimizing EV energy utilization in trading systems remains a key challenge.

B. Vehicle-to-Grid Energy Trading

Recent researches in the field of V2G interactions includes Gümrükcü 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.

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,

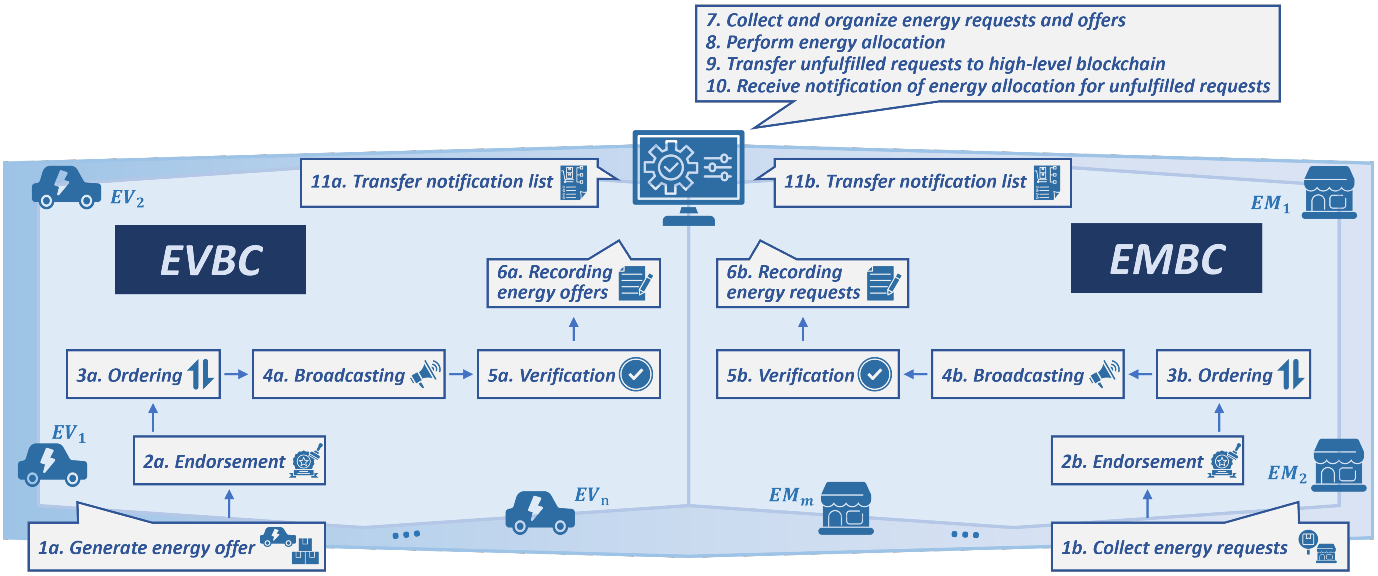

Fig. 2: A request-response blockchain in edge-driven dynamic two-tier V2G, comprising the electric vehicles blockchain (EVBC) and the energy market blockchain (EMBC). The workflow details the process from generating energy offers and collecting energy requests to completing energy allocation and transferring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

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 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.

