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Trustworthy Energy Trading System and Algorithms in Distributed Vehicle-to-Grid Network

by

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List of Abbreviations

AI	Artificial Intelligence
BC	Blockchain
BoCS	Blockchain of Control Systems
BoE	Blockchain of Exchanges
BoEV	Blockchain of Electric Vehicles
CS	Control System
DER	Distributed Energy Resource
ECP	Energy Consumption
EMS	Energy Management System
ETRM	Energy Trading and Risk Management
EV	Electric Vehicle
FL	Federated Learning
IoT	Internet of Things
OTC	Over-the-Counter
PV	Photovoltaics
RET	Robust Energy Trading
RP	Remaining Power
SRET	Smart and Robust Energy Trading
V2G	Vehicle-to-Grid
V2GFTN	Vehicle-to-Grid Forecast and Trading Network
V2GNet	Vehicle-to-Grid Network
VPP	Virtual Power Plant

List of Symbols

C_i	Energy consumer numbered i
C_{ij}	Active consumer numbered j contained by E_i
E_i	Energy exchange numbered i
R_i	Energy request numbered i
$\{EL_i\}$	Temporary EV list with proper offer period
M_i	Number of consumers in energy exchanges E_i
N	Number of energy exchanges
K	Number of EVs
γ_1	Risk parameter for consumer attacks
γ_2	Risk parameter for exchange attacks
s^t	Theoretical energy supply
s^p	Practical energy supply
pct_i	Percentage of fulfilled energy supply to C_i
pct_K	Percentage of fulfilled selected requests from E_K
d_i	Initial demand of C_i
d_i^{met}	Actual demand can be met for C_i
a_K^{met}	Maximum amount of requests can be met for E_K
H_k	Discharge potential of EV_k
H_k^i	Discharge potential of EV_k when allocated to supply energy to R_i
RP_k	RP of EV_k
P_c	Max output capacity of charging stations
E_k^i	Energy utilization efficiency parameter of EV_k
F_i^k	Fulfilling rate of R_i energy demand by EV_k
H_i	Energy demand capacity of R_i
P_i	Penalty list to counter consumer attacks from C_i
Q_K	Penalty list to counter exchange attacks from E_K
T_1	Time cost for request submission to energy exchange
T_2	Time cost for request uploading to BoE and CS
T_3	Time cost for offer submission to BoEV
T_4	Time cost for winner selection of CS with RET
T_5	Time cost for trading plan notification
t_{ij}^r	Time cost for C_{ij} to send a request to E_i
t_i^r	Time cost for E_i to receive requests from all its consumers
t_i^c	Time cost for E_i to collect requests into a list
t_i^s	Time cost for E_i to collect BoE nodes' lists in its pool
t_i^{e1}	Endorsement time associated with E_i

t^{o1}	Ordering time in BoE
t_i^{b1}	Broadcasting time in BoE
t_i^{v1}	Verification time in BoE
t^{r1}	Recording time for nodes in BoE
t^{d1}	Recording time for nodes in BoE
t_i^{inf}	Notification time of new trading round from CS to EV$_i$
t^{RET}	Time cost for CS to download request list block from BoE
t_{ij}^{n}	Notification time of E_i to C_{ij}
T_k	Time span when EV_k can supply energy
TX_i	Transaction of request list for E_i

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I am here to express my sincere gratitude to Prof. Abderazek Ben Abdallah for his invaluable support and guidance throughout my research work. Your expertise and insights have been instrumental in shaping my methodology in both research and life. I would also like to thank Prof. Junji Kitamichi, Prof. Yuichi Okuyama, Prof. Daisuke Suzuki, and Prof. Khanh Nam Dang from the University of Aizu for taking the time to revise my thesis. Their expertise is critical in shaping the final outcome of my research.

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Abstract

Energy issues are a key concern in the present era, and the energy trading market is the crucial sector to facilitate supply-demand balance and sustainable development. Nowadays, energy trading is revolutionizing the efforts and policies geared toward addressing global warming and protecting energy security. For better demand response and grid balancing, smart grids and electric vehicles (EVs) are utilized as time-saving tools for power management, and vehicle-to-grid (V2G) technology is rapidly gaining importance in energy markets. Since EVs can act as both energy consumers and suppliers, V2G enables plugged EVs to make bidirectional energy transform between their batteries and the electrical grid. V2G thus has the potential to provide numerous benefits from EVs' mobile energy storage, including improving grid stability, reducing carbon emissions, and lowering the energy cost for EV owners. However, the adoption of V2G is still in its early stages, and the gap between ideal V2G goals and actual applications needs significant refinement, especially in terms of the reliability decline of typical centralized structure, inflexible timeline adaptation, and limited market scale and economic return. Another key challenge is distributing EVs' energy rationally to achieve better demand response and energy utilization while keeping the balance between promoting V2G market efficiency and controlling trading time costs.

In this dissertation, we propose a trustworthy energy trading system for comprehensive distributed V2G scenarios. We summarize the work in three main contributions.

First, to manage the market securely and efficiently, we propose V2GNet, a trustworthy V2G energy trading system for sharing EV fleets. To apply energy management and trading security practically from an economic viewpoint, we address the attack issue by proposing a robust energy trading (RET) algorithm with a penalty mechanism against malicious attacks from consumers and exchanges.

Second, based on the V2G trading process and market network in a single campus, we propose a cross-cluster architecture containing a blockchain of energy exchanges (BoE) and a blockchain of EVs (BoEV), with the distinct transmission of energy requests and offers. A complete analysis of the response time of energy requests in the overall architecture is carried out in five divided stages. As each control system (CS) makes a mediator between the network of exchanges and EVs, we move a step further and make every CS of campus V2GNet a node to form a blockchain of campus control systems (BoCS). Thus the BoCS links multiple V2G networks as one and is able to carry on cross-campus V2G trading.

Third, on top of V2GNet, we take time factor and energy prediction into account and propose a smart V2G forecasting and trading network named V2GFTN. V2GFTN integrates energy consumption forecasting functions for driving EVs with a smart energy trading and EV allocation algorithm called SRET so that the

EVs with driving tasks can also supply their extra power to the grid as soon as they connect. To guarantee the efficiency of energy requests and offers along the V2G trading workflow in an hour-ahead V2G market ensures the total profit and accurate energy allocation under dynamic scenarios.

The experimental results for the proposed V2G system demonstrate high robustness against malicious attacks, and malicious attackers are excluded progressively from the trading market during each trading round. Also, the RET algorithm achieves better energy fulfillment and higher profit compared to state-of-the-art approaches. On top of that, through rigorous testing and experimentation, our proposed V2GFTN system has demonstrated even higher economic profit and better energy demand fill rate. The excess energy of EVs can be predicted and traded in an efficient, secure, and accurate manner, therefore forming a promising V2G approach to be applied in various scenarios and paving the way for a more secure and reliable energy trading ecosystem within V2G networks.

分散型車両-グリッドネットワークにおける信頼性の高いエネルギー取引システムとアルゴリズム

概要

エネルギー問題は現代社会での重要な関心事であり、エネルギートレーディング市場は供需のバランスと持続可能な発展を促進する重要な分野です。現在、エネルギートレーディングは、地球温暖化対策とエネルギー安全保障のための取り組みや政策の革新を通じて進化しています。需要への適切な対応とグリッドのバランシングの向上のために、スマートグリッドと電気自動車（EV）が電力管理の時間節約ツールとして活用され、車車間通信（V2G）技術がエネルギーマーケットで急速に重要性を増しています。EVはエネルギーの消費者と供給者の両方として機能するため、V2G は EV が電子グリッドとの間でバイダイレクショナルなエネルギー変換を行うことを可能にします。V2G は、EV のモバイルエネルギーストレージから多くの利点を提供する可能性があり、これにはグリッドの安定性向上、炭素排出の削減、EV オーナーのエネルギーコストの削減が含まれます。

ただし、V2G の採用はまだ初期段階にあり、理想的な V2G の目標と実際の適用との間には、特に典型的な中央集権型構造の信頼性の低下、柔軟なタイムラインの適応性、制限された市場規模と経済的リターンの観点から、大幅な改良が必要です。EV のエネルギーを合理的に配分して需要への適切な対応とエネルギー利用の向上を実現するための主な課題のもう一つは、V2G 市場の効率を促進し、取引時間のコストを制御しながら、バランスを保つことです。

この論文では、包括的な分散型 V2G シナリオのための信頼できるエネルギートレーディングシステムを提案しています。主な貢献は 3 つに要約されます。

第一に、市場を安全かつ効率的に管理するために、EV フリートを共有するための信頼できる V2G エネルギートレーディングシステムである V2GNet を提案しています。経済的な観点からエネルギー管理とトレーディングセキュリティを適用するために、適切なエネルギートレーディング（RET）アルゴリズムを提案し、悪意のある消費者や取引所からの攻撃に対するペナルティメカニズムを考えました。

第二に、V2G 取引プロセスと単一キャンパスの市場ネットワークに基づいて、エネルギー交換（BoE）のブロックチェーンと EV（BoEV）のブロックチェーンを含むクロスクラスターアーキテクチャを提案します。エネルギーリクエストの応答時間の全体的なアーキテクチャでの完全な分析を 5 つの段階に分けて実施しました。各コントロールシステム（CS）が取引所のネットワークと EV の間の中継者となるため、キャンパスの V2GNet の各 CS をノードにすることでキャンパス制御システム（BoCS）を形成し、複数の V2G ネットワークを 1 つにリンクさせ、クロスキャンパスの V2G 取引を実施できるようにしました。

第三に、V2GNet の上に立ち、時間要因とエネルギー予測を考慮に入れ、SRET と呼ばれるスマートエネルギートレーディングおよび EV 割り当てアルゴリズムを用いたスマート V2G 予測およ

びトレーディングネットワークである V2GFTN を提案します。V2GFTN では、運転中の EV のためのエネルギー消費予測機能を統合し、接続した EV が運転中でも余分な電力をすぐに供給できるようにしました。時間先読みの V2G 市場では、ダイナミックなシナリオの下で正確なエネルギー割り当てと合計利益を保証し、効率的かつ安全な方法で EV の余剰エネルギーを取引できるため、潜在的に有望な V2G アプローチとなり、様々なシナリオで適用される可能性を秘めており、V2G ネットワーク内のより安全で信頼性の高いエネルギートレーディングエコシステムの道筋を示しています。

Chapter 1

Introduction

1.1 Energy Trading Network and Power Management of Virtual Power Plant

Presently, nations globally are fighting with challenges related to imbalanced energy supply and inefficient utilization systems [5]. Traditional energy supply and trading mechanisms, while historically reliable, grapple with a low share of renewable energy development, adverse environmental effects, and limited resources susceptible to supply disruptions and price fluctuations [6]. These drawbacks necessitate an enhancement in both the security and efficiency of energy supply and trading [7]. It is crucial to embrace secure, efficient, and low-carbon energy technologies that have emerged in recent years.

With the emergence of new technologies, the global power industry is undergoing a multidimensional transformation and exhibiting five major trends. These trends encompass a notable upsurge in the integration of renewable energy within the energy mix, a widening reach of distributed energy supply, the burgeoning growth of energy consumption propelled by the electrification of transportation, increased active participation of energy consumers in the market, and an overarching drive towards enhancing energy system efficiency [8–11]. Notably, these trends are interconnected, each amplifying the others, consequently fostering the

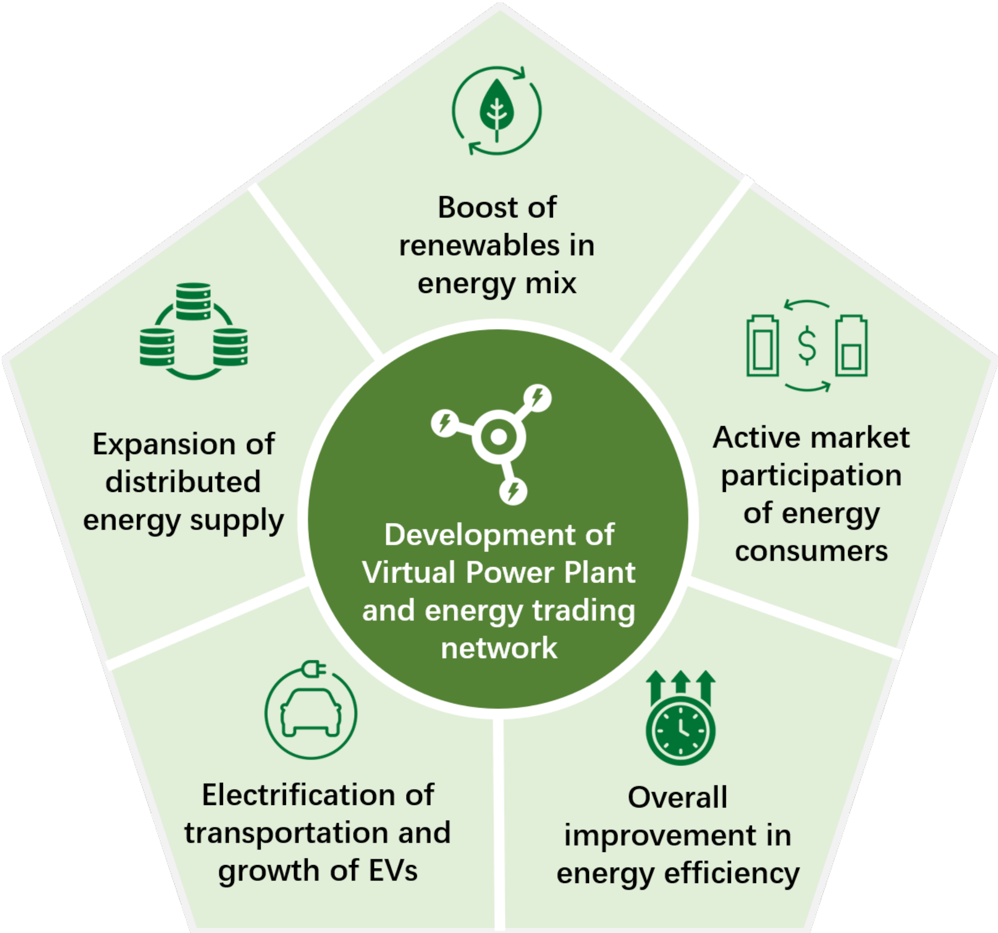


Figure 1.1: Five major emerging trends of the global power industry caused by new technologies in recent years.

advancement of energy trading networks and the Virtual Power Plant (VPP), as depicted in Figure 1.1.

A conventional energy trading network is basically a system or platform that facilitates the buying, selling, and exchange of energy resources among various participants in the energy market. It provides a framework for market players, including energy producers, consumers, and retailers. Nevertheless, nowadays more and more prosumers (entities that both supply and consume energy, such as energy storage batteries, electric vehicles, etc.) come to trade energy assets bidirectionally, and new networks are asked to accommodate a growing number of participants and adapt to changing market dynamics, emerging technologies, and evolving regulatory frameworks [12]. Under such conditions, energy trading networks need to provide a virtual marketplace or platform where participants can list their energy offerings, bids, or requests to buy energy from distributed resources [13]. This further introduces the concept of VPP to enhance efficiency, transparency, and sustainability in energy trading streamlining.

A VPP is basically a network of decentralized power generation resources, such as gas turbines, battery storage, or any kind of Distributed Energy Resource (DER), that are aggregated and coordinated to act as a single power plant. A VPP can be managed and controlled through software platforms to dispatch energy in response to changing demand and supply conditions, thus providing demand response and energy trading services [14].

Besides, VPPs allow for greater integration of renewable energy resources into the grid, for they can balance the intermittent nature of renewable energy by providing flexible energy sources to keep grid stability. They can also help to reduce the need for investment in power generation infrastructure and provide backup power to critical facilities in the event of an outage [4]. For those benefits, VPPs are becoming increasingly popular in the energy industry as a means of creating a more flexible and resilient energy system that can respond to the challenges of a changing energy landscape.

Meanwhile, energy consumers' demands are shifting towards digitization, personalization, convenience, and openness, hoping that energy suppliers can provide digital and diversified one-stop energy services. This further promotes the integration of VPP into energy trading networks. Currently, a VPP in a network of energy trading usually integrates a virtual power aggregator with energy consumers and suppliers. Such a network with VPP has the characteristics of diversity, collaboration, and flexibility, which can meet the urgent requirements of energy consumers in terms of diverse interaction, high marketization, and lower cost. It can be expected that VPPs will have good development prospects worldwide and help promote renewable power, energy storage batteries, and smart energy trading networks as the new infrastructure in power grids while cultivating a green industrial system and a low-carbon world [15].

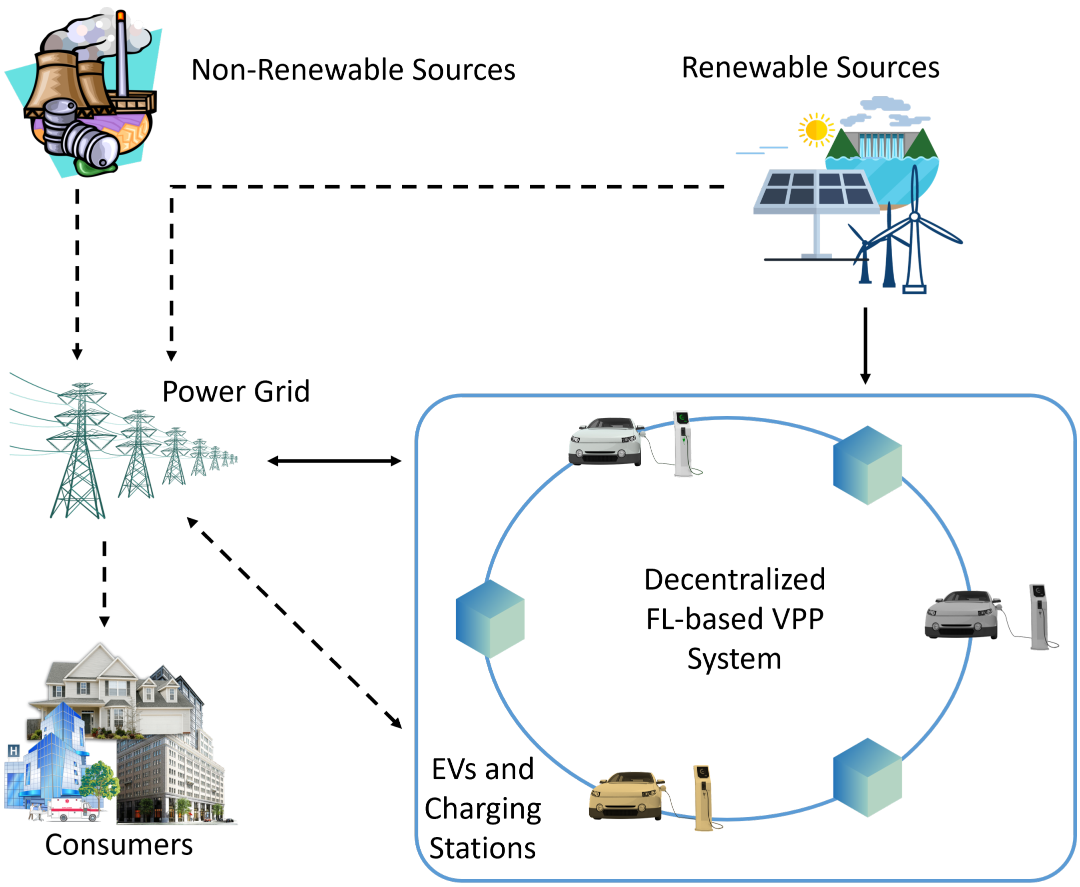


Figure 1.2: An illustration of a virtual power plant (VPP) in Network of EVs (NoEV) [1]. A VPP usually integrates the power grid, electricity market, renewable and non-renewable resources, energy storage system, energy consumers, etc. The NoEV goes further and integrates a VPP aggregator and EVs in FL and blockchain system.

Technically, the new power trading networks with VPP are facing the challenges of protection and automation, real-time optimization, network restructuring, operation planning, risk dispatch, and grid distribution planning. On the generation side, the main direction of future transformation is the popularization of renewable energy assets, including utility-scale photovoltaic farms, hydro-power plants, onshore wind turbines, and multi-energy complementary energy sources. At the same time, the green electricity generated by new energy sources will gradually participate in electricity market transactions, bringing opportunities for power generation enterprises to provide auxiliary services such as green electricity trading and carbon management [16].

On the consumption side, energy interconnection is becoming the main trend.

The energy form of the user side is diverse, including distributed photovoltaic and other power generation equipment, as well as various energy storage devices. Energy interconnection makes the markets focus more on retail-side services and energy management, providing power generation enterprises with opportunities to offer a variety of services for distributed energy storage, Electric Vehicle (EV) charging, and DERs. At the same time, with the popularization of electrification and intelligence, terminal electrical equipment will become more diverse, and power enterprises can provide services such as energy management for EVs, energy efficiency improvement, and demand-side response [17].

Along with generation and consumption, new issues and functions in energy transmission and distribution are just as important in energy trading networks, which include stability evaluation, load/generation balance, and market regulation functions. Due to the volatility of renewable energy generation and the integration of devices such as EVs and energy storage into the grid, the requirement for maintaining grid stability is increasing. Power generation enterprises need to achieve source-grid-load-storage coordination and balance through digital technologies such as intelligent interaction and smart microgrids in transmission and distribution [18].

1.2 Development of Electric Vehicle and Integration of Vehicle-to-Grid Technology

With the advancement in energy storage and bidirectional charging technologies, EVs now serve as both energy consumers and suppliers in power grids. In the last decade, their development has experienced significant progress and transformation, driven by growing environmental awareness and policy incentives promoting sustainable transportation. Stringent emission standards and targets for reducing greenhouse gas emissions have been implemented in many regions, compelling automakers to accelerate the production and adoption of EVs. Substantial advancements in battery chemistry and energy density have notably extended the driving range of EVs on a single charge, and the proliferation of fast-charging and high-power charging stations reduces their charging times, addressing range anxiety concerns and making EVs more practical for everyday use. Improved power-train efficiency and compact electric drive systems also reduce the weight and cost of EVs. Automotive manufacturers have introduced an extensive range of EV models catering to various market segments, and governments worldwide have offered various incentives like tax credits, rebates, and grants to encourage EV adoption, making EVs more attractive and affordable for consumers. As a result, EVs have gained a growing market penetration and a larger automotive market share. The transportation sector has witnessed a shift from traditional internal combustion engine vehicles towards electric vehicles, and the trend is expected to continue with the ongoing focus on technological innovation and policy support for greener and more sustainable traffic systems [19].

The integration between vehicular networks and energy infrastructure is expected as a viable measure to remedy energy peak load, improve energy utility efficiency, and accelerate the balance of power supply and demand. Unlike traditional fuel vehicles, EVs can provide a series of reliable optimizations for current energy trading, such as load shifting and peak shaving, arbitrage on price differentials, improving grid resilience, renewable integration, and frequency regulation and ancillary services. EVs are universally acknowledged as key to a more efficient, sustainable, and reliable energy trading ecosystem benefiting both grid operators and EV owners. However, many shared EVs and renewables are supported by government subsidies rather than being integrated into the regular electricity market. This is partly because the trading mechanism of the current energy market is neither profitable nor safe for EVs, and partly because there are not enough EV prosumers to propel extensive smart grid upgrades and support market-oriented Vehicle-to-Grid (V2G) transition. Still, the singularity of a mature V2G market is near with the rapid growth of EV owners and standardized communication protocols between EVs and the grid. According to Bloomberg data, in 2020 the number of global passenger and commercial EVs exceeded 10 million, and in 2030 EVs in China could reach 60 million, even if only a small proportion equipped with two-way charging can output electricity to the power grid, it can create huge opportunities for V2G technology [20].

