Novel Charging and Discharging Schemes for Electric Vehicles in Smart Grids

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TO MY FAMILY

Abstract

This thesis presents smart Charging and Discharging (C&D) schemes in the smart grid that enable a decentralised scheduling with large volumes of Electric Vehicles (EV) participation. The proposed C&D schemes use different strategies to flatten the power consumption profile by manipulating the charging or discharging electricity quantity. The novelty of this thesis lies in:

1. A user-behaviour based smart EV charging scheme that lowers the overall peak demand with an optimised EV charging schedule. It achieves the minimal impacts on users' daily routine while satisfying EV charging demands.

2. A decentralised EV electricity exchange process matches the power demand with an adaptive blockchain-enabled C&D scheme and iceberg order execution algorithm. It demonstrates improved performance in terms of charging costs and power consumption profile.

3. The Peer-to-Peer (P2P) electricity C&D scheme that stimulates the trading depth and energy market profile with the best price guide. It also increases the EV users' autonomy and achieved maximal benefits for the network peers while protecting against potential attacks.

4. A novel consensus-mechanism driven EV C&D scheme for the blockchain-based system that accommodates high volume EV scenarios and substantially reduces the power fluctuation level.

The theoretical and comprehensive simulations prove that the penetration of EV with the proposed schemes minimises the power fluctuation level in an urban area, and also increases the resilience of the smart grid system.

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List of Abbreviations

AdBEV	Adaptive Blockchain-based Electric Vehicle
AGC	Automatic Generation Control
BFT	Byzantine Fault Tolerance
C&D	Charging & Discharging
DSO	Distributed System Operator
EV	Electric Vehicle
EVM	Ethereum Virtual Machine
ePoB	Enhanced Proof of Benefit
GA	Genetic Algorithm
G2V	Grid-to-Vehicle
ICT	Information & Communication Technology
ISO	Independent System Operator
PEBT	Peer-to-Peer Electricity Blockchain Trading
POB	Proof of Benefit
PoA	Proof of Authority
PoBr	Proof of Burn
PoET	Proof of Elapsed Time
PoW	Proof of Work
PoS	Proof of Stake

PBFT	Practical Byzantine Fault Tolerance
PFL	Power Fluctuation Level
P2P	Peer-to-Peer
SOC	State-of-Charge
SG	Smart Grid
Tx	Transaction
UNL	Unique Node List
UTXO	Unspent Transaction Outputs
V2G	Vehicle-to-Grid

Chapter 1

Introduction

The traditional power grids are generally used to carry power from the central generators to a large number of users or customers. In contrast, the Smart Grid (SG) uses two-way flows of electricity and information to create an automated and distributed advanced energy delivery network, which is expected to be the next generation power grid [MJA+14]. SG utilises modern information technologies and computational intelligence in an integrated version to deliver power that features in self-monitoring, adaptive recovery and distributed generation.

The electrification in the transportation sector has become an important issue in recent decades due to the potential of reducing the nationwide energy consumption [AAGG14]. With the relaxation on subsidies and incentive programs to promote EV adoption, EV sales in vehicle markets are blooming [Li]. Thus, it is inevitable that the considerable large penetrations of EVs will impact the power grid. In order to meet the increasing power demand, utilities will require capacity and incentive mechanisms to address potential or sudden peaks in consumption. Therefore, the concept of vehicle-to-grid (V2G) and gird-to-vehicle (G2V) are introduced that act as the provision of energy and as an ancillary service to support the electrical grid [SC12]. V2G-featured and G2V-featured EVs can provide peak shaving, frequency regulation by matching the power generation amount to the load demand, and spinning & non-spinning reserves by optimising V2G energy scheduling and coordination [YWS17].

1.1 Research Motivation

The massive adoption of EVs will impose significant challenges to future power grids as the uncertain power demands lead to unpredictable fluctuation in the distribution network [WW13]. Moreover, the centralised power generation structure faces the single point of failure, hence, decentralised power grid system and power delivery mechanism are needed. Henceforth, the battery-assisted EV needs to address the following challenges in order to act as distributed energy resources:

1. Distribution grid overload: The increasing EV market penetration will burden the power grid network, especially in the electricity consumption peak time, which might exceed the substation power capacity [KG14].

2. Adaptivity: EV charging and discharging are highly uncertain and random, such as charging profiles of EV arriving, future load demand in the grid, battery requirement, etc. Moreover, the operation time is extremely high due to the large-scale and frequent EV charging and discharging [SC12].

3. System decentralisation: The current grid distribution is a hierarchical system and requires a centralised grid operator, where the structure is vulnerable to natural disaster and imposes a single-point failure [CWQZ15]. Moreover, the power exchange process is complicated and time-consuming, where electricity users lack power exchange autonomy.

4. Power exchange efficiency: The high volume and mobility of EVs generate a significant number of charging and discharging demands with respect to various stakeholders such as EV users, electricity dealers, utilities, etc [SC12].

In summary, the increasing number of EVs could be used as potential micro-distributed energy resources in the SG to increase the grid network stability and resilience. Efficient C&D schemes that consider the uncertainty of EV profiles and power grid constraints should be designed to improve the power grid performance whilst achieve the power demand and supply balance in a large scale of EV participation.

1.2 Research Scope and Objectives

This thesis focuses on developing novel schemes for scheduling EV charging and discharging in the smart grid, where charging refers to withdrawing energy from the grid network while discharging referring to injecting energy back to the grid. The aim is to minimise the overall power fluctuation level of the distribution grid while satisfying the EV charging or discharging demands. To accommodate the decentralised feature of the smart grid in power generation and distribution, this thesis uses the blockchain technology to schedule the EV C&D electricity demand where consensus mechanism is envisaged to enhance automation process and autonomy of participants.

Novel charging and discharging schemes for EV are proposed to improve the scheduling efficiency to accommodate increasing adoption of EVs, where the C&D schemes feature in:

1. EV user-behaviour associated schemes aim to address the relationship between the EV user driving pattern (charging habits, work routine, etc.) and charging demands and adapt the residential power consumption profile to flatten the overall power curve.

2. Adaptive EV participation scheme aims to adapt to dynamic EV profiles that consider the uncertainty of future events such as arrival and leaving, which can improve the system flexibility for unpredictable changes.

3. P2P EV C&D scheme aims to change the conventional electricity exchange process using the smart contract in the blockchain system, which can accommodate more EV participation and increase the C&D autonomy of EV users.

4. Consensus mechanism-driven EV scheme aims to handle the C&D transactions in a

digital contract which is executed in a decentralised system, which enables a more secure and efficient electricity exchange platform.

1.3 Contributions

Four smart charging and discharging schemes for EV in smart grids are proposed to minimise the power fluctuation level. A decentralised system is proposed that adopts blockchain technology to enable P2P electricity exchange where all EV users can submit charging or discharging demands.

- A smart EV charging scheme based on the user-behaviour is proposed to minimise the power consumption fluctuation in a typical weekday without interfering with drivers' daily routine activities [LCL$^+$17]. Genetic Algorithm (GA) is implemented to determine the optimum charging schedule at every time segment with an acceptable level of computation complexity.

- An adaptive EV-participation decentralised C&D scheme on a blockchain-enabled smart grid system is developed [LCZ$^+$18]. A C&D schedule is formulated to minimise the Power Fluctuation Level (PFL) using AdBEV scheme based on the iceberg order algorithm [EM07] that executes the best order strategy to match the C&D demands.

- A P2P Electricity Blockchain Trading (PEBT) system is proposed to achieve transparent and efficient electricity trading [LCLC18a]. A novel consensus primitive proof-of-benefit (PoB) is designed to adapt electricity trading system to stabilise the smart grid system [LCZC19a]. Moreover, a benefit index generation scheme is proposed to select the winning block to achieve the minimum power fluctuation.

- A blockchain-enabled consensus mechanism is designed for the decentralised system to accommodate the smart grid infrastructure from scheduling EV C&D [LCZC19b]. An enhanced proof-of-benefit (ePoB) consensus mechanism with an online benefit generating algorithm is proposed to achieve power load flattening in the future smart grid, which demonstrates better performance in terms of validity, scalability and security.