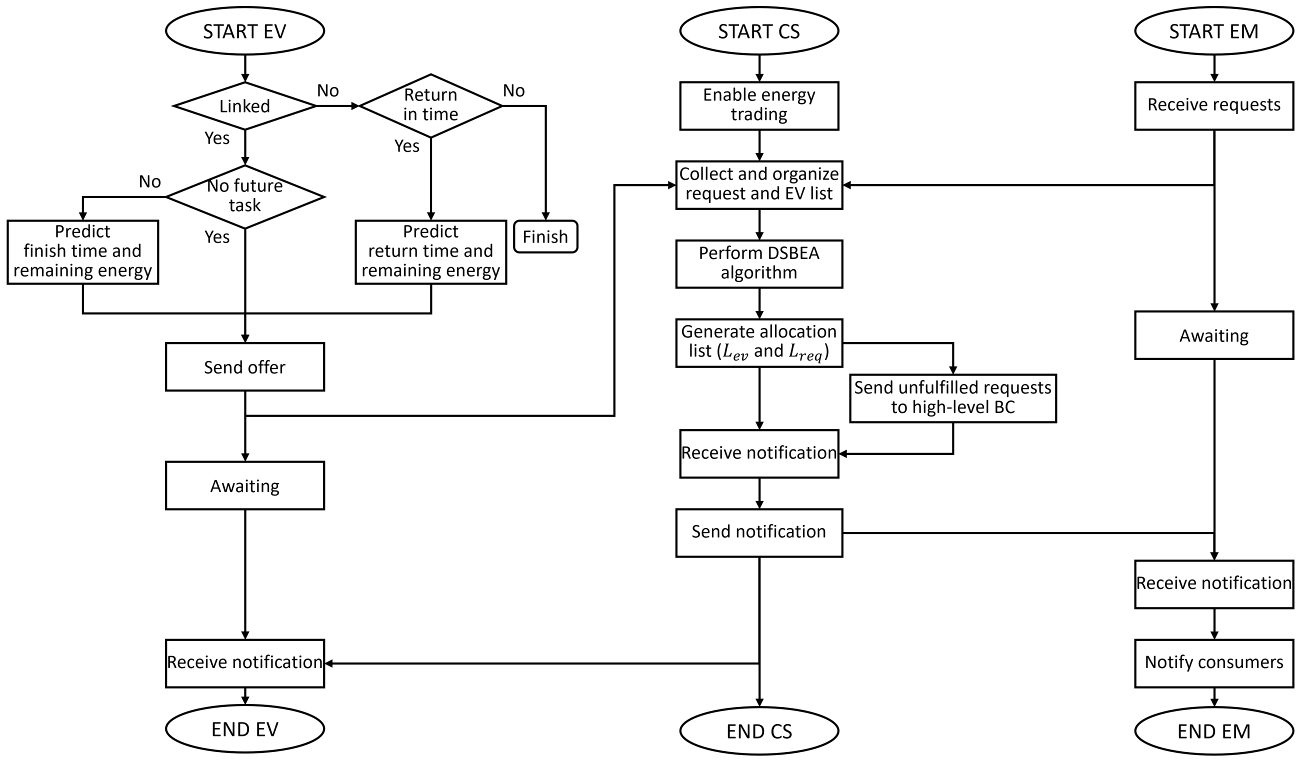

Fig. 3: Flowchart depicting the operational procedure of energy allocation between electric vehicles and energy markets through the control system in a dual blockchain architecture.

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:

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

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:

$$PP_i = E_i^{dem} \times B_i \tag{2}$$

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:

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

  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:

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

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

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

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

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

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

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

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

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:

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

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.

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.

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

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 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

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

Input: Request list $\mathbf{R}$, EV list $\mathbf{EV}$
Output: Discharge allocation list L^{dis}
Step 1: Preprocessing
  Calculate energy demand for all Req_i in $\mathbf{R}$
  Calculate profit potential for all Req_i in $\mathbf{R}$
  Sort $\mathbf{R}$ by profit potential in descending order
Step 2: EV selection and potential calculation
  For each Req_i in $\mathbf{R}$ do
    Step 2.1: Initialization
    $EligibleEV$: Temporary list of available EVs
    $SumPT$: Temporary summation of trading potentials
    Step 2.2: Calculate single EV's trading potential
    For each EV_j in $\mathbf{EV}$ do
      If $State_j$ allows and E_j^{rem} is sufficient
        Calculate trading potential $PT_{i,j}$
        Append EV_j and $PT_{i,j}$ to $EligibleEV$
    Step 2.3: Calculate EV's total trading potential
    For each $(EV_j, PT_{i,j})$ in $EligibleEV$ do
      $SumPT \leftarrow SumPT + PT_{i,j}$
    Step 2.4: Decide EV allocation and update list
      If $SumPT \geq E_i^{dem}$ then
        Break from the loop
      If $SumPT < E_i^{dem}$ then
      Move on to next request
    Else
        If $PT_{i,j} \geq E_i^{dem}$ then
          Allocate EV_j to Req_i
          Update E_j^{rem} and $State_j$
          Add entry to discharge list
    If no single EV_j can meet Req_i then
      Use multiple EV_j to fulfill Req_i
      Update discharge list and EV_j status accordingly
    If Req_i cannot be met, add to unmet requests list
  Return discharge list

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 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

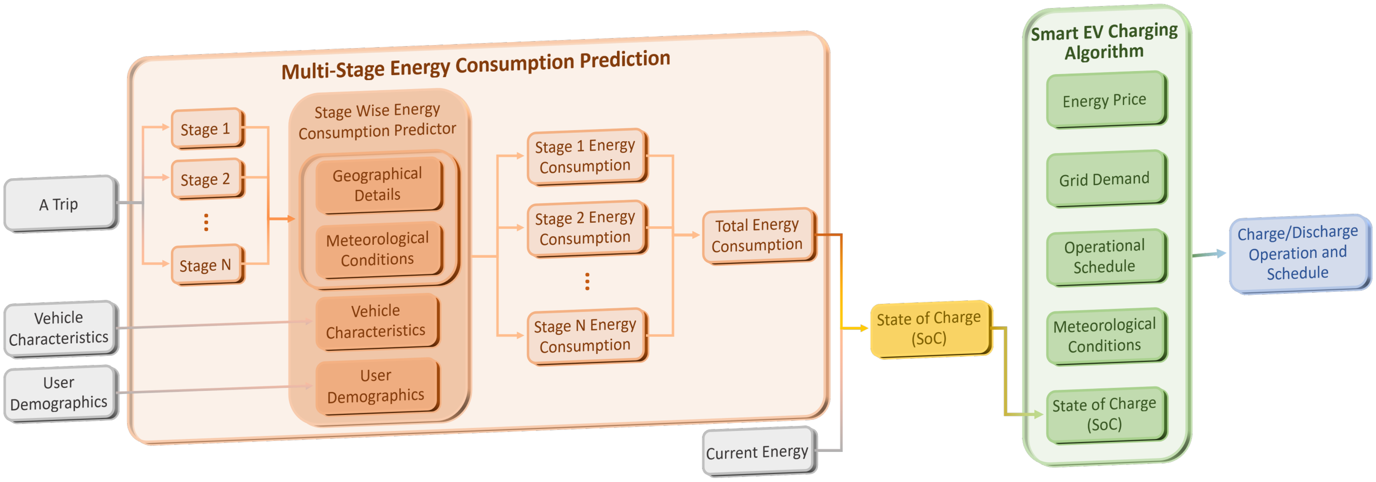

Fig. 4: Smart EV Charging Management and Scheduling with an Energy Consumption Prediction Method.