The V2G technology represents an innovative approach that allows EVs to not only consume power from the grid but also return excess electricity back to the grid when needed. It essentially transforms EVs into flexible energy storage units and grid assets. Still, one concern for V2G energy trading is the optimal dispatch of energy. The electricity demand for EVs and charging infrastructure is concentrated during peak hours, with EVs mostly being used during rush hours. Therefore, there is a great potential for adjusting charging schedules. As the number of EVs increases, the load growth causes the charging process to increasingly stress the power grid. This creates a burden on the system and exacerbates the load difference between peak and off-peak periods. Additionally, due to the varying behavior of EV users and their charging times and locations, the EV charging load has a high degree of randomness. Moreover, the charging load of EVs is a non-linear load, and the power electronics in charging equipment can generate harmonic distortion, which may cause power quality problems [21]. The solution is to regard EVs as participating entities in demand response programs and use V2G technology to upgrade one-way charging facilities to two-way ones. With the dual-directional regulation and fast response characteristics of EVs, through a VPP, EVs can provide frequency regulation and spinning reserve services, while achieving the balance and optimization of power supply and demand between the power grid and EVs [22].

To achieve efficient energy utilization and high profits, game theoretical pricing mechanisms and auction-based incentive mechanisms are proposed. Referring to the existing development experience, peak-shaving arbitrage is an important source of revenue for user-side energy storage projects. The optimization objective should be based on the highest utilization of renewable energy, the smoothest load, the lowest generation cost, and the highest benefits for EV owners. By analyzing the charging habits and duration of users, operators can adjust and optimize their operational strategies. Still, most works focus on optimal scheduling for either the EV or the consumer side while failing to manage both energy demand and response concurrently [23].

1.3 Distributed Energy Supply & Trading

The acceleration of low-carbon energy transformation, the vigorous evolution of system diversification, the acceleration of industrial intelligent upgrading, and the deepening evolution of the multi-polar supply-demand pattern have led to the emergence of the distributed intelligent power grid. Driven by climate change, user expectations, emerging new technologies, the rise of the network economy, and the increasing penetration of renewable energy in the energy network, distributed energy generation, consumption, and trading are inevitable trends in the power sector [24].

The intermittency, variability, and uncertainty of wind and solar energy make it difficult to operate independently, requiring measures such as power compensation or smoothing to support safe and grid-connected operations. The initial flexibility transformation of thermal power units, energy storage, demand response, and electric vehicles are some of the options, and the latter two are both flexible and uncertain measures. At the same time, the current distributed networks are designed for one-way flow and do not have the technical potential to effectively integrate large amounts of distributed power sources, as shown in Fig. 1.3. Besides, there are many obstacles to decentralizing generation and grid connection, such as the fragility of power systems in response to malicious behavior or natural disasters, etc. For the purpose of distributed energy systems in the near future, the differences between the distribution network, microgrid, building units (buildings,

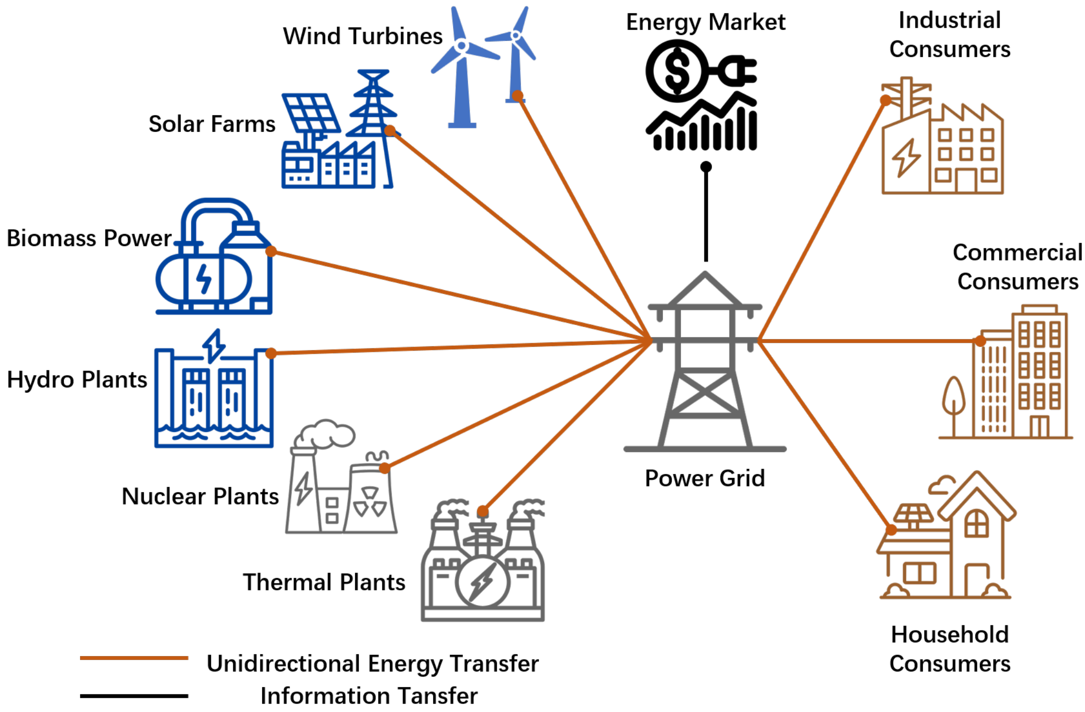


Figure 1.3: A typical conventional power transfer system.

factories, and residences, etc.), and transmission systems will gradually disappear, and they will all have the characteristics of local power generation and bidirectional power flow, all equipped with Energy Management System (EMS) and managed according to the norms of decomposing the system into hierarchical clusters. Each cluster maintains its own net energy balance and self-optimization [22].

Consequently, the proliferation of numerous distributed power sources has presented a daunting challenge for individuals, creating an intricate power grid system necessitating significant flexibility and reliability. This underscores the critical importance and priority of studying energy supply and trading architectures. The energy supply architecture constitutes the highest-level conceptualization of the entire power grid, embodying a top-tier model. An intelligent energy supply system, structured with a hierarchical and clustered architecture, stands as the epitome, ensuring the fundamental safety of energy supply. This intelligent grid design draws parallels to the Internet in terms of intelligence and boasts a solid mathematical foundation, rendering it ideally suited to meet the future requirements of the power grid. The hierarchical and clustered architecture equips the energy supply system to effectively respond to disruptions and engage in self-healing actions [25]. It enables the attainment of ”adaptive island operation” during emergency scenarios, facilitating a swift restoration to normal operations across the entire system and thereby minimizing losses incurred due to power outages. Envisaging the future of the distributed energy supply and trading, each cluster will represent a robust local energy supply and trading system characterized by a distinct structure, localized resilience, and rapid recovery capabilities.

1.4 Predictive Supply & Trading in Distributed Energy Networks

The landscape of the power industry is undergoing a profound shift, manifesting in the substitution of traditional energy consumption with end-point energy. On the power generation front, digital solutions take center stage, aiming to empower power generation companies with enhanced intelligent operation and maintenance capabilities [26]. Leveraging these digital tools, companies achieve functionalities like weather and power generation forecasting, intelligent inspections, and predictive maintenance. This translates into optimizing the power output curves of new energy assets, augmenting power generation, and curbing operational costs for power generation entities. Concurrently, these digital solutions enable power companies to closely monitor power market dynamics, aiding in trading, predicting power supply and demand, electricity prices, and subsequently maximizing revenue. This transformation highlights a shift from the conventional asset-heavy, service-light model to a contemporary paradigm centered around exemplary customer service [27].

In light of the rapid advancements in distributed renewable energy and intelligent power grid technologies, the widespread utilization of distributed energy is inevitable. However, this transition is accompanied by a set of formidable challenges rooted in the nature of distributed energy: relatively small individual capacities, vast user numbers, uneven distribution across regions, high costs for integrating individual units, and complexities in management and visibility. The surge in distributed energy integration, while promising, poses a range of technical hurdles for power grid stability, including alterations in power flow patterns, potential line congestion, voltage fluctuations, harmonic interference, and more [28].

Further impediments to large-scale distributed energy integration stem from prevalent operational paradigms, notably the ”install and forget” mode of operation and the inherent capacity constraints of existing power markets. These factors collectively restrict the seamless grid integration of distributed energy at a significant scale. Microgrids and active distribution networks, although offering viable solutions, come with their limitations. Microgrids, primarily tailored for on-site utilization of user-side distributed energy, are bound by geographic confines, limiting their efficiency in harnessing large-scale distributed energy across diverse regions and leveraging economies of scale within the power market. On the other hand, active distribution networks extend their purview to a broader spectrum but often overlook the substantial contributions that distributed energy can make to enhance both the power grid and the energy market [29].

In this evolving landscape, the imperative arises to develop predictive energy supply and trading technology that anticipates, navigates, and mitigates these challenges. This technology would be instrumental in optimizing the integration of distributed energy into the grid, forecasting power flow alterations, alleviating congestion risks, managing voltage dynamics, and harmonizing the coexistence of various energy sources. Additionally, it can revolutionize energy trading by forecasting market trends, enabling strategic decision-making, and ensuring efficient utilization of distributed energy resources [30]. Through a forward-thinking approach grounded in predictive technology, the gaps between the potential of distributed energy, the complexities of the power grid, and the dynamics of the energy market can be bridged, ushering in a new era of sustainable and optimized energy utilization.

1.5 Thesis Objectives, Contributions, and Outline

To address the challenges mentioned above, based on our previous works, we propose a secure and intelligent multi-blockchain-based V2G energy trading system, with robust V2G algorithms and mechanisms based on EV networks to address efficient energy trading and malicious attacks. A cross-cluster structure ensuring the security and privacy of V2G trading between minor grids is also designed. Within each campus, a control system (CS) works as a mediator between the network of energy exchanges and EVs. To adapt the system to more applicable scenarios, we propose a smart hour-ahead energy management network and dynamic allocation strategies with time constraints and EV energy prediction. The contributions are summarized as follows:

- An energy trading system V2GNet that supports the V2G workflow of energy request, offer, and allocation between consumers and campus sharing EVs.
- A robust energy trading algorithm (RET) that efficiently ensures the energy fill rate and total profit with a penalty mechanism against malicious attacks from consumers and exchanges.
- A novel cross-cluster architecture containing a blockchain of energy exchanges (BoE) and a blockchain of EVs (BoEV) to protect campus V2G trading. And a multi-blockchain V2G structure based on a blockchain of campus control systems (BoCS), which takes every CS as a node to carry on cross-campus V2G trading.
- A smart and robust energy trading algorithm (SRET) to optimize vehicle trading and charging/discharging strategies based on market conditions and EV energy prediction.
- Two energy trading approaches that facilitate energy allocation with time slots, utilizing double and single time boundary strategies, respectively.

- A fully connected neural network scheme is utilized to predict dynamic EV energy consumption through driving task segments.
- A complete analysis of the response time of energy requests is formulated by dividing the entire workflow into five stages.

The rest of this paper is organized as follows:

- In Chapter 2, the historical and theoretical background is given to demonstrate the significance of our research in larger academic and practical contexts. We first provide an overview of the current energy trading market and systems. Then we introduce the basic idea of Virtual Power Plant and smart grid. We also talk about centralized and decentralized V2G energy trading, blockchain-based energy trading systems, and predictive neural networks.
- In Chapter 3, we present related works on distributed and decentralized energy trading, secure energy trading and integration of Blockchain, V2G energy trading systems, and smart energy forecasting systems.
- In Chapter 4, we present a trustworthy V2G energy trading system named V2GNet, which is based on multiple blockchains to store and transmit data.
- In Chapter 5, we introduce the multi-blockchain V2G Energy Trading Networks.
- In Chapter 6 presents a Smart and Robust Energy Trading (SRET) Algorithm for V2G Forecast and Trading Network (V2GFTN).
- In Chapter 7, the conclusion and discussion are presented to end this thesis.

Chapter 2

Background

2.1 Current Energy Trading Market and Systems

Energy trading is a critical component of modern society, providing the necessary fuel for transportation, manufacturing, and electricity generation. The energy trading market has undergone significant changes in recent years, with the increasing adoption of renewable energy sources, automated technical advancements, and regulatory reforms. The current energy trading market is characterized by a high degree of complexity and uncertainty, with a diverse range of participants, products, and trading mechanisms. A classification of energy trading and some hot research orientations are shown in Fig. 2.1.

One of the key drivers of change in the energy trading market is the growing use of renewable energy sources such as wind, solar, and hydropower. These sources of energy are becoming increasingly cost-competitive with traditional fossil fuels, and are also more environmentally sustainable. The adoption of renewable energy sources has created new challenges for energy traders, who must manage the intermittent nature of these sources and balance supply and demand in real time.

Another important trend in the energy trading market is the emergence of advanced technologies such as Blockchain (BC), smart contracts, Artificial Intel-

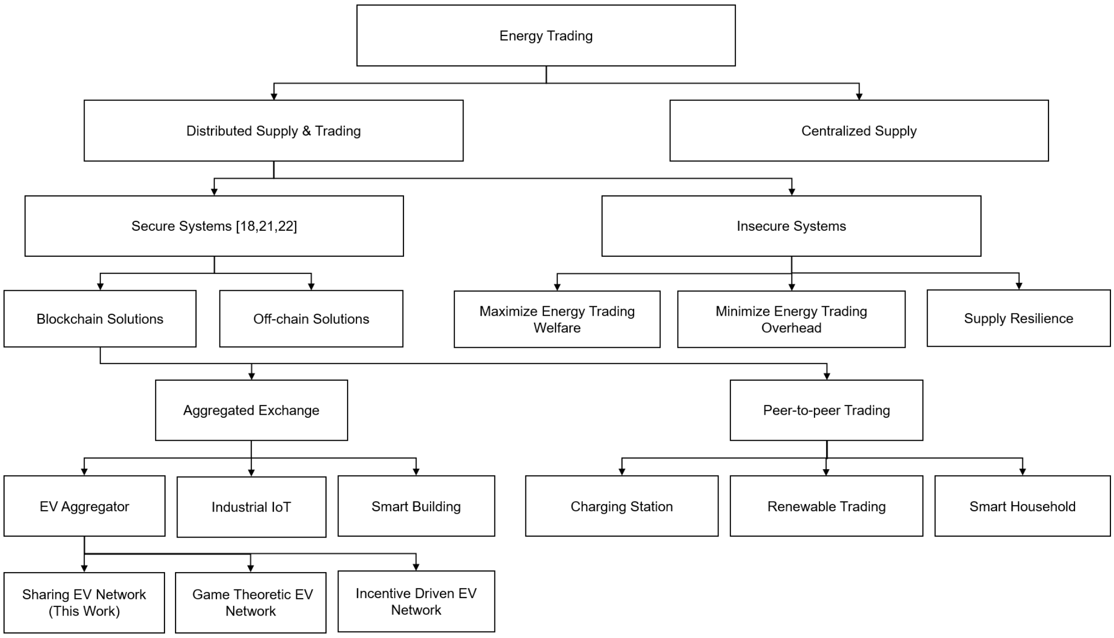


Figure 2.1: Overview of energy trading classification and research orientations. According to the system structure, energy trading systems can be roughly divided into centralized ones and distributed ones. Distributed energy supply and trading systems can be further divided by their functions and security features.

ligence (AI), data analytics, and the Internet of Things (IoT). Energy market manages the clearing and settlement processes, ensuring that transactions are validated, reconciled, and settled in a secure and transparent manner. This involves handling payments, ensuring compliance with regulations, and resolving disputes. The new technologies have the potential to revolutionize energy trading by enabling efficient and transparent transactions, improving forecasting and risk management, and reducing costs.

In addition to technological advancements, regulatory reforms are also driving change in the energy trading market. Compliance with regulatory requirements, market rules, and policies is crucial for energy trading, and the market ensures that all transactions and operations adhere to applicable laws and regulations. Governments around the world are implementing policies to encourage the adoption of renewable energy sources and reduce greenhouse gas emissions. These policies include feed-in tariffs, renewable portfolio standards, and carbon pricing mechanisms. They are creating new opportunities for energy traders to participate in markets for renewable energy credits and emissions allowances.

The energy trading market is also characterized by a diverse range of participants, including energy producers/generators/suppliers, utilities, traders/distributors, brokers, and consumers. These participants may have more than one specific role in the trading process and are involved in a range of products, including spot markets, futures markets, and Over-the-Counter (OTC) markets. Energy transactions occur within the network, involving the negotiation, agreement, and execution of contracts for buying or selling energy. These transactions can be immediate (spot market) or future-based (futures market). The complexity of the market requires sophisticated trading systems that can manage the flow of information and transactions between participants [31].

The current energy trading market is supported by a range of trading systems, including electronic trading platforms, energy management systems (EMS), and Energy Trading and Risk Management (ETRM) systems. These systems provide a range of functionalities, including real-time data monitoring, forecasting, risk management, and trade execution.

Despite the advancements in technology and regulatory reforms, the energy trading market remains vulnerable to a range of risks and uncertainties. These risks include price volatility, demand fluctuation, geopolitical instability, and cyber threats. In current energy trading, market-participating entities keep separate business records of their transactions. A record must be kept for each transaction to verify the trading process [32]. Therefore, individual traders' records are unique and fragmented, prone to a single point of failure. While data related to energy production, consumption patterns, market prices, forecasts, and other relevant information are made available within the market to help participants make informed trading decisions, the rapid growth of trading data is worsening the situation. The situation raises an urgent need for new distributed solutions with higher resilience, confidentiality, and flexibility. Or else traders must remain vigilant in ensuring the security and integrity of the market [33].

In conclusion, the current energy trading market is undergoing significant changes due to the adoption of renewable energy sources, technological advancements, and regulatory reforms. The market is characterized by a high degree of complexity and uncertainty, with a diverse range of participants, products, and trading mechanisms. The market is supported by a range of trading systems that provide sophisticated functionalities to manage the flow of information and transactions between participants. Despite the challenges, the energy trading market continues to evolve and adapt to meet the demands of the changing energy landscape.

2.2 Virtual Power Plant & Smart Microgrid

The goal of the current electricity market reform is to establish a new power governance system that is low-carbon, energy-efficient, safer, more reliable, and achieves comprehensive resource-optimized allocation. As the realm of power generation continues to expand, a fundamental shift towards demand-side resource management has emerged, demonstrating its equivalence to the traditional approach of augmenting supply-side resources. This transformation comprehensively addresses both the supply and demand facets of the electricity landscape. Leveraging operational data from distribution substations and user demand patterns, precise optimization controls are employed over discharging/charging schedules and power levels. The overarching goal is to maximize the existing power supply capacity, deferring or obviating the necessity for expansions in charging infrastructure. Consequently, this strategy amplifies the utilization efficiency of prevailing DERs.

At the heart of this paradigm lies the concept of a Virtual Power Plant (VPP), a potent aggregation of diverse distributed energy sources encompassing distributed power generation, flexible loads, and energy storage systems, as shown in Fig. 2.2. The configuration of VPPs exhibits a versatile array of combinations, prominent among them being distributed wind power coupled with energy storage,

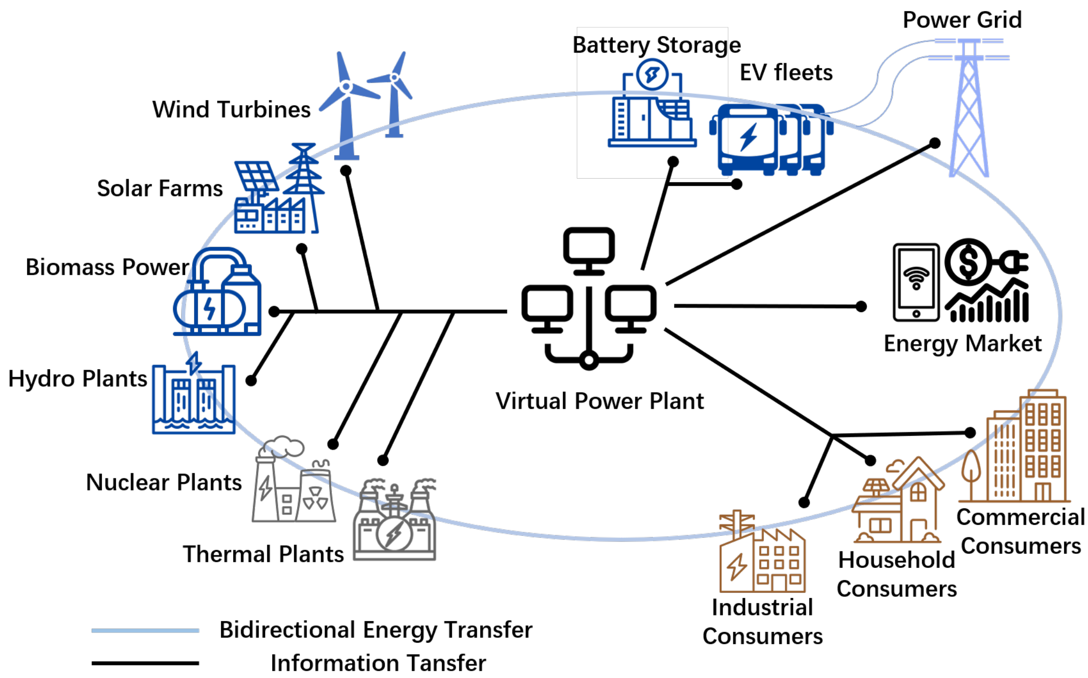


Figure 2.2: A power transfer system updated with VPP and energy storage departments.

distributed wind power integrated with electric vehicles, and synergies between buildings and energy storage. Employing artificial intelligence technology, the load curves of users with distinct load characteristics are clustered and smoothed within VPPs, harnessing the complementary effects arising from variations in daily load rates, daily peak-to-valley ratios, and daily maximum utilization times. VPPs harness the ability to aggregate and control flexible loads, thereby achieving demand-side response. This response encompasses a diverse range of participants, including EVs, individual users, industrial consumers, and various types of buildings. Industry-specific solutions have been crafted to cater to the diverse demand-side response needs [34].

For instance, the demand-side response in smart homes is orchestrated through smart home management service platforms, enabling a two-way exchange of energy and information between users and the power grid. These platforms collect usage data from household electrical appliances, facilitate remote control, promote load leveling, and contribute to energy efficiency and emissions reduction. In the case of buildings, smart building demand-side response is orchestrated, encompassing the collection of electricity consumption data and remote control of building lighting and switches through smart building management platforms. The controllable loads within buildings are aggregated and actively participate in demand response initiatives.

This evolutionary transition underscores the pivotal role of demand-side grid reform. The contemporary global energy technology revolution emphasizes a diversified power supply system driven by distributed power generation and smart microgrids. Distributed power generation not only furnishes combined heat and electricity to industrial and residential users but also significantly reduces carbon emissions and elevates overall power generation efficiency. Combining distributed power generation with smart microgrids augments power resource availability on-site and fortifies grid dispatch capabilities, offering ancillary services like frequency and voltage regulation, and backup power. Meanwhile, the integration of energy storage systems at the demand side unlocks their inherent technical flexibility and rapid response advantages. Ultimately, demand-side grid reform charts a new trajectory for the burgeoning energy storage industry, heralding a future characterized by enhanced efficiency and sustainability.

