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RESEARCH ARTICLE

Robust Vehicle-to-Grid Energy Trading Method Based on Smart Forecast and Multi-Blockchain Network

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ABSTRACT In the present era, energy issues are a significant concern, and the energy trading market is the crucial sector to facilitate supply-demand balance and sustainable development. For better demand response and grid balancing, vehicle-to-grid (V2G) technology is rapidly gaining importance in energy markets. To narrow the gap between ideal V2G goals and actual applications needs, energy trading system has to overcome the challenges of over-centralized structure, inflexible timeline adaptation, limited market scale and energy efficiency, excessive feedback time costs, and low rate of economic return. To address these issues and ensure a secure energy market, we propose a decentralized intelligent V2G system called V2G Forecasting and Trading Network (V2GFTN) to achieve efficient and robust energy trading in campus EV networks. A multiple blockchain structure is proposed in V2GFTN to ensure trading security and data privacy between energy requests and offers. V2GFTN also integrates energy forecasting functions for EVs with a smart energy trading and EV allocation mechanism called SRET so that the EVs with driving tasks can supply their extra power back to the grid and achieve higher energy efficiency and economic profit. Through rigorous experimentation and compared with equivalent studies, V2GFTN system has demonstrated higher economic profit and energy demand fill rate by up to 1.6 times and 1.9 times than the state-of-the-art V2G approaches.

INDEX TERMS Energy trading, vehicle-to-grid, energy forecast, multi-blockchain.

I. INTRODUCTION

In modern society, energy is a fundamental concern that impacts economic growth, environmental consequences, renewable transition, and geopolitical stability [4], [5], [6]. A reliable and efficient power supply is critical to industry, transportation, and economic stability on a national and even global scale [7], [8], [9]. Maintaining a stable power supply system requires balancing electricity supply and demand to avoid energy shortages or surpluses, and an effective energy trading market is one of the most effective ways to maintain supply-demand balance and ensure energy security [10]. Energy trading markets connect energy suppliers and consumers and encourage their competition, contributing to the efficient allocation of energy resources. In addition to improving efficiency and reducing waste, energy trading markets provide platforms for integrating renewable energy sources into the energy mix, facilitating a clean energy transition and industry innovation [11], [12]. Among all the technological advancements emerging in energy commercialization, vehicle-to-grid (V2G) occupies a significant position due to its potential to change how energy sources and networks are managed [13]. In short, V2G is a network that enables electric vehicles (EVs) to consume energy from the grid and return excess energy to the grid when needed.

V2G allows EV batteries to act as decentralized energy storage during high-demand periods, which is critical to reducing peak loads on the grid, aggregating solar and wind sources, reducing infrastructure investment, and promoting

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demand response [14], [15], [16], [17], [18]. The increasing number of EVs and EV users makes V2G a better solution than expensive peak load power plants [19]. While V2G is theoretically promising, its practical applications still face challenges related to efficiency, system stability, market size, incentive mechanisms, and consumer trust concerns. This is partly because current V2G infrastructure and participation in most regions have not reached the scale necessary to support viable energy markets, even though an ideal V2G network requires many EVs to contribute to flexible energy storage and balancing. Limited economic incentives in many areas exacerbate the situation, creating an urgent need for new decentralized solutions that provide a desired financial incentive for EV owners and energy consumers. In the meantime, consumer acceptance based on trust is necessary to promote the practical adoption and implementation of V2G markets, so privacy and security of V2G commerce also need to be improved [20]. Distributed databases, particularly blockchain, operate through a consensus process in a peer-to-peer network, eliminating the need for a central administrator and allowing individuals to regain control over their data. Introduced as a decentralized and immutable distributed ledger technology, blockchain ensures secure, authentic, and widely distributed data among network peers. Its features, like absence of a central authority in transactions, make it applicable across diverse domains, including trading, AI, data security, and IoT integrity [21]. Innovative blockchain-inspired mechanisms enhance security in V2G operations [22]. However, despite its potential, blockchain faces challenges, notably scalability concerns due to block size and latency tradeoffs, slow block propagation, and the risk of selfish mining strategies. Addressing these challenges is crucial for evaluating its performance and ability to manage trading data in various applications [23].

To accelerate the practical process of V2G trading, recent work identifies several solutions, including optimizing market participation mechanisms, developing flexible energy pricing strategies, engaging in multiple markets, optimizing battery management, establishing energy service contracts, and reducing transaction costs [13], [24], [25], [26], [27], [28], [29]. While these works help mitigate market access, transaction barriers, and power system constraints, the complexity and uncertainty of V2G markets are inevitably amplified as more vehicle owners participate in market competition. Uncertain market prices and demand make predicting the optimal timing for charging and discharging challenging. Besides, managing multiple energy markets requires additional monitoring to maintain demand response programs and prevent blackouts or brownouts during peak periods. These additional transaction costs and management fees can reduce the net economic returns of V2G trading, especially for small V2G participants.

In summary, the existing methods mainly focus on refining the bidding strategy to optimize profits for energy consumers and managing the allocation of tasks for discharging electric vehicles in parking lots. However, the remaining challenges are as follows. Firstly, current methods of energy trading primarily utilize parked electric vehicles as energy suppliers and overlook the potential contributions of driving vehicles. This approach limits the scope of available energy resources as it does not take into account vehicles that are actively on the move. Secondly, there is a significant gap in establishing an efficient matching system. Existing systems do not adequately pair energy consumers with appropriate suppliers, leading to inefficiencies in the distribution and utilization of energy resources. Thirdly, the integration of time constraints into the energy trading process is not sufficiently detailed. Previous methods assume a static scenario in which all EVs are parked and available for task distribution. However, for efficient energy management, the specific time period of energy demand and the periods when EVs are either busy or idle are crucial, especially in dynamic, real-world scenarios where vehicle availability fluctuates.

To address the above gaps and realize the potential of V2G technology, based on our previous work on V2GNet [1], as shown in Fig. 1 and NoEV [2], we propose V2GFTN, a smart campus V2G energy trading system for sharing EV fleets based on energy consumption forecasting and multiple blockchains. The architecture of V2GFTN is shown in Fig. 2. Each college campus's shared EV fleet is centrally managed and dispatched by a campus control system (CS) to achieve larger energy reserves and transactions. To keep privacy and information security at a smaller scale, a blockchain of energy exchanges (BoE) and a blockchain of EVs (BoEV) are established for energy consumers and suppliers, respectively, within the campus. In a single campus, the BoE and the BoEV intersect through CS. We also establish a novel blockchain of control systems (BoCS) to interconnect different campus V2G networks. Detailed selection and trading algorithms are also presented to accommodate different V2G scenarios. In addition, we provide an efficient solution for V2G energy trading, called the smart and robust energy trading algorithm (SRET), to optimize EV charging and discharging strategies. An energy forecast function based on the driving task data and EV conditions is also implied by the V2GFTN. The main contributions of this paper are summarized as follows:

- Our system consists of a multi-blockchain-based, cross-cluster V2G energy trading framework consisting of three key components: a blockchain for control systems (BoCS), a blockchain for energy supplier electric vehicles (BoEV) and a blockchain for energy exchanges (BoE), which communicates with energy consumers.
- We proposed a Smart and Robust Energy Trading algorithm (SRET) that is integrated into smart energy management systems. This algorithm refines vehicle charging and discharging strategies by adapting them to market dynamics and specific user requirements. In addition, the system deploys a predictive neural network to forecast dynamic energy consumption of EVs based on their driving tasks, which increases the effectiveness of our charging and discharging strategies.

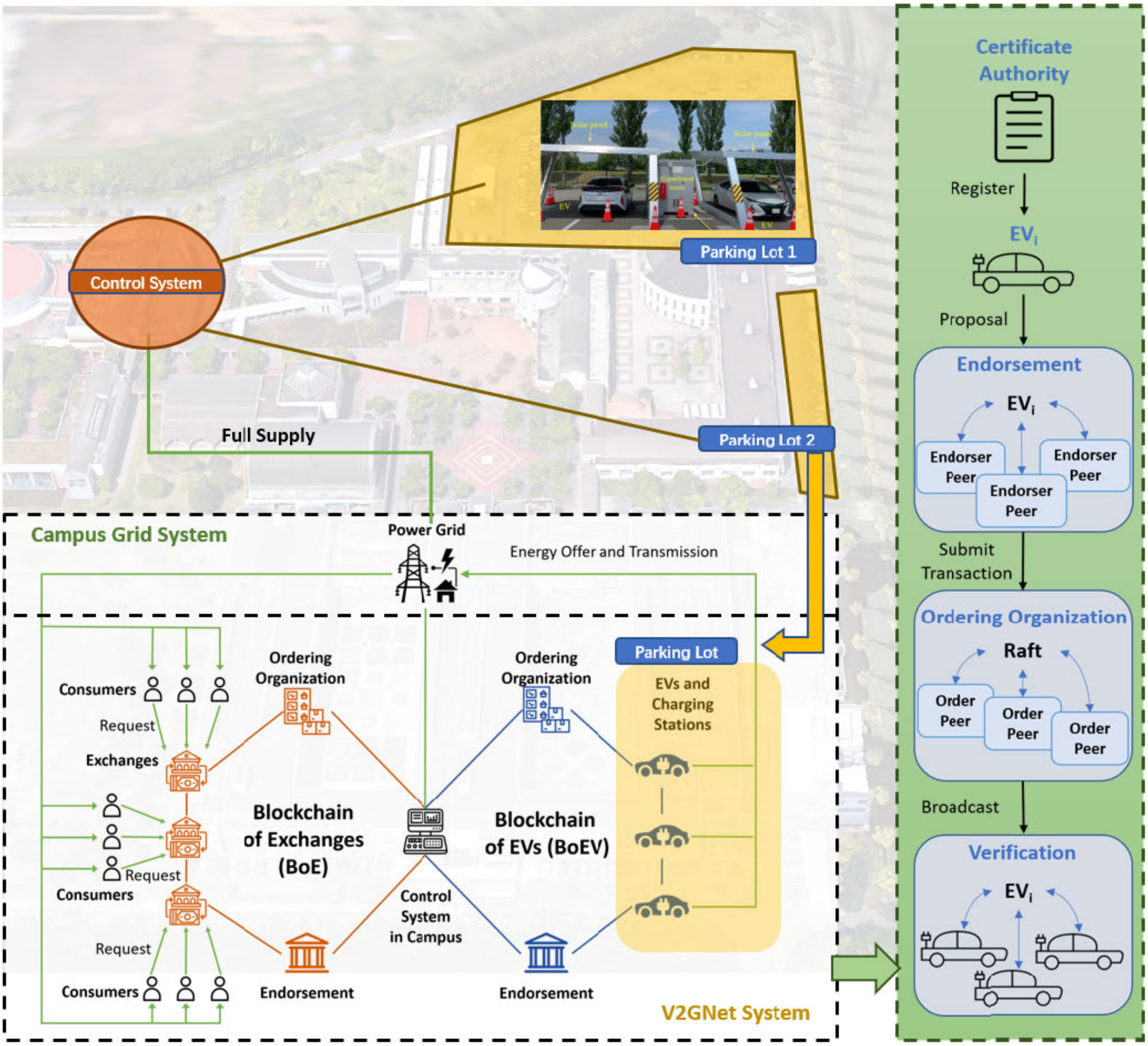


FIGURE 1. Overview of a bidirectional energy supply and trading system V2GNet [1]. To ensure a secure and efficient energy market, the system takes a virtual power plant as the control system of all the sharing EVs on a college campus, thus integrating a V2G aggregator and EV fleets in a blockchain-based energy trading system. To facilitate a seamless transmission of energy requests and offers, V2GNet incorporates two distinct consortium blockchains: the blockchain of energy exchanges (BoE) and the blockchain of EVs (BoEV).