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

$$N_i^{tx} = \lceil \frac{N_i^{req} \times s^{req}}{s^{tx}} \rceil \tag{9}$$

The total time for endorsing all transactions is formulated by

$$T_i^{rc,endo} = N_i^{tx} \times t_i^{rc,endo} \tag{10}$$

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 $T_i^{rc,order}$, $T_i^{rc,bcst}$, 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:

$$T_i^{rc,total} = T_i^{rc,endo} + T_i^{rc,order} + T_i^{rc,bcst} + T_i^{rc,ver} + T_i^{rc,rec} \tag{11}$$

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:

$$\begin{aligned} T^{rc,EM} = max(&T_1^{rc,total} + T_1^{rc,proc}, T_2^{rc,total} + T_2^{rc,proc}, \\ &..., T_{N_{em}}^{rc,total} + T_{N_{em}}^{rc,proc}) \end{aligned} \tag{12}$$

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

$$N_j^{tx} = \lceil \frac{N_j^{offer} \times s^{offer}}{s^{tx}} \rceil \tag{13}$$

The total time for endorsing all transactions is formulated by

$$T_j^{oc,endo} = N_j^{tx} \times t_j^{oc,endo} \tag{14}$$

Where $t_j^{rc,endo}$ 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 $T_j^{oc,order}$, $T_j^{oc,bcst}$, 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:

$$T_j^{oc,total} = T_j^{oc,endo} + T_j^{oc,order} + T_j^{oc,bcst} + T_j^{oc,ver} + T_j^{oc,rec} \tag{15}$$

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:

$$\begin{aligned} T^{oc,EV} = max(&T_1^{oc,total} + T_1^{oc,proc}, T_2^{oc,total} + T_2^{oc,proc}, \\ &..., T_{N_{ev}}^{oc,total} + T_{N_{ev}}^{rc,proc}) + T^{oc,org} \end{aligned} \tag{16}$$

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:

$$S_{un} = N_{un}^{req} \times s^{req} + N_{un}^{offer} \times s^{offer} \tag{17}$$

The number of transactions is formulated as:

$$N_{un}^{tx} = \lceil S_{un}/s_{tx} \rceil \tag{18}$$

The total time for endorsing all transactions is formulated by:

$$T_{un}^{endo} = N_{un}^{tx} \times t_{un}^{endo} \tag{19}$$

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:

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

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:

$$S_{mat} = N_{mat} \times s_{mat} \tag{21}$$

The number of transactions is formulated as:

$$N_{mat}^{tx} = \lceil S_{mat}/s_{tx} \rceil \tag{22}$$

The total time for endorsing all transactions is formulated by:

$$T_{mat}^{endo} = N_{mat}^{tx} \times t_{mat}^{endo} \tag{23}$$

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:

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

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:

$$S_{sel}^{req} = N_{sel}^{req} \times s_{sel}^{req} \tag{25}$$

The number of transactions is formulated as:

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

The total time for endorsing all transactions is formulated by:

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

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:

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

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:

$$S_{sel}^{ev} = N_{sel}^{ev} \times s_{sel}^{ev} \tag{29}$$

The number of transactions is formulated as:

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

The total time for endorsing all transactions is formulated by:

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

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:

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

IV. Evaluation

A. Evaluation Methodology

We first evaluate the time cost of a single trading round under three blockchain architectures: V2GNet [14], V2GFTN [15], and the proposed dynamic two-tier V2G. Table II summarizes their architectural features, request processing methods, allocation strategies, and scalability considerations. V2GNet and V2GFTN both apply static one-shot matching strategies. V2GFTN also requires global synchronization across subnetworks, which increases communication overhead. In contrast, our two-tier architecture uses localized matching with dynamic EV status updates through DSBEA, resulting in reduced communication and improved scalability. The following evaluation examines time cost, energy fulfillment, and profit. We also assess the time cost associated with blockchain operations in EMBC and EVBC. Parameters are defined to represent the number of energy markets, the volume of requests and EVs, transaction sizes, and the size of requests, offers, and notifications. Blockchain phase durations

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						

include endorsement, ordering, broadcasting, verification, and recording. The simulation is implemented in Python, based on the Blocksim structure [39], with parameter configurations adapted to the proposed system. Tables III and IV provide the full blockchain configuration.

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

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.
- 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 includes EV and request lists generated using the parameters in Table V, following modeling assumptions that reflect typical V2G scenarios. DSBEA is tested under various combinations of EV counts and request volumes.

To evaluate robustness, we conduct an additional experiment involving 180 requests and 75 EVs, where 20 percent of the requests come from attacker consumers. These requests fully participate in the allocation process but do not perform energy transactions, leading to energy waste. This setup allows us to test the system's ability to mitigate malicious behavior.