The evolution of modern energy systems has spurred a twofold focus: incremental distribution networks striving to solve the ”last mile” electricity dilemma, and microgrids catering to areas grappling with power shortages or geographical remoteness. A smart microgrid, a cornerstone of this progression, stands as a compact yet robust power distribution system. The scale of intelligent microgrids is smaller than that of the main power grid, so the load fluctuation rate and failure rate are relatively high. To embody a sophisticated and autonomous system with the ability for self-control, protection, and comprehensive management, smart microgrids need to comprise distributed generators, energy storage units, energy conversion equipment, related loads, and monitoring and protection devices. The dual operational capability to seamlessly switch between the primary power grid and autonomous functioning makes a defining characteristic of smart microgrids, especially in remote regions where grid connectivity is challenging. Within this framework, advanced components like smart circuit breakers ensure vital protection mechanisms, while edge controllers wield the power to deliver flexible control to buildings within the microgrid's domain [35].

2.3 Centralized & Decentralized V2G Energy Trading

In this emerging epoch dominated by new energy, the power industry grapples with a shift from controllable to stochastic in the primary energy source. Simultaneously, the traditional forms of power generation and load are morphing, from mechanical and electrical integration to power electronics. The distribution network is metamorphosing from a passive entity to an active, responsive infrastructure. The control paradigm is also evolving from a centralized to a distributed model, reflecting a paradigm shift in the very fabric of the vehicle-to-grid system [36].

The landscape of V2G energy trading is shaped by two key paradigms: centralized and decentralized structures, each with distinct characteristics and implications. Centralized V2G refers to electric vehicles in a certain area being centralized in a charging station and uniformly dispatched according to the instructions of the power grid. The charging station generally serves as an intermediate agency, as introduced in Fig. 2.3a. Distributed V2G refers to electric vehicles being charged through scattered charging piles, and electric vehicles independently carry out charging and discharging according to incentive measures from a decentralized energy system, as shown in Fig. 2.3b. The decentralized V2G approach introduces a level of randomness that can create anti-peak periods, making it challenging to attain optimal outcomes. To overcome this, practical trading mechanisms are imperative for effectively dispatching V2G energy and optimizing EV capacity. There is also Battery-swapping V2G, which is based on the EV battery-swapping mode by replacing batteries in EV battery-swapping stations.

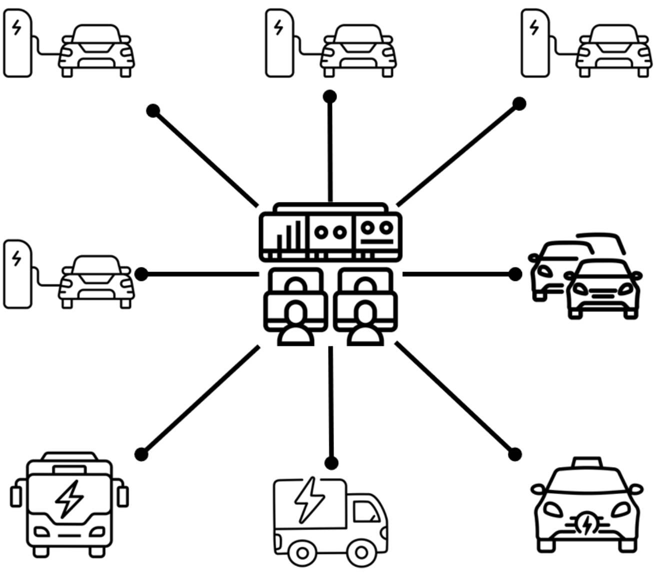
Still, the EV battery-swapping model faces obstacles such as non-uniform battery models, huge battery redundancy, and higher relative cost. Currently, centralized V2G stands as a more reliable and cost-effective alternative, offering a promising direction for V2G development.

In the realm of centralized V2G, an intelligent energy service system efficiently manages each substation, aiming to expand services across substations. The existing system, often managed within a single substation, lays a strong foundation for cross-substation interconnection. However, implementing centralized V2G necessitates modifications such as transformer reconstruction to facilitate bidirectional energy transfer. Coordination and management between V2G applications and the distribution scheduling system are crucial aspects of this structure.

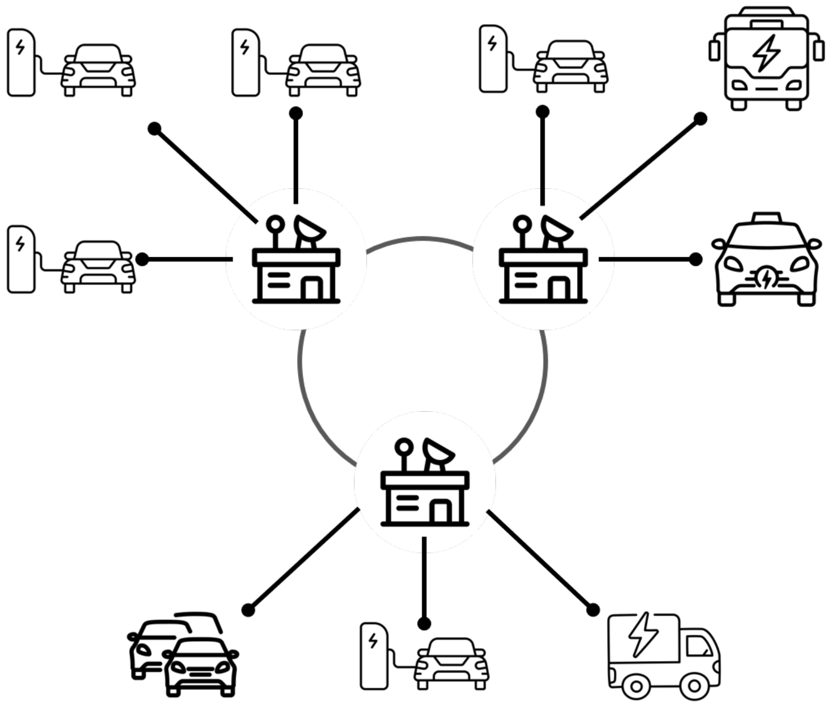
Centralized V2G boasts several advantages, including enhanced operational flexibility, ease of reactive and voltage control, and seamless participation in grid frequency regulation. It offers a relatively short construction period, efficient adaptability to diverse environments, low operating costs, and centralized management ease. Moreover, this approach is highly scalable, less constrained by space, and facilitates long-distance transmission of electric power through high-voltage connections.

However, centralized V2G is not without its drawbacks. Long-distance power supply to the grid via power transmission lines results in power loss and line loss. The high construction cost, dependence on national subsidies, and limitations due to space restrictions pose significant challenges. Additionally, the lack of supporting energy storage leads to uncontrollable power, voltage drops, and reactive power compensation issues, particularly when influenced by the instability of electric vehicles. Centralized V2G, especially when deploying a large capacity, requires multiple transformers to be combined for cooperative operation, and unified management is still a maturing aspect.

On the other hand, distributed V2G, with power sources located on the user side and typically connected to the grid nearby, offers compelling advantages. It



(a) Centralized V2G energy trading structure.



(b) Decentralized V2G energy trading structure.

Figure 2.3: Centralized & decentralized V2G energy trading structures.

allows for local power generation and usage, reducing reliance on grid power and minimizing line losses. Distributed V2G can optimally utilize private garages, underground parking lots, and building spaces, leading to a smaller power station footprint and material savings. Moreover, it provides operational flexibility and, under specific conditions, can function independently of the grid [37].

Nonetheless, distributed V2G presents challenges such as the inability for mass production due to its household-based nature, high maintenance costs, and safety risks associated with parking lots. Technical challenges such as difficulty in voltage and reactive power regulation and the need for an energy management system at the distribution network level underscore its complexities.

In the evolving landscape, resilience and sustainability goals are driving new electrical demands and fostering the growth of distributed V2G trading. However, unless incentivized and integrated strategically into grid services, this growth could escalate operational challenges and infrastructure costs. Building intelligent distributed V2G networks could usher in a new era, integrating renewable energy and IoT technology, and reconstructing the existing infrastructure.

2.4 Blockchain-Based Energy Trading Systems

Energy trading has historically been facilitated through centralized markets with transactions mediated by brokers or exchanges. However, the emergence of decentralized technologies, notably blockchain, holds promise to revolutionize energy trading by offering secure, efficient, and transparent transaction mechanisms [38].

A primary challenge facing energy trading is security. Energy markets are prime targets for cyber attacks, potentially causing widespread disruption and economic damage. Traditional centralized trading systems are vulnerable to cyber attacks, being single points of failure. In contrast, blockchain-based systems present a decentralized architecture that enhances resilience against cyber threats.

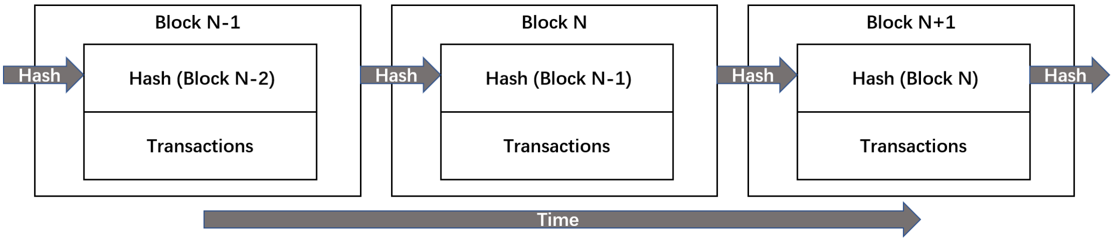


Figure 2.4: A typical Blockchain structure.

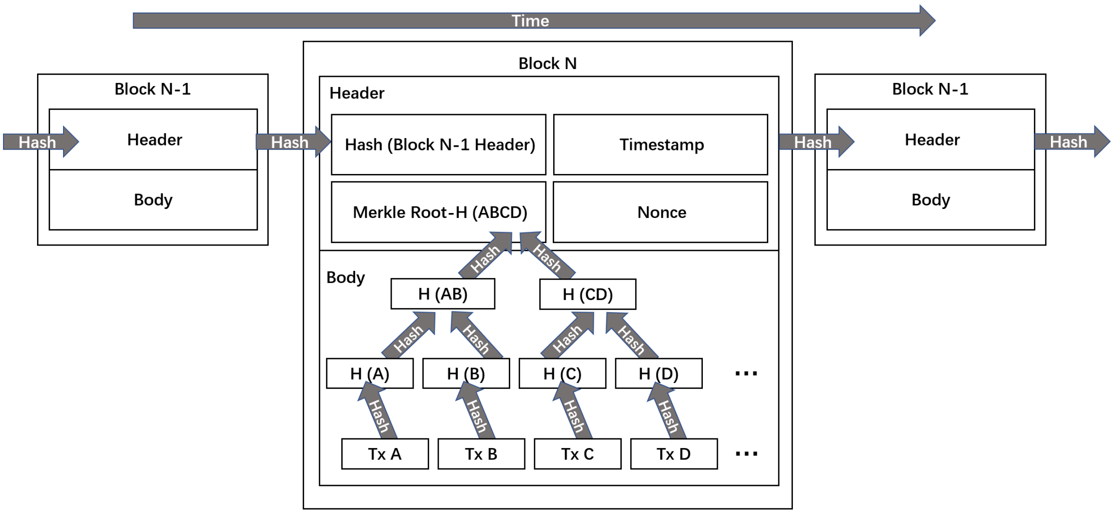


Figure 2.5: A Blockchain structure with Merkle tree.

Blockchain technology functions as a distributed ledger, continuously growing with records stored in blocks as illustrated in Fig. 2.4. Each block includes a timestamp and a link to the previous block, forming an immutable and transparent chain. This secure and efficient platform serves as a foundation for energy trading. A cryptographic data structure named Merkle tree is also utilized to summarize all the transactions in a block. The hierarchical structure of hashes ensures that any change in the transactions will alter the Merkle root, indicating potential tampering and enabling efficient verification of transactions within the block, thus allowing for efficient and secure verification of the integrity and consistency of the data within the tree. A structure of the Merkle tree is shown in Fig. 2.5.

To address security concerns in energy trading, researchers have explored blockchain-based distributed architectures. These architectures can be categorized as permissionless and permissioned blockchains. Permissionless blockchains rely on probabilistic consensus algorithms, while permissioned blockchains involve vetted nodes in the consensus process. The latter, with a trusted ordering organization, diminishes the risk of ledger divergence [39].

Transparency is a key benefit of blockchain-based systems for energy trading. The blockchain ledger provides a transparent record of all transactions, eliminating the need for intermediaries. This reduction in transaction costs and increase in market efficiency is further complemented by the automation capabilities of smart contracts, self-executing contracts with terms directly written into code [40].

Efficiency gains are another advantage. Traditional systems involve multiple intermediaries, each adding transaction fees. Blockchain-based systems remove intermediaries, reducing transaction costs and increasing transaction speed. Additionally, the decentralized architecture of blockchain networks enhances their resilience against cyber attacks.

Security is significantly bolstered in blockchain-based systems for energy trading. The decentralized nature of blockchain networks and cryptographic measures employed in each block make altering the ledger exceedingly difficult. The transparency of the ledger empowers regulators to detect and prevent fraud, thus enhancing market integrity.

In conclusion, blockchain-based systems possess the potential to reshape energy trading by offering heightened security, efficiency, and transparency. As blockchain technology evolves, it is likely to become a crucial component of the energy trading landscape. However, challenges, both technical and regulatory, need to be addressed for widespread adoption in the energy sector.

Chapter 3

Related Works

3.1 Distributed and Centralized Energy Trading

Energy trading systems, based on their system structure, can be broadly categorized into centralized and distributed systems. Within distributed energy supply and trading systems, further classifications can be made based on functions and security features. In conventional energy markets, the energy flow primarily occurs unilaterally, moving from generation companies to consumers [41].

Such grids are mature in containing fossil-fired power plants yet cannot absorb changing renewables and minor suppliers. Though some research tries to establish bidirectional energy systems upon the conventional centralized ones [42], the conflict between energy trading security and transparency remains a dilemma.

As a result, distributed energy supply and trading systems are growing globally to optimize outdated market systems and relieve energy shortages. Luo et al. proposed a distributed electricity trading system to facilitate trusted and secured peer-to-peer electricity sharing among consumers [43].

Yahaya et al. [44] proposed a secured Peer-to-Peer energy trading model with an authentication layer to defend against impersonation attacks and an energy trading layer to minimize the number of malicious validators.

Among decentralized energy trading solutions, several systems relating to charging stations, renewable trading, or intelligent households employ peer-to-peer energy trading. Doan et al. [45] improved consumer profits through peer-to-peer energy trading and a double auction-based game theoretic approach.

Kang et al. [16] also proposed a localized peer-to-peer electricity trading model for plug-in hybrid electric vehicles in smart grids.

Hassan et al. [46] developed a blockchain-based approach for secure and private microgrid energy auctions.

Gao et al. [47] developed and validated an intelligent microgrid management system to secure Singapore's energy market by leveraging the inherent synergy between Peer-to-Peer blockchain and fog computing.

Alskaif et al. [48] proposed households' strategies for bilateral trading preferences in a local Peer-to-Peer energy market using permissioned blockchain.

These distributed peer-to-peer energy systems mostly trade with limited counterparts and have a relatively high transaction cost, which lowers the overall trading welfare and throughput. By contrast, distributed trading systems with aggregators can organize market orders among authorized traders to cut the matching overhead in a free market.

Plenty of papers have been devoted to the very research orientation. Tesfamicael et al. [49] put forward a blockchain application for secure macro grid energy trading of mega power generation. Huang et al. [50] proposed a multi-objective optimization model and a genetic sorting algorithm to ensure the security and privacy of energy trading within a multi-blockchain. Aggarwal et al. [33] proposed an energy trading blockchain scheme across EVs, charging stations, and utility centers.

Aggregated energy trading systems are also applied to Industrial IoT [51, 52] and smart building [53,54] to address the security and fairness challenges in energy trading.

3.2 Secure Energy Trading and Integration of Blockchain

Some related works [55–59] focus on optimizing the system performance by maximizing overall trading welfare, minimizing trading overhead, and enhancing resilience in unpredicted outages. Nevertheless, their neglect of trading security can be fatal, for data leaks, malicious tampering, and intentional attacks may lead to considerable losses during energy trading.

For this reason, abundant references highlight trading security in their energy systems. Khorasan et al. [60] proposed a decentralized peer-to-peer energy trading scheme for secure forward market trading using the primal-dual gradient method. Ma et al. [61] introduced a novel secure communication scheme to prevent potential false data injection attacks and other cyber risks.

Although these works strengthen energy trading security through different solutions, recently, blockchain has been employed by many researchers as an ideal way to reinforce systematic security in distributed energy trading.

Yang et al. [62] proved the blockchain effective in securing the distributed control systems against false data injection attacks in a hierarchical prosumer microgrid. Gai et al. [31] presented a consortium blockchain-oriented approach to solving the privacy leakage without restricting trading functions. Aitzhan and Svetinovic [63] addressed the transaction security in decentralized smart grid energy trading by implementing proof-of-concept, multi-signatures, and anonymous encrypted messaging streams. Li et al. [64] introduced a blockchain-combined superconducting energy storage unit to avoid transaction failure in EV Peer-to-Peer energy trading.

The work in [65] 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. [66] 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. [67] 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. [68] 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 [69] by exploring the scalability of blockchain.

Lin et al. [70] 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.

3.3 V2G Energy Trading Systems

The rapid rise of EV fleets in the V2G energy network hampers the implementation of aggregated trading systems. This is because the energy trading mechanism needs to maintain scalability for more EVs and consumers while keeping the efficiency and security of the blockchain system. To solve these bottlenecks, some trading mechanisms in V2G energy systems take game-theoretic solutions, such as Yu et al. [23] optimized the Bayesian game in PEV microgrids to share energy with maximized profit, and Yassine et al. [17] adopted cloudlet residing aggregators and a dynamic double auction model to trade electricity. Others apply an incentive-driven strategy, like Kim et al. [4], who formulated a trading incentive mechanism for EVs and mobile charging stations.

Chen et al. [20] 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. [71] 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. [72] 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 [73], 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. [74] 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. [75] 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.

In V2G energy networks, the trading parties are virtually known entities with a certain degree of trust and acting for a common purpose. However, most game-theoretic V2G networks only regard their traders as competitors and take non-cooperative games, which is an excessive drag on the network scalability. On the other hand, incentive-driven V2G networks usually require a native cryptocurrency to fuel the trading execution, which increases the time and computational costs and adds some significant risk. In such a context, an active energy distribution strategy for V2G trading under more cooperative and sharing situations needs to be considered.

3.4 Smart Energy Forecasting Systems

The original hybrid deep learning algorithm in the work [76] 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 [77] 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 [78] 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 [79], 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. [80] 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 [81] identified a hybrid photovoltaic forecasting framework based on the temporal convolutional network for enhancing hours-ahead utility-scale Photovoltaics (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.

Chapter 4

Trustworthy V2G Energy Trading System V2GNet

4.1 System Composition and Energy Trading Process

The proposed energy trading process for Vehicle-to-Grid Network (V2GNet) is illustrated in Fig. 4.1. The energy exchanges receive energy requests from connected consumers and forward them to the Control System (CS). The CS then informs the EVs about the energy requested. Each EV checks its availability based on remaining energy and future tasks. The available EV responds to the CS about its EV ID and the amount of energy requested. The CS obtains both the consumers' energy requests and the EVs' energy offers, then selects the successful bidder using the RET algorithm (see Section 4.3.2). The result comprises two lists, namely the charge, and the discharge list. The charge list contains information about winning consumers and the amount of energy supplied. The discharge list holds information about the selected EVs that supply energy. The charge list is sent to the exchanges, and each consumer receives a notification afterward. The discharge list is not transmitted to the vehicular network, but each EV receives instructions on whether to discharge or not. Finally, the payment clearing is performed on the CS side.

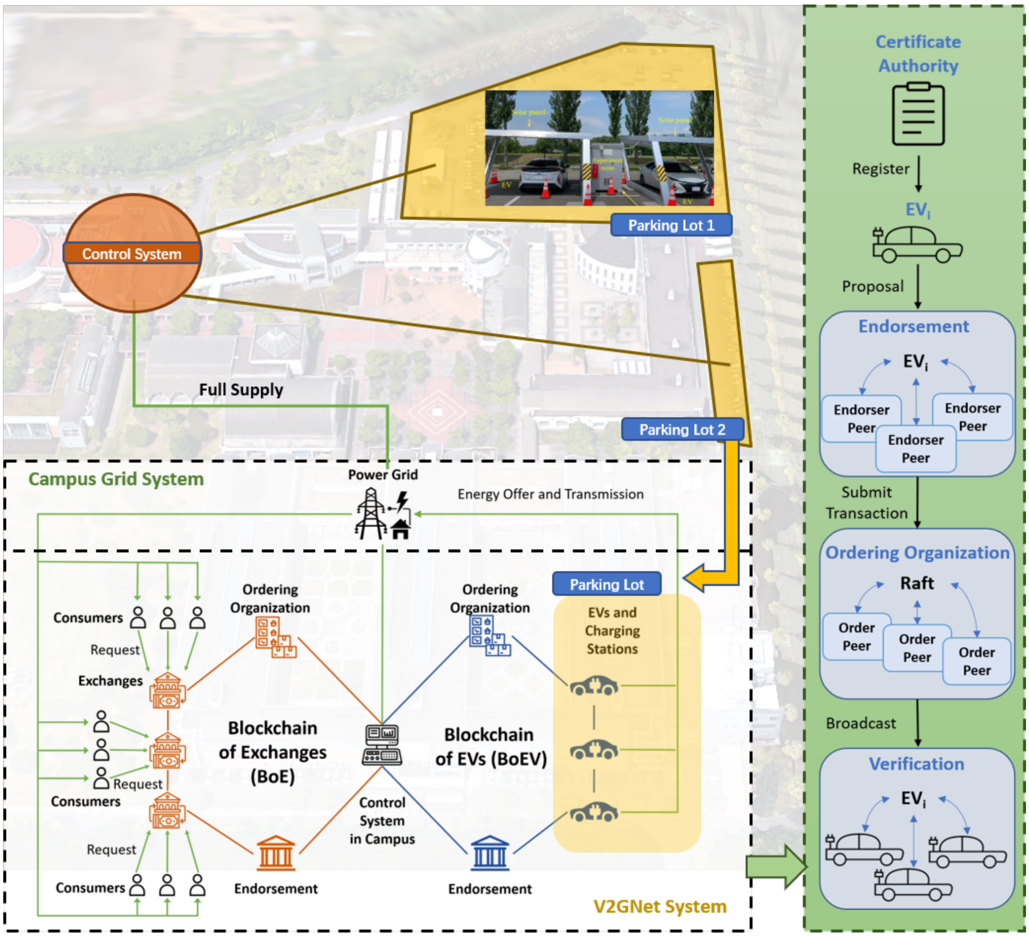


Figure 4.1: Overview of the proposed V2GNet. Each campus' control system (CS) works as a mediator between energy consumers and suppliers (EVs). Each consumer connects and submits the energy request to the energy exchange. The blockchain of exchanges (BoE) integrates exchanges and the CS, where the request lists (exchanges to CS) and notification of supply results (CS to exchanges) are transmitted. Besides, the blockchain of EVs (BoEV) integrates EVs and the CS, where the offer lists (EVs to CS) and notification of discharge tasks (CS to EVs) are transmitted. The CS works as an information mediator, while the power grid works as a mediator for energy transmission between EVs and consumers.