- Our approach also introduces two innovative energy trading methods that streamline the entire process of energy requests and offers. These methods facilitate the efficient allocation of energy from EVs to consumers, using both double- and simple-time-boundary strategies for different trading scenarios.

The rest of this paper is organized as follows. Section II discusses the related works on vehicle-to-grid energy supply and trading, smart energy forecasting systems, and energy trading systems based on multiple blockchain networks. Section III presents the proposed V2GFTG, including the energy trading process, data storage and transmission across campuses based on multiple blockchains, the smart and robust energy trading algorithm, and a data analysis and energy forecasting function. Section IV provides the performance evaluation of the proposed V2GFTN system. In Section V and VI, some discussions and the conclusion are presented.

II. RELATED WORK

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

A. VEHICLE-TO-GRID ENERGY SUPPLY & TRADING

Chen et al. [13] proposed an optimal V2G pricing strategy using the Stackelberg game, setting EV users' benefits as game factors and creating EV users' benefit models with historical charging costs and inconvenience costs. Gümrükcü et al. [28] introduced decentralized management for urban charging stations, where EVs can access multiple charger clusters, each controlled by an aggregator. Since the work only prescribes daily schedules and power peaks of aggregators to constrain the energy supply of grid-to-vehicle and vehicle-to-grid services, it has difficulty dealing with the natural immediacy and fluidity of EV interactions in V2G scenarios. Huang et al. [29] formulated the V2G scheduling problem as a constrained Markov decision process and then developed a simulation-based primal-dual approach to decompose the original problem into a continuous optimization subproblem on the supply side and a discrete optimization subproblem on the demand side. In the work [30], a novel adaptive demand-side energy management framework was developed by employing federated learning-based privacy preservation for wireless charging V2G systems, which learns the temporal evolution of energy consumption of dynamic charging EVs in a distributed fashion and exploits the reinforcement learning model for cost-saving and reward maximization. Wan et al. [31] proposed V2GEx. This privacy-preserving fair exchange scheme comprises an extended blockchain that supports zero-knowledge funds, a fair exchange smart contract based on the hash chain micropayment mechanism, and a privacy-preserving protocol for V2G under the universal composability model. Though a simpler and more efficient scheme, Uni-V2GEx, was provided, the monetary costs of a complete V2GEx settlement session are still relatively high in gas consumption, which turns out to be one of the main shortcomings hindering the application of these rigorous secure V2G schemes on the public chain, especially in developing countries and areas. Tao et al. [32] presented a data-driven matching protocol for vehicle-to-vehicle energy management, utilizing deep reinforcement learning for the long-term reward of the matching action based on the formulated Markov decision process. A matching optimization model is established and converted into a bipartite graph problem to enhance the computation efficiency. However, the number of EVs covered in the energy framework is relatively tiny compared with many vehicles needing short-term energy trading in current communities and campuses.

B. SMART ENERGY FORECASTING SYSTEMS

The original hybrid deep learning algorithm in the work [33] was developed to make a computer-assisted forecasting energy management system, and a Hankel matrix is created for processing gathered automatic metering infrastructure load information by applying the Copula function. A robust energy management system in work [34] with an inconsistent energy supply aiming to minimize energy costs while avoiding failing to satisfy energy demands was proposed through an algorithm based on safe reinforcement learning, which can effectively exploit short-horizon forecasts on system uncertainties. Authors in [35] proposed an attention temporal convolutional network built on stacked dilated causal convolutional networks and attention mechanisms to perform the ultra-short-term spatiotemporal forecasting of renewable resources. In the work [36], the authors proposed a spatiotemporal decomposition agent for the unbundled smart meter based on artificial intelligence, which helps users optimize their energy usage and helps distribution system operators utilize building assets for grid operation. Deep learning models can customize the energy usage strategy developed for different users according to the different energy users' consumption habits. However, the uncertainty with EVs is not addressed, and the nonlinearity in the time-series data for the actual distribution grid operation is not fully considered. Meng et al. [37] proposed a nonparametric multivariate density forecast model based on deep learning, which offers the whole marginal distribution of each random variable in forecasting targets and reveals the future correlation between them. Authors in [38] identified a hybrid photovoltaic forecasting framework based on the temporal convolutional network for enhancing hours-ahead utility-scale PV forecasting. The formulated hybrid framework consists of two forecasting models: a physics-based trend forecasting model and a data-driven fluctuation forecasting model. However, the above-mentioned strategies were mostly adopted without containing a rapidly changing market. Considering that the edge nodes in V2G networks are prone to take swift vary through a few energy trading rounds, an hour-ahead robust V2G energy forecast mechanism is essential to achieve stable V2G marketing.

C. ENERGY TRADING SYSTEMS BASED ON MULTIPLE BLOCKCHAIN NETWORKS

The work in [39] discussed a resource trading environment of mobile devices and proposed a novel intelligent resource trading framework that integrates multi-agent deep reinforcement Learning, blockchain, and game theory to manage dynamic resource trading environments. However, the formulated optimization problem in a multi-agent environment is too complex and dynamic to solve directly by any game, particularly for the industrial Internet of Things. Guo et al. [40] proposed B-MET, a blockchain-based system trading multiple energies by executing a designed byzantine-based consensus mechanism that relies on nodes' credit model to improve throughput and cut latency. In the introduced credit model, a consensus is achieved by the sum of voting nodes' credits rather than their number. It is in accord with intuition but needs further rigorous mathematical derivation to prove its strict correctness. Zhao et al. [41] proposed a secure intra-regional-inter-regional peer-to-peer electricity trading system for EVs, where blockchain is introduced to support transaction payments and data security.

A trading prediction model based on ensemble learning was introduced to maximize the regional overall social welfare, and a super-modular game was taken to investigate neighbor regions' competition. One main limitation of the work is the lack of transaction data protection in their Ethereum module during the whole trading process, for the security and privacy of transaction payments and data storage are vital for integrating blockchain and energy trading systems. Hua et al. [42] designed a novel blockchain-based peer-to-peer trading architecture that integrates negotiation-based auction and pricing mechanisms in local electricity markets through automating, standardizing, and self-enforcing trading procedures by intelligent contracts. To analyze the balance between decentralization and platform performance in the controllable scenario of a smart grid, a fair and efficient main/side chain framework was introduced in the work [43] by exploring the scalability of blockchain. Lin et al. [44] combined artificial intelligence, the Internet of Things, and blockchain technology to create a vehicle-to-everything power trading and management platform to enable multi-level power transactions for EV charging stations around commercial buildings. Nevertheless, only 30 EV charging piles were simulated in the evaluation part, far from meeting rapidly increasing EVs' charging/discharging demands. The real-time supply and demand imbalance caused by the high proportion of renewable energy also poses a considerable challenge to blockchain-based learning networks.

III. V2G FORECASTING AND TRADING NETWORK

This section presents the integrated architecture of the proposed V2GFTN, focusing on an effective multi-blockchain energy trading approach in V2G networks. The V2GFTN system and its inherent SRET operational algorithms aim to fulfill a larger number of energy requests, higher energy demand, and better economic profit. These implicit objectives and the outcomes highlight how our V2G system contributes to maximizing operational energy efficiency and financial returns while enhancing the overall stability and resilience of the power grid. The section is divided into four parts: 1) Multi-blockchain-based V2G networks in V2GFTN; 2) Energy trading process in V2GFTN; 3) Smart and Robust Energy Trading (SRET) algorithm for V2GFTN; 4) Learning-enabled energy forecasting for EVs in V2GFTN.

The first subsection outlines the overarching structure of our proposed system, which includes a dedicated blockchain for customers, another for electric vehicles and an overarching blockchain for managing control systems. The second section then addresses the trading methods for energy consumers (customers) and suppliers (EVs). The third section presents the algorithm used to bring customers and electric vehicles together to facilitate the allocation of energy resources. In the fourth section, a method for predicting the power consumption of electric vehicles is presented. This approach aims to gain a more accurate understanding of the status of electric vehicles, especially in terms of battery information. This enhanced knowledge is crucial for improving the efficiency of energy management and maximizing the overall profit.

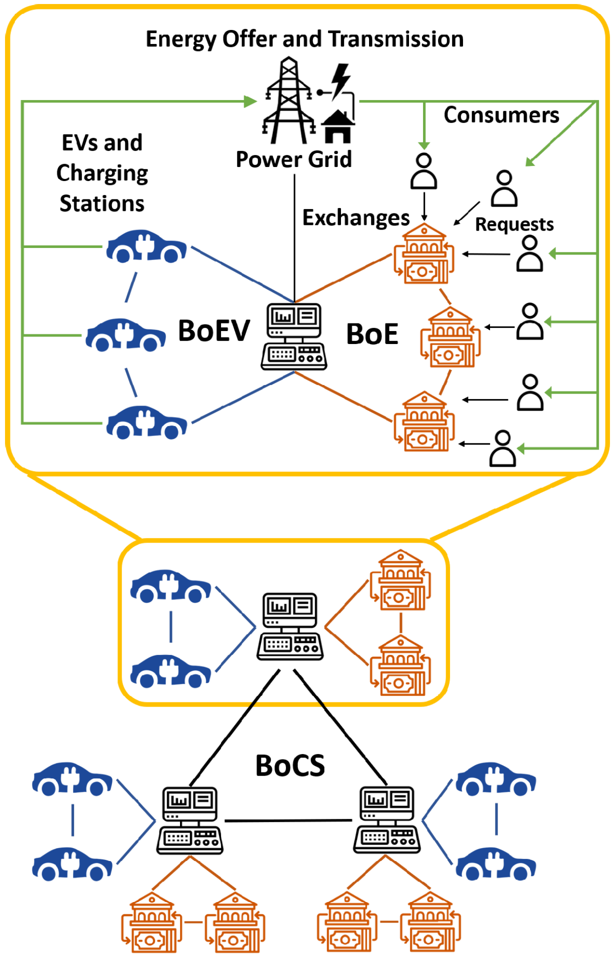


FIGURE 2. Overview of the proposed V2GFTN with the blockchain of campus control systems (BoCS), the blockchain of electric vehicles (BoEV), and the blockchain of exchanges (BoE). The BoCS is where inter-campus energy trading is planned and recorded, and each CS makes a node of the BoCS. Besides, each campus's CS works as an information mediator between energy consumers and EV suppliers and as a blockchain connection between the BoEV and BoE of each campus. Each BoEV integrates the EVs and CS for a single campus, where the energy offer lists (EVs to CS) and notification of discharge tasks (CS to EVs) are transmitted. Each BoE integrates the energy exchanges and CS for a single campus, where the energy request lists (exchanges to CS) and notifications of chosen consumers (CS to exchanges) are transmitted.

A. MULTI-BLOCKCHAIN-BASED V2G NETWORKS

The proposed V2GFTN blockchain network includes three parts: a blockchain of electric vehicles (BoEV), a blockchain of exchanges (BoE), and a blockchain of campus control systems (BoCS), as shown in Fig. 2. According to the workflow of the proposed energy trading algorithms, we divide the data storage and transmission into five parts: 1) Starting the operation of BoE; 2) Starting the operation of BoEV; 3) Preceding the operation of BoEV; 4) Preceding the operation of BoE; 5) Operating BoCS.