1.4 Author's Publications

Journal papers

1. **C. Liu**, K. K. Chai, X. Zhang and Y. Chen, "Peer-to-peer electricity trading system: smart contracts based proof-of-benefit consensus protocol," in *Wireless Networks*, 1572-8196, 2019/02/13. doi: 10.1007/s11276-019-01949-0

2. **C. Liu**, K. K. Chai, X. Zhang, E. T. Lau and Y. Chen, "Adaptive Blockchain-Based Electric Vehicle Participation Scheme in Smart Grid Platform," in *IEEE Access*, vol. 6, pp. 25657-25665, 2018. doi: 10.1109/ACCESS.2018.2835309

Conference papers

1. **C. Liu**, K. Chai, X. Zhang, Y. Chen, "Enhanced Proof-of-Benefit: a Secure Blockchain-enabled EV Charging System," *2019 IEEE 90th Vehicular Technology Conference* , Honolulu, Hawaii, USA, 2019. (Accepted)

2. **C. Liu**, K. Chai, X. Zhang, Y. Chen, "Proof-of-Benefit: a Blockchain-enabled EV Charging Scheme," *2019 IEEE 89th Vehicular Technology Conference* , Kuala Lumpur, Malaysia, 2019. (Accepted)

3. **C. Liu**, E. Lau, K. Chai, Y. Chen, "Blockchain-Based Energy Trading Model for Electric Vehicle Charging Schemes," *2018 International Conference on Smart Grid Inspired Future Technologies* , Auckland, New Zealand, 2018. (Accepted)

4. **C. Liu**, K. Chai, E. Lau, Y. Wang, Y. Chen, "Optimised Electric Vehicles Charg-

ing Scheme with Uncertain User-Behaviours in Smart Grids," *IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)* , Montreal, Canada, 2017. (Accepted)

5. **C. Liu**, E. Lau, K. Chai, Y. Chen, "A Review of Wireless Power Transfer Electric Vehicles in Vehicle-to-Grid Systems," *2017 International Conference on Smart Grid Inspired Future Technologies* , London, UK, 2017. (Accepted)

1.5 Thesis structure

This thesis is organised as follow.

Chapter 2 covers the relevant knowledge and literature review in this research area. The ancillary services provided by EVs are introduced, the state-of-art of charging schemes, and the blockchain technology applications are summarised.

Chapter 3 introduces the proposed user-behaviour associated charging scheme that incorporates the randomness of EV drivers and charging variables. This part gives a description of the system model and problem formulation. The simulation results of the proposed algorithm and the performance analysis are given under the comparison with existing charging algorithms.

Chapter 4 presents a novel adaptive blockchain-based electric vehicle participation (AdBEV) scheme that uses Iceberg order execution algorithm to obtain an improved EV charging and discharging schedule. A best order strategy to match the smart grid electricity charging and discharging demand is introduced, and simulation results demonstrate the improvement of the proposed algorithm compared to the existing GA approach.

Chapter 5 presents a new PEBT system based on the current charging and discharging schemes for EV in the smart grid to enable users to participate in the trading process. Moreover, PoB is proposed to achieve demand response by providing incentives to balance local electricity demand.

Chapter 6 investigates the consensus mechanism in the blockchain-enabled system. It begins with the proposed ePoB consensus mechanism to support EV C&D transactions. Based on that, an online benefit generating algorithm is presented to achieve power load flattening. The performance evaluation provides guidelines on the protocol and system design analysis.

Chapter 7 gives conclusions of the thesis, and the idea about future work based on the research carried out in this work is also presented.

Chapter 2

Background and State-of-the-Art

Electric power grid infrastructure has revolutionised our world, which has changed the way of living. A smart grid applies technologies, tools and techniques to the existing power grid to enable a more efficient and stable grid system. The emergence of EV in the energy market brings the concept of V2G and G2V that aims to transform the problematic loads into a beneficial resources. With the increasing adoption of EV, the large volume of electricity exchange requires a secure platform to accommodate frequent transactions where blockchain technology is envisaged to be a feasible solution.

This chapter presents the introduction of the smart grid key components, structure and technologies. Special focus is given to the V2G and G2V concepts which utilise the EV to provide ancillary services, Section 2.2 describes the fundamentals of blockchain technology and applications in the smart grid system. In section 2.3, a study of state-of-the-art C&D scheme, including offline and online strategies is conducted, and the current and trend about consensus mechanisms are presented.

2.1 Vehicle-to-Grid System

2.1.1 Smart grid system

The current grid is a hierarchical structure distribution system that transfers electricity in a single dicrection. With the ongoing grid system evolution, the SG concept is introduced, which studies the interaction between mass elementary electricity loads and the power grid. SG is expected to be the next generation power grid which combines small-scale grids and large-scale electric power plants.

1. **Two-way flow -** Conventional grid uses electromechanical components to transfer electricity and information goes from power generating units and utilities to consumer in a single direction way. In the smart grid, it adopts Information and Communication Technology (ICT) to allow two-way communication flow, and the electricity can be delivered bidirectionally [MJA+14].

2. **Distributed energy resources -** Smart grid utilises micro sources such as renewable energy and forms the microgrid to support distributed energy system. However, the traditional grid system is centralised, where generation and distribution are hierarchical.

In conclusion, the smart grid utilises modern technologies and advanced infrastructure to create an automated and distributed energy delivery network, which delivers power in a more reliable and controllable way. To be more specific, the SG uses information, computational intelligence in an integrated version that features in self-monitoring, adaptive recovery and distributed generation. By utilising micro sources to form the microgrid, SG can control and optimise electricity demands in local areas more economically and reliably. The distributed generation promotes the development of new grid paradigms, which benefits from smart energy subsystem technologies. These two paradigms are regarded as important components of the future SG.

Fig. 2.1 illustrates the framework of SG power system. In the SG system, microgrids are connected to the main grid via transmission lines under the surveillance and control by the aggregator. Each microgrid component can:

- connect to the grid for electrical energy flow;
- access and proceed the communication signal from the operator;
- control the interior elements, such as appliances and EVs, in response to different scenarios. These requirements vary according to the operation deployment [KT05].

The bi-directional electricity and information flows can provide advanced performance in SG applications. An aggregator can be a utility managing EV groups or a third party operating a virtual power plant. It can be viewed as the market coordinator that passes through the system signals and manages the system capacity required to enter the electricity market [HHS10]. Moreover, it is the place that bids with the market participants to provide the most valuable services [YWS17]. The grid operator such as the Independent System Operator (ISO) broadcasts control signal via the cell phone network, direct Internet connection, or power line carrier [KT05]. The ISO is capable of issuing Automatic Generation Control (AGC) signal to address the ancillary services for

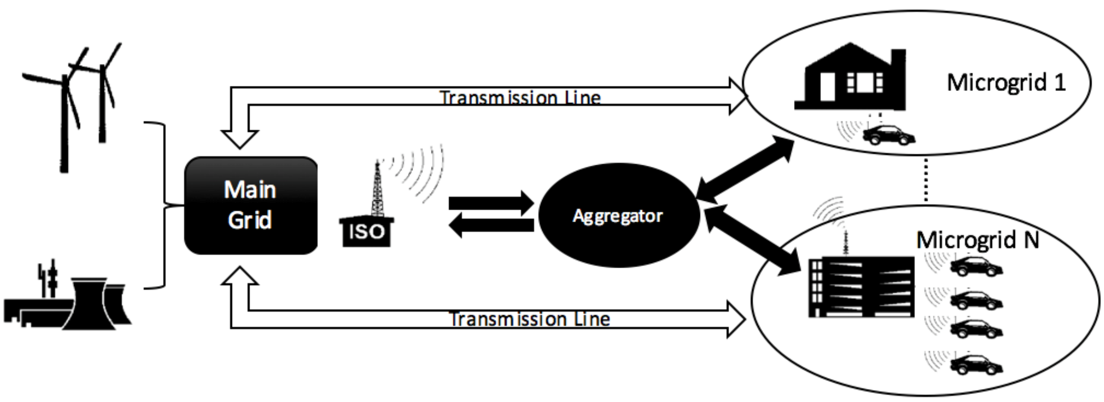

Figure 2.1: Smart grid power system with ISO, Aggregator, signal transmission and the electric power grid

SG system stakeholders. In the United States, the ISOs purchase the regulation capacity service to help aggregators to reduce the financial risk and price volatility [YWS15].