The following describes the process on the EV side and the CS side. The EV's process begins with "Start A." At first, If an EV is not yet connected to the grid and/or is currently performing a charge/discharge process, it cannot participate in preceding processes. Otherwise, the vehicle checks its Remaining Power (RP) and predicts the Energy Consumption (ECP) shortly. If the remaining energy is not enough, the vehicle must be recharged. The energy consumption prediction method is presented in [82]. Therefore, only EVs with sufficient energy and connected to the power grid are considered "available" for energy supply. When an

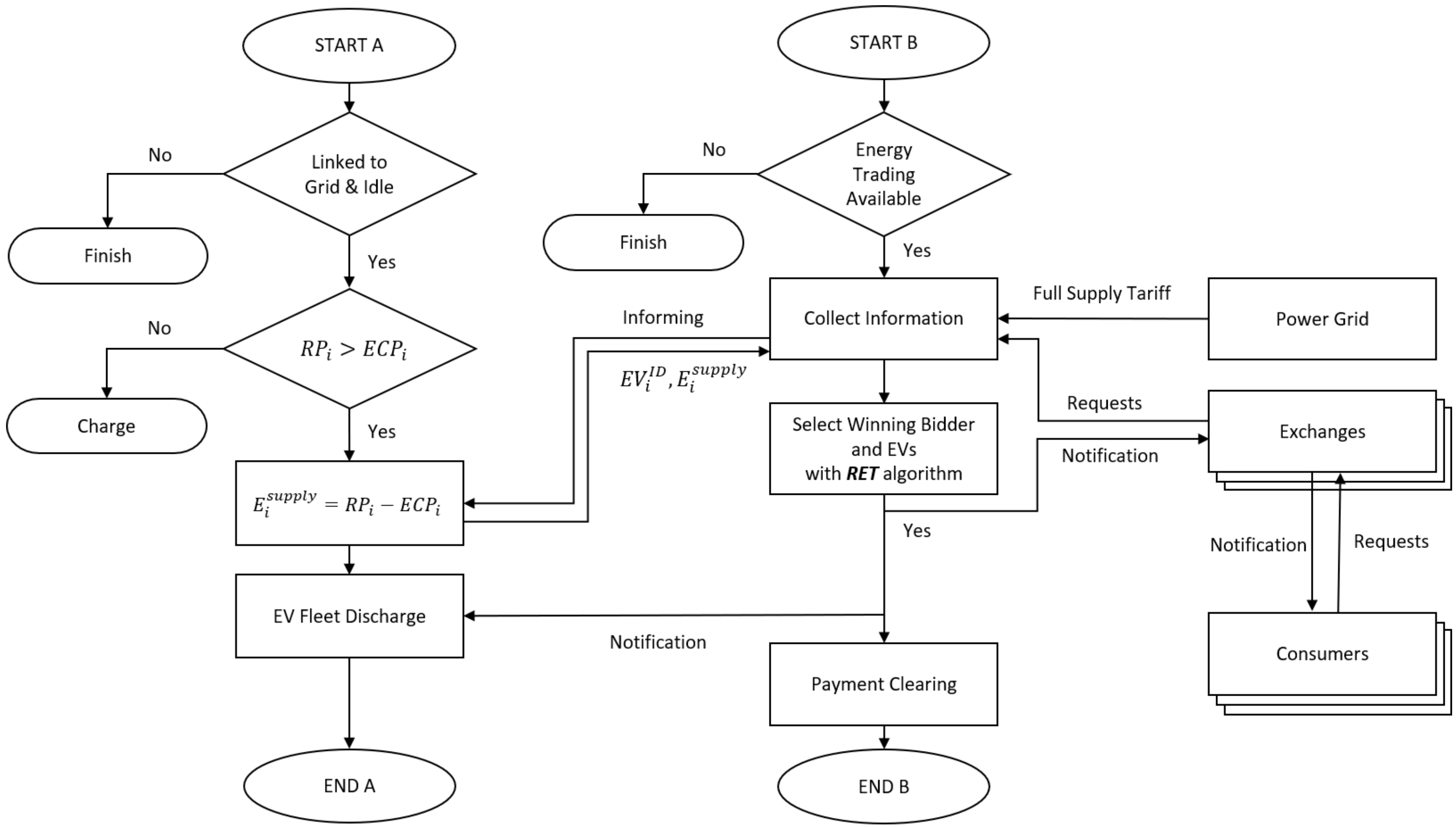


Figure 4.2: Energy trading algorithm in V2GNet for both EV side and CS side. The EV side begins from "Start A" and the CS side begins from "Start B." The power grid provides CS with a full supply tariff. The exchanges collect energy requests from consumers and communicate with the CS.

available EV receives energy requesting information from the CS, the EV sends a response that includes the amount of energy to be supplied and its identification. Afterward, the EV begins discharging when it receives the discharge notification from the CS.

The process on the CS side begins with "Start B." Initialization of the CS indicates that energy trading is now available. The CS collects energy requests from consumers and informs the EVs about the start of energy trading, then receives information about energy offers from EVs. To decide which consumer receives energy from which EV, the RET algorithm is performed. However, the information of all selected consumers is not required for the selected EVs. Similarly, the information about all selected EVs is needless for selected consumers. Therefore, these details are not transmitted for efficiency and confidential reasons.

4.2 Malicious Attacks on Energy Trading

4.2.1 Consumer Attack

Fig. 4.3 describes an attack scenario caused by a consumer. Consumer Energy consumer numbered i (C_i) falsifies multiple fake requests (Request i_1 to i_m). These fake requests contain the same or different data about the time of electric usage, input electric power, bid price, etc. When a large portion of fake requests is selected, a group of EVs are thus assigned discharge tasks but cannot properly discharge. Moreover, the requests from other consumers are therefore not met. To counter consumer attacks, in our proposed strategy, we consider two issues, one is multiple requests, and the other one is fake requests. First, we deal with multiple requests coming from a single consumer. We reserve the request with the latest submission time and discard all others. After that, we deal with fake requests. The fake requests are difficult to detect. Thus we get around this problem by focusing on the malicious consumer directly. A penalty list Penalty list to counter consumer attacks from C_i (P_i) is initialized and is empty. We set a risk

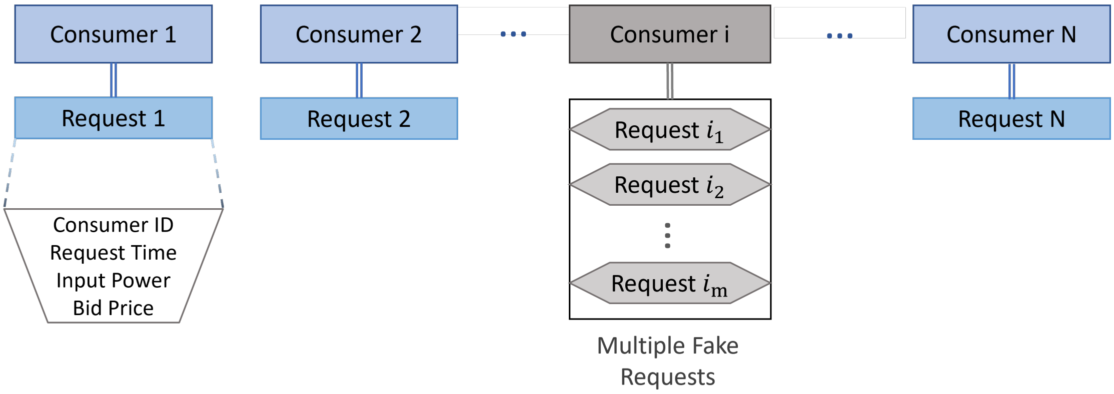


Figure 4.3: An example of consumer attack. A malicious consumer C_i submits multiple fake requests (i_1 to i_m).

parameter denoted by Risk parameter for consumer attacks (γ_1). The theoretical and practical energy supply with respect to C_i is denoted by Theoretical energy supply (s^t) and Practical energy supply (s^p) respectively. When $s^t = s^p$ at any trading round, C_i is considered trustful and not malicious. If $s^t > s^p$, we denote the percentage of fulfilled energy supply by Percentage of fulfilled energy supply to C_i (pct_i):

$$pct_i = s^p/s^t \tag{4.1}$$

When $pct_i < 1 - \gamma_1$, C_i is considered malicious now. A penalty value $pct_i + \gamma_1$ is added into P_i. When $pct_i \geq 1 - \gamma_1$, if P_i is not empty, $p_{ij} \in P_i$, $n(P_i)$ is the element number of P_i, then the last element of P_i is removed. If a consumer is "malicious", his/her request cannot be fully met. Given an Initial demand of C_i (d_i), the Actual demand can be met for C_i (d_i^{met}) can be denoted by :

$$\begin{cases} d_i^{met} = d_i & \text{if } P_i = \emptyset \\ d_i^{met} = d_i \prod_{j=1}^{n(P_i)} p_{ij} & \text{if } P_i \neq \emptyset \end{cases} \tag{4.2}$$

4.2.2 Exchange Attack

In V2GNet, all energy exchanges are protected by permissioned blockchain, where participants must have proven identities to transact on the network. This

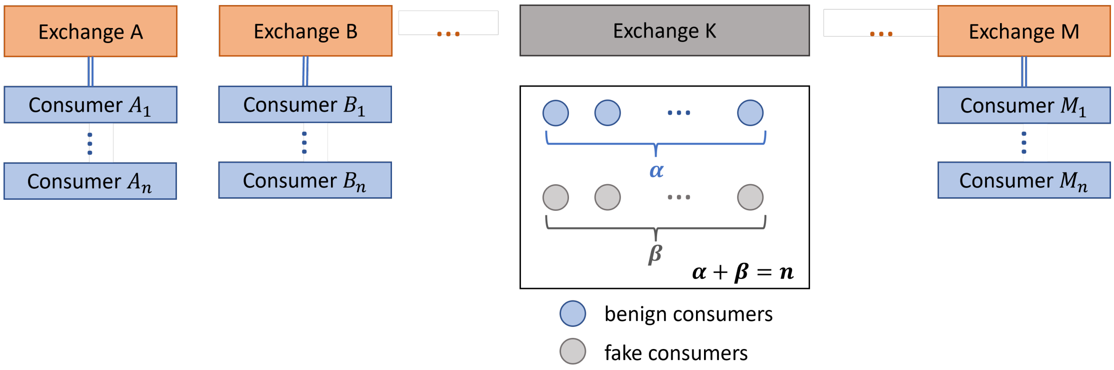


Figure 4.4: An example of an exchange attack. A malicious exchange E_K is associated with n consumers, including α benign consumers and β fake consumers.

shields exchanges against direct intrusions such as data scrubbing or tempering. Nevertheless, latent malicious exchanges could sneak in from round one, and manipulated exchanges could be depraved over any trading process. For every trading round, each exchange is supposed to upload a request list of its consumers' energy demands. Those malicious exchanges generate fake request lists by meddling with the real ones or fabricating fake requests for their consumers. Fig. 4.4 depicts a malicious exchange E_K that fabricates a group of fake consumers. To minimize the damage of malicious exchanges, we designed a strategy that gradually lessens their winning chance in bidding. For example, for a single exchange E_K. A Penalty list to counter exchange attacks from E_K (Q_K) is initialized and is empty. We set a Risk parameter for exchange attacks (γ_2). After the CS performs the RET algorithm, the set of selected requests is denoted by R_K. The set of fulfilled requests in R_K is denoted by R'_K. Finally, the Percentage of fulfilled selected requests from E_K (pct_K) is denoted by :

$$pct_K = \frac{n(R'_K)}{n(R_K)} \tag{4.3}$$

When $pct_K < 1 - \gamma_2$, E_K is considered "malicious" now. A penalty value $pct_K + \gamma_2$ is added into Q_K. When $pct_K \geq 1 - \gamma_2$, if Q_K is not empty, $q_{Kj} \in Q_K$, $n(Q_K)$ is the element number of Q_K, then the last element of Q_K is removed.

Given an initial request list R_K^0 from E_K, the Maximum amount of requests can be met for E_K (a_K^{met}) is denoted by :

$$\begin{cases} a_K^{met} = n(R_K^0) & \text{if } Q_K = \emptyset \\ a_K^{met} = \left\lfloor n(R_K^0) \prod_{j=1}^{n(Q_K)} q_{Kj} \right\rfloor & \text{if } Q_K \neq \emptyset \end{cases} \tag{4.4}$$

4.3 Matching Algorithms and Optimization

4.3.1 Matching Strategy between Requests and EVs

For maximum profitability and the best possible energy utilization, the CS must reorder both the requests and the offer lists first. Each request is associated with an expected profit for the request list, which is the product of input power and unit bid tariff. The request list is reordered based on the expected profit in descending order. The offer list is reordered based on the amount of energy supplied. Furthermore, the CS begins allocating energy between requests and offers, starting from the request with the highest profit. Given a request, the CS traverses the offer list, and if an offer cannot meet the demand of the request, the CS allocates the offer to this request and moves on to the next offer until the entire demand for the request is met. To minimize the waste of EV energy, if more than one offer meets the demand of the request, the offer with the least energy supply is selected. The procedure ends when all requests are fulfilled or all offers are selected.

4.3.2 Robust Energy Trading (RET) Algorithm

Based on our approach against malicious consumers and exchanges and the matching strategy between requests and EVs, A summary of the proposed Robust Energy Trading (RET) algorithm is as shown in Algorithm 1. We denote the set of request lists from each exchange by $\{R_i^0\}, i \in N$, N is the number of exchanges. The total request list is denoted by $\{r_{ij}\}, i \in N, j \in N_i$, N_i is the number of requests of exchange E_i. We have

$$\{r_{ij}\} = \bigcup R_i^0 \tag{4.5}$$

Each r_{ij} contains an exchange ID (ID_i^E) and a consumer ID ($ID_{im}^C, m \in M_i$. M_i is number of consumers of exchange E_i), (B_{ij}) a bid tariff, submission time of request denoted by (t_{ij}^r), and quantity of energy demand denoted by (d_{ij}). We denote the offer list by $\{O_i\}, i \in K$, where K is the number of available EVs and offers. Each O_i contains the EV ID (ID_i^{EV}) and the amount of energy to be offered denoted by (o_i). W denotes the capacity of the charging pile. We also denote two risk parameters by γ_1 and γ_2, the penalty list for consumer C_{ij} by P_{ij} and for exchange E_i by Q_i . We initialize an empty list R^W for winning requests and an empty list O^W for winning offers. In addition, we initialize an empty list Π for storing the expected profit of each request and a list U for recording whether an offer has been selected. All element in U is set to zero by default and when an offer O_k has been selected, $u_k \in U$ is set to one.

We only reserve one request with the latest submission time for each consumer while discarding the rest. We then adjust the amount of energy request according to the penalty list of the consumer given by Equation 4.2. The request list $\{r_{ij}\}$ is rearranged according to the expected profit regarding each request in descending order. Also, the maximum number of energy requests that could be fulfilled for each exchange is adjusted according to Equation 4.4. For each offer O_k, the amount of offered energy o_k is adjusted according to the capacity of charging pile W:

$$o_k = min(o_k, W) \tag{4.6}$$

The offer list $\{O_k\}$ is rearranged according to the amount of offered energy in descending order. Begin with the first request, we select a group of offers that gives the best possible match. If the demanded energy can be met by at least one offer, we select the offer having the least energy amount. Otherwise, we select

Algorithm 1 Robust Energy Trading Algorithm

Require:
1: A set of request lists from each exchange $\{R_i^0\}, i \in N$, total request list $\{r_{ij}\}$, $i \in N, j \in N_i$, exchange ID $\left\{ID_i^E\right\}$, consumer ID $\left\{ID_{im}^C\right\}$, $m \in M_i$, bid tariff $\{B_{ij}\}$, submission time of request $\left\{t_{ij}^r\right\}$, and quantity of energy demand $\{d_{ij}\}$
2: Offer list $\{O_k\}, k \in K$, EV ID $\left\{ID_k^{EV}\right\}$, amount of energy offer $\{o_k\}$
3: Capacity of charging pile W
4: A set of penalty lists for consumers $\{P_{im}\}$
5: A set of penalty lists for exchanges $\{Q_i\}$
Ensure: A list of selected requests and a list of selected offers
6: Initialize an empty list R^W for winning requests
7: Initialize an empty list O^W for winning offers
8: Initialize an empty list A for storing the maximum number of requests to be fulfilled regarding each exchange
9: Initialize an empty list Π for storing expected profit of each request
10: Initialize a list U for recording whether an offer has been selected. All elements are set to zero.
11: for $\forall i \in N$ and $\forall m \in M_i$:
12:   for $\forall p, q \in N_i$:
13:     if $t_{ip}^r > t_{iq}^r$:
14:       remove r_{iq} from $\{r_{ij}\}$ and R_i
15:       remove q from N_i
16: for $\forall i \in N$ and $\forall j \in N_i$:
17:   if $P_{im} \neq \emptyset$:
18:     $d_{ij} = d_{ij} \prod_{l=1}^{n(P_{im})} p_{iml}$
19:   Calculate expected profit π_{ij} regarding each request,
20:   $\pi_{ij} \leftarrow B_{ij} \times d_{ij}$, add π_{ij} into Π
21: Rearrange $\{r_{ij}\}$ according to Π in descending order.
22: for $\forall i \in N$:
23:   if $Q_i = \emptyset$:
24:     $a_i = n(R_i^0)$
25:   else:
26:     $a_i = \left\lfloor n(R_i^0) \prod_{l=1}^{n(Q_i)} q_{il} \right\rfloor$
27:   add a_i into A
28: for $\forall k \in K$:
29:   $o_k = min(o_k, W)$
30: Rearrange $\{O_k\}$ according to $\{o_k\}$ in descending order
31: while $\{r_{ij}\} \neq \emptyset$ or $\exists u_k \in U, u_k = 0$:
32:   for $\forall r_{ij} \in \{r_{ij}\}$:
33:     if $a_i > 0$:
34:       for $k = 1$, k in K, $k{+}{+}$
35:         if $d_{ij} \leq o_k$ and $k = K$ and $u_k = 0$:
36:           $u_k \leftarrow 1$

37: $r^w \leftarrow$ exchange ID, consumer ID, d_{ij}
38: add r^w into R^W
39: $o^w \leftarrow$ EV ID, d_{ij}
40: add o^w into O^W
41: remove r_{ij} from $\{r_{ij}\}$
42: $a_i \leftarrow a_i - 1$
43: break
44: else if $d_{ij} \leq o_k$ and $d_{ij} > o_{k+1}$ and $u_k = 0$:
45: $u_k \leftarrow 1$
46: $r^w \leftarrow$ exchange ID, consumer ID, d_{ij}
47: add r^w into R^W
48: $o^w \leftarrow$ EV ID, d_{ij}
49: add o^w into O^W
50: remove r_{ij} from $\{r_{ij}\}$
51: $a_i \leftarrow a_i - 1$
52: break
53: else if $d_{ij} > o_k$ and $u_k = 0$:
54: $u_k \leftarrow 1$
55: $r^w \leftarrow$ exchange ID, consumer ID, o_k
56: add r^w into R^W
57: $o^w \leftarrow$ EV ID, o_k
58: add o^w into O^W
59: $r_{ij} \leftarrow r_{ij} - o_k$
Return R^W and O^W

the offer with the largest energy supply and move on to the next offer until the energy demand can be met. It is worth noting that once an offer is selected, it is added to the winning offer list and will be considered unavailable in the round. Also, if a request is fulfilled, we add it to the winning request list and move on to the subsequent request. The matching procedure ends when all the requests have been fulfilled or all the offers have been selected.

At last, we analyze the time complexity of the RET algorithm. There are 5 loops in the RET algorithm. As shown in Algorithm 1, the first loop starts from line 11 and ends at line 15. In the loop, we keep the request with the latest timestamp of each consumer and then discard the other redundant requests from the same consumer. The time complexity of loop 1 is $O(NM_i)$. The second loop starts from line 16 and ends at line 20. Here we deal with malicious consumers by applying the consumer penalty list P_{im} to their energy requests. And the time complexity of loop 2 is $O(NN_i)$. Since we already cut the number of requests in loop 1, $O(NN_i) = O(NM_i)$. The third loop starts from line 22 and ends at line 27. Here we deal with malicious exchanges by applying the exchange penalty list Q_i, and the time complexity of loop 3 is $O(N)$. The fourth part starts at line 28 and ends at line 29. Here we define the amount of each energy offer, and the time complexity of loop 4 is $O(K)$. The fifth loop starts from line 31 and ends at line 59. Here we distribute available EVs for energy consumers. And the time complexity of loop 5 is $O(NM_iK)$. Besides, in line 21 and line 30 we rearrange the energy demand list and offer list, respectively. And their time complexities are both taken as $O(n^2)$. Therefore, the overall time complexity of Algorithm 1 is:

$$\begin{aligned} T(n) &= O(NM_i + NM_i + N + K + NM_iK) \\ &+2O(n^2) = O(n^3 + 4n^2 + 2n) = O(n^3) \end{aligned} \tag{4.7}$$

4.4 Evaluation

This section verifies our proposed energy trading system's security properties and economic efficiency.

Table 4.1: Configuration for the V2G Trading in V2GNet Simulation.

Input Feature	Value	Unit
Discharge Capacity	0 to 10	kWh, Int
Charge Capacity	1 to 20	kWh, Int
Request Time Slot	21 to 22	-, Float
No. of Consumers	100, 150, 200, 400	-, Int
No. of EVs	50, 100, 150, 200	-, Int
No. of Exchange	3	-, Int
No. of Malicious Exchanges	1	-, Int
No. of Malicious Consumers	1, 5, 10, 20, 50	-, Int
Maximum No. of Requests from One Malicious Consumer	10	-, Int
Bid Price	22.39 to 42.84	JPY, Float

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

4.4.1 Evaluation Methodology

To show that the proposed system achieves better energy demand satisfaction and higher profit, we compare the system with an action-based incentive scheme as offered by [4] and a double auction mechanism as proposed by [17]. We experiment 100 times using different request and EV number combinations for the following examples; request numbers to 100, 150, 200, and 400, and EV numbers to 50, 100, 150, and 200, respectively. In addition, to show the robustness of our proposed algorithm, we simulate experiments on consumer attacks and exchange attacks, respectively. The configuration is as shown in Table 4.1. For consumer attacks, we simulate a single-consumer scenario with one malicious node and several multi-consumer scenarios with 5, 10, and 20 malicious nodes. Each malicious node submits up to 10 fake requests. We compare trading performance differences first under no attack and then under consumer attack. Also, we evaluate how the RET algorithm serves as an advantage to the trading system while considering these three indicators: 1) Energy demand fill rate; 2) Number of fulfilled requests; 3) Total profit. For the exchange attack, we create one malicious exchange and two benign exchanges. Therefore, each exchange is associated with 100 consumers while the malicious exchange is associated with 50 benign and 50 malicious consumers. Three indicators are considered: 1) Energy Fulfillment; 2) Number of fulfilled requests, and 3) Total profit. The meaning of each indicator is as follows:

- Energy demand fill rate: the percentage of energy demand met.
- Energy Fulfillment: total amount of energy demand met.
- Number of fulfilled requests: the number of energy requests fulfilled.
- Total profit: total profit of energy trading.