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

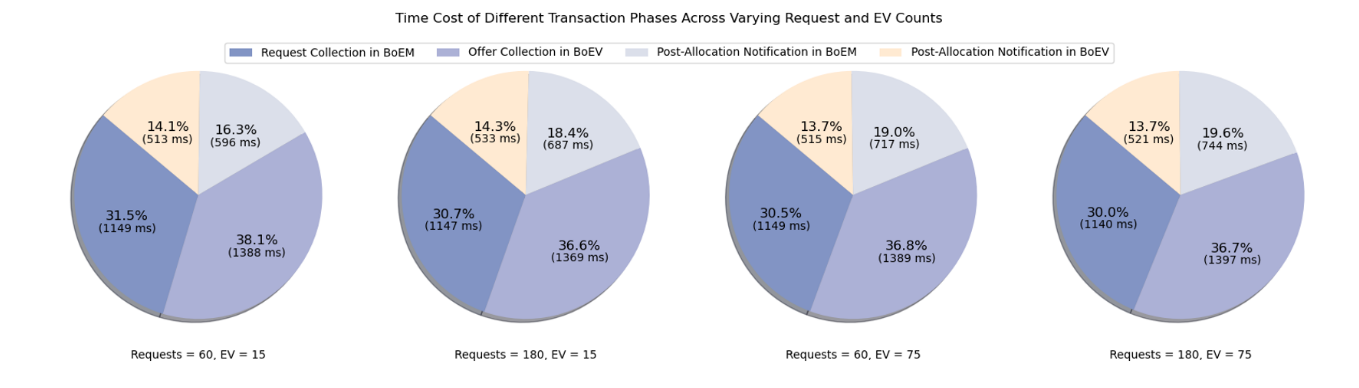

Fig. 5: Evaluation of the time cost distribution of transaction phases in different scenarios, illustrated by pie charts. These charts compare systems with different volumes of requests (60 or 180) and electric vehicles (15 or 75). The sequence illustrates the increasing complexity and responsiveness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

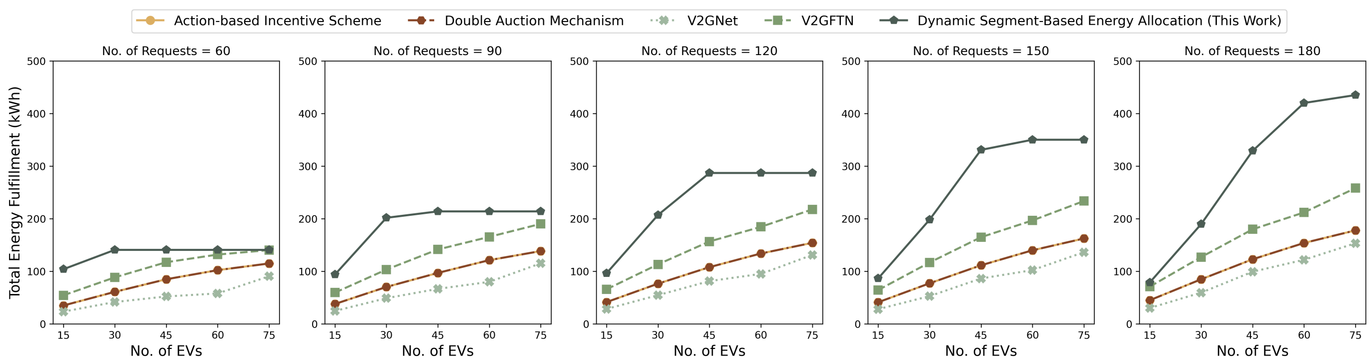

Fig. 6: Evaluation of trading strategies of action-based incentive scheme [40], double auction mechanism [41], V2GNet [14], V2GFTN [15], and the proposed work on sum fulfillment. Different combinations of EVs and request amounts were investigated.

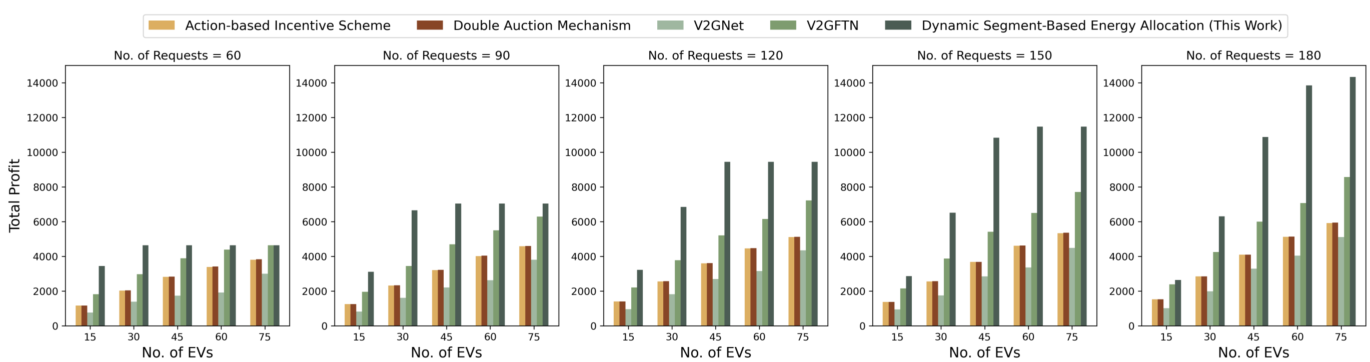

Fig. 7: Evaluation of trading strategies of action-based incentive scheme, double auction mechanism, V2GNet, V2GFTN, and the proposed work on total profit. Different combinations of EVs and request amounts were investigated.