From Fig. 2.1, the electricity is generated from power generators and then transmitted through the grid to electricity users. Furthermore, electricity can also flow back from microgrids to the main grid, where microgrids are inter-connected in a mesh strcuture. The ISO sends control signals to the aggregator, and the aggregator develops dispatch algorithms to make responses for the ISO requests. In the SG system, the microgrid system acts as both the electricity consumer as well as the producer. Fig. 2.2 depicts a simplified model of a microgrid. The power generation for the system loads, such as houses and offices, is shared among central power generators and distributed generators from the main grid. In this case, the distributed generators can be aggregated to form a virtual power plant and facilitate the integration of generators to the microgrid.

As shown in Fig. 2.2, the storage system can be used in the virtual power plant or the nearby loads. The storage system comprises of the distributed electricity generators such as the renewable energy sources, and fast response devices including batteries and

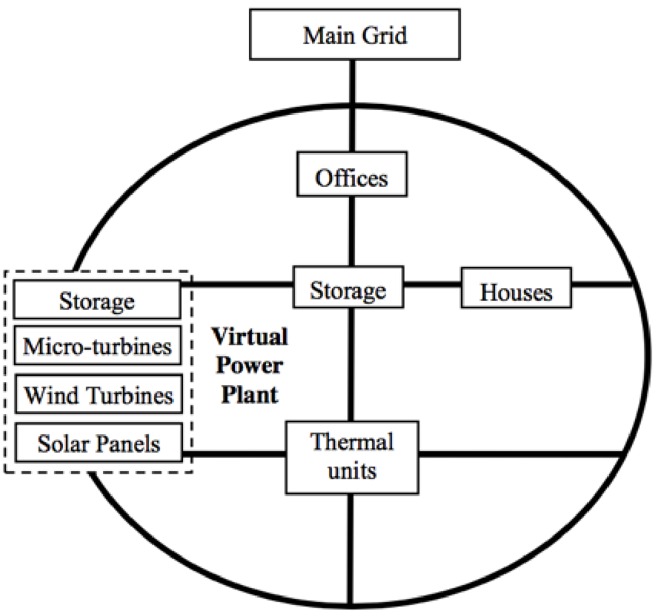

Figure 2.2: Simplified microgrid model

EVs, which add the control flexibility of the microgrid. By storing energy at times of excess power and generating energy at times of low generation, the microgrid system can accommodate the power demand profile fluctuation. Furthermore, the characteristics of different storage devices can be utilised to tune the frequent and rapid power changes in renewable resources, which brings the economic advantages for the microgrid as well as improve the power quality.

The technologies used in the smart grid can be divided into four groups, including the power and energy technologies, power system capacity, power system performance, and end-user integration [FSF+14].

1. Power and energy technologies: Storage technologies are a challenging paradigm as electricity tends to be used instantaneously and cannot be stored easily. With proper energy storage technology, system capacity, reliability, and power quality can be improved. Moreover, the mastering DC power, including DC generation, DC switching equipment and consumer DC bus line shall be developed to increase the use domain. Other technologies include variable frequency, power electronic interfaces, beamed power, and so on [AA13].

2. Power system capacity: The smart grid system increases the power system capacity either by adding energy or reducing the energy losses. The system capacity can be harnessed by including hydro, wind, large power generation, solar, geothermal, islanding (external power generation being cut off), demand response, etc [Sio11].

3. Power system performance: The reliability and power quality can be managed via using the smart control system, including intelligent transmission system, fault prevention, auto restoration, and so on.

4. End-user integration: The smart grid should be adaptable to the existing power grid infrastructure, where the conventional end-users such as industrial, commercial and residential installations should be integrated. Moreover, the new loads such as electric transportation and EV should be integrated through more intelligent

interfaces.

2.1.2 V2G/G2V Ancillary Services

As the ongoing market penetration of EV, the V2G/G2V concept is introduced to study the interaction between mass EV fleets and the power grid. The basic concept of the V2G system is that EVs can be both charged and discharged in the grid. The V2G/G2V system features in transforming EVs from potentially problematic loads into distributed energy sources that generate values for both the utility and EV owners. The electricity sources shall be controlled in real-time by the ISO to ensure the efficiency of power transfer. For instance, if a large number of EVs start charging at the same time interval during the power consumption peak-time interval, the large power generators have to start the subsidiary (reserve) generators which has less response time to start the power generation to supplement the power consumption, where there is delay for the subsidiary generators to start generating and offering power. They usually take 10 to 15 minutes to start providing power. In [ZCY16], a three-party architecture including the power grid, EVs and smart community renewable energy generations and storage capabilities is proposed to build an energy management framework, which provides insight for applying feasible optimisation methods to achieve effective and intelligent energy management in the power system. Some services such as frequency regulation, spinning reserve and load hiding are discussed in this section, along with the challenges associated with the services.

The frequency regulation techniques in [YWS17, YWS15, HGM^{+}15] are used to regulate the frequency and voltage of the grid for alternating current by matching the generation to the load demand. The distributed power of the EVs can either be sold to the grid or be used to provide frequency regulation service when V2G-G2V is implemented. The paper [SW11] studies the real-time V2G control under price uncertainty. Then, the electricity price is modelled as a Markov chain, and a Markov decision process is formulated. The conventional approach would start charging at the maximum rate once plugged in until the expected State-of-Charge (SOC) is reached while maximising the profit for EV users. By using the fast-ramping feature of EVs, the generated electricity frequency can be controlled under direct real-time control. However, determining the regulation capacity can be difficult in the process as the individual EV's user behaviour is randomised though there are certain pattern can be analysed for a large group of users. Hence, the intelligent dispatch algorithm is required. In [SC12], the dispatch algorithm is proposed according to the price-based or event-based, and unidirectional or bidirectional charging rate scenarios to control the frequency. However, the massive load caused by huge penetrations of EVs into the power grid raises concerns about the potential impacts on the operating cost and voltage stability.

Spinning reserve refers to the additional generating capacity that remains in standby mode to provide power upon request. Spinning reserves are remunerated by the amount of time they are available and ready to use [KT05]. In a V2G system, EVs have a high response rate and require a short time to provide power. The challenge is to report the number of EVs that can remain online during the contracted/tendered period. Furthermore, the contract length is limited by the SOC in the EV battery. The stochastic modelling of EV user behaviour was proposed to predict the contract/tender length and duration.

V2G system can also be used in the application of load hiding in household electricity consumption profile. The appliance operation activities such as air conditioner, heating and so on can be mapped with household routines, which can further be exploited to infer customer preferences and privacy [SLW15]. V2G system utilises EV rechargeable battery as a controllable load to mitigate the privacy leakage of the customers. The key concept is to distort the household consumption profile based on different algorithms, such as the best effort and stepping approach in [YCZP14]. However, the current researches are based on a series of idealisation for the driving pattern and household baseload. The future work should include the uncertainty of household load, EV arrival time and SoC [AAGG14].

2.1.3 EV C&D Schemes State-of-the-arts

As the number of EVs increases, it is predicted that up to 60% of electricity consumption will be consumed by EVs in 2050 [KG14]. This is a vast and randomised load to the energy grid. Energy management for the large EV groups is essential for the energy grid to ensure the balance of supply and demand. Hence, more companies and coorporations are increasingly putting their efforts on the EV studies. Additionally, consideration of the energy grid distribution will become essential to EV system. When the EV is connected to the smart grid, it can be operated as an active load that drains energy from the main grid as well as an energy storage device that allows power to be discharged from the EV battery. It is inevitable that EVs are expected to play a major role in the road transport system. However, numerous EVs connected to the distributed network may cause the distribution grid to overload. Henceforth, it is critical to develop an efficient charging/discharging scheme for sufficient and superior grid operation.

In this subsection, the existing charging schemes are reviewed into three types:

(1) EVs are charged instantly when the owner arrived at the home, which means that there is no pre-planned strategy for the charging process. By this use, it can be controlled by the aggregator. It is referred to as the dumb scenario C&D scheme.