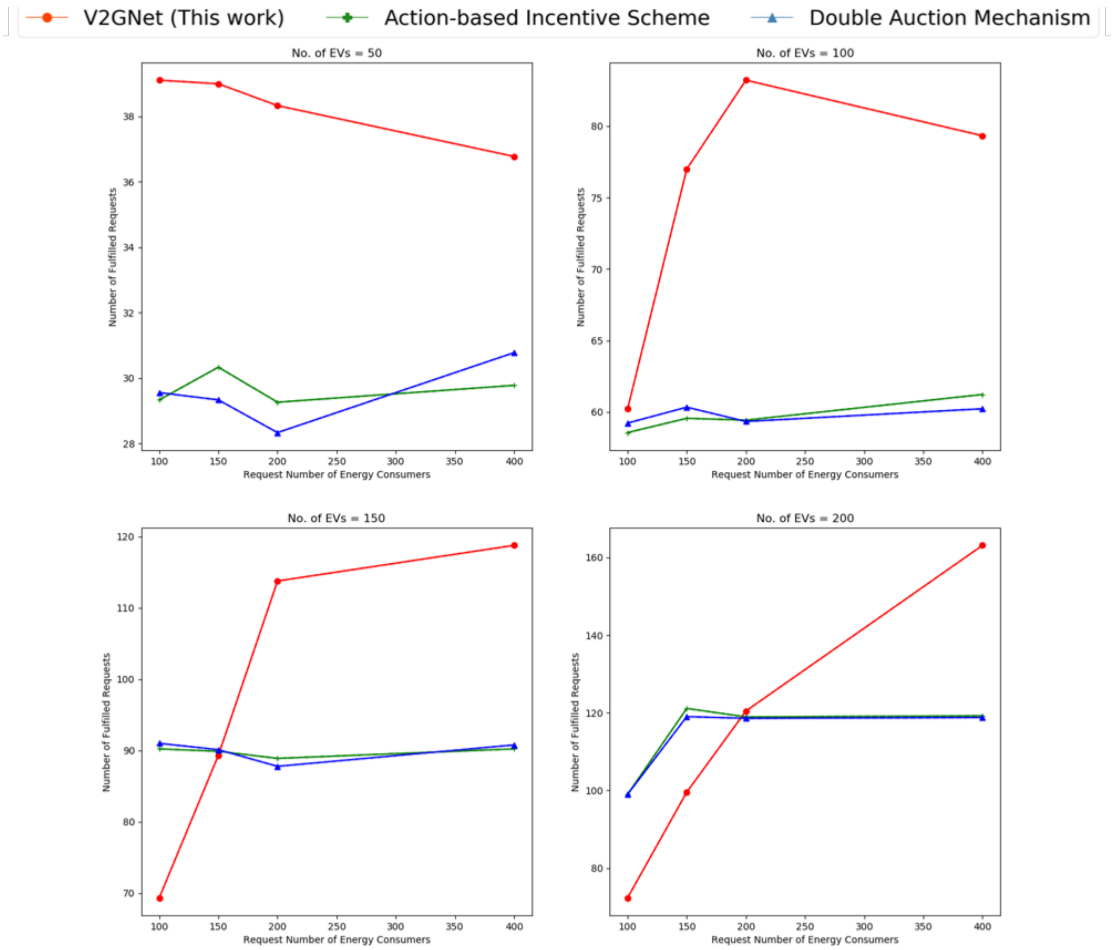


Figure 4.5: Comparison between V2GNet, action-based incentive scheme and double auction mechanism with combinations of EV and request amount considering the Number of Fulfilled Requests.

4.4.2 Evaluation Results

As shown in Fig. 4.5, the V2GNet demonstrates a higher number of fulfilled requests compared to the action-based incentive scheme and double auction mechanism. Increasing the number of EVs from 50 to 200, the proposed algorithm extends its lead in fulfilled requests from around 38 to 160. Compared to the other methods, V2GNet expands its advantage in fulfilled requests with the increase in request numbers.

As shown in Fig. 4.6, the V2GNet also shows a higher energy demand fill rate compared to the rest two mechanisms. Increasing the number of EVs from 50 to 200, the proposed algorithm performs better when there are more energy requests than EVs.

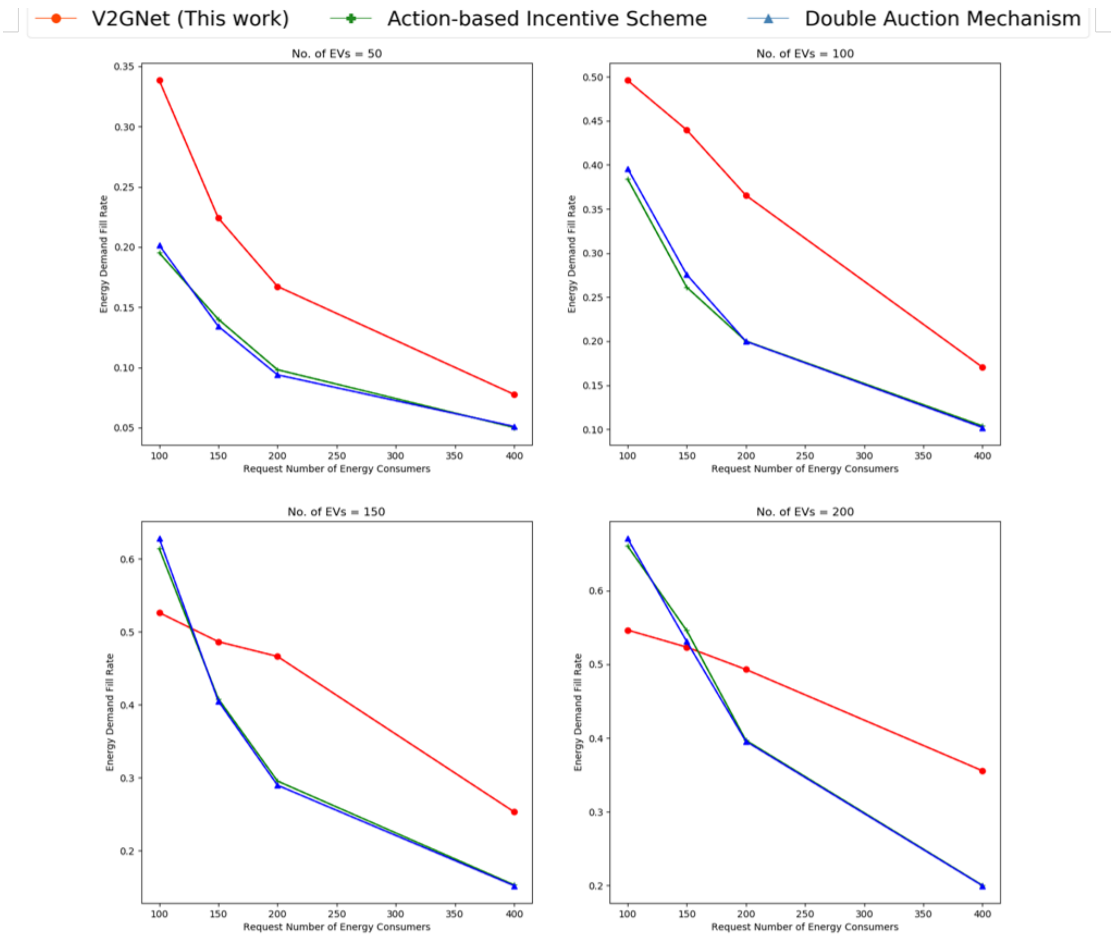


Figure 4.6: Comparison between V2GNet, action-based incentive scheme and double auction mechanism with combinations of EV and request amount considering the Energy Demand Fill Rate.

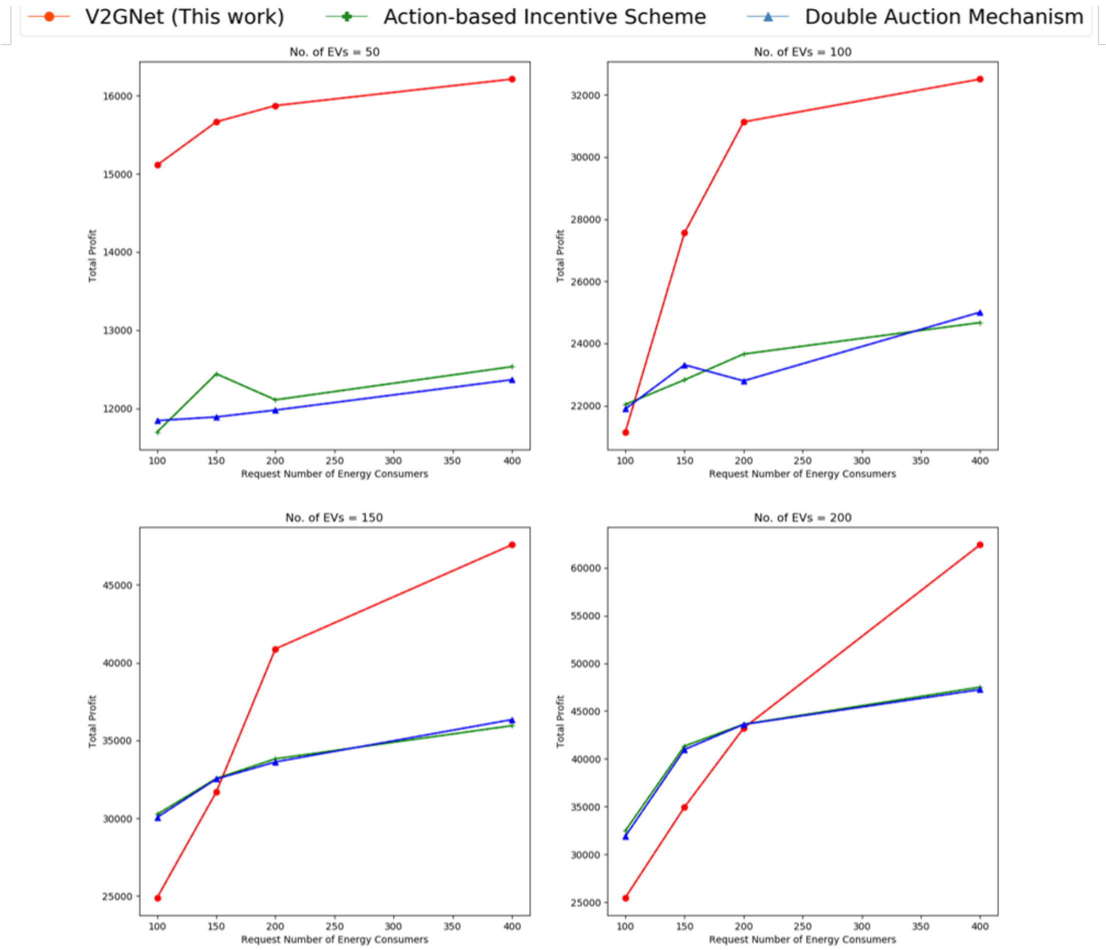


Figure 4.7: Comparison between V2GNet, action-based incentive scheme and double auction mechanism with combinations of EV and request amount considering the Total Economic Profit.

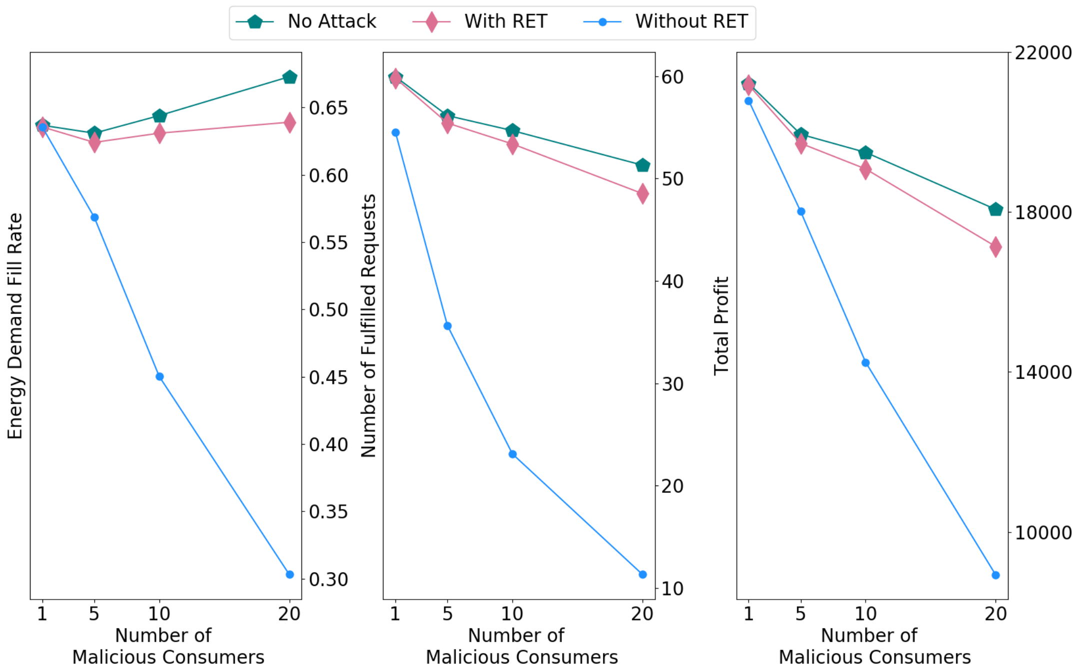


Figure 4.8: Comparison between three instances of consumer attack: 1) No attack; 2) Apply RET algorithm under consumer attack; 3) Do not apply RET algorithm under consumer attack. Three evaluation indicators are considered: 1) Energy Demand Fill Rate; 2) Number of Fulfilled Requests; 3) Total Profit.

In Fig. 4.7, the V2GNet demonstrates a higher total economic profit in a trading round compared to the action-based incentive scheme and double auction mechanism. Increasing the number of EVs from 50 to 200, the three methods show similar variation trends as the number of fulfilled requests.

From the above figures we know that when the number of EVs remains constant, V2GNet shows better performance compared to the other methods when energy requests outnumber available EVs. This is due to V2GNet's comprehensive consideration of energy supply amount and economic profit in the meantime, whose advantage can only be made full use of when there are enough energy requests available for selection and combination.

We then compare the system performance of energy trading under three scenarios: 1) No attack; 2) Apply RET algorithm under consumer attack; 3) Do not apply RET algorithm under consumer attack. The trading efficiency is presented by the energy demand fill rate, the number of fulfilled requests, and total profit. Fig. 4.8 demonstrates that the efficiency drops dramatically when there is an increase in the number of malicious consumers. For instance, if there are 20 malicious consumers in the exchange, the energy demand fill rate drops from 68% to 30% under the consumer attack, while with RET protection, the energy demand fill rate can maintain 64%. The RET also blocks most of the damage caused by consumer attacks on the total trading profit and fulfilled request number, thus improving the system's robustness against malicious consumers.

To validate the effectiveness of RET against malicious exchange attacks, we present the energy fulfillment, number of fulfilled requests, and total profit during consecutive energy bidding. As observed from Fig. 4.9, there is no difference between the index of the system with and without RET algorithm at the first trading round. As the round of auction iteration increases from 1 to 10, in the system without RET the proportion of traded energy, fulfilled requests, and profit occupied by malicious exchange all keep changing around their initial levels, while the matched index in the system with RET all drop progressively. The amount of traded energy, number of fulfilled requests, and total profit in the system with RET also transcend the system without RET round by round, respectively. This shows that the RET gradually eliminates the adverse effect of malicious exchange attacks.

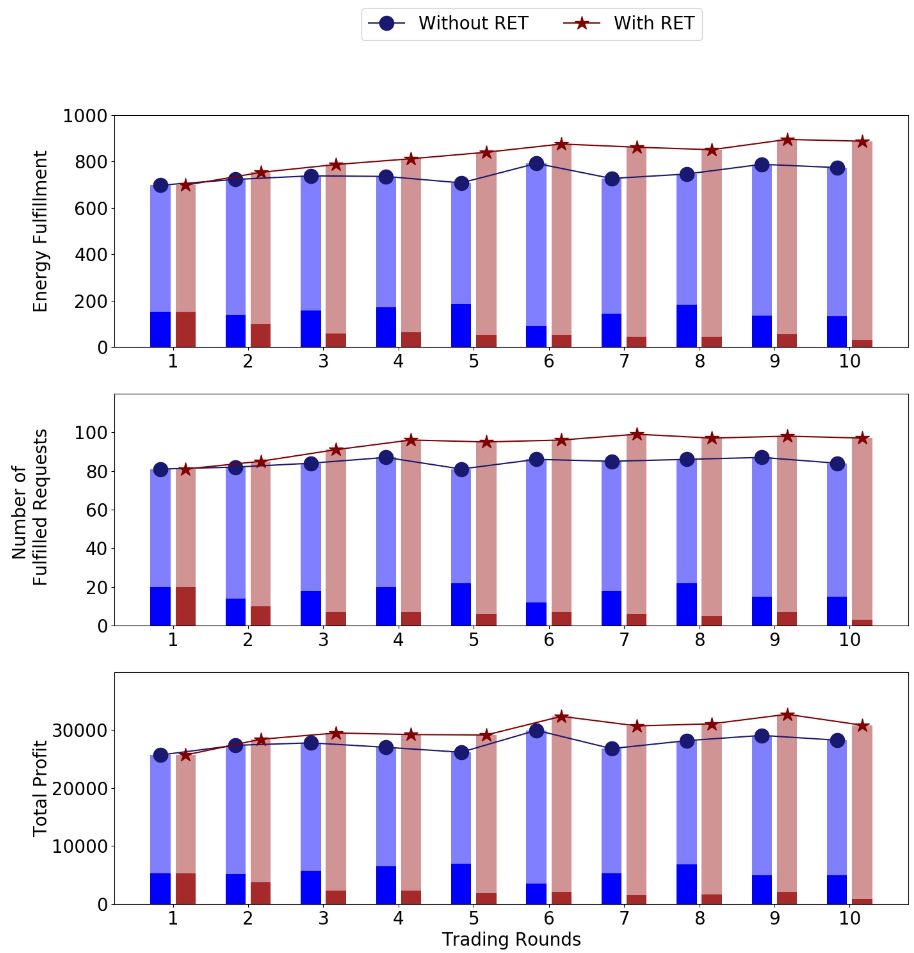


Figure 4.9: Comparison between two scenarios of exchange attack: 1) Apply RET algorithm under exchange attack; 2) Do not apply RET algorithm under exchange attack. Three evaluation indicators are considered: 1) Energy Fulfillment; 2) Number of Fulfilled Requests; 3) Total Profit. The darker parts show the proportion of indicators occupied by energy requests from malicious exchanges.

Chapter 5

Multi-blockchain V2G Energy Trading Networks

5.1 Semi-Decentralized Blockchain in Campus V2G Grid

The proposed V2GNet includes a Blockchain of Electric Vehicles (BoEV) and a Blockchain of Exchanges (BoE), as shown in Fig. 5.1. According to the workflow of the proposed (energy trading) algorithm, we divide data storage and transmission into four parts: 1) First-time operation in BoE; 2) First-time operation in BoEV; 3) Second-time operation in BoEV; 4) Second-time operation in BoE.

The first-time operation in BoE starts when an exchange receives all requests from affiliated consumers. The exchange accumulates all requests into a request list and stores the list in a transaction. Then, the exchange broadcasts the transaction and waits for a response from other exchanges. Each exchange is associated with a transaction pool where whenever the transaction pool is full, i.e., all the transactions have been collected, the exchange will send the transactions to be endorsed by a group of endorsing exchanges. Once the endorsement is completed, the transactions are transmitted to the ordering organization, where transactions are ordered in a fixed sequence and packed into a new block. The block is broadcast to all exchanges for verification and after the block is verified, the CS downloads

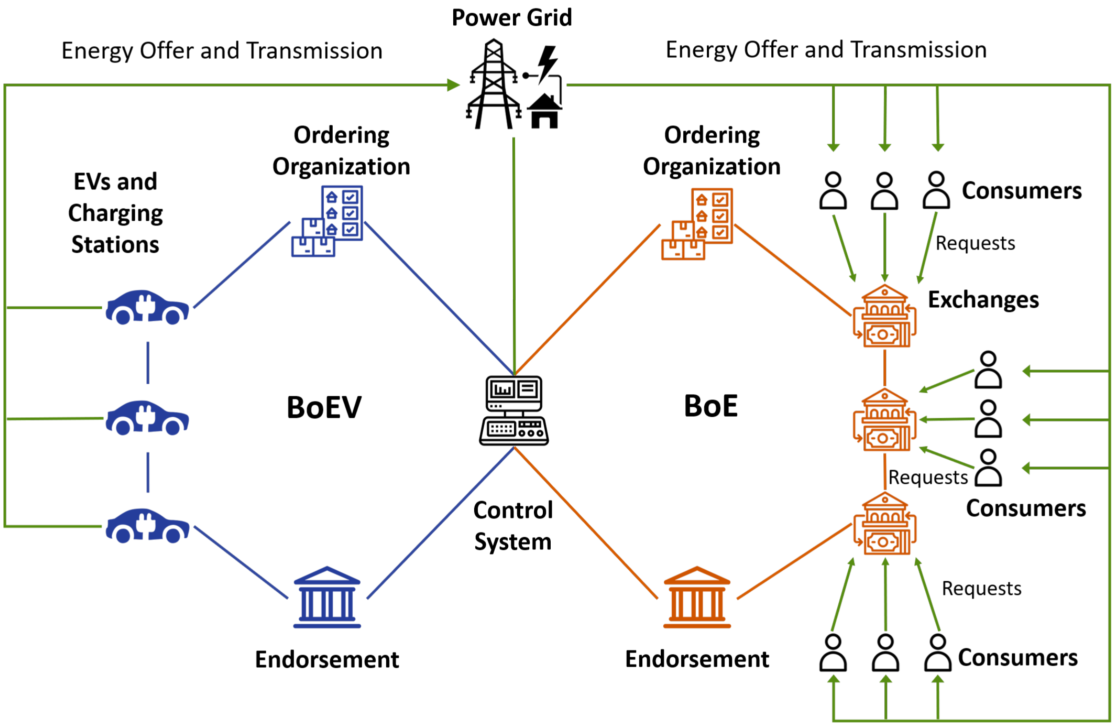


Figure 5.1: Overview of the proposed secure semi-decentralized blockchain framework in V2GNet. The blockchain of exchanges (BoE) integrates exchanges and the CS, and the blockchain of EVs (BoEV) integrates EVs and the CS. The division of BoE and BoEV cuts the chain size and risk of privacy leaks.

the block and obtains the request lists. Each request list is associated with the exchange and is consolidated into a larger, single request list.

Operation in the BoEV begins when EVs receive the energy requesting information from the CS. An available EV packs its ID number and the amount of offered energy into a new transaction and then broadcasts it to other EV nodes. When the transaction pool is full, the EV will send the transactions to be endorsed by a group of endorsing EVs. Once the endorsement is completed, the transactions are transmitted to the ordering EVs, where transactions are ordered in a fixed sequence and packed into a new block. The block is broadcast to all EVs for verification. After the block is verified, the CS downloads the block and obtains the offers from EVs, and then converts them into an offer list.

The preceding operation in the BoEV begins when the CS finishes bidder selection. Then, the CS generates a result list of selected consumers (energy consumers) and selected EVs (energy suppliers) simultaneously. For an EV that is selected to supply energy, its ID and amount of energy to be supplied are recorded on the list, and If an EV is not selected, the information "unselected" is written on the list instead. The EVs' result list is stored in a transaction from the CS side, which is endorsed by the endorsing EVs. The transaction is packed in a block, verified, and recorded by the EV nodes. Afterward, each EV downloads the block and acquires the result list of selected EVs.