A detailed introduction of the proposed multi-blockchain architecture is given in Fig. 3. A blockchain network is a decentralized and immutable distributed ledger technology that ensures secure, authentic, and widely distributed data among network peers. It eliminates the need for a central administrator, allowing individuals to regain control over their data securely. The innovative multi-blockchain mechanism cuts the length of each chain and its time cost, helping to keep the privacy of peers. In summary, blockchain technology provides a secure and decentralized way to store and share data, making it an applicable solution for V2G operations. Here we choose consortium blockchains for the blockchain implementation, to avoid mining and cut time and energy consumption within and across blockchains. We take hyperledger fabric as a tool to integrate consortium blockchain and Raft as an ordering service.

The starting operation of each BoE commences with any of its energy exchange gathering and aggregating all energy requests from its affiliated consumers. These requests are then compiled into a comprehensive list encapsulated in a transaction. Subsequently, this transaction is broadcast across the BoE network, awaiting responses from other exchanges operating within the network. Each exchange is linked to a transaction pool. As transactions accumulate within this pool, the exchange proceeds to dispatch them for endorsement to a designated group of endorsing exchanges. Upon successful endorsement, the transactions move forward for ordering and packaging into a block facilitated by the ordering organization. This block is then disseminated across all energy exchanges for verification. Once the block's authenticity is verified, the CS of the campus linked to the BoE proceeds to download the block, extract the associated request lists, and consolidate these request lists to form a comprehensive and combined overall request list. Each transaction is authenticated by verifying the digital signatures of its originators, ensuring the legitimacy of each exchange within the BoEV, BoE and BoCS networks. In addition, the integrity of the blockchain is maintained through cryptographic verification, where the hash value of each new block is compared to that of its predecessor to ensure a secure and continuous chain. Crucial to the security of our network is the use of consensus algorithms that enable agreement between nodes on the validity of transactions, protecting against tampering and strengthening the reliability of the blockchain. These robust security protocols on the V2GFTN network are critical to maintaining a secure, trustworthy platform for energy trading, improving the resilience of the system and promoting trust between participants.

The initiation of operation in each BoEV commences when EV fleets within V2GFTN are informed of energy demands by their respective CS. Each EV, upon receiving the information, encapsulates its unique identity and energy-related data into a transaction, broadcasting it across the network of its BoEV. As the trading round progresses, every available EV within the network generates its respective transaction and shares it with others in the same BoEV. Once an EV collects all transactions for the trading round, the EV compiles these transactions and submits them for endorsement to a designated group of endorsing nodes. After endorsement, the transactions proceed to the ordering nodes, which are meticulously arranged in a fixed sequence and packaged into a new block. Subsequently, this newly formed block is disseminated across all EVs within the BoEV for verification. Upon successful verification, the CS linked to the BoEV downloads each EV's energy-related data and offers and aggregates them to form a comprehensive offer list.

The preceding operation of each BoEV begins once the CS completes the process of the planning phase. First, the CS generates a result list with the help of SRET, encompassing the selected EV suppliers. For an EV selected to supply energy, specific details like its unique ID, predicted time and energy consumption of driving tasks, and the quantity of energy supplied are recorded on this list. Conversely, the notation "*unselected*" is entered in the list if an EV isn't selected. This result list for the EVs is then securely stored in a transaction from the CS end. Subsequently, this transaction is presented for endorsement by the endorsing EVs. Following endorsement, the transaction is encapsulated into a block, systematically verified, and then downloaded and permanently recorded by the EV nodes of the BoEV. Upon completing this process, each EV within the BoEV extracts the result list with corresponding energy trading details from the block and discharges during the execution phase accordingly.

The preceding operation in the BoE unfolds when SRET generates the result list of chosen consumers. The unique ID of each selected consumer and its vital trading details, such as the energy supply duration, the energy trading price, etc. are recorded in the result list. Following the compilation of this result list for consumers, it is stored in a transaction within the CS and then subjected to endorsement by designated endorsing exchanges. Upon successful endorsement, the transaction is packaged into a block, systematically verified, and recorded within the exchange nodes of the BoE network. Upon completion of the process, every exchange within the BoE network extracts the result list containing the outcomes for the selected consumers and their respective energy deals from the downloaded block. Consequently, each exchange retains the trading specifics regarding its consumers and generates individual notifications accordingly. The notified consumers must finish payment clearing by the end of the execution phase.

The initial step in the BoCS begins once any CS completes the process of the preceding operations in its BoE and BoEV. When the result lists of chosen consumers and EVs are generated and uploaded to BoE and BoEV, each CS packs its unselected EV suppliers and consumers' requests into a transaction along with necessary energy details, as mentioned above. The transaction is broadcast on the BoCS and then sent to the transaction pool of each CS. Once enough transactions are collected within any pool; the corresponding CS will dispatch them for endorsement to a designated

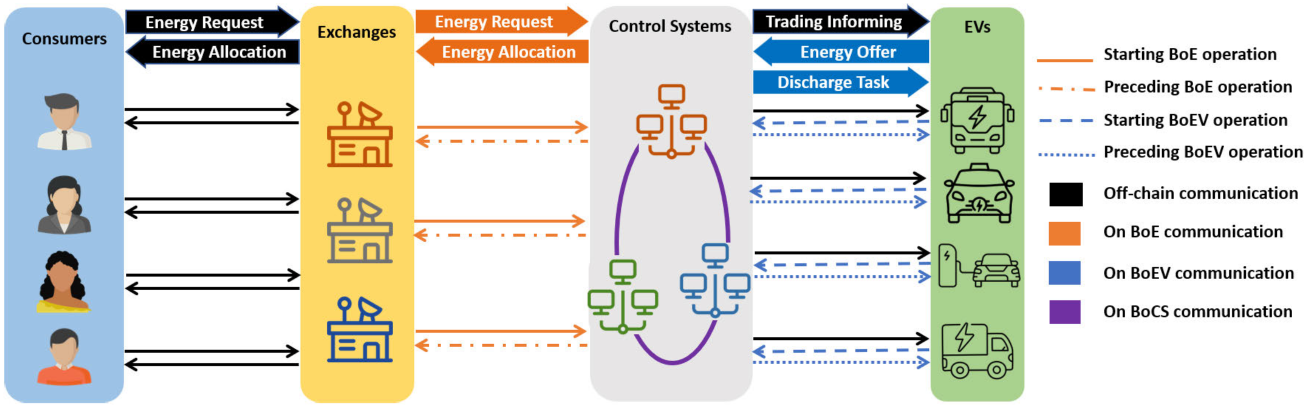


FIGURE 3. Overview of the proposed multi-blockchain architecture of exchanges (BoE), blockchain of EVs (BoEV), and blockchain of control systems (BoCS). Each trading round performs the two-time operation in all these blockchains, respectively. Communication between consumers and exchanges and the task of informing EVs to trade take place off the blockchain.

group of endorsing CSs. Upon successful endorsement, the transactions move forward for ordering and packaging into a block facilitated by the ordering organization. This block is then broadcast across the BoCS for verification. After the block is verified, each CS of the BoCS proceeds to download the block, extracting the associated lists and consolidating these lists into an overall request list and an overall EV supplier list. Each CS then competes on working out all the feasible trading plans across the two overall lists with SRET and uploading the outcome in a transaction back to the BoCS. Once a transaction is successfully endorsed, packaged into a block, and systematically verified, the new block is downloaded and permanently recorded by all the CS nodes of the BoCS network. From the block, every CS within the BoCS extracts the cross-campus energy trading outcomes and notifies its related consumers and EVs about their trading specifics accordingly.

In our framework for V2G energy trading, we recognize that practical vulnerabilities can arise in several areas, requiring a comprehensive approach to security. First, the communication channels between EVs, charging stations and the power grid are exposed to the risk of cyber-attacks, such as man-in-the-middle attacks that could disrupt the accuracy of energy demand and supply data. In addition, the integrity of the data within the trading platform is of great importance; it is vulnerable to tampering, which could lead to problems related to the business or energy distribution. To protect against these potential attacks, our framework includes advanced encryption for data in transit and at rest, as well as strict access controls to prevent unauthorized data modification. We also propose the implementation of real-time monitoring systems that use anomaly detection algorithms to immediately detect and respond to unusual activity. Regular security audits will improve the system's defenses against emerging threats. By addressing these vulnerabilities, our V2G energy trading system aims to offer a secure and reliable platform for all stakeholders involved in the energy trading process.

B. ENERGY TRADING METHODS AND PROCESS IN V2GFTN

1) HOUR-AHEAD COMPREHENSIVE ENERGY TRADING METHOD

The proposed energy trading process in V2GFTN can be divided into the process on the campus power grid, a control system (CS), and the process of sharing EV fleets. We denote the process on the grid with CS as part A and the process on EV fleets as part B. These two parts of the trading process are illustrated in Fig. 4. We then describe part A (CS side) and part B (EV side), respectively.

The V2GFTN system starts an hour-ahead energy trading round on the CS side. A full V2GFTN trading round consists of an hour-long planning phase and an hour-long execution phase. During the planning phase, the system analyzes the market conditions and risks, determines trading strategies, and formulates the V2G trading plans. In the execution phase, participants complete energy transactions and fulfill contracts reached in the planning phase. Once CS has verified that energy trading is available, CS informs all EVs at the beginning of the planning phase to check their energy status. The EVs not connected to the grid quit the trading round directly, as their link-in time and energy supply to the grid are unknown. For the EVs already connected to the grid, each EV checks if it has future driving tasks. The EVs with driving tasks will quit the trading round directly. For the rest EVs, each EV checks if there's enough remaining energy (RP) for supply. The EV with enough RP sends its ID, the quantity of RP, and the available period for discharge to the CS, while the EVs without enough RP quit the trading round.

While the EVs respond to the CS, the energy consumers also send their energy requests to the CS through energy exchanges. Each request contains the consumer ID, energy demand quantity, demand period, and a bid price per energy unit. The CS then selects the best energy requests and allocates EVs' energy offers to them through the SRET algorithm (see Section III-C). Once the CS obtains the request selection results and the corresponding energy