(2) EVs are controlled by simple strategies, where the charging process is time-delayed to avoid peak demand periods and in particular is responsive to user-behaviour, which is referred to as the user-behaviour associated C&D scheme.

(3) EVs are controlled by an intelligent algorithm using the characteristics of the V2G-G2V system to improve the operation efficiency of the power network [WW13]. Then this charging scheme is referred to as the smart C&D scheme.

These are discussed in more detail below.

2.1.3.1 Dumb C&D schemes

In this situation, the EV is plugged into the electricity network as soon as the driver arrives at home. However, the charging process is controlled by the smart grid aggregator based upon the time frame. According to [AAGG14], the charging periods considered by the aggregator are considered to model the power demand profile in the main transformer. In the conventional EV charging/discharging scheme, the aggregator is used to gather the electricity consumption demand and further give commands the power transfer in [YWS17, CWQZ15]. With the assistance of the aggregator, the control schemes can be applied to control the power flow in the peak hours and off-peak hours, respectively. In dumb charging schemes, the EV charging starts just when they are plugged in at home. However, there are many potential problems in using dumb charging. For example, it might arise a sudden peak demand which directly burdens the distributed network for a substation transformer in an area. Furthermore, the dumb charging scheme might also increase the cost of electricity.

[KM11] estimates the costs of plug-in EVs in a future power system as well as the benefits of smart charging and discharging EVs by modelling the annual electricity price. The dumb electric vehicles are used to calculate the electricity cost. However, the market prices for modelling the charging cost are based upon the limited historical EV data where the EV user driving preference is not well considered.

In [AAGG14], three charging schemes, including the dumb charging, are presented to compare the ability to level the load profile. It is shown that the peak power demand using dumb charging exceeds the transformer capacity. Hence, a smart charging scheme to minimise the power fluctuation in the distributed network is required.

2.1.3.2 User-behaviour associated C&D schemes

Various control strategies were proposed to provide various types of ancillary services in related papers [WW13, HWIZ13, CJT14a, RSC15]. However, the user behaviours of EV groups are highly uncertain in future events, as well as the arrival and departure time for EV, the residual in the battery and the maximum capacity of the battery depending on the type of the EV.

A comprehensive inspection of EV user behaviour was studied in [JOS+13], where the driving and charging patterns from Dutch EV drivers are surveyed. The research provides direct inspection on various perspectives regarding the EV charging behaviour, which is divided into qualitative measurements for the behaviour analysis. It is shown that most EV drivers adopt routinised behaviour regarding charging their EVs, and clear peaks of charging time of a day are visible on working days. The charging behaviour dimensions can be concluded by the quantitative and qualitative influence factors with each corresponding relation to demonstrate a deeper understanding of charging behaviour.

A. Charging point location and type

The decision for choosing the charging point is based upon routines other than the battery level. Furthermore, the private and semi-public charging points (such as an office parking lot) are mostly used, as the statistics show that 77% EV drivers use less than three charging points [JOS+13]. As for the charging type for driver behaviour, the most often used power output for EV in the Netherlands is 11kWh. However, the charging power transfer amount should be combined with the local charging point standardisation.

B. Charging frequency and time

In practice, the charging frequency is mainly influenced by the anxiety range of the drivers, where they tend to charge more frequently if they have higher anxiety for the amount of power residual in the battery. During weekdays, the peak charging time for home users is from 17:30 to 07:20(+1), and the office peak charging time is from 08:20 to 18:20 [JOS+13]. However, it should be noticed that the charging time at home is much longer than in the office as their preference [Ele13]. However, there is an irregular and less strict pattern at weekends.

Regarding the charging durations, it should be noted that 92% charging transactions are connected to the charging point for up to 3 times longer than they are theoretically required to, which is reached in 8.4 hours approximately [JOS+13].

C. Energy transfer

According to [CJT14b], the average energy transfer is 6.34kW; however, the amount of energy transfer is decided by the battery capacity and the SOC. The peaks are 2.5kW, 8.6kW, 10.5kW, 11.3kW, where it should be noticed that the records are from the public and semi-public charging points as most of the fully electric vehicles are charged fully at home, but the capacity of the plug-in hybrid electric vehicle is small according to the current market hybrid vehicles [CJT14b].

The above analysis showed that most EV drivers adopt a routine behaviour concerning charging their EV, which is also referred to as low user battery interaction [SC12]. With regard to the charging time of day, clear peaks of starting and stopping charging transactions are visible on working days, which shows that EV drivers have a similar charging routine. Moreover, the charging transactions are evenly spread with regard to the SOC, and the EV battery capacity does not influence a drivers' decision to charge on a high or low power charging point. The benefits of using the aforementioned charging schemes include that they do not require much pre-installed hardware and software. However, the potential problems to the existing grid system such as the sudden overloading could be shaped or flattened by using a smart charging schedule for the EV batteries. Moreover, the optimal scheduling of EV battery charging could allow higher EV penetration without requiring an upgrade to the existing electricity infrastructure [KH13]. The optimisation of EV C&D is a demand-response strategy that can be implemented by an EV aggregator to improve the flexibility of the distribution network [FFC12].

2.1.3.3 Smart C&D schemes

To improve the efficiency and superiority of grid operations, various smart control strategies for EV charging and discharging scheme were proposed to control the amount and duration of power transfer. With the aid of the aggregator, the C&D schemes can be applied to control the power flow in the peak hours and off-peak hours, respectively. EV is characterised as a diversely distributed power load to the grid system due to the EV high mobility. In [AAGG14], an optimal charging schedule is proposed for EV to minimise the deviation of the power profile demand in consecutive hours; however, the SOC of the EVs was only assumed at a static value. In the meantime, the choice of the SOC value will largely affect the overall power capacity potential. Also, the model did not consider the intrinsic characteristic of EV behaviour, where the system was designed with enough EV numbers to ensure the reliability of the V2G system.

To consider the dynamic arrival and departure times of EVs, the authors in [YWS17] used an automated generation control signal to regulate the EV charging or discharging schedule to improve the performance of frequency regulation service. In [ZWM+13], an aggregation-based optimisation model for EV charging strategy, was proposed with the consideration of stochastic features of the charging procedure in arrival time and SOC. However, it was noted that the aforementioned EV C&D schedule algorithms use the static parameters to estimate the available charging time for EVs. The aforementioned schemes rely on electricity consumption or bill predictions, and the training data is based on historical power consumption and user profiles.

In order to achieve a more adaptive C&D scheme with dynamic features, authors in [ZWM+13] proposed an optimisation model for EV charging strategy by taking into consideration the stochastic features of the charging procedure and a Genetic Algorithm (GA) was further used to determine the parameters in the system model. The stochastic features of the charging procedure in arrival time and SOC are determined via the GA, where all parameters are estimated via searching a minimum cost function. A stochastic program that incorporates risk management in [YWS15] is proposed to provide a frequency regulation service with the aid of EVs and an aggregator. However, the schemes mentioned above rely on predictions of energy consumption and a day-ahead profile based on historical power consumption and user profiles where the parameter estimations and theoretical calculations undermine the EV user flexibility.

According to different scenarios, various smart C&D control schemes are proposed based on the objectives of the application. For example, to minimise the impact of user daily patterns on the EV integration, centralised control scheduling techniques are proposed to provide the peak shaving service. In [SC12], an automated demand response scheduling algorithm, was introduced to accommodate a large number of EVs. In [AAGG14], the authors, introduced a smart charging schedule for a low-voltage residential level grid by considering the SOC values as the battery capacity and the battery residual that will primarily affect the overall grid offload. In the case of handling natural disasters, the authors in [NKH16] proposed an optimal scheduling and load curtailment problem for the microgrids to support an islanded operation mode in the disaster scenario where the parallel computation is used to run the optimisation problem. The proposed scheme ensures a minimal amount of load curtailment while maintaining a reliable operation.

Furthermore, based on different electricity regulation and grid standardisation, different charging scheme should be adapted in accordance with the charging rate, network line limit, etc. An approach based on a non-dominated sorting GA is utilised to plan the optimal level of EV penetration and renewable distributed generation sources [SES13] which provides a framework of EV-injected microgrid network. However, the charging management algorithm is applied with estimated parameters, in which the pattern of charging behaviour might be different from the theoretical calculation.