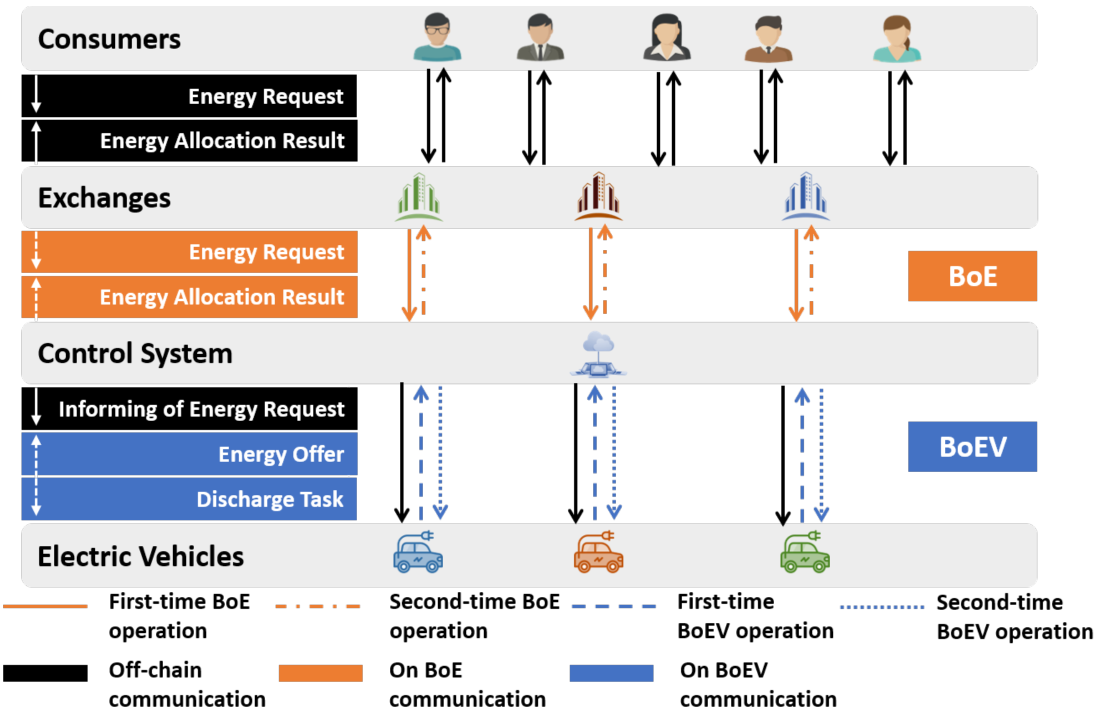


Figure 5.2: Overview of the proposed blockchain of exchanges (BoE) and blockchain of EVs (BoEV). Each trading round performs the two-time operation in BoE and BoEV, respectively. Communication between consumers and exchanges does not take place on the blockchain. Moreover, the control system informs EVs about energy demand without the blockchain. The off-chain communication is colored black.

The preceding operation in the BoE begins when the result list of selected consumers is generated. The result list has the ID of each selected consumer. Also, the period of energy supply and the trading price are recorded in the list. The consumers' result list is stored in a transaction in the CS, endorsed by the endorsing exchanges. The transaction is packed in a block, verified, and recorded by the exchange nodes. After that, each exchange downloads the block and acquires selected consumers' results. The result list contains the supply information of all exchanges, so each exchange reserves the information regarding its consumers and then creates a notification for each of them. All the operations in BoE and BoEV are shown in Fig. 5.2.

5.2 Response Time Analysis in V2GNet

For an active consumer, 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. Active means the consumer participates in the trading at this round. 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. Since there is a minor difference between these two definitions, we will explain them in Fig. 5.3.

We consider a group of exchanges $\{E_i\}, i \in N$, N is the Number of energy exchanges (N). An Energy exchange numbered i (E_i) contains a group of active consumers $\{C_{ij}\}, j \in M_i$, M_i is the Number of consumers in energy exchanges E_i (M_i). Also, a group of EVs is denoted by $\{EV_i\}, i \in K$, K is the Number of EVs (K). We divide the entire response process into five phases: 1) Request List Preparation, 2) Consensus of Request Lists; 3) Consensus of Offer List; 4) Energy Allocation, and 5) Notification.

5.2.1 Request List Preparation

For Active consumer numbered j contained by E_i (C_{ij}), the time a C_{ij} sends a request to the exchange E_i is denoted by Time cost for C_{ij} to send a request to E_i (t^r_{ij}). The time E_i receives all requests depends on the latest consumer. Time cost for E_i to receive requests from all its consumers (t^r_i) is formulated as:

$$t^r_i = max(t^r_{i1}, t^r_{i2}, \cdots, t^r_{im_i}) \tag{5.1}$$

Subsequently, the collection of requests is organized into a request list and

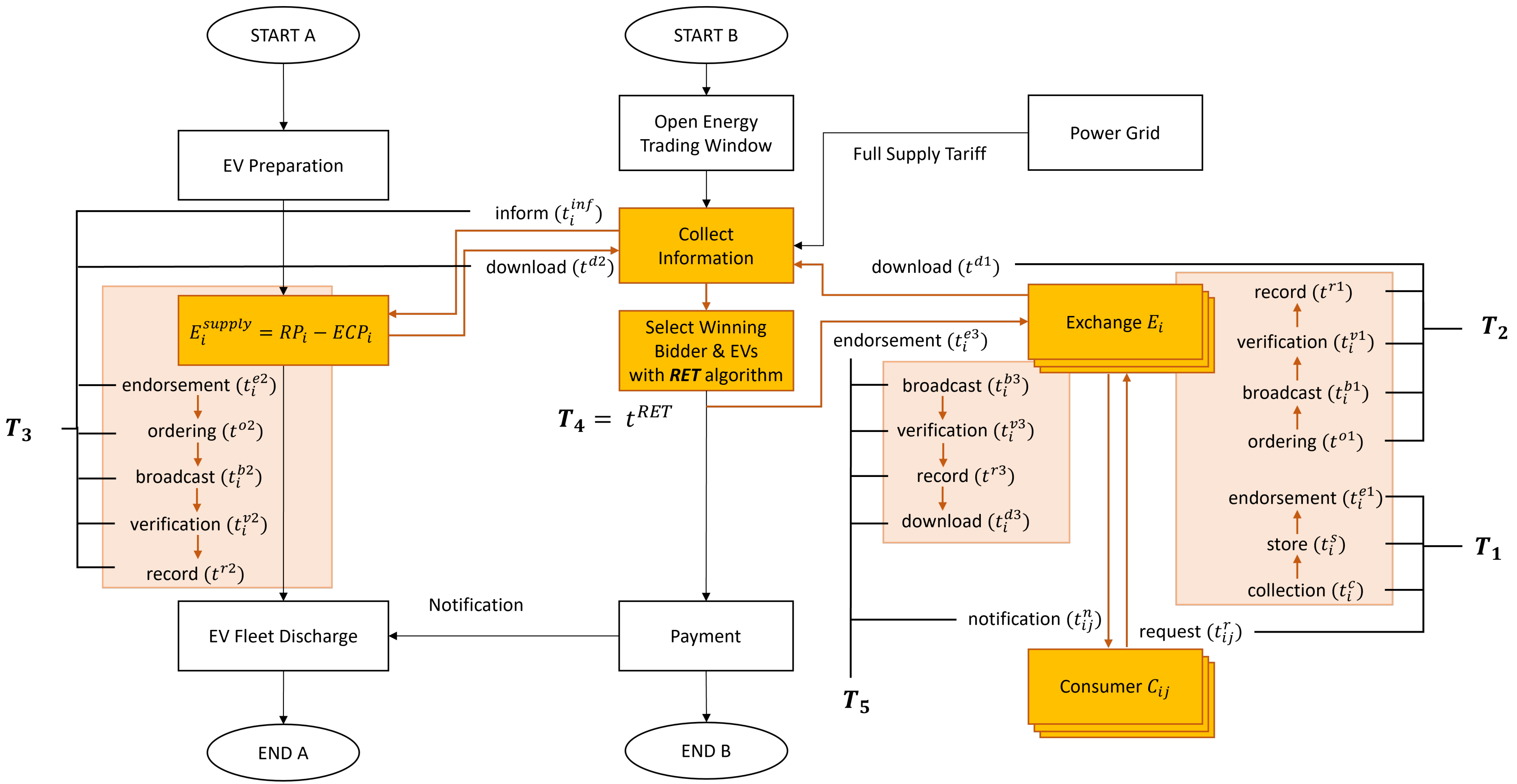


Figure 5.3: Analysis of Response Time in V2GNet. The whole workflow can be divided into five stages. T_1: From the request submission until the endorsement of transactions (containing request lists) is finished. T_2: From the ordering of transactions until the CS collects the request lists. T_3: From the CS informs EVs until it receives offers from EVs. T_4: Select winning consumers and offers with RET algorithm. T_5: From the endorsement of the result about winning consumers until the consumers receive the notification.

stored in a Transaction of request list for E_i (TX_i), which costs Time cost for E_i to collect requests into a list (t_i^c). Each exchange broadcasts its transaction and receives transactions from other exchanges. For an exchange E_i, the time until all transactions are stored in the transaction pool is denoted by Time cost for E_i to collect BoE nodes' lists in its pool (t_i^s). Once a transaction pool is prepared, the corresponding exchange sends these transactions to be endorsed by a group of endorsing exchanges. The endorsement time associated with E_i is denoted by Endorsement time associated with E_i (t_i^{e1}). The time consumption depends on the first exchange that finishes this phase. The time cost for exchange E_i in Phase I is denoted by:

$$t_i = t_i^r + t_i^c + t_i^s + {t_i}^{e1} \tag{5.2}$$

Therefore, the total time for request list preparation is:

$$T_1 = min(t_1, t_2, \cdots, t_i, \cdots, t_N) \tag{5.3}$$

5.2.2 Consensus of Request Lists

When the exchange receives acknowledgments from endorsing nodes, the transactions are transmitted to the ordering organization. They are arranged in a fixed order based on a consensus protocol and then packed into a new block. The ordering time is denoted by Ordering time in BoE (t^{o1}). The block is broadcast to all nodes for verification and the time of broadcasting to each node is denoted by Broadcasting time in BoE (t_i^{b1}), $i \in N$. The time of verification of each node is denoted by Verification time in BoE (t_i^{v1}), $i \in N$. After block verification, each node records the block on its ledger, and the recording time is denoted by Recording time for nodes in BoE (t^{r1}). The CS downloads the block(s) and obtains the request lists, and the corresponding time is denoted by Recording time for nodes in BoE (t^{d1}). The total time for consensus of request lists is

$$T_2 = t^{o1} + max(t_1^{b1} + t_1^{v1}, \cdots, t_N^{b1} + t_N^{v1}) + t^{r1} + t^{d1} \tag{5.4}$$

5.2.3 Consensus of Offer List

The CS notifies the EV fleet of the new trading round, and the notification time to EV_i is denoted by Notification time of new trading round from CS to EV_i (t_i^{inf}). If EV_i is available to discharge, it generates a transaction containing its ID and the available energy. Available EVs send their transactions to be endorsed by a group of endorsing EVs, and the endorsement time associated with EV_i is denoted by ${t_i}^{e2}$. When the EV receives the acknowledgment from endorsing nodes, the transactions are transmitted to the ordering organization, arranged in a fixed order, and packed into a new block. The ordering time is denoted by t^{o2}. The block is broadcast to all nodes for verification. The time of the broadcasting and the verification of each node is denoted by $t_i^{b2}, i \in K$ and $t_i^{v2}, i \in K$, respectively. After block verification, each node records the block on its ledger, and the recording time is denoted by t^{r2}. More so, the CS downloads the block and obtains a collection of offers which is then stored in an offer list, and the corresponding time is denoted by t^{d2}. The total time for consensus of the offer list is

$$\begin{aligned} T_3 = min(t_1^{inf} + t_1^{e2}, \cdots, t_K^{inf} + t_K^{e2}) + t^{o2} \\ +max(t_1^{b2} + t_1^{v2}, \cdots, t_K^{b2} + t_K^{v2}) \\ +t^{r2} + t^{d2} \end{aligned} \tag{5.5}$$

5.2.4 Energy Allocation Scheduling

After the request and the offer list are prepared on the CS side, the CS begins scheduling energy allocation using the proposed RET algorithm. The time consumption of the RET depends on the following factors: 1) The total number of energy requests; 2) The total number of energy offers; 3) The results of energy trading (energy demand fill rate, number of fulfilled requests, and total profit) from the last trading round. We denote the time consumption of this phase by Time cost for CS to download request list block from BoE (t^{RET}), $T_4 = t^{RET}$.

5.2.5 Notification

When energy allocation is scheduled, the CS broadcasts a notification to endorsing exchanges, including 1) Winning consumer ID, 2) Amount of energy supply, and 3) Period of energy supply. After the endorsement, whose time is denoted by t^{e3}, the CS packs the winning requests into a block. Then the ordering organization broadcasts the block to all exchanges for verification. The time of the broadcasting and the verification of each node is denoted by $t_i^{b3}, i \in N$ and $t_i^{v3}, i \in N$, respectively. Next, the verified block is recorded in the ledger of each exchange, and the recording time is denoted by t^{r3}. Each exchange downloads the block and obtains the notification. For the exchange E_i, the corresponding time is denoted by t_i^{d3}. Finally, E_i notifies its consumers whether their requests are selected in the energy auction. The notification time for a consumer C_{ij} is denoted by Notification time of E_i to C_{ij} (t_{ij}^n); however, the time when all notifications are received depends on the last consumer. The notification time for an exchange E_i is formulated as:

$$t_i^n = max(t_{i1}^n, t_{i2}^n, \cdots, t_{im_i}^n) \tag{5.6}$$

Until all the consumers receive notifications, the total time consumption of this phase is:

$$\begin{aligned} T_5 = t^{e_3} + max(t_1^{b3} + t_1^{v3}, \cdots, t_N^{b3} + t_N^{v3}) \\ +t^{r3} + max(t_1^{d3} + t_1^n, \cdots, t_n^{d3} + t_N^n) \end{aligned} \tag{5.7}$$

In summary, the response time for one complete trading round is:

$$T^{response} = T_1 + T_2 + T_3 + T_4 + T_5 \tag{5.8}$$

For a consumer C_{ij}, the response time is:

$$\begin{aligned} T^{response} = T_1 + T_2 + T_3 + T_4 + t^{e_3} + max(t_1^{b3} + t_1^{v3}, \cdots, t_N^{b3} + t_N^{v3}) \\ +t^{r3} + t_i^{d3} + t_{ij}^n \end{aligned} \tag{5.9}$$

5.3 Multi-blockchain-based V2G Networks

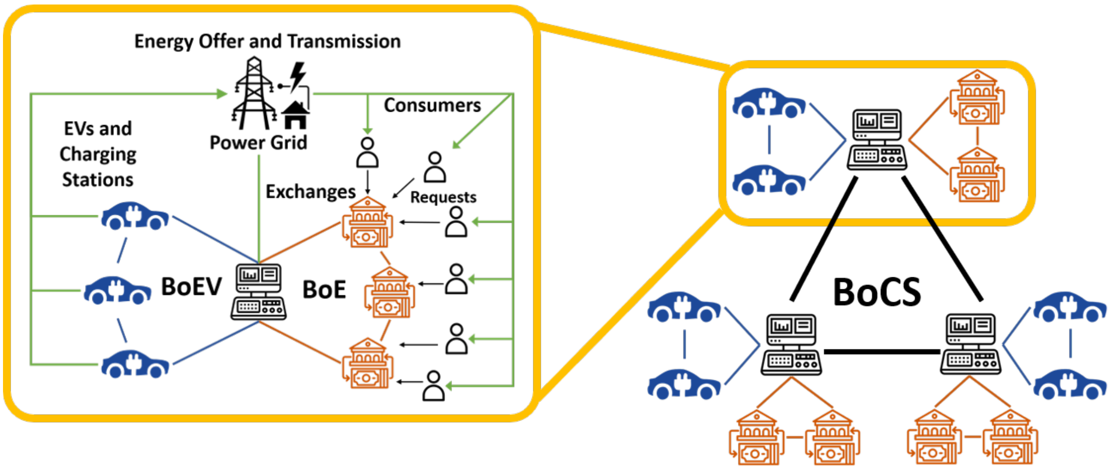


Figure 5.4: Overview of the proposed V2GFTN with the BoCS [2], the blockchain of electric vehicles (BoEV), and the blockchain of exchanges (BoE). The BoCS is where inter-campus energy trading is planned and recorded, and each CS makes a node of the BoCS. Besides, each campus's CS works as an information 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.

Once we establish a V2GNet system along with a blockchain of electric vehicles (BoEV) and a blockchain of exchanges (BoE) within more than one campus, we can take each campus V2G control system as a node to establish a blockchain of campus control systems (BoCS) for cross-grid V2G energy trading scheme, as shown in Fig. 5.4. As mentioned above, once any node of BoCS has finished the starting operation of BoE, the starting operation of BoEV, the preceding operation of BoEV, and the preceding operation of BoE, it can start operating on BoCS as the fifth part of energy data transmission and storage. The details of BoCS operation are given as follows.

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 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.

5.4 Response Time Analysis in V2GFTN

When the BoCS is taken into consideration, the response time has to add its time cost up, so we present a further time analysis in V2GFTN for cross-campus energy trading.

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 $\{C_{ij}\}, j \in N^i_{req}$, N^i_{req} is the number of consumers. Also, the group of EVs in the BoE is denoted by $\{EV_i\}, i \in N^k_{ev}$, N^k_{ev} 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.

5.4.1 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 $t^{ij}_{c\_e}$. $t^{ij}_{c\_e}$ includes the information transfer time and relative transmission latency. The time E_i receives all requests depends on the latest consumer. The corresponding time $t^{i}_{c\_e}$ is formulated as:

$$t^{i}_{c\_e} = max(t^{i1}_{c\_e}, t^{i2}_{c\_e}, \cdots, t^{iN^i_{req}}_{c\_e}) \tag{5.10}$$

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^{req}_{prcs}, so the corresponding time for request listing t^i_l is formulated as:

$$t^i_l = t^{req}_{prcs} \times N^i_{req} \tag{5.11}$$

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:

$$N^{boe,i}_{tx} = \lceil \frac{N^i_{req} \times S_{req}}{C_{tx}} \rceil \tag{5.12}$$

For a single transaction $\{TX_j\}, j \in N^{boe,i}_{tx}$, the average time for its endorsement in BoE is denoted by $t^{boe,k}_{endo}$. 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 $t^{boe,k}_{o}$; the time to broadcast the block to BoE is denoted by $t^{boe,k}_{bcst}$; the time to verify the block in BoE is denoted by $t^{boe,k}_{ver}$; and the time to record the block in all BoE nodes is denoted by $t^{boe,k}_{rec}$.

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

$$t^i_{u\_ex} = N^{boe,i}_{tx} \times t^{boe,k}_{endo} + t^{boe,k}_{o} + t^{boe,k}_{bcst} + t^{boe,k}_{ver} + t^{boe,k}_{rec} \tag{5.13}$$

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

$$t^i_1 = t^i_{c\_e} + t^i_l + t^i_{u\_ex} \tag{5.14}$$

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

$$T^k_1 = max(t^1_1, t^2_1, \cdots, t^i_1, \cdots, t^{N_{ex}}_1) \tag{5.15}$$

5.4.2 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^{blk}_{prcs}; 2) The total number of energy requests in BoE $N^{total,k}_{req}$; 3) The time to traverse the available EV list $t^k_{traverse}$; 4) The time to filter EVs based on time boundaries t^k_{filter}; 5) The time to allocate EVs $t^k_{allocate}$.

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:

$$N^{total,k}_{req} = \sum_{i=1}^{N_{ex}} N^i_{req} \tag{5.16}$$

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

$$t^k_{traverse} = c^k_1 p_k \times N^{total,k}_{req} \times N^k_{ev} \tag{5.17}$$

c^k_1 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:

$$t_{filter}^{k} = c_2^k p_k \times N_{req}^{total,k} \times N_{ev}^{k} \tag{5.18}$$

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:

$$t_{allocate}^{k} = c_3^k p_k q_k \times N_{req}^{total,k} \tag{5.19}$$

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:

$$T_2^k = t_{prcs}^{blk} \times N_{ex} + t_{traverse}^{k} + t_{filter}^{k} + t_{allocate}^{k} \tag{5.20}$$

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

5.4.3 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

3-1) 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:

$$N_{req}^{s,k} = N_{req}^{total,k} \times p_k \tag{5.21}$$

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

$$N_{req}^{r,k} = N_{req}^{total,k} - N_{req}^{s,k} \tag{5.22}$$

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:

$$N_{tx}^{cs\_ex} = \lceil \frac{N_{req}^{s,k} \times S_{allocate}}{C_{tx}} \rceil \tag{5.23}$$

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

$$t_{u\_cs}^{k} = N_{tx}^{cs\_ex} \times t_{endo}^{boe,k} + t_{o}^{boe,k} + t_{bcst}^{boe,k} + t_{ver}^{boe,k} + t_{rec}^{boe,k} \tag{5.24}$$

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

$$t_{n}^{ij} = t_{u\_cs}^{k} + t_{prcs}^{blk} + t_{c\_e}^{ij} \tag{5.25}$$

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

$$T_{3-1}^{k} = max(t_n^{11}, \cdots, t_n^{1N_{req}^{1}}, \cdots, t_n^{ij}, \cdots, t_n^{N_{ex}1}, \cdots, t_n^{N_{ex}N_{req}^{N_{ex}}}) \tag{5.26}$$

3-2) 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 $N_{req}^{r,k}$ is given in Phase 3-1, and the number of remaining EVs $N_{ev}^{r,k}$ is formulated as:

$$N_{ev}^{r,k} = N_{ev}^{k} - p_k q_k \times N_{req}^{total,k} \tag{5.27}$$

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:

$$N_{tx}^{bocs,k} = \lceil \frac{N_{req}^{r,k} \times S_{req} + N_{ev}^{r,k} \times S_{ev}}{C_{tx}} \rceil \tag{5.28}$$

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

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

$$\begin{aligned} T_{3-2}^{k} = t_{prcs}^{req} \times N_{req}^{r,k} + t_{prcs}^{ev} \times N_{ev}^{r,k} + N_{tx}^{bocs,k} \times t_{endo}^{bocs} \\ + t_o^{bocs} + t_{bcst}^{bocs} + t_{ver}^{bocs} + t_{rec}^{bocs} \end{aligned} \tag{5.29}$$

5.4.4 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 $N_{total\_req}^{r}$; 2) The total number of remaining EVs in BoCS $N_{total\_ev}^{r}$; 3) The time for CS_k to traverse the available EV list $t_{traverse}^{r,k}$; 4) The time for CS_k to filter EVs based on time boundaries $t_{filter}^{r,k}$; 5) The time to allocate EVs $t_{allocate}^{r,k}$.