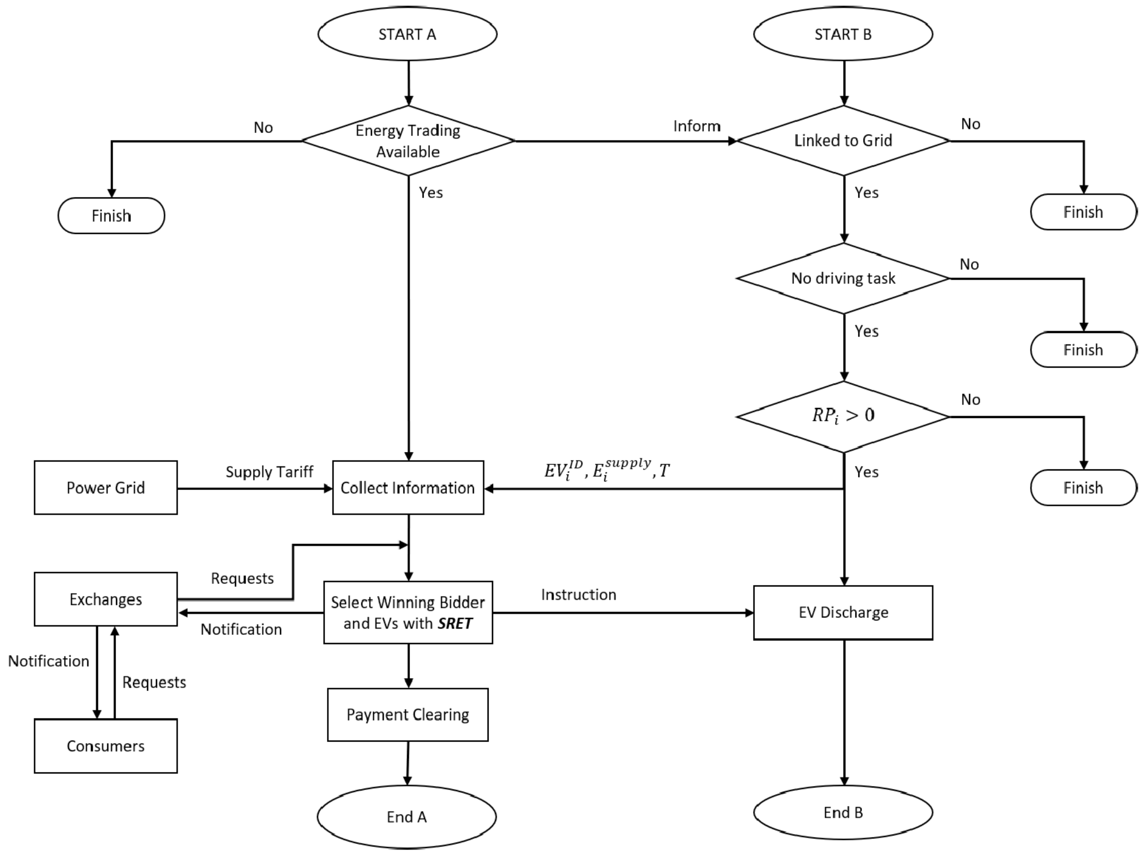


FIGURE 4. Energy trading algorithm without the energy forecasting data for EVs in V2GFTN for both EV and CS sides. The CS side begins from "Start A," and the EV side begins from "Start B" at the planning phase of each energy trading round. The power grid provides CS with a supply tariff, and the energy exchanges collect consumer energy requests and send them to the CS. The EVs also evaluate their availability, and those available ones send their information to the CS for selection. Once the execution phase starts, the selected EVs begin to discharge to the chosen consumers according to the trading contracts worked out by SRET in the planning phase.

allocation, each consumer receives a notification from the CS through their exchanges. Each selected EV receives discharge instructions for its execution phase. The planning phase lasts one hour to ensure that CS has enough time to choose the most appropriate strategy and optimize the trading plan. When the planning phase ends, the execution phase begins, and all selected EVs stop charging and begin discharging as instructed. When a selected EV finishes its discharge task or runs out of energy, CS settles its payments with the consumer of the request through energy exchange. When all of CS's payments are settled, the execution phase ends, and the trading round also ends.

2) DYNAMIC PREDICTIVE ENERGY TRADING METHOD

In addition to the EVs already counted as available in the original energy trading process, many EVs with driving tasks through the energy trading rounds still have the potential to provide energy to consumers. Using EV energy forecasting, our system can utilize EVs with driving tasks. The proposed energy trading process with energy forecasting for EVs in V2GFTN is illustrated in Fig. 5. At the beginning of each trading round, when CS is sure that energy trading is available, it collects energy consumers' energy requests from the connected energy exchanges. It informs all EVs to check their energy status for the next trading round. For the EVs that are still busy with driving tasks and not connected to the grid, each EV uses its forecast data models to evaluate whether it can connect to the grid before the end of the trading round. The EVs that cannot connect to the grid in time leave the trading round directly. Meanwhile, the EVs that can connect in time check whether their remaining power covers the predicted energy consumed until they connect. If the forecast result shows that an EV has no energy to supply when it connects to the grid, it leaves the trading round directly. Otherwise, the EV sends its ID, the predicted energy supply amount, and the predicted connection time to the CS.

For the EVs already linked to the network, each EV checks if it has future driving tasks during the trading round. During the trading round, the EVs involved in a charging task stop charging as soon as they are fully charged or have started their assigned energy requirements for the trading round. The EVs with future driving tasks that do not finish in time will exit the trading round directly. Each EV involved in future driving tasks that could finish on time checks if it has enough energy

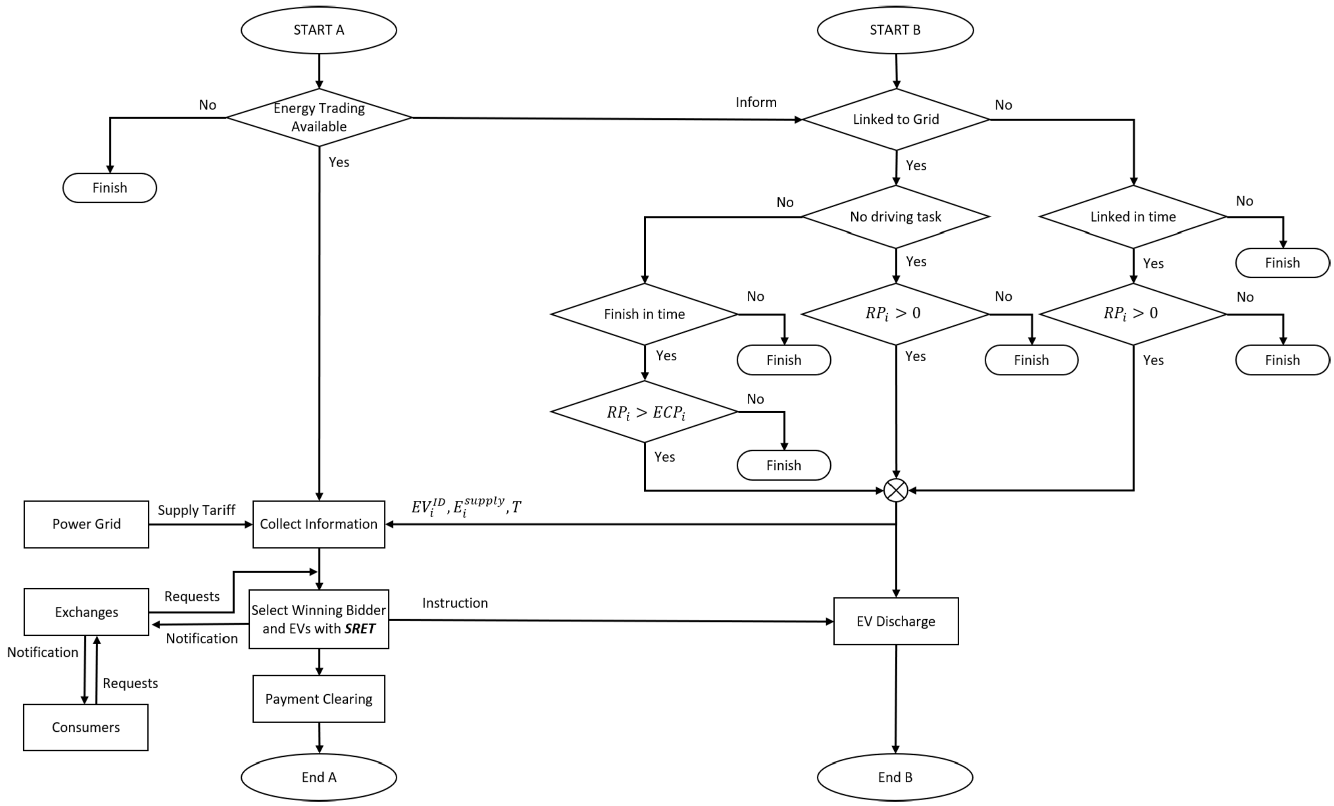


FIGURE 5. Energy trading algorithm with the energy forecasting data for EVs in V2GFTN for both the EV and CS sides. Since EVs can predict the energy consumption of their driving tasks before and during each driving task, EVs with driving tasks can also trade and supply their excess energy according to the prediction results.

to cover the estimated energy consumption of its driving task. The EV exits the trading round if no energy is left after the driving task. Otherwise, the EV sends its ID, the forecast energy supply quantity, and the estimated time for the end of the driving task (before the end of the trading round) to the CS.

The linked EVs with no driving tasks also check to see if they have enough energy available. EVs with sufficient remaining energy send their ID and forecast energy delivery amount to the CS, while EVs with no energy to supply quit the trading round. The rest of the trading process is the same as the original one. According to the collected data, the CS matches the EVs' energy offers to the consumers' energy requests via the SRET algorithm. The CS notifies the winning requests and the corresponding energy allocation to each consumer through their exchanges. And the selected EVs discharge as scheduled. In the end, the payment is processed through CS, and the trading round is finished.

C. SMART AND ROBUST ENERGY TRADING (SRET) ALGORITHM FOR V2GFTN

This section presents an allocation algorithm for our energy trading system called the Smart and Robust Energy Trading (SRET) algorithm. The goal of the SRET algorithm is to make the best use of the energy provided by the EVs to achieve maximum profit through V2G energy allocation. To provide the optimal energy allocation solution for the most profitable energy requests, CS executes SRET after data collection. CS goes through the request list to rank the requests by reward and then sequentially satisfies them with the EV list. Since each request and EV has a certain amount of available period, we must consider temporal constraints. Here, we define the qualification of temporal constraints in SRET as time limits. Thus, SRET can apply different EV selection strategies depending on the number of assumed time limits.

1) REQUEST SELECTION STRATEGY

First, CS has to reorder the request list by the unit bid tariff in descending order and the EV list by their remaining power (RP) in descending order. The CS then starts allocating EVs with the highest bid tariff for the request. Once the request's energy demand is fulfilled or skipped, CS begins allocating EVs for the next request in the list until no more requests or EVs are available.

2) EV SELECTION STRATEGY WITH DOUBLE TIME BOUNDARIES

Here, we present two types of allocation methods, taking different timing strategies for EV selection. First, we take the strategy with double time boundaries, where the CS only allocates the EVs that can fulfill a couple of each request's timing constraints. Given a request R_i, $i \in N$, the CS traverses the EV list $\{EV_k\}$, $k \in M$, and picks out EVs with proper offer period to form a temporary EV list $\{EL_i\}$, the EV number in $\{EL_i\}$ is denoted by M_i. For R_i, only those EVs that start energy supply earlier than the request's start time and end energy supply later than the request's end time are taken into $\{EL_i\}$. When no EV meets the time boundaries, the CS removes R_i from the request list and allocates EVs for the next request. Since the EVs in $\{EL_i\}$ are still listed in descending RP order, the CS compares the RP of the first EV in the list with the energy demand of R_i to check if any single EV can fulfill R_i. When the largest RP of EVs in $\{EL_i\}$ is not less than the energy demand of R_i, the EV with the least RP that can fulfill the demand of R_i is selected. When the most extensive RP of EVs in $\{EL_i\}$ is less than the energy demand of R_i, the CS then sums up all EVs' RP in $\{EL_i\}$ and compares it with the energy demand of R_i. If the sum of RP is less than the energy demand of R_i, R_i can't be fulfilled by EVs in $\{EL_i\}$, the CS skips R_i and moves on to allocate EVs for the next request. If the sum of RP equals the energy demand of R_i, all EVs in $\{EL_i\}$ are allocated to R_i and the CS moves on to allocate EVs out of $\{EL_i\}$ for the rest requests. If the sum of RP is larger than the energy demand of R_i, CS allocates EVs along $\{EL_i\}$ sequentially to R_i until the entire demand of R_i is met. To minimize the waste of EV energy, if more than one EV meets the left demand of the request, the EV with the least RP is selected.