The centralised based system lags behind the decision-making process and undermines the autonomy of the individual grid participants, where participants are incapable of controlling their charging or discharging process [KG14]. In [Caz10], the proposed scheme uses a centralised aggregator to optimise the power loads, which does not fully consider the individual preference and undermines the autonomy of the grid participants. In general, almost all electricity retail consumers are currently making transactions with the average market price that does not reflect the actual wholesale price at the time of consumption [MRLG10]. This hampers the need to adapt to the fluctuating power demand with respect to the different operation costs. The local distribution markets for energy services can actually be used as a means of efficiently incentivising and dispatching the distributed energy resources [CWQZ15].

In summary, an aggregator compromises the objective of the smart grid where it is designed to decentralise the conventional power grid structure and support the micro-distributed renewable generators [MJA+14]. The availability for scheduling power exchange has a huge impact on the scheduling result, where a deterministic scheduling method may not account for all possible factors that could affect the power system [UHAM+17]. Henceforth, a more dynamic and adaptive C&D scheme is needed for a decentralised-featured smart grid system.

2.2 Blockchain technology

2.2.1 Fundamentals of blockchain

Blockchain is a shared and trusted distributed ledger technology that permits the recording of any digital asset transaction between parties over a decentralised, encrypted network which was initially developed as a mechanism to record financial transaction [ATDM17]. Bitcoin is known as the first blockchain application, and the technology is continuously evolving [BCEM15]. The advanced features of blockchain is a genuine combination of several technologies including distributed computing, cryptography, peer-to-peer communication and game theory, where the technological and economic primitives are elegantly considered [Gra17]. Data integrity is guaranteed via the nature of the distributed feature, and the encryption system that uses public and private keys offers the capabilities for users to sign transactions [Pil16].

The blockchain can be classified into three types according to the participation methods: public blockchain, private blockchain and consortium blockchain [HCK17]. It can also be classified as the parent chain and side chain according to the relationship between chains. The comparison between different types of blockchain is demonstrated in Table 2-A.

- In the public blockchain, participants are allowed to take part anonymously, and can access to the network and blockchain without anyone's permission. The transactions on the blockchain are available for inspection, and all peers can make transactions. The public blockchain is a complete decentralised network which reaches consensus in an anonymous network environment. Typical applications include Bitcoin and Ethereum, and public Blockchaina are used for cryptocurrency, E-commerce, Internet banking, etc [JB17].

- In the consortium blockchain, the access and update operations are only allowed for its consortium members. Only the selected set of nodes are responsible for validating the blockchain in the network. It is generally suitable for making payments, accounting and auditing between banks where one block can be globally confirmed after 2/3 nodes confirmation.

- In the private blockchain, it is applied in the private organisation for database management and auditing. The value of private blockchain is that it provides a secure, trackable, immutably and automated platform [Pil16].

A complete blockchain system is composed of complex technologies, for example,

Table 2-A: Comparison among public blockchain, consortium blockchain and private blockchain.

	Public blockchain	Consortium blockchain	Private blockchain
Consensus Process	Permissionless participation	Consortium member (Permissioned participation)	Permissioned participation
Centralised	Decentralised	Multi-centered	Centralised
Data transparency	Public	Private	Private
Reward Policy [KKKT16]	Yes	Optional	No
Trust model	Untrusted	Semi-trusted	Trusted
Consensus Protocols	PoW, PoS, DPoS [ZXD+18]	PBFT, RAFT [SMC+17]	RAFT [WWA+16]
	Large energy consumption	Low energy consumption	Low energy consumption
Finality [AM+17]	No	Enabled	Enabled
Scalability	Good	Bad	Bad
Transaction throughput (per second) [FP16]	3–200,000	1,000–10,000	1,000–100,000
Transaction Approval frequency	Slow	Medium	Fast
Network [BM16b]	P2P network	High-speed network	High-speed network
Use cases	Cryptocurrency (C2C, B2C or C2B) [Nak08]	Payment, accounting (B2B) [YHKC+16]	Auditing, database management (Within the organisation) [KS18]

digital signature and time stamps for the data storage, consensus mechanisms in the Peer-to-Peer (P2P) network, mining and Proof-of-Work (PoW), bitcoin wallet for the anonymous transaction technique, Merkle tree for data structure, and so on [IL17]. It is because the aforementioned technologies that keep the blockchain system keep constantly transacting, validating and expanding. The fundamental components of blockchain technology are shown below:

- Data block: Transactions are stored in the data block where the block generation rate is roughly 10 minutes for each block, and each data block contains a header and body. The header encapsulates the version number, previous block address, timestamp, nonce, Merkel root (a data structure), etc., and the body contains the transaction counts and details [OEKO17]. Each transaction is permanently stored in the data block and available for anyone to check. The Merkle tree in the block body will apply the digital signature to each transaction so as to ensure the transactions are not repeated or forged [LYC+17].

- Mining and forks: Mining is the process of searching a random number (nonce) which makes the hash value satisfy the requirement to obtain the block selection leadership [Nov18]. The newly generated block will be broadcast immediately for validation in case of fraud, and the blocks can be traced back through the hash value. However, there will be forks when two miners successfully mine two blocks at the nearly same time. After forking, the system will continue mining and chooses the parent chain by calculating the maximum proof-of-work where the fork chain will be abandoned [ZSJ+18].

- Timestamps: In the blockchain system, the node needs to add the time stamp when generating a new block to record the block write time. The following block will add an approved time stamp to certify the previous block, which forms a chronic increasing time chain. The timestamp is a significant parameter for the proof of existence which ensures the immutability of the blockchain system [ZXD+18].

- Unspent Transaction Outputs (UTXO) [DSPSNAHJ18]: UTXO is the basic unit in the bitcoin transaction process. Except for the genesis block, all transactions (Tx) in the block contain the origin of funds (TX_in) and the output of funds (Tx_out). Only the UTXO stored in the network nodes with the digital signature can be transacted. In this way, the system does not need to check its complete transaction history to confirm its legitimacy.

- Hash function: The hash function coded the original transaction data into a fixed-length string which is composed of numbers and alphabets [ZN+15]. This process is single directed so that the coded hash value cannot be interpreted [KPA+18]. SHA 256 is the most commonly used hash function which uses Merkle - Damgard function to generate a 256-bit has value [Kar16].

- P2P network [HL16]: P2P network is a distributed application framework that is used to assign tasks and workloads between peers. The blockchain system is established based upon the IP communication protocols and distributed networks. Each node in the peer network has equal rights, where it does not exist any centre point or hierarchical structure.

In Fig, 2.3, it demonstrates a data block generation in the blockchain system. The provider and customer agree on a transaction and determine the variables in the transaction such as recipient, sender, size, etc. Then individual transactions are combined into a block, and the data contained in each block is verified using algorithms that only produce the correct hash only if the right combination is found (mining). Then the new block is stored in the decentralised global network in a tamper-proof manner and thus verified and is added at the end of the continuously growing blockchain.

As a complex combination of various technologies, the blockchain is an elegant design of computer science, telecommunication, encryption and economy. The core technologies include consensus mechanism, unlocking script [AS16], Merkel proof [ZXL+18], transaction rules [ZN+15], Recursive Length Prefix [FM19], etc. In particular, this thesis focuses on the following technologies:

1. The consensus mechanism guarantees its robustness against misbehaving and malicious participants and incentivises participants to validate transactions [ZXD+18]. Henceforth, the blockchain is a promising technology for broad business sectors where transparency, trust, and efficiency are needed.