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:

$$N^{r}_{total\_req} = \sum_{k=1}^{N_{cs}} N^{r,k}_{req} \tag{5.30}$$

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

$$N^{r}_{total\_ev} = \sum_{k=1}^{N_{cs}} N^{r,k}_{ev} \tag{5.31}$$

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

$$t^{r,k}_{traverse} = c^{k}_{1} p' \times N^{r}_{total\_req} \times N^{r}_{total\_ev} \tag{5.32}$$

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

$$t^{r,k}_{filter} = c^{k}_{2} p' \times N^{r}_{total\_req} \times N^{r}_{total\_ev} \tag{5.33}$$

The time for CS_k to allocate EVs in BoCS is:

$$t^{r,k}_{allocate} = c^{k}_{3} p' q' \times N^{r}_{total\_req} \tag{5.34}$$

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

$$N^{cs}_{tx} = \lceil \frac{p' \times N^{r}_{total\_req} \times S_{allocate}}{C_{tx}} \rceil \tag{5.35}$$

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

$$t^{k}_{u\_bocs} = N^{cs}_{tx} \times t^{bocs,k}_{endo} + t^{bocs,k}_{o} + t^{bocs,k}_{bcst} + t^{bocs,k}_{ver} + t^{bocs,k}_{rec} \tag{5.36}$$

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

$$t^{k}_{4} = t^{blk}_{prcs} \times N_{cs} + t^{r,k}_{traverse} + t^{r,k}_{filter} + t^{r,k}_{allocate} + t^{k}_{u\_bocs} \tag{5.37}$$

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

$$T_4 = min(t_4^1, \cdots, t_4^k, \cdots, t_4^{N_{cs}}) \tag{5.38}$$

5.4.5 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:

$$t_5^k = t_{prcs}^{blk} + \frac{N_{tx}^{cs} t_{endo}^{boe,k}}{N_{cs}} + t_o^{boe,k} + t_{bcst}^{boe,k} + t_{ver}^{boe,k} + t_{rec}^{boe,k} \tag{5.39}$$

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

$$t_5^{ij} = t_5^k + t_{prcs}^{blk} + t_{c\_e}^{ij} \tag{5.40}$$

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

$$t_{c\_e}^k = max(t_{c\_e}^{11}, \cdots, t_{c\_e}^{1N_{req}^1}, \cdots, t_{c\_e}^{ij}, \cdots, t_{c\_e}^{N_{ex}1}, \cdots, t_{c\_e}^{N_{ex}N_{req}^{N_{ex}}}) \tag{5.41}$$

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

$$T_5 = t_{prcs}^{blk} + max(t_{c\_e}^1 + t_5^1, \cdots, t_{c\_e}^k + t_5^k, \cdots, t_{c\_e}^{N_{cs}} + t_5^{N_{cs}}) \tag{5.42}$$

5.4.6 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:

$$T_{1st}^{resp,k} = T_1^k + T_2^k + T_{3-1}^k \tag{5.43}$$

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:

$$T_{1st}^{resp,k,ij} = T_1^k + T_2^k + t_n^{ij} \tag{5.44}$$

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

$$T_{2nd}^{resp} = max(T_1^k + T_2^k + T_{3-2}^k) + T_4 + T_5 \tag{5.45}$$

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:

$$T_{2nd}^{resp,k,ij} = max(T_1^k + T_2^k + T_{3-2}^k) + T_4 + t_5^{ij} \tag{5.46}$$

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

$$T_r = max(T_{1st}^{resp,1}, \cdots, T_{1st}^{resp,k}, \cdots, T_{1st}^{resp,N_{cs}}, T_{2nd}^{resp}) \tag{5.47}$$

5.5 Evaluation

Here we carry out simulations to evaluate the time cost of a whole trading round of the proposed V2G system, including the given multi-blockchain architecture. The time cost ratio of each phase we pointed out in the last section 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 5.1.

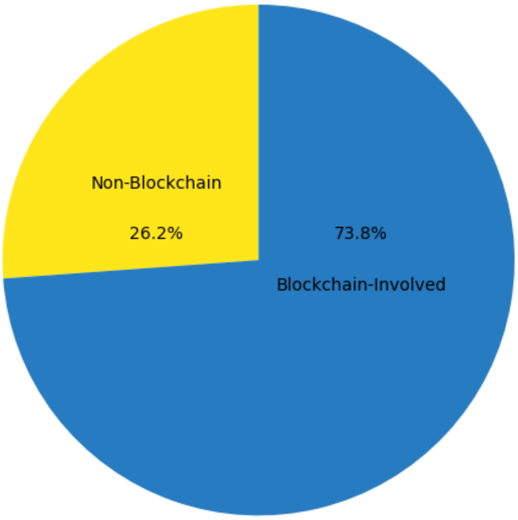
The results of the simulations are presented in Fig. 5.5. As shown in Fig. 5.5a, in a trading round 73.8% of the time is consumed by blockchain-involved time

Table 5.1: Configuration for the Time Analysis Simulation.

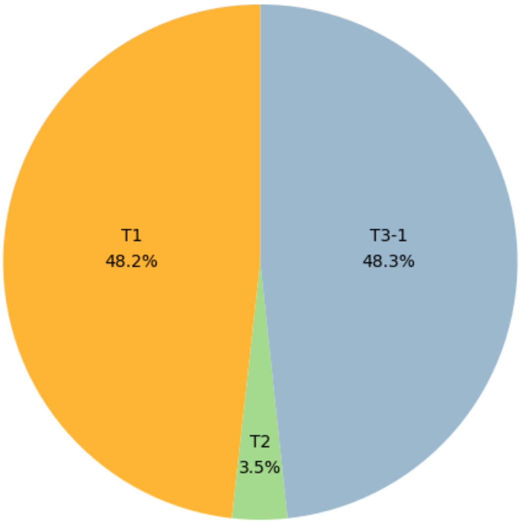
Parameter	Meaning	Value
N_{cs}	No. of control systems	3
N_{ex}	No. of exchanges in a BoE	3 to 5
N_{ev}	No. of EVs in a BoEV	75 to 900
N^i_{req}	No. of requests in an exchange	30 to 150
t^{req}_{prcs}	Average time to process a request	0.1ms
t^{ev}_{prcs}	Average time to process an EV	0.2ms
t^{blk}_{prcs}	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

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. 5.5b, 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. 5.5c, 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.

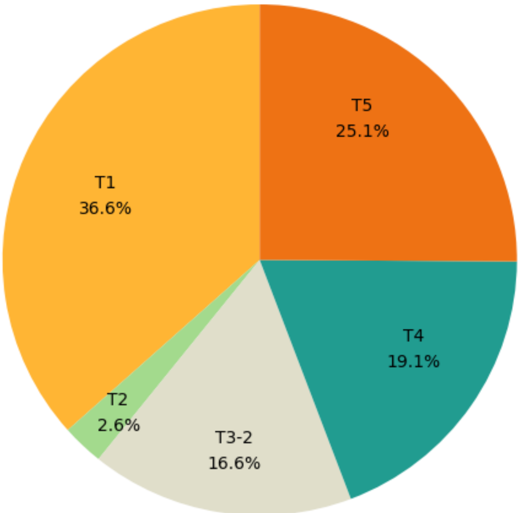
The multi-blockchain processing time makes the most of the overall time cost of V2GFTN. And getting notifications from cross-campus V2G trading on the BoCS takes more time than from V2G trading within a single campus from the CS. This is because the BoCS takes extra time to upload and download the data of the remaining EVs and requests.



(a) Time cost ratio of blockchain-involved and non-blockchain process.



(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 5.5: Comparative analysis of time cost ratios in different scenarios.

Chapter 6

Smart and Robust Energy Trading Algorithm for V2G Forecast and Trading Network

6.1 Energy Trading Methods and Process in V2GFTN

6.1.1 Hour-ahead Comprehensive Energy Trading Method

In V2GNet we only consider EVs without driving tasks and linked to the grid through the trading rounds. The practical scenarios can be much more complicated. To utilize more EVs in sharing fleets we take both charging/discharging tasks, driving tasks, and time constraints into the following work. By doing so we designed a Vehicle-to-Grid Forecast and Trading Network (V2GFTN).

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. 6.1. 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

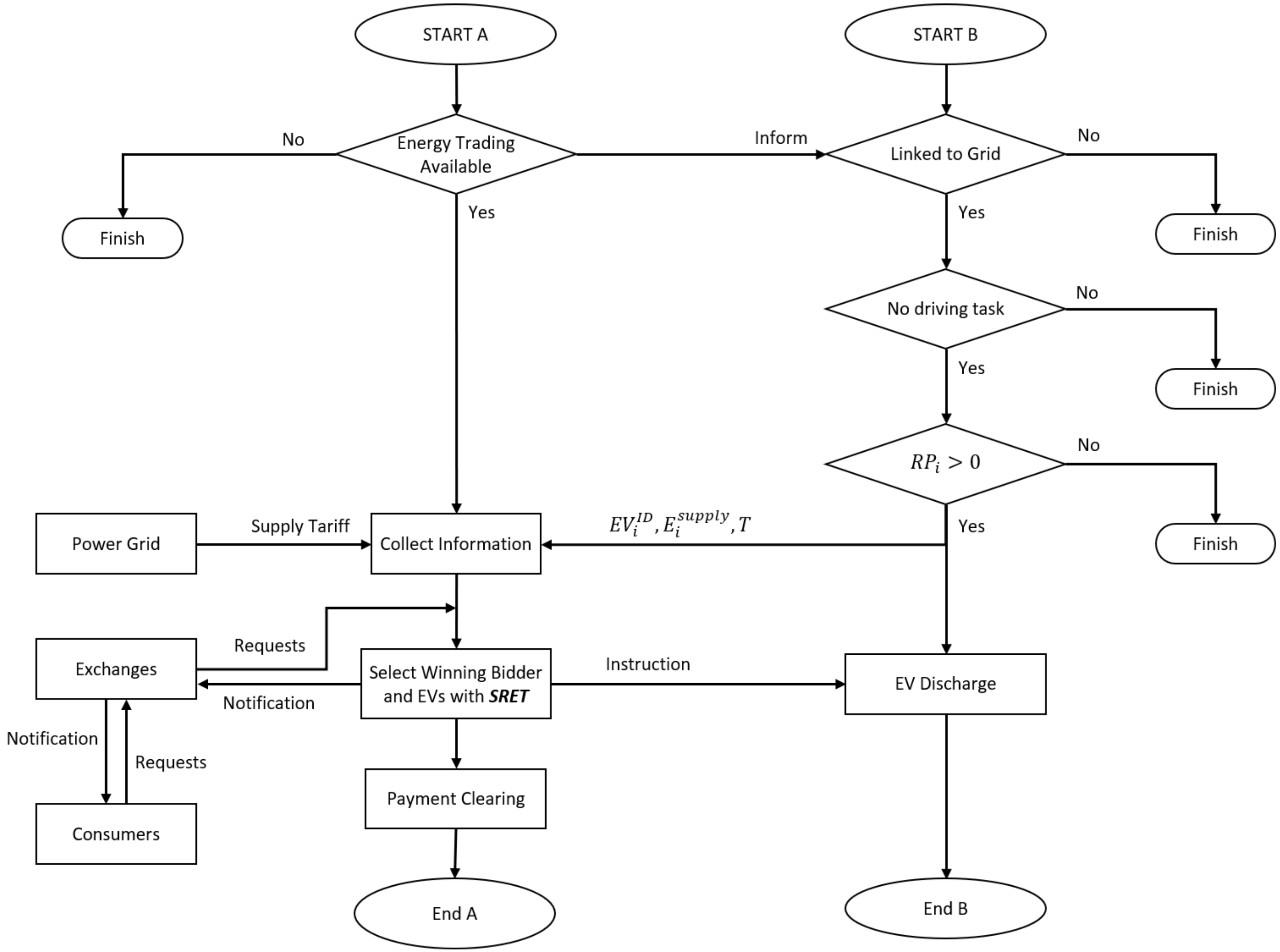


Figure 6.1: Energy trading algorithm without the energy forecasting data for EVs in V2GFTN for both EV and CS sides. The CS side begins from "Start A," and the EV side begins from "Start B" at the planning phase of each energy trading round. The power grid provides CS with a supply tariff, and the energy 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.

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 6.2). Once the CS obtains the request selection results and the corresponding energy 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.

6.1.2 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. 6.2. 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 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

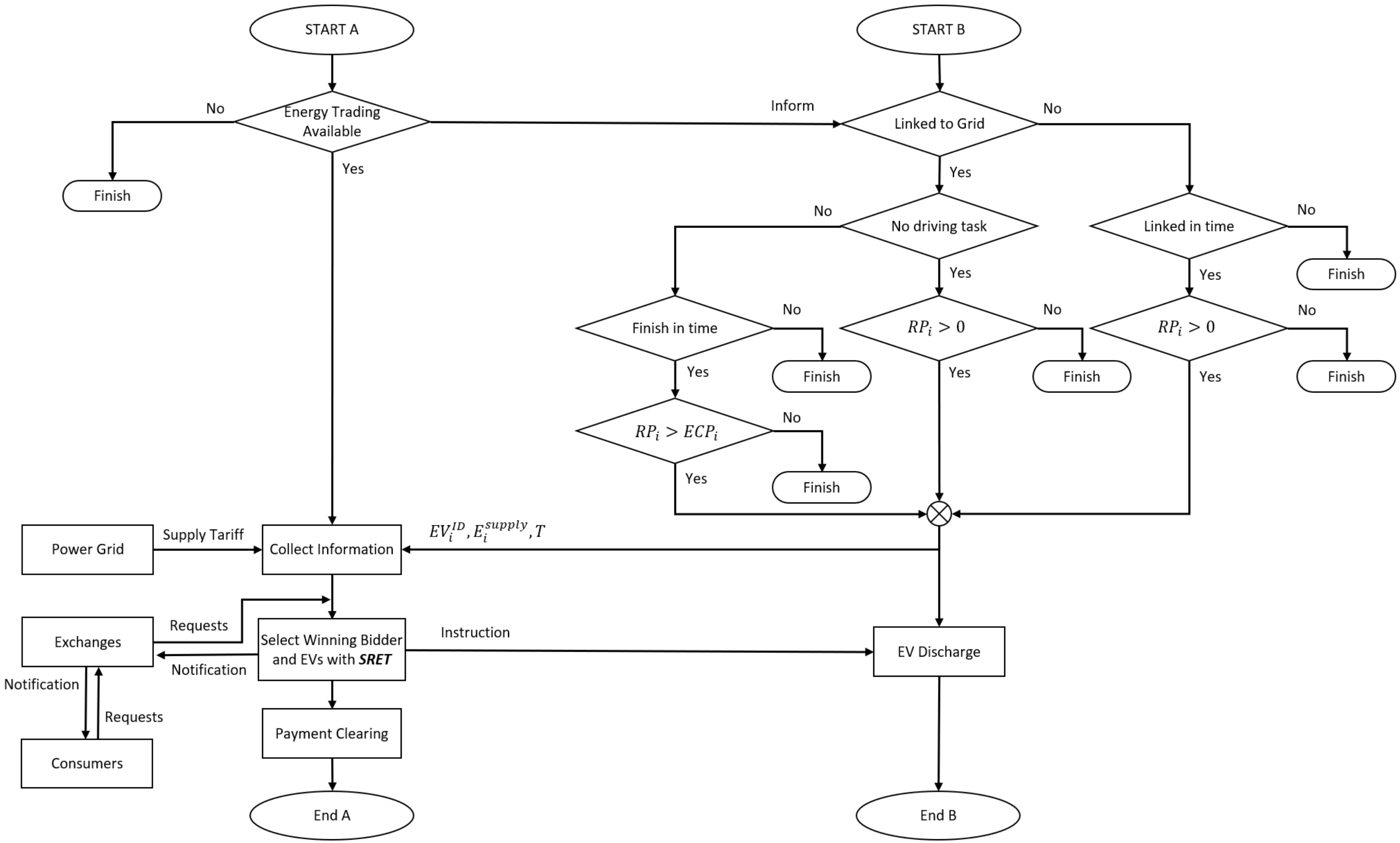


Figure 6.2: Energy trading algorithm with the energy forecasting data for EVs in V2GFTN for both the EV and CS sides. Since EVs can predict the energy consumption of their driving tasks before and during each driving task, EVs with driving tasks can also trade and supply their excess energy according to the prediction results.

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.

6.2 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.

6.2.1 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.

6.2.2 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 an Energy request numbered i (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 with proper offer period ($\{EL_i\}$), 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.

6.2.3 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 Discharge potential of EV_k (H_k):

$$H_k = min(RP_k, P_c T_k) T_k \tag{6.1}$$

Here we define RP of EV_k (RP_k), Max output capacity of charging stations (P_c), and Time span when EV_k can supply energy (T_k).

When EV_k is allocated to supply energy to a request R_i, the Discharge potential of EV_k when allocated to supply energy to R_i (H_k^i) turns out to be:

$$H_k^i = min(RP_k - P_i T_k^i, P_c(T_k - T_k^i))(T_k - T_k^i) \tag{6.2}$$

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:

$$E_k^i = \frac{H_k - H_k^i}{H_k} \tag{6.3}$$

The larger Energy utilization efficiency parameter of EV_k (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:

$$F_i^k = \frac{H_k - H_k^i}{H_i} \tag{6.4}$$

The larger Fulfilling rate of R_i energy demand by EV_k (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 Energy demand capacity of R_i (H_i) is denotes by:

$$H_i = P_i T_i^2 \tag{6.5}$$

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 $\sum_{k=1}^{M_i} min(RP_k, P_c T_k^i)$ 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 $RP_{k1} - P_i T_{k1}^i$ 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 consumption for V2G energy trading.

6.2.4 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:

$$T_d(n) = O(N + NM + 2NM_i) = O(3n^2 + n) = O(n^2) \tag{6.6}$$

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 $\left\{F_i^k\right\}$ 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:

$$\begin{aligned} T_s(n) &= O(N + NM + M + NM_i + N(M_i^2 + M_i)) \\ &= O(n^3 + 3n^2 + 2n) = O(n^3) \end{aligned} \tag{6.7}$$

6.3 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 [1]. 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% [1]. A simplified structure of our learning-enabled energy forecasting component is shown in Fig. 6.3. 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.

Several parameters are considered to predict the energy consumption for each section: the start time of each section, the prevailing weather conditions (humidity,

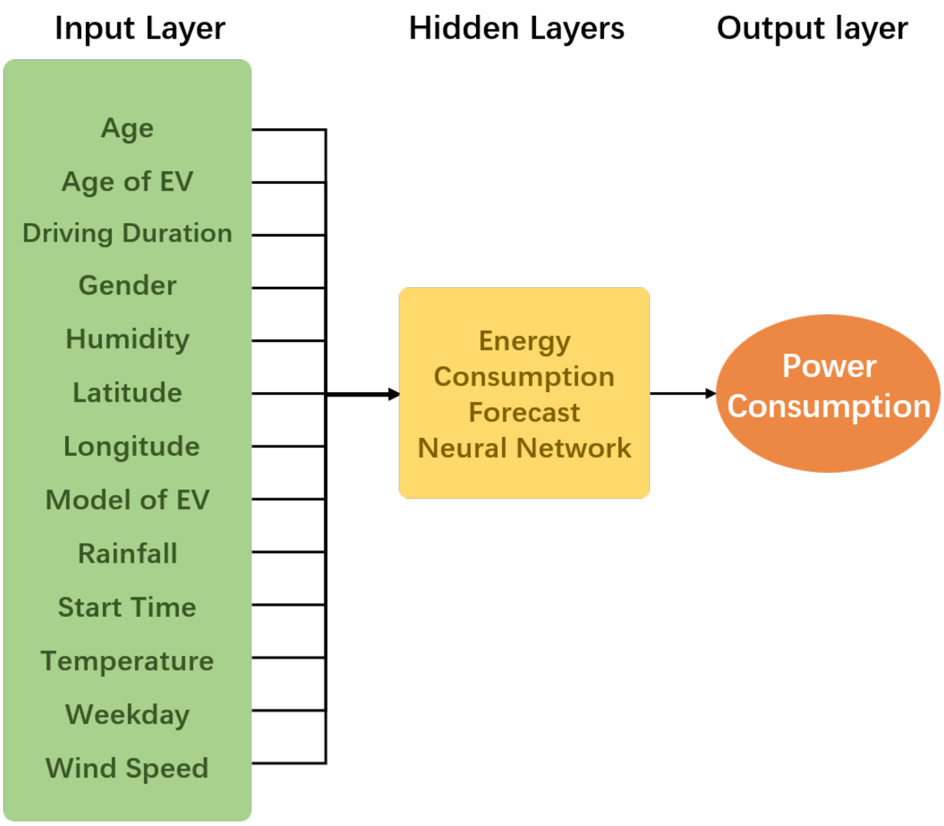


Figure 6.3: Overview of the multi-layer neural network for energy consumption forecast in V2GFTN. The input layer contains 13 input features, including start time, weekday, temperature, rainfall, humidity, wind speed, latitude, longitude, gender, age, driving duration, EV model, and EV age. The number of hidden layers is flexible. The output layer has one output neuron for power consumption prediction.

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 [1].

6.4 Evaluation

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

6.4.1 Evaluation Methodology

Table 6.1: Configuration for V2G Trading in V2GFTN Simulation.

Input Feature	Value
No. of Consumers	200, 400, 600
No. of EVs	60 to 270
EV State	Idle, Charging, Driving
Battery Capacity	60 kWh
Charge Power	15 kW
Discharge Power	0 to 10 kW
Driving Power	10 kW
Driving Time Slot	20 to 22
Charge Time Slot	20 to 21
Request Time Slot	21 to 22
Requests Capacity	0 to 10 kWh
Bid Price	22.39 to 42.84 JPY

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

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 [3] and an action-based incentive scheme as offered by [4]. 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 6.1.

We consider four indicators: 1) Number of fulfilled requests; 2) Energy demand fill rate; 3) Total economic profit; 4) Total time consumption. 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 consumption: the amount of time needed to allocate energy for all available requests in the planning phase of a trading round.

6.4.2 Evaluation Results

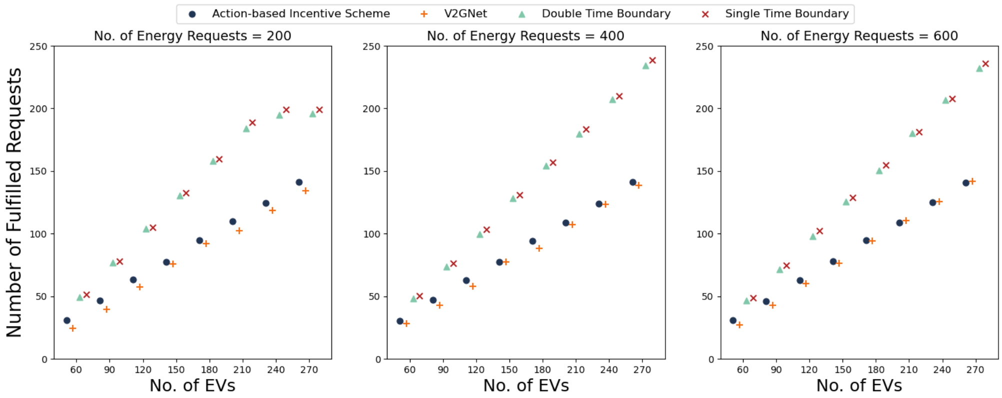


Figure 6.4: Number of fulfilled requests evaluation. This experiment compares the number of fulfilled requests between trading strategies of double time boundaries and single time boundary in V2GFTN (this work), V2GNet [3], and the action-based incentive scheme [4]. Different combinations of EV and request amount are used, as shown in Table 6.1.

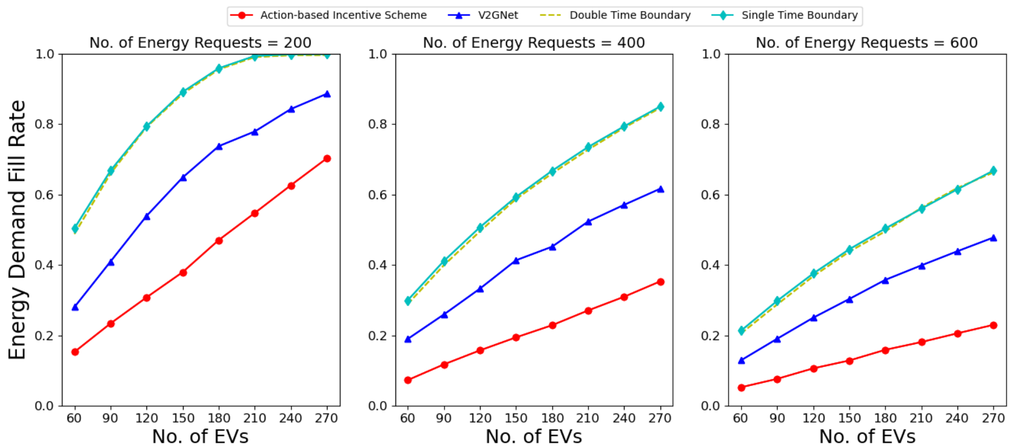


Figure 6.5: Energy demand fill rate evaluation. This experiment compares the energy demand fill rate between trading strategies, focusing on double time boundaries and single time boundary approaches within the V2GFTN, the trading strategy presented in V2GNet [3], and the action-based incentive scheme [4]. Diverse combinations of EVs and request amounts were explored to ensure a robust evaluation across a spectrum of scenarios.