We first evaluate the time distribution across blockchain transaction phases under varying numbers of requests and EVs. As shown in Figure 5, the share of time spent on request collection (30.0–31.5%) and offer collection (36.6–38.1%) remains nearly constant, with minimal variation in the two notification phases. Absolute time costs are also stable, with the largest deviation observed being only 148 ms, indicating good scalability. Table VI further confirms efficiency. For 60 requests and 45 EVs, the proposed method completes trading in 8.68 seconds, which is 42% faster than V2GNet and 55% faster than V2GFTN. Under larger-scale settings with 180 requests and 75 EVs, the time cost is 16.28 seconds, representing a reduction of nearly 80% compared to V2GFTN.

Regarding allocation performance, DSBEA consistently outperforms baseline algorithms. As shown in Figure 6, it achieves up to 400 kWh of energy fulfillment with 75 EVs, whereas the action-based and double auction schemes deliver less than 200 kWh under the same conditions. V2GFTN reaches a maximum of approximately 250 units. In Figure 7, DSBEA attains a total profit of 14,300 JPY, which is 67%

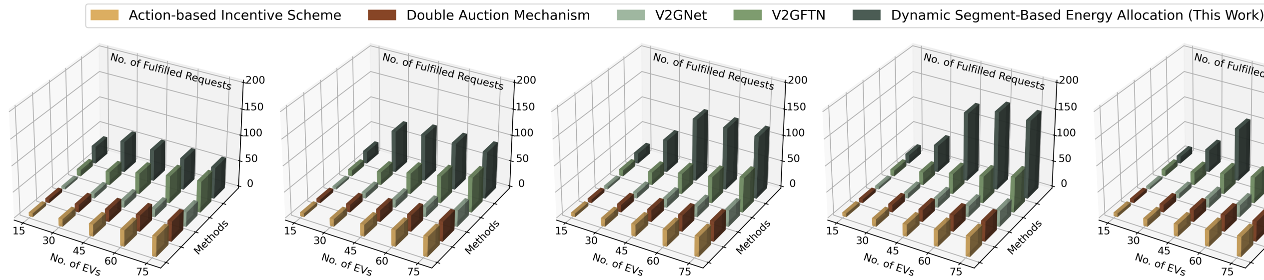

Fig. 8: Evaluation of trading strategies of action-based incentive scheme, double auction mechanism, V2GNet, V2GFTN, and the proposed work on the number of fulfilled energy requests. Different combinations of EVs and request amounts were investigated.

higher than the 8,540 JPY generated by V2GFTN. Figure 8 further shows that DSBEA can fulfill up to three times as many requests as competing methods, particularly under limited EV availability.

Performance gains 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.

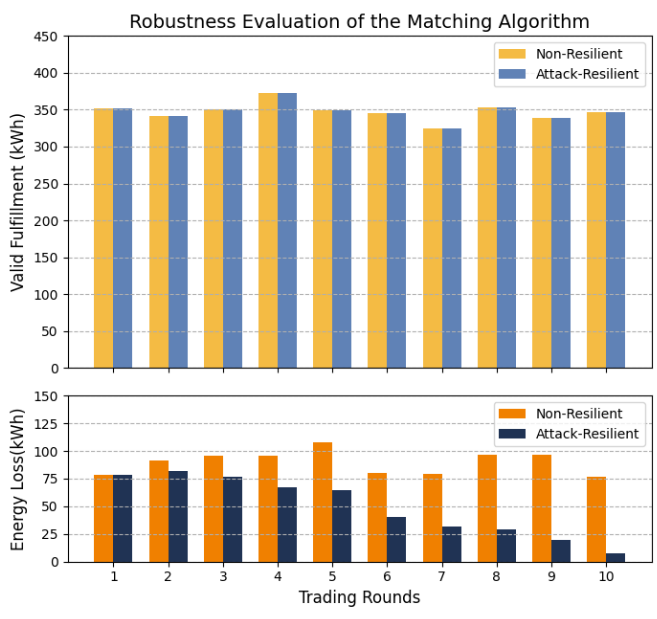

Fig. 9: Evaluation of the proposed algorithm regarding robustness against consumer attackers. The top plot shows the valid energy fulfillment delivered to legitimate consumers under non-resilient and attack-resilient configurations. The bottom plot illustrates the corresponding energy loss due to attacker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

To evaluate the robustness of the proposed algorithm, we simulated a scenario where 20% of energy requests came from attackers who joined allocation but did not complete transactions. As shown in Figure 9, both the non-resilient and attack-resistant configurations achieved a similar effective energy fulfillment of about 348 kWh per round. However, the resistant configuration reduced average energy loss from 90 kWh to 46 kWh per round (a 49% reduction) and cut losses by over 90% from the first to the last round, demonstrating its effectiveness in suppressing attackers over time.