2. The smart contract that resides on the blockchain allows the automation of multi-

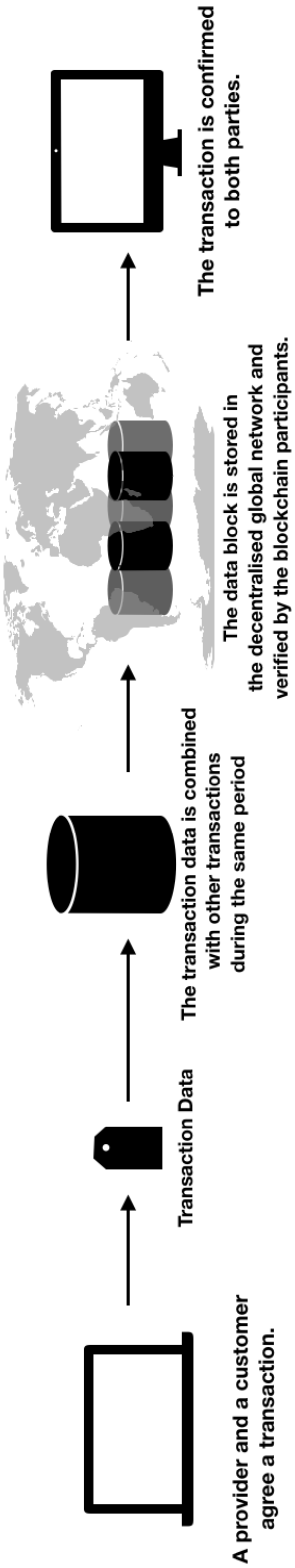

Figure 2.3: Data block generation process in the blockchain system.

step processes to self-execute distributed and heavy workflows, envisaged for the energy industry and the Internet of things [CD16]. The use of the smart contract in blockchain technology is driven by open-source agreements, which also provides the potential to balance supply and demand in the transactional energy market. The smart contract also provides the insight to allow the automation of multi-step processes to self-execute the distributed and heavy workflows, which is envisaged in the energy industry and the Internet of things.

2.2.2 Applications of blockchain-enabled system

Blockchain technology is primarily known from cryptocurrency applications which are viewed as the first stage blockchain; however, the blockchain technology is envisaged to have the capacity to reform financial markets, supply chains, and business-to-business services [BART17]:

- Digital securities trading: proof of ownership for asset registries and title transfer of hard assets to secure recording of intangible assets [Swa15].
- Foreign exchange: currency exchange and conversions such as Coinbase (wallet) and Kraken [MHH$^+$18].
- Digital identity: protects the privacy of consumers by providing an immutable digital identity for users.
- Supply chain: improves transparency in supply chain records with the certification of manufactured products or diamonds certification [Tia16].

The variety of proposed applications expect blockchain technology to bring significant process optimisation and novel business models. The potential lies in the distributed ledger technology can redefine the digital trust and remove intermediaries which disrupt traditional forms of hierarchical governance. The disruptive nature of blockchain technology can use consensus within the network to enable an open-source and transparent

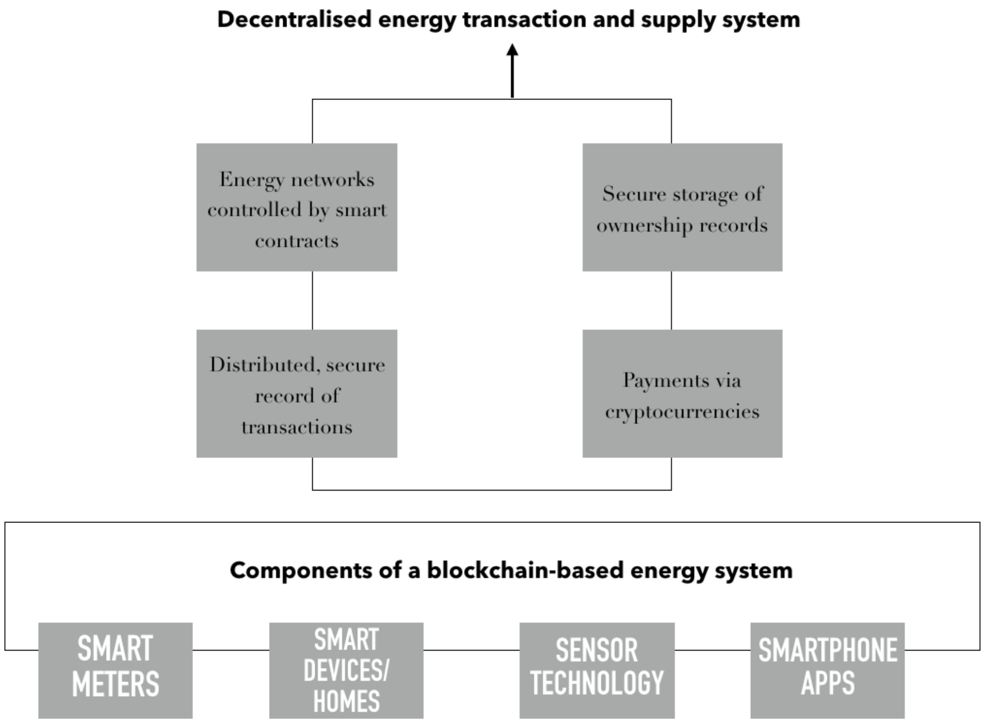

Figure 2.4: Cornerstones of a decentralised energy transaction and supply system.

community to support decision making and system running.

2.2.2.1 Blockchain-based transactional energy market

Along with use cases and pilot projects in various sectors, the potential of blockchain technology in the energy industry is enormous, which is deemed as the game-changer. The blockchain technology enables a trustless network to eliminate the operational cost of the intermediary participation, which will realise a quicker, safer and cheaper way in the energy transaction market. According to commercial reports from Deloitte [Car17] and PWC [ISDBP17], blockchain has the capability to disrupt energy-related products and commodities, which can be traded interoperably as digital assets.

In the Fig. 2.4, it demonstrates the cornerstones of the blockchain-based energy system. Transactions for energy trading are recorded on a blockchain in a tamper-proof way and the energy delivered via the network (power grid). In general, transactions (consumer-producer matching) are affected either automatically (smart contract-based) or manually. With the integration of digital and communication technology, a full energy system with residential use can be achieved along with smart meters, smart devices, sensors and end interface. As depicted in the figure, there are some key points with respect to the blockchain technology:

1. Energy networks: The supply and demand are balanced via smart contracts with the aid of balancing the market, microgrids, virtual power plants, storage, and so on [LCLC18a].

2. Energy transactions: Transactions data is stored on the blockchain using a decentralised mechanism, with parties identifying themselves through their digital identities, for example, in the context of energy storage, renewable energy, electric mobility, and energy trading [LYC+17].

3. Record storage: The storage for the ownership records, including emission allowances, renewable energy certificates and asset management can be securely stored on the blockchain [CV17].

4. Payment: The payment for transactional energy in the blockchain-enabled energy system does not limit to the fiat currency but also the cryptocurrencies, which increased the efficiency and security of the trading process [ZXD+18].

The energy system is undergoing a revolutionary reform which is advanced by the ICT and distributed energy resources. One of the main challenges is to decentralise and digitalise the current grid system, where blockchain is designed to decentralise the structure and operation. In [ODA+11], the transactional energy system is introduced where a sequence of energy transactions for the delivery of an amount of energy commodity in the specified timeframe and location to support business for all parties including power generators and distributed system operator. The concept of transactional energy provides an insight to treat electricity as a commodity in the market where the control mechanism can be applied to achieve various objectives. In Fig. 2.5, it depicts the transactional energy market structure where the conventional power generators are connected to the wholesale market, which trades with large power demand offers between electricity brokers and dealers [LCLC18a]. Besides providing the wholesale market in the conventional grid system, transactional energy offers a vision for the coordination of retail customers using large numbers of frequent tranching/dividing transactions executed automatically by the blockchain-enabled platform, therefore reducing the centralised features of the next-generation grid system [PG16]. The information exchange is the same for a large generator, distributed energy resource, renewable energy generators such as wind and solar, EV, microgrid, energy trader, broker, exchange, aggregator or system operator. The transactions can be executed between retail and wholesale markets which equalises the opportunity for all components. Furthermore, the transactions must also account for the transmission and distribution limits and other physical constraints on the grid.

Blockchain technology has the potential to be applied to various business processes and operations in the energy system, where it brings novel business models or applications in the following areas:

- Tariff: A smart contract based energy system could enhance the automation process in billing for both consumers and distributed generators, where utility companies may change their tariff and billing plan according to the consumer energy profile, real-time cost or individual preferences [PCA+18, MPM17].