As shown in Fig. 6.4, the number of fulfilled requests increases for all four strategies as the number of electric vehicles increases, with the V2GFTN strategies

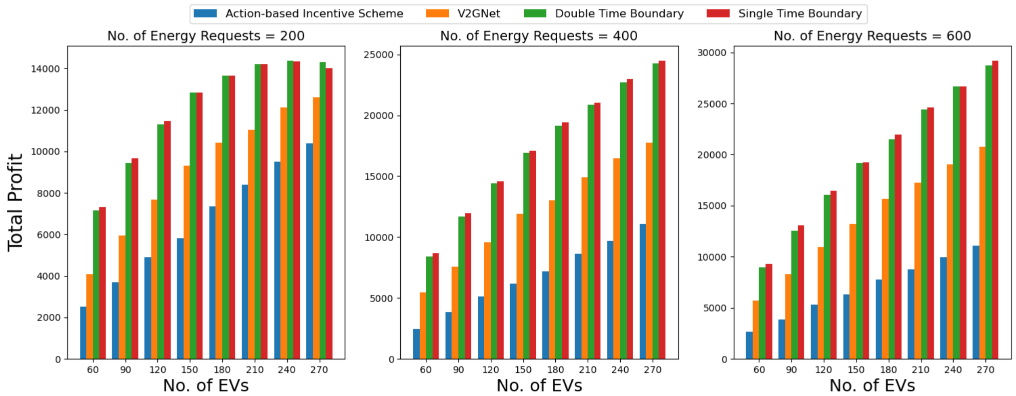


Figure 6.6: Total profit evaluation. This experiment compares the total economic profit in trading strategies of proposed V2GNet [3], the action-based incentive scheme [4], and both double time boundaries and single time boundary approaches within the V2GFTN. A wide array of combinations of EVs and request amounts reveal nuanced insights into the relative performance of these trading strategies.

having a much higher number of fulfilled requests compared to the action-based incentive scheme and the V2GNet system. Once the number of EVs in V2GFTN exceeds the number of energy requests, almost all requests can be satisfied by the double and single time boundary strategies. As the number of EVs increases, the average growth rate of fulfilled requests for the single time boundary strategy, double time limit 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. 6.5. 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, to which the intensifying trading competition between EVs and the relative deficiency of ideal requests with high demand and profit may be the cause.

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. 6.6, when the number of energy requests remains the same, the economic profit produced by all four strategies grows with the increasing number of EVs. The V2GFTN strategies show higher total profit compared to the action-based incentive scheme and V2GNet scheme. Still, 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. 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 6.2 shows the total time consumption of an energy trading round across four trading strategies. For the same number of energy requests, the time consumption of all four strategies in a trading round increases with the number of EV suppliers. However, the time consumption 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 consumption correlates more with the number of EVs. With the different number of EVs, the trading round time consumption 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. 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.

Table 6.2: The total time consumption 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 Consumption (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 Consumption (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

Chapter 7

Thesis Summary and Discussion

In this dissertation's concluding chapter, we encapsulate the main contributions and outcomes of our research. We provide a thorough review of the results we obtained. Additionally, we conclude by offering insights into potential enhancements for this work and highlighting other pertinent considerations that have not been explicitly addressed in this dissertation.

7.1 Contributions Summary

In this thesis, we propose an energy trading system V2GNet that supports the efficient V2G work-flow of energy request, offer, and allocation between consumers and campus sharing EVs. The V2GNet works on the base of a robust energy trading algorithm (RET), with a penalty mechanism proposed against malicious attacks from consumers and exchanges, and ensures the energy fill rate and total profit.

We also propose a novel cross-cluster architecture containing a blockchain of energy exchanges (BoE) and a blockchain of EVs (BoEV) to protect campus V2G trading with a control system (CS) connecting the network of exchanges and EVs. A complete analysis of the response time of energy requests is formulated in five stages. On top of that, we take a further step to design a multi-blockchain V2G structure based on a blockchain of campus control systems (BoCS). The BoCS takes every CS as a node to carry on cross-campus V2G trading.

We introduce an intelligent hour-ahead energy management system called V2GFTN with dynamic strategies of trading time constraints and EV energy prediction. A smart and robust energy trading algorithm (SRET) is also proposed to optimize vehicle trading and charging/discharging strategies based on market conditions and EV energy prediction. Besides, we show two energy trading approaches that facilitate energy allocation in SRET with time slots, utilizing double and single time boundary strategies, respectively.

7.2 Results Summary

In our study, we delved into assessing the performance of our proposed V2G energy trading system for electric vehicles, focusing on both the effectiveness of V2GNet and V2GFTN within V2G scenarios.

We observed that V2GNet excels particularly in scenarios abundant with available energy requests. Moreover, the RET algorithm showcased a significant advantage in the face of malicious attacks. We conducted an in-depth examination of how consumer attacks and exchange attacks affect various indicators both with and without RET. When subjected to consumer attacks involving 20 malicious consumers, the energy demand fill rate plummeted by up to 55% without RET protection. In contrast, with RET in place, the energy demand fill rate dropped by no more than 7%. This reduction can be attributed to the imposition of penalties on malicious consumers, effectively curbing their influence.

We also conducted a comprehensive analysis of the performance variations between the single-time-boundary and double-time-boundaries strategies across different scenarios. We observed that, for a constant number of requests, the variance in the number of requests fulfilled by these strategies was considerably higher compared to the action-based incentive scheme and V2GNet. This outcome is attributed to the smart predictive approaches incorporated in SRET, which consider time constraints and energy predictions. In our V2GFTN framework, predictions of trip energy consumption, transmitted to the CS for trading planning, significantly expanded the available pool of EVs and their potential energy supply amounts and durations. However, it is worth noting that the two SRET approaches required more time due to the added complexity of handling energy trading, timing data, and EV selection. While the single-time-boundary strategy offered optimal trading planning performance, it was also the most time-consuming. In an hour-ahead V2G market within our framework, where EV fleets are shared among college campuses, ample time for trading planning was available, making the single-time-boundary strategy viable. As conditions vary, V2GFTN is able to seamlessly switch to the double-time-boundaries strategy to optimize time consumption. In extreme cases where available EVs significantly surpassed requests, and the planning time was limited, V2GFTN can adopt the V2GNet scheme for expediency. The adaptability demonstrates the robustness and versatility of our V2G energy trading system.

7.3 Discussion

While our proposed blockchain-based architecture exhibits promising prospects for efficient and robust energy trading, it is imperative to acknowledge and address certain challenges.

Primarily, we envision enhancing the scalability and decentralization of the V2G Network. This involves further research and development to ensure that the architecture can seamlessly handle a growing volume of transactions while maintaining a distributed structure. Additionally, investigating smart trading anticipation for energy demand and considering scenarios involving private EVs will be essential for a more comprehensive and adaptable V2GNet.

Furthermore, we aim to venture into real-time scenarios to align our work with practical applications. Integrating multiple distributed renewable energy resources into V2GFTN will enhance its feasibility and create a more comprehensive and responsive trading network. This extension will encompass the complexities and intricacies of real-world energy systems, enabling a more accurate assessment of our architecture's performance and adaptability.

References

[1] Z. Wang and A. B. Abdallah, “A robust multi-stage power consumption prediction method in a semi-decentralized network of electric vehicles,” IEEE Access, vol. 10, pp. 37 082–37 096, 2022.

[2] 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, vol. 12, pp. 8135–8153, 2024.

[3] ——, “V2gnet: Robust blockchain-based energy trading method and implementation in vehicle-to-grid network,” IEEE Access, vol. 10, pp. 131 442–131 455, 2022.

[4] 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, vol. 10, pp. 56 331–56 347, 2022.

[5] B. Han, E. Bompard, F. Profumo, and Q. Xia, “Paths toward smart energy: A framework for comparison of the eu and china energy policy,” IEEE Transactions on Sustainable Energy, vol. 5, no. 2, pp. 423–433, 2014.

[6] S. Falahati, S. A. Taher, and M. Shahidehpour, “Grid secondary frequency control by optimized fuzzy control of electric vehicles,” IEEE Transactions on Smart Grid, vol. 9, no. 6, pp. 5613–5621, 2018.

[7] S. S. Arnob, A. I. M. S. Arefin, A. Y. Saber, and K. A. Mamun, “Energy demand forecasting and optimizing electric systems for developing countries,” IEEE Access, vol. 11, pp. 39 751–39 775, 2023.

[8] K. Khan, I. El-Sayed, and P. Arboleya, “Multi-issue negotiation evs charging mechanism in highly congested distribution networks,” IEEE Transactions on Vehicular Technology, vol. 71, no. 6, pp. 5743–5754, 2022.

[9] Y. B. Heng, V. K. Ramachandaramurthy, R. Verayiah, and S. L. Walker, “Developing peer-to-peer (p2p) energy trading model for malaysia: A review and proposed implementation,” IEEE Access, vol. 10, pp. 33 183–33 199, 2022.

[10] 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, vol. 24, no. 2, pp. 2282–2295, 2023.

[11] C. Silva, P. Faria, R. Barreto, and Z. Vale, “Fair management of vehicle-to-grid and demand response programs in local energy communities,” IEEE Access, vol. 11, pp. 79 851–79 860, 2023.

[12] C. O’Malley, L. Badesa, F. Teng, and G. Strbac, “Frequency response from aggregated v2g chargers with uncertain ev connections,” IEEE Transactions on Power Systems, vol. 38, no. 4, pp. 3543–3556, 2023.

[13] A. Ghosh and V. Aggarwal, “Menu-based pricing for charging of electric vehicles with vehicle-to-grid service,” IEEE Transactions on Vehicular Technology, vol. 67, no. 11, pp. 10 268–10 280, 2018.

[14] J. Kim et al., “Battery-wear-model-based energy trading in electric vehicles: A naive auction model and a market analysis,” IEEE Transactions on Industrial Informatics, vol. 15, no. 7, pp. 4140–4151, 2018.

[15] A. A. Al-Obaidi and H. E. Farag, “Decentralized quality of service based system for energy trading among electric vehicles,” IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 7, pp. 6586–6595, 2021.

[16] J. Kang et al., “Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains,” IEEE Transactions on Industrial Informatics, vol. 13, no. 6, pp. 3154–3164, 2017.

[17] A. Yassine et al., “Double auction mechanisms for dynamic autonomous electric vehicles energy trading,” IEEE Transactions on Vehicular Technology, vol. 68, no. 8, pp. 7466–7476, 2019.

[18] G. Sun et al., “Optimal energy trading for plug-in hybrid electric vehicles based on fog computing,” IEEE Internet of Things Journal, vol. 6, no. 2, pp. 2309–2324, 2019.

[19] 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, vol. 66, no. 4, pp. 2880–2890, 2019.

[20] P. Chen, L. Han, H. Ren, and A. Zhang, “Game theory based optimal pricing strategy for v2g participating in demand response,” IEEE Transactions on Industry Applications, vol. 59, no. 4, pp. 4673–4683, 2023.

[21] I.-I. Avramidis and G. Takis-Defteraios, “Flexicurity: Some thoughts about a different smart grid of the future,” IEEE Transactions on Smart Grid, vol. 14, no. 2, pp. 1333–1336, 2023.

[22] K. Kaur, N. Kumar, and M. Singh, “Coordinated power control of electric vehicles for grid frequency support: Milp-based hierarchical control design,” IEEE Transactions on Smart Grid, vol. 10, no. 3, pp. 3364–3373, 2019.

[23] Y. Yu et al., “A game theoretical pricing mechanism for multi-microgrid energy trading considering electric vehicles uncertainty,” IEEE Access, vol. 8, pp. 156 519–156 529, 2020.

[24] W. Zhong, K. Xie et al., “Topology-aware vehicle-to-grid energy trading for active distribution systems,” IEEE Transactions on Smart Grid, vol. 10, no. 2, pp. 2137–2147, 2018.

[25] Y. Yu et al., “Residential microgrids energy trading with plug-in electric vehicle battery via stochastic games,” IEEE Access, vol. 7, pp. 174 507–174 516, 2019.

[26] S. Zheng, Y. Sun, B. Qi, and B. Li, “Incentive-based integrated demand response considering s&c effect in demand side with incomplete information,” IEEE Transactions on Smart Grid, vol. 13, no. 6, pp. 4465–4482, 2022.

[27] D. Said and H. T. Mouftah, “A novel electric vehicles charging/discharging management protocol based on queuing model,” IEEE Transactions on Intelligent Vehicles, vol. 5, no. 1, pp. 100–111, 2020.

[28] F. Liu, C. Chen, C. Lin, G. Li, H. Xie, and Z. Bie, “Utilizing aggregated distributed renewable energy sources with control coordination for resilient distribution system restoration,” IEEE Transactions on Sustainable Energy, vol. 14, no. 2, pp. 1043–1056, 2023.

[29] 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, vol. 23, no. 1, pp. 499–512, 2022.

[30] F. Heymann, F. vom Scheidt, F. J. Soares, P. Duenas, and V. Miranda, “Forecasting energy technology diffusion in space and time: Model design, parameter choice and calibration,” IEEE Transactions on Sustainable Energy, vol. 12, no. 2, pp. 802–809, 2021.

[31] K. Gai et al., “Privacy-preserving energy trading using consortium blockchain in smart grid,” IEEE Transactions on Industrial Informatics, vol. 15, no. 6, pp. 3548–3558, 2019.

[32] H. Abubakr, J. C. Vasquez, K. Mahmoud, M. M. F. Darwish, and J. M. Guerrero, “Comprehensive review on renewable energy sources in egypt—current status, grid codes and future vision,” IEEE Access, vol. 10, pp. 4081–4101, 2022.

[33] S. Aggarwal et al., “An efficient blockchain-based authentication scheme for energy-trading in V2G networks,” IEEE Transactions on Industrial Informatics, vol. 17, no. 10, pp. 6971–6980, 2020.

[34] M. Baza et al., “Privacy-preserving blockchain-based energy trading schemes for electric vehicles,” IEEE Transactions on Vehicular Technology, vol. 70, no. 9, pp. 9369–9384, 2021.

[35] C.-C. Lin et al., “Optimal charging control of energy storage and electric vehicle of an individual in the internet of energy with energy trading,” IEEE Transactions on Industrial Informatics, vol. 14, no. 6, pp. 2570–2578, 2017.

[36] J. Kim et al., “Joint demand response and energy trading for electric vehicles in off-grid system,” IEEE Access, vol. 8, pp. 130 576–130 587, 2020.

[37] H. N. Abishu et al., "Consensus mechanism for blockchain-enabled vehicle-to-vehicle energy trading in the internet of electric vehicles," IEEE Transactions on Vehicular Technology, vol. 71, no. 1, pp. 946–960, 2021.

[38] A. Miglani and N. Kumar, "Blockchain-based co-operative caching for secure content delivery in ccn-enabled v2g networks," IEEE Transactions on Vehicular Technology, vol. 72, no. 4, pp. 5274–5289, 2023.

[39] V. Hassija et al., "A blockchain-based framework for lightweight data sharing and energy trading in V2G network," IEEE Transactions on Vehicular Technology, vol. 69, no. 6, pp. 5799–5812, 2020.

[40] A. Sadiq et al., "Blockchain based data and energy trading in internet of electric vehicles," IEEE Access, vol. 9, pp. 7000–7020, 2020.

[41] H. Khaloie, J.-F. Toubeau et al., "An innovative coalitional trading model for a biomass power plant paired with green energy resources," IEEE Transactions on Sustainable Energy, vol. 13, no. 2, pp. 892–904, 2021.

[42] M. R. Hamouda et al., "Centralized blockchain-based energy trading platform for interconnected microgrids," IEEE Access, vol. 9, pp. 95 539–95 550, 2021.

[43] F. Luo, Z. Y. Dong et al., "A distributed electricity trading system in active distribution networks based on multi-agent coalition and blockchain," IEEE Transactions on Power Systems, vol. 34, no. 5, pp. 4097–4108, 2018.

[44] A. S. Yahaya, N. Javaid et al., "A two-stage privacy preservation and secure peer-to-peer energy trading model using blockchain and cloud-based aggregator," IEEE Access, vol. 9, pp. 143 121–143 137, 2021.

[45] H. T. Doan, J. Cho, and D. Kim, "Peer-to-peer energy trading in smart grid through blockchain: A double auction-based game theoretic approach," Ieee Access, vol. 9, pp. 49 206–49 218, 2021.

[46] M. U. Hassan, M. H. Rehmani, and J. Chen, "DEAL: Differentially private auction for blockchain-based microgrids energy trading," IEEE Transactions on Services Computing, vol. 13, no. 2, pp. 263–275, 2019.

[47] G. Gao, C. Song et al., "FogChain: A blockchain-based peer-to-peer solar power trading system powered by Fog AI," IEEE Internet of Things Journal, vol. 9, no. 7, pp. 5200–5215, 2021.

[48] T. AlSkaif et al., "Blockchain-based fully peer-to-peer energy trading strategies for residential energy systems," IEEE Transactions on Industrial Informatics, vol. 18, no. 1, pp. 231–241, 2021.

[49] A. D. Tesfamicael et al., "A design for a secure energy market trading system in a national wholesale electricity market," IEEE Access, vol. 8, pp. 132 424–132 445, 2020.

[50] X. Huang, Y. Zhang, D. Li, and L. Han, "A solution for bi-layer energy trading management in microgrids using multi-blockchain," IEEE Internet of Things Journal, vol. 9, no. 15, pp. 13 886–13 900, 2022.

[51] M. Li et al., "Blockchain-enabled secure energy trading with verifiable fairness in industrial internet of things," IEEE Transactions on Industrial Informatics, vol. 16, no. 10, pp. 6564–6574, 2020.

[52] Z. Li et al., "Consortium blockchain for secure energy trading in industrial internet of things," IEEE transactions on industrial informatics, vol. 14, no. 8, pp. 3690–3700, 2017.

[53] F. Wang et al., "Smart households' aggregated capacity forecasting for load aggregators under incentive-based demand response programs," IEEE Transactions on Industry Applications, vol. 56, no. 2, pp. 1086–1097, 2020.

[54] A. T. Eseye et al., "Optimal energy trading for renewable energy integrated building microgrids containing electric vehicles and energy storage batteries," IEEE Access, vol. 7, pp. 106 092–106 101, 2019.

[55] T. Zhou and B. François, "Energy management and power control of a hybrid active wind generator for distributed power generation and grid integration," IEEE transactions on industrial electronics, vol. 58, no. 1, pp. 95–104, 2010.

[56] S. Z. Tajalli et al., "Stochastic electricity social welfare enhancement based on consensus neighbor virtualization," IEEE Transactions on Industrial Electronics, vol. 66, no. 12, pp. 9571–9580, 2019.

[57] D. Gregoratti and J. Matamoros, "Distributed energy trading: The multiple-microgrid case," IEEE Transactions on Industrial Electronics, vol. 62, no. 4, pp. 2551–2559, 2014.

[58] T. R. B. Kushal and M. S. Illindala, "Decision support framework for resilience-oriented cost-effective distributed generation expansion in power systems," IEEE Transactions on Industry Applications, vol. 57, no. 2, pp. 1246–1254, 2020.

[59] L.-J. Yang, Y. Zhao et al., "Resilience-oriented hierarchical service restoration in distribution system considering microgrids," IEEE Access, vol. 7, pp. 152 729–152 743, 2019.

[60] M. Khorasany et al., "A decentralized bilateral energy trading system for peer-to-peer electricity markets," IEEE Transactions on Industrial Electronics, vol. 67, no. 6, pp. 4646–4657, 2019.

[61] Y. Ma et al., "A multi-stage information protection scheme for cda-based energy trading market in smart grids," IEEE Transactions on Smart Grid, vol. 13, no. 3, pp. 2305–2317, 2021.

[62] J. Yang et al., "Hierarchical blockchain design for distributed control and energy trading within microgrids," IEEE Transactions on Smart Grid, vol. 13, no. 4, pp. 3133–3144, 2022.

[63] N. Z. Aitzhan and D. Svetinovic, "Security and privacy in decentralized energy trading through multi-signatures, blockchain and anonymous messaging streams," IEEE Transactions on Dependable and Secure Computing, vol. 15, no. 5, pp. 840–852, 2016.

[64] Z. Li, S. Chen, and B. Zhou, “Electric vehicle peer-to-peer energy trading model based on smes and blockchain,” IEEE Transactions on Applied Superconductivity, vol. 31, no. 8, pp. 1–4, 2021.

[65] 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, vol. 20, no. 1, pp. 166–181, 2023.

[66] J. Guo, X. Ding, and W. Wu, “An architecture for distributed energies trading in byzantine-based blockchains,” IEEE Transactions on Green Communications and Networking, vol. 6, no. 2, pp. 1216–1230, 2022.

[67] 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, vol. 71, no. 12, pp. 12 576–12 587, 2022.

[68] 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, vol. 14, no. 2, pp. 1607–1620, 2023.

[69] W. Bing, C. Mingxi, C. Yuquan, and W. Xiaoyue, “Scheduling management of controllable load participating in power grid enhanced by double-chain structure,” IEEE Access, vol. 10, pp. 103 028–103 040, 2022.

[70] 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, vol. 10, pp. 75 932–75 948, 2022.

[71] 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, vol. 9, no. 2, pp. 2367–2381, 2018.

[72] 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, vol. 20, no. 3, pp. 1851–1863, 2018.

[73] S. R. Pokhrel and M. B. Hossain, “Data privacy of wireless charging vehicle to grid (v2g) networks with federated learning,” IEEE Transactions on Vehicular Technology, vol. 71, no. 8, pp. 9032–9037, 2022.

[74] 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, vol. 19, no. 4, pp. 2442–2456, 2022.

[75] 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, vol. 9, no. 1, pp. 968–980, 2023.

[76] 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, vol. 18, no. 8, pp. 5698–5704, 2022.

[77] S.-H. Hong and H.-S. Lee, "Robust energy management system with safe reinforcement learning using short-horizon forecasts," IEEE Transactions on Smart Grid, vol. 14, no. 3, pp. 2485–2488, 2023.

[78] 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, vol. 13, no. 5, pp. 3798–3812, 2022.

[79] C. Qin, A. K. Srivastava, and K. L. Davies, "Unbundling smart meter services through spatiotemporal decomposition agents in der-rich environment," IEEE Transactions on Industrial Informatics, vol. 18, no. 1, pp. 666–676, 2022.

[80] 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, vol. 38, no. 5, pp. 4900–4915, 2022.

[81] 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 Power Systems, vol. 14, no. 5, pp. 4073–4085, 2023.

[82] Z. Wang, M. Ogbodo, H. Huang, C. Qiu, M. Hisada, and A. B. Abdallah, "AEBIS: AI-enabled blockchain-based electric vehicle integration system for power management in smart grid platform," IEEE Access, vol. 8, pp. 226 409–226 421, 2020.