3) EV SELECTION STRATEGY WITH SINGLE TIME BOUNDARY

We then present the strategy with a single time boundary. In this EV selection strategy, CS allocates any EVs that can fulfill a time constraint of each request. The energy supply potential of an EV is decided by its RP and the available time span for discharging. To calculate the potential energy supply capacity of each EV, we take both its available energy and the time span into consideration and denote the discharge potential of EV_k, $k \in M$ as:

$$H_k = min(RP_k, P_cT_k)T_k \tag{1}$$

Here RP_k denotes the RP of EV_k, P_c denotes the max output capacity of charging stations, T_k denotes the time span when EV_k can supply energy.

When EV_k is allocated to supply energy to a request R_i, the discharge potential of EV_k turns out to be:

$$H_k^i = min(RP_k - P_iT_k^i, P_c(T_k - T_k^i))(T_k - T_k^i) \tag{2}$$

Here P_i denotes the average output demand of request R_i, and T_k^i denotes the time span of EV_k supplying energy to R_i.

To analyze the energy utilization efficiency of EV_k, the corresponding efficiency parameter is formulated as:

$$E_k^i = \frac{H_k - H_k^i}{H_k} \tag{3}$$

The larger E_k^i is, the higher ratio of energy in EV_k could be utilized when it is allocated to R_i.

Meanwhile, the fulfillment of requests' energy demands can also be taken as an indicator of EV selection to meet the demand of each request with fewer EVs. And the fulfilling rate of the energy demand of R_i by EV_k can be formulated as:

$$F_i^k = \frac{H_k - H_k^i}{H_i} \tag{4}$$

The larger F_i^k is, the higher ratio of the energy demand of R_i could be fulfilled by EV_k. Here H_i represents the energy demand capacity of R_i, and H_i is denotes by:

$$H_i = P_iT_i^2 \tag{5}$$

To simplify the selection process, we only consider the scenario involving requests from home users, so the average output demands of requests are limited by $P_i \leqslant P_c$.

Compared with the selection strategy with double time boundaries, in the strategy with single time boundary, the $\{EL_i\}$ takes the EVs that start the energy supply earlier than the demand start time of R_i or end the energy supply later than the demand end time of R_i. This greatly enlarges the number of available EVs in the $\{EL_i\}$, yet more EVs are not able to fulfill the demand of R_i alone, which makes the selection procedure much more complicated. After $\{EL_i\}$ is generated, the CS sums up the available energy for R_i within as $\sum_{k=1}^{M_i} min(RP_k, P_cT_k^i)$ and compares it with the energy demand of R_i. When the energy demand of R_i is larger, the CS skips R_i and works on the next request.

When the CS wants to fulfill R_i with the least energy cost, $\{EL_i\}$ is rearranged according to the efficiency parameter E_k^i regarding R_i in descending order. The EV_{k1} with the largest E_k^i is allocated to R_i during T_{k1}^i, and when EV_{k1} is still able to supply energy, then its remaining power RP_{k1} and supply time span T_{k1} in the EV list is updated with $RP_{k1} - P_iT_{k1}^i$ and $T_{k1} - T_{k1}^i$. When R_i is not yet fully fulfilled, RP_{k1} is eliminated from $\{EL_i\}$, and the quantity and time span of energy demand in R_i is updated accordingly. The CS rearranges $\{EL_i\}$ again according to E_k^i in descending order and takes the top performer. The procedure circulates until R_i is fully fulfilled.

When the CS wants to fulfill R_i with the least number of EVs, then during the selection procedure $\{EL_i\}$ is rearranged by the request fulfilling rate F_i^k rather than the efficiency parameter E_k^i. This selection mode generates more leftover energy in the allocated EVs. Still, it can fulfill each request faster, thus cutting down the circulation rounds for each request and the overall time cost for V2G energy trading.

4) TIME COMPLEXITY OF THE SRET ALGORITHM

Here we present the time complexity of the SRET algorithm in steps. The time complexity of request selection is $O(N)$. In the EV selection strategy with double time boundaries, the time complexity for CS to traverse EV list and form $\{EL_i\}$ is $O(NM)$; the worst case time complexity for CS to allocate

EVs for R_i is $O(2M_i)$. The overall time complexity of the SRET algorithm with the strategy of double time boundaries is:

$$\begin{aligned} T_d(n) &= O(N + NM + 2NM_i) \\ &= O(3n^2 + n) = O(n^2) \end{aligned} \quad (6)$$

In the EV selection strategy with single time boundary, the time complexity for CS to traverse the EV list and form $\{EL_i\}$ is $O(NM)$; the time complexity for CS to calculate the $\{H_k\}$ is $O(M)$; the time complexity for CS to calculate the $\{H_k^i\}$, $\{E_k^i\}$, and $\{F_i^k\}$ for R_i is all $O(M_i)$. So the worst case time complexity for CS to allocate EVs for R_i is $O(M_i^2 + M_i)$. The overall time complexity of the SRET algorithm with the strategy of single time boundary is:

$$\begin{aligned} T_s(n) &= O(N + NM + M + NM_i + N(M_i^2 + M_i)) \\ &= O(n^3 + 3n^2 + 2n) = O(n^3) \end{aligned} \quad (7)$$

D. LEARNING-ENABLED ENERGY FORECASTING

Accurate EV energy consumption forecasting is critical to stabilizing the V2G network. It facilitates efficient power distribution among interconnected units during peak demand periods. Moreover, a campus charging station (CS) can effectively utilize the overall energy schedule of a known EV fleet to select an optimal real-time balancing strategy for the energy demand side.

To meet the energy forecasting requirements, we use a federated learning-based approach that aims to predict power consumption accurately through an integrated neural network, as introduced in detail in [2]. Considering a large distributed vehicular network, the federated learning method not only increases the efficiency of prediction models by aggregating data from different nodes in the network but also excels in handling non-IID (Independent and Identically Distributed) and small datasets. This capability is particularly important in environments where data is diverse and not uniformly distributed. By utilizing both small and non-IID data, the approach improves the accuracy and reliability of power consumption forecasts. This enables more effective management of energy resources and supports the optimization of grid operations in response to real-time demand fluctuations. The neural-network-based algorithm achieves 5.7% lower root mean square error (RMSE) compared to the traditional energy forecast method. Besides, the robustness of the federated learning algorithm has been proved against model attacks up to 40% [2]. A simplified structure of our learning-enabled energy forecasting component is shown in Fig. 6. It should be noted that the architecture of the neural prediction network is designed to be flexible, especially concerning the hidden layers. The number of hidden layers is not fixed, so the model can be adjusted and tuned to meet specific prediction requirements. This flexibility ensures that the model can be optimized for different use cases and adapt to evolving requirements in power consumption prediction.

The neural network is tailored for energy in different travel scenarios and predicts the energy demand for a single trip from a starting city to a given destination. Each city within the trip route is characterized by its latitude and longitude. The trip is divided into numerous segments, and the power consumption for each segment is predicted and then aggregated to estimate the total energy consumption of an EV driving task.

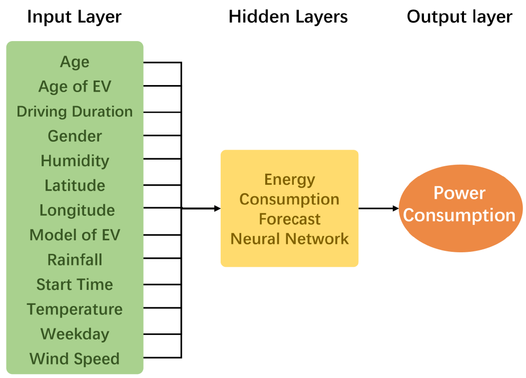


FIGURE 6. Overview of the multi-layer neural network for energy consumption forecast in V2GFTN. The input layer contains 13 input features, including start time, weekday, temperature, rainfall, humidity, wind speed, latitude, longitude, gender, age, driving duration, EV model, and EV age. The number of hidden layers is flexible. The output layer has one output neuron for power consumption prediction.

Several parameters are considered to predict the energy consumption for each section: the start time of each section, the prevailing weather conditions (humidity, rainfall, temperature, and wind speed), the geographic coordinates (latitude and longitude), relevant user information (age, gender, and model of the EV), and the total driving time. The neural prediction network is activated when the electric vehicle starts the respective driving section. This allows it to predict energy consumption in real-time for the planning phase of V2GFTN trading rounds. A more detailed understanding of this methodology can be found in the work [2].

E. ANALYSIS OF RESPONSE TIME

For a consumer participating in the energy trading round, we define the response time as the time from when the consumer submits the energy request until it receives the notification about the energy supply. For the whole system, we define the response time as the time from when the first consumer submits the energy request until the last consumer receives the notification about the energy supply.

In the BoCS there is a group of control systems $\{CS_k\}, k \in N_{cs}$, N_{cs} is the number of CS in the BoCS. In each BoE, we consider a group of exchanges $\{E_i\}, i \in N_{ex}$, N_{ex} is the number of exchanges in BoE. An exchange E_i contains a group of active consumers $\{C_{ij}\}, j \in N_{req}^i$, N_{req}^i is the number of consumers. Also, the group of EVs in the BoE is denoted by $\{EV_i\}, i \in N_{ev}^k$, N_{ev}^k is the number of EVs in the BoEV of CS_k. We divide the entire response process into six phases: 1) Request Collection and List Preparation in BoE; 2) Energy Allocation in the CS; 3-1) First Time Notification in BoE;

3-2) Consensus Processing of BoCS; 4) Energy Allocation in BoCS; 5) Second Time Notification in BoE.

1) REQUEST COLLECTION AND LIST PREPARATION IN BOE

In the BoE of CS_k, the time of a request's transmission between a consumer C_{ij} and the exchange E_i is denoted by $t_{c\_e}^{ij}$. $t_{c\_e}^{ij}$ includes the information transfer time and relative transmission latency. The time E_i receives all requests depends on the latest consumer. The corresponding time $t_{c\_e}^{i}$ is formulated as:

$$t_{c\_e}^{i} = max(t_{c\_e}^{i1}, t_{c\_e}^{i2}, \cdots, t_{c\_e}^{iN_{req}^{i}}) \tag{8}$$

The collection of requests is then organized into a request list by the exchange E_i. Here we denote the average time cost for blockchain nodes to process a single request as t_{prcs}^{req}, so the corresponding time for request listing t_l^i is formulated as:

$$t_l^i = t_{prcs}^{req} \times N_{req}^{i} \tag{9}$$

We denote the data size of a single request as S_{req}, and the variable transaction capacity per transaction as C_{tx}. According to the overall data size, E_i divides its request list and stores the data into minimum transactions. The number of transactions involved is formulated as:

$$N_{tx}^{boe,i} = \lceil \frac{N_{req}^{i} \times S_{req}}{C_{tx}} \rceil \tag{10}$$

For a single transaction $\{TX_j\}, j \in N_{tx}^{boe,i}$, the average time for its endorsement in BoE is denoted by $t_{endo}^{boe,k}$. And for E_i, the time to send the transactions to the ordering organization of BoE and finish ordering and block packing is denoted by $t_{o}^{boe,k}$; the time to broadcast the block to BoE is denoted by $t_{bcst}^{boe,k}$; the time to verify the block in BoE is denoted by $t_{ver}^{boe,k}$; and the time to record the block in all BoE nodes is denoted by $t_{rec}^{boe,k}$.