- Trading: The blockchain-enabled grid system is capable of trading transactional energy with distributed energy producers which is a completely different way compared to the traditional wholesale market management [ZZG+17]. The commodity trading transactions, risk management and energy trading strategies are being explored to accommodate the new system [ZWLC17, MGR+18].

- Automation: By enabling P2P energy trading, the blockchain technology could

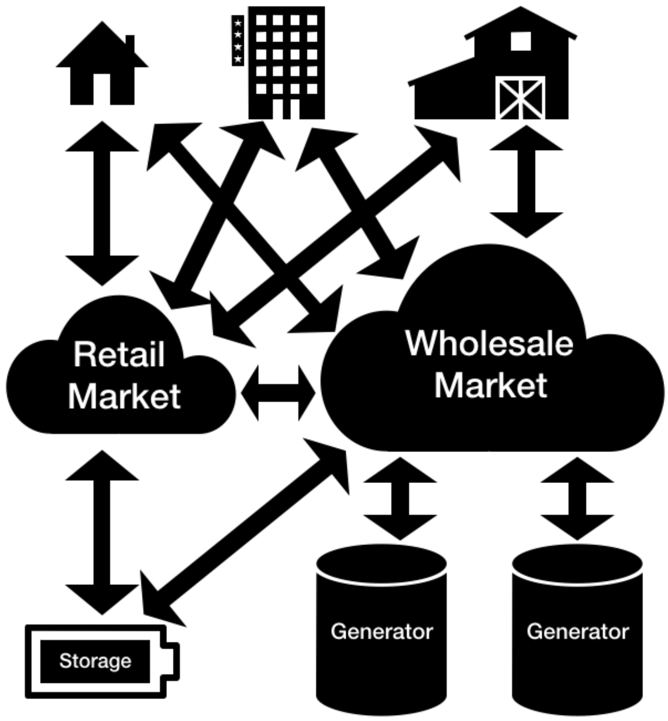

Figure 2.5: Transactional energy market system model with retail and wholesale markets in smart grids where arrow represents the price offers and transactions.

integrate locally produced energy, which increases energy self-production and self-consumption [CM18]. The automation process also significantly improves electricity trading and delivery efficiency and thus generates more revenues [DGM17].

- Smart grid management: The smart devices integrated energy system utilises advanced communication and machine learning technologies to provide energy monitoring, control and management services. The grid management could not only provide additional services to end-users but also lead to enhanced network performance regarding to the grid stability, resilience and robustness [ZFL18, PCA$^+$18, NYG$^+$18].

- Security and authentication: The protection of transactions and security is guaranteed via cryptographic techniques, which provides a safeguard for user privacy, data confidentiality and improves auditing and regulatory compliance [TSG16].

According to the features of the transactional energy, the blockchain technology matches the requirements for frequent and large-scale transactions, thus is being widely adopted. In [MJVM+14], a novel energy trading mechanism based on blockchain technology is proposed to adopt the decentralised and competitive environment of the locally generated electricity, but the blockchain in this paper is only used as a database to record transactions. In [MNB+17], the authors, further evaluate the economic features of the market mechanism for local energy trading. A comprehensive internet of thing business model is designed in [ZW17] to enable P2P trade for paid data based on blockchain and smart contract. However, the trading model may not be suitable for the energy sector trading to address frequent transaction needs and overall system performance consideration. In [HKMS17], a dynamic price incentives market mechanism is proposed to balance the local renewable energy production and support flexible demand. In [MMM17], the blockchain-based trading platform is proposed to support decentralised energy market with distributed optimisation and control. In [IDSKG12], a more sophisticated dynamic power network infrastructure can advance small-scale generators and overall resilience. Henceforth, the distributed electricity trading platform is based on the transparent and frequent communication of offers and demands among the power consumers and operators, respectively.

Blockchain-based energy trading model that allows prosumers (Energy producer & customer) to trade energy in the grid is proposed to enable the autonomy of prosumers in blockchain power exchange platform, which can inject and draw energy to the smart grid public blockchain trading platform [AS16]. Henceforth, the blockchain has generated broad interest in the energy trading sector where all energy traders are the peers in the blockchain network.

2.2.2.2 EV-integrated transactional energy market

The transformation to the decentralised transactional energy market can be achieved based on the small-scale energy generators and EV, in which they may produce, consume, and sell excess electricity capacity like a commodity [ISDBP17]. It does not require hierarchical system structure, no information exchange; instead, it offers the energy transaction and the agreements on transactions. Hence, all the loads, such as the residents, offices and plants, in the grid are connected to both the retail for end-users and wholesale market for large generator offers.

In the blockchain-based energy trading model, each component including the power generators and power load components that are connected to the retail markets is capable of publishing and transmitting the charging or discharging order to the smart grid public blockchain trading platform. For EVs, the charging and discharging process can be realised by a programmable charge installation [SWX+18]. This is to enable the instant on/off switching of the power transmission as instructed by EVs (assuming the sophisticated design of switches). The energy providers in the public blockchain power exchange platform are the conventional large power plants, distributed micro-renewable generators, the storage which composes the electricity provider side and EVs [JDL+18]. Besides, traditional power loads, for example, from the residential areas, hospitals, EVs are also connected to the public blockchain power exchanging platform. The information exchange in the blockchain platform is at 30-minute intervals [LZY18]. And the components are capable of deciding the price for their produced energy to incentivise users to balance the supply and demand, loading, to reduced power generation and consumption peaks.

In order to adapt the large volumes of EV charging/discharging demand, the blockchain concept is introduced that allows peer-to-peer transaction platforms that utilise decentralised storage to record all transaction data [BM16a]. Henceforth, the blockchain technology enables a trustless network to eliminate the operational cost of the intermediary participation, which will realise a quicker, safer and cheaper way in the transactional energy market to reflect fluctuating wholesale prices to the end-user. In the meantime, blockchain technology has the capability of shifting the high-load household appliances to off-peak hours to not only reduce their electricity costs but also to help to reduce the peak overloads [SDSG+17]. The authors in [MMM17] further demonstrated that the decentralised consensus techniques and blockchains can be used both to coordinate the scheduling of distributed energy resources in a microgrid and to guarantee a fair payment without requiring a centralised aggregator.

The QuorumChain developed by JPMorgan Chase executes smart contracts with the Ethereum virtual machine which designs an alternative consensus protocol of the public Ethereum blockchain [CV17]. The smart contract in the blockchain is implemented by open-source agreements, which is used by this protocol to validate blocks. In [CD16], the authors provided the insight of the smart contract to allow the automation of multi-step processes to self-execute the distributed and heavy workflows, which is envisaged in the energy industry and the internet of things. The use of smart contract offers flexibility to implement alternative consensus primitives, which in consequence provides the potential to balance supply and demand in the transactional energy market.

In the Fig. 2.6, it depicts the overview of an EV-integrated blockchain-based transactional energy market. In the process of P2P trading, EV as a fast-ramping power source is envisaged as the most active participants to trade their excess electricity, and the power flow is delivered in the grid network [SWX+18]. Moreover, the smart contract-driven blockchain system could improve the automation process efficiency where it acts as the consensus mechanisms in the network for the overall benefits to increase the network stability [WFN+16]. The energy trading process in the decentralised system can achieve demand response by incentivising EV owners to trade electricity regarding their self-interest [MJA+14]. Applying the market-based electricity trading system to the grid network is envisaged to reduce the dependency of agents on the aggregator, wherein the existing energy management architectures lacks coordination among actors which limits

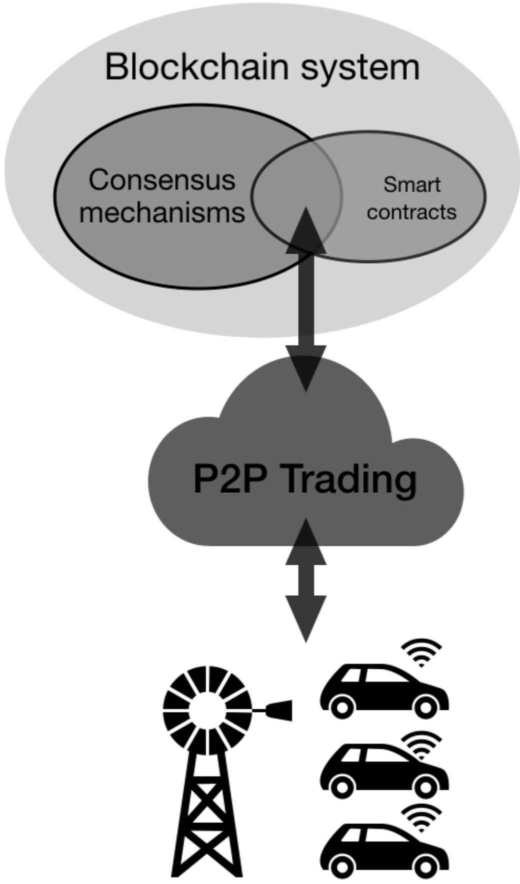

Figure 2.6: An overview of EV-integrated blockchain based transactional energy market.

the capability of peer-to-peer trading. In this sense, a blockchain system that utilises the consensus mechanism to optimise the electricity trading process could significantly enhance grid performance.