V. Discussion

The proposed DSBEA algorithm, embedded in a two-tier blockchain framework, improves EV energy management by dynamically updating allocation decisions based on real-time status. Unlike static methods, it accommodates practical constraints such as power limits, time windows, and pricing, enabling flexible and realistic matching. It also shows resilience against attacker requests, reducing energy loss through adaptive penalization.

However, challenges remain. Urgent requests with minimal notice and sudden EV unavailability complicate planning. Participation in multiple markets and lack of EV-to-EV communication further increase system complexity. Economic mechanisms like dynamic pricing are not yet fully integrated, as the system currently operates with single-round allocation and fixed offers. Scalability and deployment raise additional concerns. While the tiered blockchain reduces overhead, large-scale scenarios may require advanced consensus methods—such as sharding or proof-of-stake (PoS)—to ensure performance, as demonstrated in Ethereum 2.0 [42] and Polkadot [43]. Furthermore, modeling of network congestion, dynamic loads, and communication reliability (e.g., fault tolerance) remains essential for real-world implementation.

The system holds promise for smart cities and microgrids, where dynamic trading and renewable integration are key to future sustainable energy ecosystems.

VI. Conclusion

This paper introduced a dynamic two-tier blockchain system with the DSBEA algorithm for V2G energy trading. By processing most transactions locally and delegating only residual tasks to the upper blockchain, the system cuts communication overhead by up to 80% while boosting energy fulfillment and profit by over 67% compared with baselines. DSBEA also remains effective under adversarial conditions by penalizing malicious requests.

Future work will address urgent, short-notice requests, integrate dynamic pricing and multi-round allocation, and enhance blockchain scalability to enable broader, real-time deployment in large-scale energy trading environments.

REFERENCES

[1] P. Chen, L. Han, G. Xin, A. Zhang, H. Ren, and F. Wang. Game theory based optimal pricing strategy for v2g participating in demand response. *IEEE Transactions on Industry Applications*, 59(4):4673–4683, 2023.

[2] S. Zhang and K.-C. Leung. Joint optimal power flow routing and vehicle-to-grid scheduling: Theory and algorithms. *IEEE Transactions on Intelligent Transportation Systems*, 23(1):499–512, 2022.

[3] D. Said and H. T. Mouftah. A novel electric vehicles charging/discharging management protocol based on queuing model. *IEEE Transactions on Intelligent Vehicles*, 5(1):100–111, 2020.

[4] Japan Bidirectional Charger Market Share Insights. https://www.linkedin.com/pulse/japan-bidirectional-charger-market-share-pd5mf/. Accessed: November 13, 2024.

[5] A. Ghosh and V. Aggarwal. Menu-based pricing for charging of electric vehicles with vehicle-to-grid service. *IEEE Transactions on Vehicular Technology*, 67(11):10268–10280, 2018.

[6] H. Liang, Y. Liu, F. Li, and Y. Shen. Dynamic economic/emission dispatch including pevs for peak shaving and valley filling. *IEEE Transactions on Industrial Electronics*, 66(4):2880–2890, 2019.

[7] J. Guo, X. Ding, and W. Wu. An architecture for distributed energies trading in byzantine-based blockchains. *IEEE Transactions on Green Communications and Networking*, 6(2):1216–1230, 2022.

[8] W. Hua, Y. Zhou, M. Qadrdan, J. Wu, and N. Jenkins. Blockchain enabled decentralized local electricity markets with flexibility from heating sources. *IEEE Transactions on Smart Grid*, 14(2):1607–1620, 2022.

[9] A. Miglani and N. Kumar. A blockchain based matching game for content sharing in content-centric vehicle-to-grid network scenarios. *IEEE Transactions on Intelligent Transportation Systems*, 25(5):4032–4048, 2024.

[10] Z. Wan, T. Zhang, W. Liu, M. Wang, and L. Zhu. Decentralized privacy-preserving fair exchange scheme for v2g based on blockchain. *IEEE Transactions on Dependable and Secure Computing*, 19(4):2442–2456, 2022.

[11] X. Fang, W. Zhang, Y. Guo, J. Wang, M. Wang, and S. Li. A novel reinforced deep rnn–lstm algorithm: Energy management forecasting case study. *IEEE Transactions on Industrial Informatics*, 18(8):5698–5704, 2022.

[12] S.-H. Hong and H.-S. Lee. Robust energy management system with safe reinforcement learning using short-horizon forecasts. *IEEE Transactions on Smart Grid*, 14(3):2485–2488, 2023.

[13] Yuxiao Liang. *Trustworthy Energy Trading System and Algorithms in Distributed Vehicle-to-Grid Network*. Ph.d. dissertation, The University of Aizu, 2024.

[14] Y. Liang, Z. Wang, and A. B. Abdallah. V2GNet: Robust blockchain-based energy trading method and implementation in vehicle-to-grid network. *IEEE Access*, 10:131442–131455, 2022.

[15] Y. Liang, Z. Wang, and A. B. Abdallah. Robust vehicle-to-grid energy trading method based on smart forecast and multi-blockchain network. *IEEE Access*, 12:8135–8153, 2024.