Therefore, the total time for uploading request list of E_i to BoE is:

$$t_{u\_ex}^{i} = N_{tx}^{boe,i} \times t_{endo}^{boe,k} + t_{o}^{boe,k} + t_{bcst}^{boe,k} + t_{ver}^{boe,k} + t_{rec}^{boe,k} \tag{11}$$

The time cost for exchange E_i in *Phase 1* is denoted by:

$$t_1^i = t_{c\_e}^{i} + t_l^i + t_{u\_ex}^{i} \tag{12}$$

The time cost for all exchanges in the BoE of CS_k to upload their request lists is:

$$T_1^k = max(t_1^1, t_1^2, \cdots, t_1^i, \cdots, t_1^{N_{ex}}) \tag{13}$$

2) ENERGY ALLOCATION IN THE BOE

After all the request lists are recorded through BoE, the CS_k starts to allocate energy with the proposed SRET algorithm. The time cost of the SRET depends on the following factors: 1) The time cost for blockchain nodes to process a single block t_{prcs}^{blk}; 2) The total number of energy requests in BoE $N_{req}^{total,k}$; 3) The time to traverse the available EV list $t_{traverse}^{k}$; 4) The time to filter EVs based on time boundaries t_{filter}^{k}; 5) The time to allocate EVs $t_{allocate}^{k}$.

To give out their specific definition, we denote the mathematical expectation of fulfilling a request in one trading round of CS_k by p_k, the average number of EVs required to fulfill a request in CS_k by q_k, and the number of requests in the BoE of CS_k by:

$$N_{req}^{total,k} = \sum_{i=1}^{N_{ex}} N_{req}^{i} \tag{14}$$

The time to traverse the available EV list $t_{traverse}^{k}$ can be denoted by:

$$t_{traverse}^{k} = c_1^k p_k \times N_{req}^{total,k} \times N_{ev}^{k} \tag{15}$$

c_1^k is a constant representing the average time for CS_k to process each EV in the EV lists.

The time to filter EVs based on time boundaries t_{filter}^{k} can be denoted by:

$$t_{filter}^{k} = c_2^k p_k \times N_{req}^{total,k} \times N_{ev}^{k} \tag{16}$$

c_2^k is a constant representing the average time for CS_k to check each EV against the energy requests' time boundaries.

The time to allocate EVs $t_{allocate}^{k}$ can be denoted by:

$$t_{allocate}^{k} = c_3^k p_k q_k \times N_{req}^{total,k} \tag{17}$$

c_3^k is a constant representing the average time for CS_k to allocate V2G tasks to a single EV.

We denote the time cost of CS_k in this phase by:

$$T_2^k = t_{prcs}^{blk} \times N_{ex} + t_{traverse}^{k} + t_{filter}^{k} + t_{allocate}^{k} \tag{18}$$

t_{prcs}^{blk} is the time cost for blockchain nodes in V2GFTN to extract data from transactions in a single block.

3) ENERGY TRADING DIVERSION

The requests that are fulfilled in the BoE allocation by CS_k go with the process in *Phase 3-1* and those unfulfilled requests go with the process in *Phase 3-2* to *Phase 5*

a: FIRST-TIME NOTIFICATION IN BOE

In BoE of CS_k, the number of selected requests with fulfilled demand in *Phase 2* is denoted by $N_{req}^{s,k}$, and the number of remaining requests with unfulfilled demand is denoted by $N_{req}^{r,k}$. We can give out $N_{req}^{s,k}$ by:

$$N_{req}^{s,k} = N_{req}^{total,k} \times p_k \tag{19}$$

So $N_{req}^{r,k}$ can be formulated as:

$$N_{req}^{r,k} = N_{req}^{total,k} - N_{req}^{s,k} \tag{20}$$

We denote the data size of a single allocation result by $S_{allocate}$, so the CS_k divides the list of allocation results into the minimum transactions of:

$$N_{tx}^{cs\_ex} = \lceil \frac{N_{req}^{s,k} \times S_{allocate}}{C_{tx}} \rceil \tag{21}$$

The time cost for CS_k to upload the allocation result to BoE is:

$$t^k_{u\_cs} = N^{cs\_ex}_{tx} \times t^{boe,k}_{endo} + t^{boe,k}_{o} + t^{boe,k}_{bcst} + t^{boe,k}_{ver} + t^{boe,k}_{rec} \tag{22}$$

The time cost for consumer C_{ij} to receive the notification in *Phase 3-1* is denoted by:

$$t^{ij}_n = t^k_{u\_cs} + t^{blk}_{prcs} + t^{ij}_{c\_e} \tag{23}$$

The time cost for all selected consumers in the BoE of CS_k to receive their first-time notification is:

$$T^k_{3-1} = max(t^{11}_n, \cdots, t_n^{1N^1_{req}}, \cdots, t^{ij}_n, \cdots, t_n^{N_{ex}1}, \cdots, t_n^{N_{ex}N^{Nex}_{req}}) \tag{24}$$

b: CONSENSUS PROCESSING OF BOCS

Once the *Phase 2* comes to an end, the CS_k uploads the information about remaining requests and EVs in its BoE to BoCS. The number of remaining requests $N^{r,k}_{req}$ is given in *Phase 3-1*, and the number of remaining EVs $N^{r,k}_{ev}$ is formulated as:

$$N^{r,k}_{ev} = N^k_{ev} - p_k q_k \times N^{total,k}_{req} \tag{25}$$

We denote the data size of a single EV by S_{ev}, and the CS_k divides the list of remaining requests and EVs into transactions of:

$$N^{bocs,k}_{tx} = \lceil \frac{N^{r,k}_{req} \times S_{req} + N^{r,k}_{ev} \times S_{ev}}{C_{tx}} \rceil \tag{26}$$

For a single transaction $\{TX_j\}, j \in N^{bocs,k}_{tx}$, the average time for CS_k to finish its endorsement in BoCS is denoted by $t^{bocs,k}_{endo}$. The average time cost for nodes to process data of a single EV is denoted by t^{ev}_{prcs} For CS_k, the time to send the transactions to the ordering organization of BoCS and finish ordering and block packing is denoted by $t^{bocs,k}_o$; the time to broadcast the block to BoCS is denoted by $t^{bocs,k}_{bcst}$; the time to verify the block in BoCS is denoted by $t^{bocs,k}_{ver}$; and the time to record the block in all BoCS nodes is denoted by $t^{bocs,k}_{rec}$.

The total time for uploading remaining requests and EVs of CS_k to BoCS is:

$$T^k_{3-2} = t^{req}_{prcs} \times N^{r,k}_{req} + t^{ev}_{prcs} \times N^{r,k}_{ev} + N^{bocs,k}_{tx} \times t^{bocs}_{endo} + t^{bocs}_{o} + t^{bocs}_{bcst} + t^{bocs}_{ver} + t^{bocs}_{rec} \tag{27}$$

4) ENERGY ALLOCATION IN BOCS

When all nodes in BoCS upload their remaining requests and EVs, each CS starts to allocate energy with the SRET algorithm and competes on block packing. Besides the aforementioned parameters, the time cost of the SRET on CS_k also depends on the following factors: 1) The total number of remaining energy requests in BoCS $N^r_{total\_req}$; 2) The total number of remaining EVs in BoCS $N^r_{total\_ev}$; 3) The time for CS_k to traverse the available EV list $t^{r,k}_{traverse}$; 4) The time for CS_k to filter EVs based on time boundaries $t^{r,k}_{filter}$; 5) The time to allocate EVs $t^{r,k}_{allocate}$.

Similar to *Phase 2*, we denote the mathematical expectation of fulfilling a request in one trading round on BoCS by p', the average number of EVs required to fulfill a request in BoCS by q'. The total number of remaining energy requests in BoCS $N^r_{total\_req}$ is:

$$N^r_{total\_req} = \sum_{k=1}^{N_{cs}} N^{r,k}_{req} \tag{28}$$

The total number of remaining EVs in BoCS $N^r_{total\_ev}$ is:

$$N^r_{total\_ev} = \sum_{k=1}^{N_{cs}} N^{r,k}_{ev} \tag{29}$$

The time to traverse the available EV list in BoCS is:

$$t^{r,k}_{traverse} = c^k_1 p' \times N^r_{total\_req} \times N^r_{total\_ev} \tag{30}$$

The time to filter EVs with time boundaries in BoCS is:

$$t^{r,k}_{filter} = c^k_2 p' \times N^r_{total\_req} \times N^r_{total\_ev} \tag{31}$$

The time for CS_k to allocate EVs in BoCS is:

$$t^{r,k}_{allocate} = c^k_3 p' q' \times N^r_{total\_req} \tag{32}$$

In BoCS, the CS_k divides the list of allocation results into the minimum transactions of:

$$N^{cs}_{tx} = \lceil \frac{p' \times N^r_{total\_req} \times S_{allocate}}{C_{tx}} \rceil \tag{33}$$

The time cost for CS_k to upload its allocation result back to BoCS is:

$$t^k_{u\_bocs} = N^{cs}_{tx} \times t^{bocs,k}_{endo} + t^{bocs,k}_{o} + t^{bocs,k}_{bcst} + t^{bocs,k}_{ver} + t^{bocs,k}_{rec} \tag{34}$$

We can then give out the time cost of CS_k to finish V2G allocation for BoCS as:

$$t^k_4 = t^{blk}_{prcs} \times N_{cs} + t^{r,k}_{traverse} + t^{r,k}_{filter} + t^{r,k}_{allocate} + t^k_{u\_bocs} \tag{35}$$

The time cost for BoCS to finish its cross-campus energy allocation in *Phase 4* is denoted by:

$$T_4 = min(t^1_4, \cdots, t^k_4, \cdots, t^{N_{cs}}_4) \tag{36}$$

5) SECOND-TIME NOTIFICATION IN BOE

After CS_k records the block of allocation results from BoCS, it transfers the information from the block and uploads it to its BoE. The time cost for the action is:

$$t^k_5 = t^{blk}_{prcs} + \frac{N^{cs}_{tx} t^{boe,k}_{endo}}{N_{cs}} + t^{boe,k}_{o} + t^{boe,k}_{bcst} + t^{boe,k}_{ver} + t^{boe,k}_{rec} \tag{37}$$

In the BoE of CS_k, the time cost for consumer C_{ij} to receive the notification in *Phase 5* is denoted by:

$$t^{ij}_5 = t^k_5 + t^{blk}_{prcs} + t^{ij}_{c\_e} \tag{38}$$

The maximum time cost for data transmission between a consumer and an exchange in BoE of CS_k can be formulated as:

$$t_{c\_e}^{k} = max(t_{c\_e}^{11}, \cdots, t_{c\_e}^{1N_{req}^{1}}, \cdots, t_{c\_e}^{ij}, \cdots, t_{c\_e}^{N_{ex}1}, \cdots, t_{c\_e}^{N_{ex}N_{req}^{N_{ex}}}) \tag{39}$$

The time cost for all selected consumers in BoCS to receive their notification in this phase is:

$$T_5 = t_{prcs}^{blk} + max(t_{c\_e}^{1} + t_5^{1}, \cdots, t_{c\_e}^{k} + t_5^{k}, \cdots, t_{c\_e}^{N_{cs}} + t_5^{N_{cs}}) \tag{40}$$

6) SUMMING UP OF RESPONSE TIME

In summary, the response time for all energy consumers in the BoE of CS_k to finish trading with EVs of CS_k and receive first-time notification is:

$$T_{1st}^{resp,k} = T_1^k + T_2^k + T_{3-1}^k \tag{41}$$

For a consumer C_{ij} in the BoE of CS_k, the response time to finish trading with EVs of CS_k and receive first-time notification is:

$$T_{1st}^{resp,k,ij} = T_1^k + T_2^k + t_n^{ij} \tag{42}$$

The response time for all energy consumers in the BoCS to finish trading with EVs in BoCS and receive second-time notification is:

$$T_{2nd}^{resp} = max(T_1^k + T_2^k + T_{3-2}^k) + T_4 + T_5 \tag{43}$$

For a consumer C_{ij} in the BoE of CS_k, the response time to finish trading with EVs in BoCS and receive second-time notification is:

$$T_{2nd}^{resp,k,ij} = max(T_1^k + T_2^k + T_{3-2}^k) + T_4 + t_5^{ij} \tag{44}$$

The response time for all V2GFTN consumers in one trading round is:

$$T_r = max(T_{1st}^{resp,1}, \cdots, T_{1st}^{resp,k}, \cdots, T_{1st}^{resp,N_{cs}}, T_{2nd}^{resp}) \tag{45}$$

IV. EVALUATION

This section delves into validating the effectiveness and economic efficiency of our proposed energy forecasting and trading system.

A. EVALUATION METHODOLOGY

For an in-depth comparative analysis and to show what the proposed V2GFTN system achieves, we compare the system with the V2GNet system as proposed by [1] and an action-based incentive scheme as offered by [45]. Furthermore, to provide insights into the broader applicability of our proposed trading methods and strategies, we also simulate a series of experiments with the SRET in the V2GFTN platform. In the simulation, we considered two key strategies for timing constraints and ranking EVs: one with double time boundaries and the other with a single time boundary. This comparative evaluation illuminated the strengths and weaknesses of the methods and allowed us to evaluate their relative merits and optimize them using objectives and rationales.

We conducted experiments using different combinations of request numbers (200, 400, and 600) and EV numbers (from 60 to 270, with increments of 30) for the scenarios described below. The EVs were categorized into three groups based on their operating state: Idle, Charging, or Driving. The idle EVs are initially connected to the grid and have no charging or discharging duties at the beginning of the trading round. Charging EVs are connected to the grid and engaged in charging or discharging tasks at the beginning of the trading round. Still, their charging tasks are completed by the end of the trading round, making them eligible to participate in energy trading. Conversely, driving EVs are on the road for driving tasks at the beginning of the trading round. Nonetheless, as the trading round concludes, they can finalize their ongoing tasks, connect to the grid, and actively participate in energy trading. Further specifics regarding the configuration can be found in Table 1.

We consider four indicators: 1) Number of fulfilled requests; 2) Energy demand fill rate; 3) Total economic profit; 4) Total time cost. The meaning of each indicator is as follows:

- ***Number of fulfilled requests***: the number of energy requests fulfilled by V2G trading in a trading round.
- ***Energy demand fill rate***: the percentage of the total energy demand from all energy requests that are fulfilled by EV suppliers' energy offers in a trading round.
- ***Total economic profit***: the overall profit paid for EV suppliers from energy consumers over a whole energy trading round.
- ***Total time cost***: the amount of time needed to allocate energy for all available requests in the planning phase of a trading round.

We also carry out simulations to evaluate the time cost of a whole trading round of the proposed V2GFTN system, including the given multi-blockchain architecture. The time cost ratio of each phase we pointed out in III-E is calculated. In the simulation, we separated the energy consumers by whether they finished V2G trading from their affiliated BoE and got the first-time notification or finished V2G trading from the BoCS and got the second-time notification. Further specifics regarding the configuration for the above simulation can be found in Table 2.

B. EVALUATION RESULTS

As shown in Fig. 7, the number of fulfilled requests increases for all four strategies as the number of electric vehicles increases, with the V2GFTN strategies having a much higher number of fulfilled requests compared to the action-based incentive scheme and the V2GNet system. As the number of EVs increases, the average growth rate of fulfilled requests for the single time boundary strategy, double time limit

TABLE 1. Configuration for the V2G trading simulation.

Input Feature	Value	Detailed Description
No. of Consumers	200, 400, 600	Number of the energy consumers willing to participate in energy trading (as buyers)
No. of EVs	60 to 270	Number of EVs that can offer energy in energy trading (as suppliers)
EV State	Idle, Charging, Driving	The state of each EV, including Idle, Charging, Driving
Battery Capacity	60 kWh	The maximum amount of energy can be stored in the EV battery
Charge Power	15 kW	An EV's charge power per unit time
Discharge Power	0 to 10 kW	The scope of EVs' discharge power per unit time
Driving Power	10 kW	The average energy spent per unit time for EVs under driving state
Driving Time Slot	20 to 22	The scheduled period for electric vehicles to execute driving tasks
Charge Time Slot	20 to 21	The scheduled period for electric vehicles to execute charge tasks
Request Time Slot	21 to 22	The scheduled time period for customers to consume electricity
Requests Capacity	0 to 10 kWh	The scope of consumer requests' energy demand
Bid Price	22.39 to 42.84 JPY	The scope of energy trading price per energy unit

[1] The currency code for the Japanese Yen is JPY.

TABLE 2. Configuration for the time analysis simulation.

Parameter	Meaning	Value
N_{cs}	No. of control systems	3
N_{ex}	No. of exchanges in a BoE	3 to 5
N_{ev}	No. of EVs in a BoEV	75 to 900
N^i_{req}	No. of requests in an exchange	30 to 150
t^{req}_{prcs}	Average time to process a request	0.1ms
t^{ev}_{prcs}	Average time to process an EV	0.2ms
t^{blk}_{prcs}	Average time for a node to process a block	2s
S_{req}	Data size of a single request	0.2kb
S_{ev}	Data size for a single EV	0.2kb
$S_{allocate}$	Data size for an allocate result	0.5kb
C_{tx}	Variable transaction capacity	256kb
c^k_1	Average time to pick an EV in SRET	0.45 to 0.55ms
c^k_2	Average time to check an EV's time boundaries	0.36 to 0.44ms
c^k_3	Average time to allocate an EV	0.23 to 0.28ms
p_k	Expected value to fulfill a request on a BoE	0.6 to 0.8
q_k	Average EV No. to fulfill a request on a BoE	1.0 to 1.2
p'	Expected value to fulfill a request on BoCS	0.7
q'	Average EV No. to fulfill a request on BoCS	1.2

strategy, action-based incentive scheme, and V2GNet system are 0.901, 0.889, 0.526, and 0.531, respectively. Accordingly, the number of fulfilled requests is most significant for the single time boundary strategy, outperforms the double time boundary strategy by 0.41% to 5.37%, outperforms the action-based incentive scheme by 40.68% to 71.84%, and outperforms the V2GNet system by 48.24% to 100.93%. On average, the single-time boundary strategy outperforms the double-time boundary strategy, the action-based incentive scheme, and the V2GNet scheme by 2.46%, 65.09%, and 74.45%, respectively.

To validate the effectiveness of V2GFTN, we present a comprehensive comparison of trading strategies in which we evaluate their impact on the energy demand fill rate, as shown in Fig. 8. When the number of EVs in V2GFTN exceeds the number of energy requests, almost all of the energy demand can be met by double and single time boundary strategies. With the number of EVs increasing from 60 to 270, the energy demand fill rate's average growth rate for single time boundary strategy, double time boundaries strategy, the V2GNet scheme, and the action-based incentive scheme dropped by 61.95%, 65.81%, 44.79%, 2.48%, respectively. On average, the single time boundary strategy outperforms the double time boundaries strategy, the V2GNet scheme, and the action-based incentive scheme by 1.34%, 44.66%, and 189.67%.

As shown in Fig. 9, when the number of energy requests remains the same, the economic profit produced by all four strategies grows with the increasing number of EVs. On average, the single time boundary strategy outperforms the double time boundaries strategy, the V2GNet scheme, and the action-based incentive scheme by 1.29%, 44.75%, and 160.20%, respectively.

Table 3 shows the total time cost of an energy trading round across four trading strategies. For the same number of energy requests, the time cost of all four strategies in a

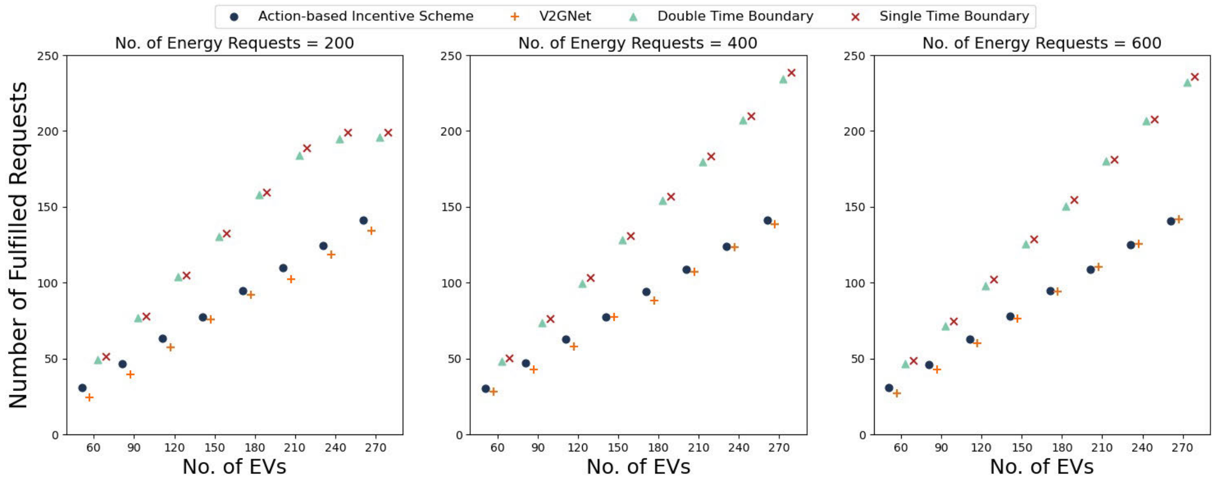


FIGURE 7. Number of fulfilled requests evaluation. This experiment compares the number of fulfilled requests between trading strategies of double time boundaries and single time boundary in V2GFTN (this work), V2GNet [1], and the action-based incentive scheme [45]. Different combinations of EV and request amount are used, as shown in Table 1.