[16] M. S. Abegaz, H. N. Abishu, Y. H. Yacob, T. A. Ayall, A. Erbad, and M. Guizani. Blockchain-based resource trading in multi-uav-assisted industrial iot networks: A multi-agent drl approach. *IEEE Transactions on Network and Service Management*, 20(1):166–181, 2023.

[17] K. Zhao, M. Zhang, R. Lu, and C. Shen. A secure intra-regional-inter-regional peer-to-peer electricity trading system for electric vehicles. *IEEE Transactions on Vehicular Technology*, 71(12):12576–12587, 2022.

[18] 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 Transactions on Systems, Man, and Cybernetics: Systems*, 50(1):43–57, 2019.

[19] A. Barnawi, S. Aggarwal, N. Kumar, D. M. Alghazzawi, B. Alzahrani, and M. Boulares. Path planning for energy management of smart maritime electric vehicles: A blockchain-based solution. *IEEE Transactions on Intelligent Transportation Systems*, 24(2):2282–2295, 2021.

[20] Y.-J. Lin, Y.-C. Chen, J.-Y. Zheng, D. Chu, D.-W. Shao, and H.-T. Yang. Blockchain power trading and energy management platform. *IEEE Access*, 10:75932–75948, 2022.

[21] V. Hassija, V. Chamola, S. Garg, D. N. G. Krishna, G. Kaddoum, and D. N. K. Jayakody. A blockchain-based framework for lightweight data sharing and energy trading in v2g network. *IEEE Transactions on Vehicular Technology*, 69(6):5799–5812, 2020.

[22] S. Aggarwal and N. Kumar. A consortium blockchain-based energy trading for demand response management in vehicle-to-grid. *IEEE Transactions on Vehicular Technology*, 70(9):9480–9494, 2021.

[23] L. Zhang, L. Cheng, F. Alsokhiry, and M. A. Mohamed. A novel stochastic blockchain-based energy management in smart cities using v2s and v2g. *IEEE Transactions on Intelligent Transportation Systems*, 24(1):915–922, 2022.

[24] A. Miglani and N. Kumar. Blockchain-based co-operative caching for secure content delivery in ccn-enabled v2g networks. *IEEE Transactions on Vehicular Technology*, 72(4):5274–5289, 2022.

[25] E. Gümrükcü, J. R. A. Klemets, J. A. Suul, F. Ponci, and A. Monti. Decentralized energy management concept for urban charging hubs with multiple v2g aggregators. *IEEE Transactions on Transportation Electrification*, 9(2):2367–2381, 2023.

[26] P. Liu, Z. Liu, N. Zhang, and F. Lin. Cooperative game-based charging-discharging efficiency optimization of electric vehicles in 6g-enabled v2g. *IEEE Transactions on Green Communications and Networking*, 7(2):1078–1089, 2022.

[27] Q. Huang, L. Yang, Q.-S. Jia, Y. Qi, C. Zhou, and X. Guan. A simulation-based primal-dual approach for constrained v2g scheduling in a microgrid of building. *IEEE Transactions on Automation Science and Engineering*, 20(3):1851–1863, 2023.

[28] Y. Tao, J. Qiu, S. Lai, X. Sun, Y. Wang, and J. Zhao. Data-driven matching protocol for vehicle-to-vehicle energy management considering privacy preservation. *IEEE Transactions on Transportation Electrification*, 9(1):968–980, 2023.

[29] I. Ahmed, M. Rehan, A. Basit, M. Tufail, and K. Hong. A dynamic optimal scheduling strategy for multi-charging scenarios of plug-in-electric vehicles over a smart grid. *IEEE Access*, 11:28992–29008, 2023.

[30] X. Cheng, T. Mamalis, S. Bose, and L. R. Varshney. On carsharing platforms with electric vehicles as energy service providers. *IEEE Transactions on Intelligent Transportation Systems*, 25(7):8158–8170, 2024.

[31] M. B. Hossain, S. R. Pokhrel, and H. L. Vu. Efficient and private scheduling of wireless electric vehicles charging using reinforcement learning. *IEEE Transactions on Intelligent Transportation Systems*, 24(4):4089–4102, 2023.

[32] S. R. Pokhrel, M. B. Hossain, and A. Walid. Modeling practically private wireless vehicle to grid system with federated reinforcement learning. *IEEE Transactions on Services Computing*, 17(3):1044–1055, 2024.

[33] G. Shen, C. Xia, Y. Li, H. Shen, W. Meng, and M. Zhang. Traceable and privacy-preserving authentication scheme for energy trading in v2g networks. *IEEE Internet of Things Journal*, 11(4):6664–6676, 2024.

[34] Z. Meng, Y. Guo, W. Tang, and H. Sun. Nonparametric multivariate probability density forecast in smart grids with deep learning. *IEEE Transactions on Power Systems*, 38(5):4900–4915, 2023.

[35] J. Liang and W. Tang. Ultra-short-term spatiotemporal forecasting of renewable resources: An attention temporal convolutional network-based approach. *IEEE Transactions on Smart Grid*, 13(5):3798–3812, 2022.