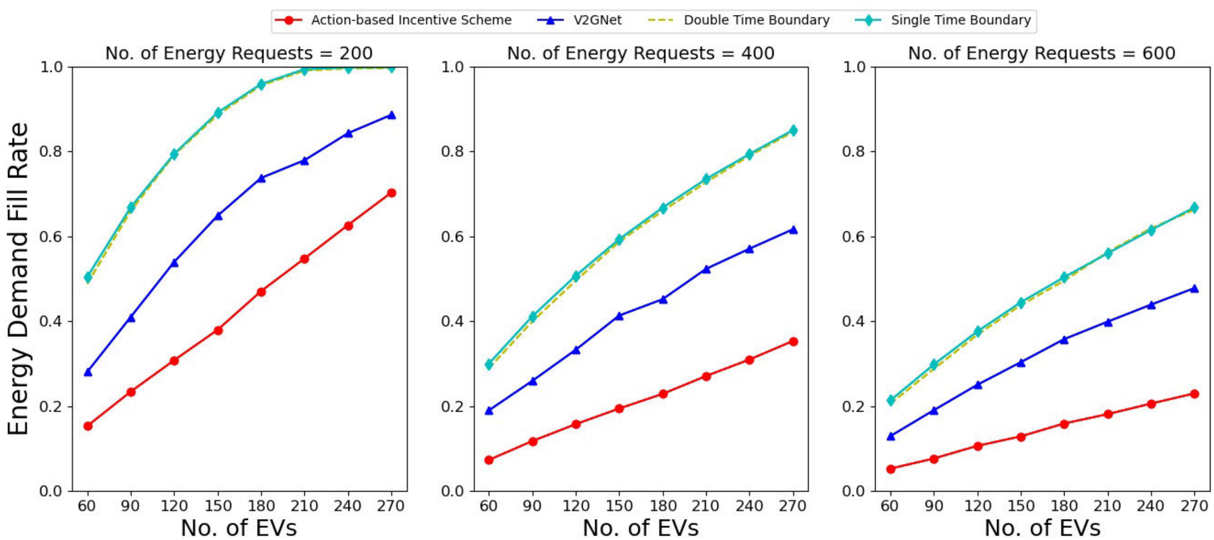


FIGURE 8. Energy demand fill rate evaluation. This experiment compares the energy demand fill rate between trading strategies, focusing on double time boundaries and single time boundary approaches within the V2GFTN, the trading strategy presented in V2GNet [1], and the action-based incentive scheme [45]. Diverse combinations of EVs and request amounts were explored to ensure a robust evaluation across a spectrum of scenarios.

trading round increases with the number of EV suppliers. With the different number of EVs, the trading round time cost is largest for the single time boundary strategy, exceeds the double time boundary strategy by 0.97 to 4.45 times, exceeds the V2GNet scheme by 0.06 to 11.77 times, and exceeds the action-based incentive scheme by 2.62 to 12.33 times. On average, the single time boundary strategy exceeds the double time boundaries strategy, the V2GNet scheme, and the action-based incentive scheme by 2.65-, 6.08-, and 7.56-fold, respectively.

As shown in Fig. 10a, in a trading round 73.8% of the time is consumed by blockchain-involved time cost, and non-blockchain time cost only makes 26.2% of the overall time cost. For the consumers taking the first-time notification as in Fig. 10b, the time cost for *Phase 1*, *Phase 2*, and *Phase 3-1* make 48.2%, 3.5%, and 48.3% of the overall time cost of their V2G energy trading. For the consumers taking the second-time notification as in Fig. 10c, the time cost for *Phase 1*, *Phase 2*, *Phase 3-2*, *Phase 4*, and *Phase 5* make 36.6%, 2.6%, 16.6%, 19.1%, and 25.1% of the overall time cost of their V2G energy trading.

V. DISCUSSION

Through evaluation, we found once the number of EVs in V2GFTN exceeds the number of energy requests, almost all requests and their energy demand can be satisfied by

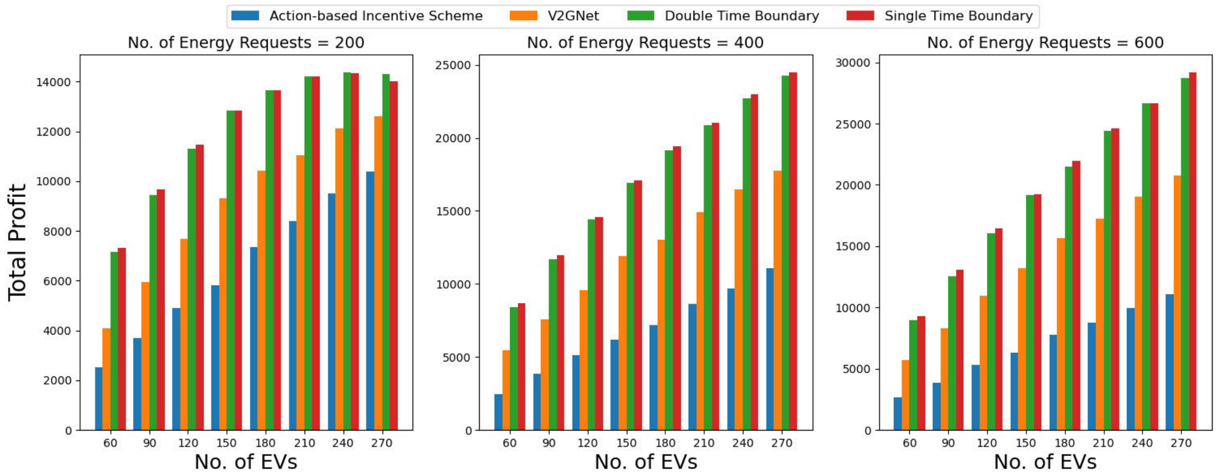
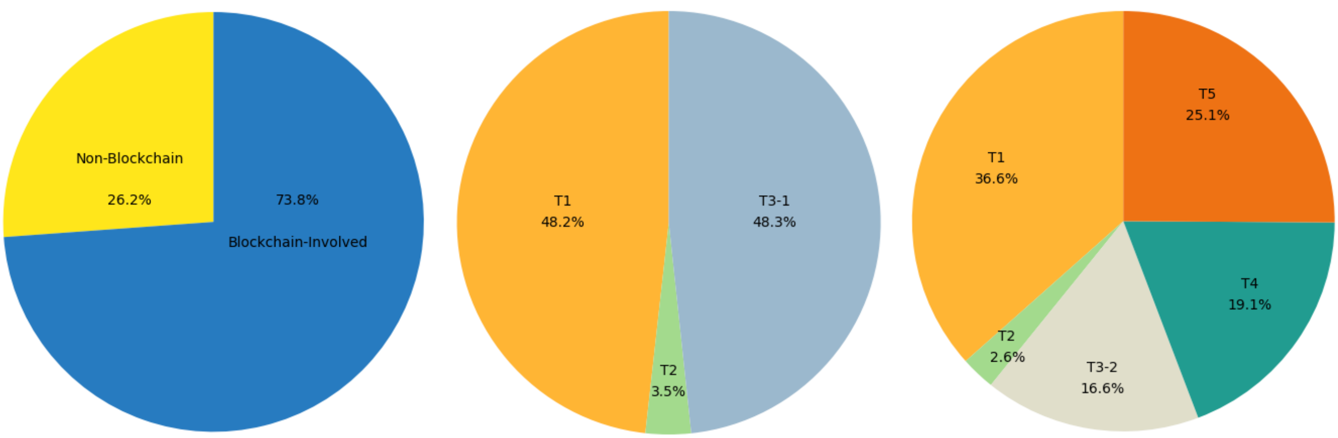


FIGURE 9. Total profit evaluation. This experiment compares the total economic profit in trading strategies of proposed V2GNet [1], the action-based incentive scheme [45], and both double time boundaries and single time boundary approaches within the V2GFTN. A wide array of combinations of EVs and request amounts reveal nuanced insights into the relative performance of these trading strategies.

TABLE 3. The total time cost of an energy trading round across four trading strategies: 1) the action-based incentive scheme; 2) V2GNet; 3) double time boundaries scheme within V2GFTN; 4) single time boundary scheme within V2GFTN.

Time Cost (s)		No. of EVs															
		Action-Based Incentive Scheme				V2GNet				Double Time Boundary (This Work)				Single Time Boundary (This Work)			
		60	90	120	150	60	90	120	150	60	90	120	150	60	90	120	150
No. of Requests	200	1.79	3.36	5.88	8.54	4.45	6.75	7.33	9.49	3.78	7.73	13.92	21.65	7.47	19.44	43.67	73.92
	400	1.84	3.37	5.84	8.53	4.21	7.37	9.49	10.56	3.44	7.40	13.13	21.09	7.25	19.90	41.10	73.44
	600	1.97	3.26	5.78	8.59	6.71	8.26	7.55	10.02	3.30	7.30	12.83	20.39	7.12	19.50	43.03	71.76

Time Cost (s)		No. of EVs															
		Action-Based Incentive Scheme				V2GNet				Double Time Boundary (This Work)				Single Time Boundary (This Work)			
		180	210	240	270	180	210	240	270	180	210	240	270	180	210	240	270
No. of Requests	200	12.48	17.09	22.15	29.87	14.04	19.22	25.62	30.50	30.92	41.78	54.30	66.23	113.90	176.27	249.86	340.09
	400	12.31	16.72	21.67	28.22	17.42	19.34	22.60	29.45	29.95	40.65	53.64	69.04	119.70	167.19	253.91	375.00
	600	12.39	16.59	25.52	28.91	12.97	16.92	22.07	30.12	29.30	40.55	53.46	77.80	117.84	176.44	248.36	338.12



(a) Time cost ratio of blockchain-involved and non-blockchain parts in V2GFTN.

(b) Time cost ratio of *Phase 1*, *Phase 2*, and *Phase 3-1* for first-time notification.

(c) Time cost ratio of *Phase 1* to *Phase 5* for second-time notification.

FIGURE 10. Comparative analysis of time cost ratios in different scenarios.

the double- and single-time-boundary strategies, thanks to the higher energy efficiency of SRET. When the number of energy requests is regulated, all four strategies' energy demand fill rate increases as the number of EVs increases. The energy demand fill rate of V2GFTN strategies is much higher than that of the other two. Still, the growth rate of the demand fill rate of all strategies decreases as the number of EVs increases, which should be caused by the intensifying trading competition between EVs and the relative deficiency of ideal requests with high demand and profit.

The V2GFTN strategies show higher total profit compared to the action-based incentive scheme and V2GNet scheme. When the EVs outnumber the energy requests, the profit growth stalled for nearly all profitable requests are fulfilled by the strategies with double time boundaries and single time boundary.

As for trading time cost, the time cost of a strategy with a fixed number of EVs is similar for different requests. The main reason is that the selection and allocation of EVs are the central part of the trading strategies, so the total time cost correlates more with the number of EVs. Although the V2GFTN strategies take more time, since the planning phase in the hour-ahead V2G trading round takes one hour, the single-time boundary strategy has enough time to determine the best energy trading plan. Even if the number of EVs is too high for the single time boundary strategy to complete the planning, the V2GFTN can seamlessly switch to the double time boundaries strategy. When it comes to specific time analysis, the multi-blockchain processing time makes the most of the overall time cost of V2GFTN. And getting notifications from cross-campus V2G trading on the BoCS takes more time than from V2G trading within a single campus from the CS. This is because the BoCS takes extra time to upload and download the data of the remaining EVs and requests.

VI. CONCLUSION

In this study, we proposed V2GFTN, a blockchain-based network that facilitates smart V2G energy trading by efficiently sharing electric vehicles using a neural network to predict energy consumption. To establish a secure and feasible energy trading workflow for energy requests, offers, and allocations, we first developed a multi-blockchain-based energy trading system. This innovative, cross-cluster architecture provides the foundation for secure energy trading transactions. In the auction models, supported by intelligent energy management systems, the introduced SRET algorithm adapts to time constraints and consumer demands and optimizes vehicle charging and EV selection strategies. SRET considers both double and single time boundary strategies, ensuring efficient energy allocation and high utility for commerce. A forecasting technique based on neural network data analysis to predict the energy consumption of EVs while driving is also introduced, contributing to more informed charging and trading strategies for driving EVs and expanding the pool of available EV suppliers. Through a comprehensive set of simulation experiments and evaluations, our study demonstrates the superior performance of the proposed SRET algorithm in V2GFTN. Compared with the action-based incentive scheme and V2GNet mechanism, our SRET algorithm achieves improved energy fulfillment and generates higher profits, highlighting its potential to revolutionize V2G energy trading. In our future work, we plan to work on a real-time scenario and integrate multiple distributed renewable energy resources into V2GFTN to create a more scalable and comprehensive trading network.

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