[36] Y. Li, L. Song, S. Zhang, L. Kraus, T. Adcox, R. Willardson, A. Komandur, and N. Lu. A tcn-based hybrid forecasting framework for hours-ahead utility-scale pv forecasting. *IEEE Transactions on Smart Grid*, 14(5):4073–4085, 2023.

[37] Huakun Huang, Mark Ogbodo, Zhishang Wang, Chen Qiu, Masayuki Hisada, and Abderazek Ben Abdallah. Smart energy management system based on reconfigurable ai chip and electrical vehicles. In *2021 IEEE International Conference on Big Data and Smart Computing (BigComp)*, pages 233–238. IEEE, 2021.

[38] Z. Wang and A. B. Abdallah. A robust multi-stage power consumption prediction method in a semi-decentralized network of electric vehicles. *IEEE Access*, 10:37082–37096, 2022.

[39] Maher Alharby and Aad van Moorsel. Blocksim: An extensible simulation tool for blockchain systems. *arXiv preprint arXiv:2004.13438*, 2020.

[40] O. T. T. Kim, T. H. T. Le, et al. Distributed auction-based incentive mechanism for energy trading between electric vehicles and mobile charging stations. *IEEE Access*, 10:56331–56347, 2022.

[41] A. Yassine, M. S. Hossain, G. Muhammad, and M. Guizani. Double auction mechanisms for dynamic autonomous electric vehicles energy trading. *IEEE Transactions on Vehicular Technology*, 68(8):7466–7476, 2019.

[42] Mikel Cortes-Goicoechea, Luca Franceschini, and Leonardo Bautista-Gomez. Resource analysis of ethereum 2.0 clients. In *2021 3rd*

Conference on Blockchain Research & Applications for Innovative Networks and Services (BRAINS), pages 1–8. IEEE, 2021.

[43] Hanaa Abbas, Maurantonio Caprolu, and Roberto Di Pietro. Analysis of polkadot: Architecture, internals, and contradictions. In *2022 IEEE International Conference on Blockchain (Blockchain)*, pages 61–70. IEEE, 2022.

Zhishang Wang received the M.S. degree in computer science from University of Freiburg, Germany, in 2019, and the Ph.D. degree in computer science from The University of Aizu, Japan, in 2023. From April 2023 to March 2025, he was a postdoctoral researcher at the University of Aizu. Since April 2025, he has been an assistant professor with the Division of Computer Engineering, Department of Computer Science and Engineering, The University of Aizu. His current research interests are in the field of Machine Learning Systems, Edge Computing, Blockchain, and Trustworthy AI. He is also interested in event-driven neuromorphic systems targeted for a new generation of brain-inspired computing technologies and adaptive edge computing systems.

Yuxiao Liang received his B.S. degree in civil engineering from Tianjin University, China, in 2016 and an M.S. degree in geotechnical engineering from the China University of Mining and Technology, China, in 2020. He received the Ph.D. degree in computer science and engineering from the University of Aizu, Japan, in March 2024. He is currently an Assistant Professor with the School of Management Science & Engineering, Shanxi University of Finance and Economics, Taiyuan, China. He is working on economic analysis of new productive force, carbon neutrality & emissions control, and emergency management & safety engineering.

Achraf Ben Ahmed received his MSE and PhD degrees in computer science and engineering from the University of Aizu, Japan, in 2013 and 2016, respectively. After one year as a postdoctoral researcher in Tokyo at the University of Electro-Communications, he joined, in 2017, one of Japan's leading market research companies, where he works in R&D to develop advanced computational tools aimed at enhancing contactless technologies for human behavior analysis. His research focuses on developing contactless real-time biosignal gathering and analysis systems, particularly for consumer behavior and driving safety. His research interests include power-efficient computing, AI-driven contactless systems, and software-defined vehicles. He is a member of IEEE.

Khanh N. Dang is an Associate Professor in the Division of Computer Engineering, Department of Computer Science and Engineering, the University of Aizu. Before joining the University of Aizu as a faculty, an assistant professor at Vietnam National University Hanoi, Vietnam. He received his Ph.D. and M.Sc. degrees from the University of Aizu and Paris-Sud University, France, in 2017 and 2014, respectively. His research interests include VLSI design, thermal awareness, fault tolerance, and neuromorphic computing.

Abderazek Ben Abdallah is a Full Professor at the University of Aizu, Japan, serving as Regent and Dean of the School of Computer Science and Engineering since April 2022. Previously, he was Head of the Computer Engineering Division (2014–2022). Dr. Ben Abdallah holds a Ph.D. in Computer Engineering from the University of Electro-communications (UEC), Tokyo, in 2002. With 20+ years in academia and research, his expertise spans computer architecture, neuromorphic circuits and systems, advanced on-chip interconnects, fault-tolerance and reliability, and embedded systems. He has authored four books, published 160+ papers, secured 15 grants, and holds 14 patents. He has led multiple research projects in collaboration with industry, including pioneering the first AI-chip-powered off-grid solar carport for renewable energy (2022–2023). He also spearheaded a parallel processor design project (2002–2007). He is a Senior Member of IEEE and ACM, as well as a member of Sigma Xi - The Scientific Research Honor Society.