2.2.3 Smart Contracts and Consensus protocols

In the distributed system, multiple peers form a network cluster through asynchronous communication, where states need to be replicated between different hosts to ensure consistency in all peers [Lam78]. However, if any of the peers in the cluster encountered attacks or failure, it might cause network congestion and broadcast tampered messages in the network. Henceforth, a fault-tolerant consensus protocol is needed for an unreliable asynchronous communications network to ensure the consistent consensus between all peers.

2.2.3.1 Smart Contracts

Smart contracts are user-defined programmes that determine the rules of writing on the ledger [LCO+16]. It is a computer protocol that is capable of self-executing and self-verifying without human intervention once it is deployed on the network [W+14]. In the technological aspect, the smart contracts are executable programs that make changes on the ledger and are triggered automatically when being called or meeting a specific requirement.

Before deploying the smart contract, contract terms and logic flows are made with relevant standards. Then they are recorded in computer language encoding legal constraints and terms of agreements. The smart contract usually provides an interface for human-contract interaction which complies the recorded logic and rules [ABC17]. With the integration of cryptographic technology, the interaction activities can be authenticated to ensure the contract execution process is without fraud and collisions [BCCS17]. For example, the management of bank accounts can be viewed as a set of smart contracts application. In a traditional banking system, the operation such as withdraw and deposit needs authentication from the centralised bank, and the system cannot run without the bank supervision. With the aid of smart contracts, any operation can be programmed with strict logic flows. In the Fig. 2.7, it depicts the logic workflow for the smart contracts on the Ethereum platform. Users can define the smart contracts using programming languages such as Solidity, Serpent and LLL, which need to be translated into Ethereum Virtual Machine (EVM) bytecodes [Dan17]. Then the code will be deployed on the Ethereum nodes with the cost of GAS using the Ethereum cryptocurrency for miners' confirmation. After being successfully deployed, users will obtain an address for contract and interface. The JavaScript API interface provided from web3.js

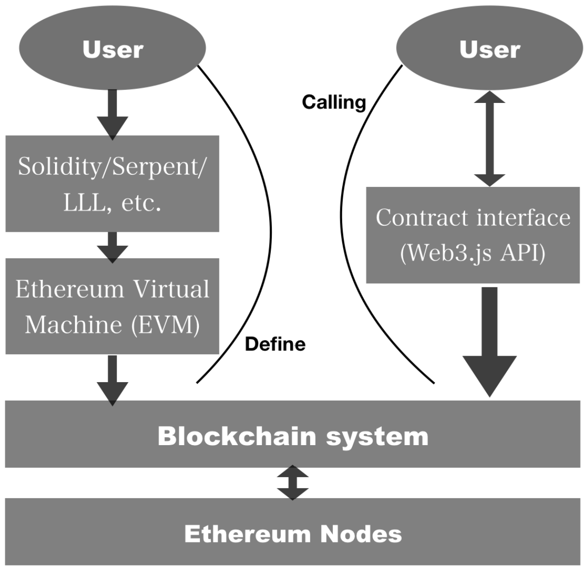

Figure 2.7: The process of smart contract deployment and calling on the Ethereum platform.

can be used for calling contracts and making interactions [Hir17].

With the complex design of smart contracts, it can be applied to many areas such as database systems, financial derivative services, etc. [Dan17] Generally speaking, the smart contract cannot be intervened by human activities once being successfully deployed. Ethereum is a blockchain platform based on smart contracts, and the advantages of smart contracts can be concluded as follows:

- Real-time updates: The response time for the smart contract supported system is almost real-time as it does not need an intermediary or a third-party authentication, which largely increases the transaction efficiency.

- Accuracy: The execution of each contract term is pre-defined and under the program's control where all outputs are accurate and predictable [GMS18].

- Low human intervention: Once the smart contract is deployed, the contract content cannot be revised by any parties so that anyone with fraud or dishonest behaviour will get punished by the contract according to the contract design [HSZ+17].

- Low operation cost: The system could achieve low-cost transactions through removing human involvement in transacting, enforcement and compliance costs [WZ18].

2.2.3.2 Consensus Protocols

As for the blockchain-based distributed ledger, the primary concern is to realise the correctness and consistency for the transaction data from different ledger nodes [AM16]. The consensus protocols in the blockchain are the mechanism or set of rules that enables all the full nodes to reach an agreement or consensus over the order of transactions [MXZ+17]. There are many types of consensus protocols in different blockchain applications or scenarios. After converging of the blockchain consensus process, the final confirmed block/order of transactions is referred to as the consensus finality [Bal17].

A. Proof of Work

Bitcoin is one of the most widely used blockchain systems that uses PoW to solve the critical challenge of reaching consensus among participants [Nak08]. PoW requires participants to dedicate computation time and energy towards "work", where the processes of initiating this consensus protocol are called miners. Miners are required to solve a hash code crypto puzzle before encapsulating the transactions into a new block [Bac02]. The miners repeatedly select a nonce which represents the difficulty level in solving the puzzle to obtain a result lower than the threshold, where the network peers are fighting using their computation source. In this way, a single attacker is merely impossible to jeopardize the system by modifying the block and solving the puzzle due to the extensive computation. So the system can only be controlled or attacked if someone gains 51% of the total network hash power [CV17].

Undoubtedly, there is a huge waste of energy and this requires a constant global effort. It is claimed that Bitcoin and Ethereum burn over $1 million worth of electricity and hardware costs per day for running the consensus mechanisms [Vuk15]. Moreover, in order to reduce the number of forks of the chain, Bitcoin's PoW is designed to produce a new block on average every 10 minutes and the difficulty of mining a new block is increasing. The PoW protocol has proved that it scales to a large number of users for the public use; however, transaction rates and finality are comparatively low [WHX+18]. The recommended waiting frame is six blocks before accepting a transaction, which makes it impossible for many applications such as electricity trading [Ros14].

B. Practical Byzantine Fault Tolerance

Byzantine Fault Tolerance (BFT) algorithms origin working on Byzantine faults which deal with unpredictable actions in the computer networks when encountering hardware breakdown, network congestion or malicious attacks [SMC+17]. The problem concerns a set of Byzantine generals to agree on a joint plan of action during the war. Generals need to perform joint action with coordination in different parts of an army to attack simultaneously; however, the message can only be delivered by senders due to the enormous territory. The challenge is to ensure loyal generals reaching the consensus on the attack plan and traitors cannot disrupt the attack plan. It is proved that the attack plan can be guaranteed if there are no more than 1/3 traitors in the system [MXZ+17].

In the blockchain system, the Practical Byzantine Fault Tolerance (PBFT) algorithm enables a system to reach consensus with a low overhead and proceed transactions within a few network information exchange which withstands up to one-third participants attack [CL+99]. The PBFT algorithm uses primary and secondary replicas where the secondary replicas check the correctness and liveness of the primary so that the complexity decreased from exponential to polynomial [ZXD+18]. PBFT enables instant consensus finality as blocks are globally verified. The problem of consensus is that participants of the distributed system must agree on and accept a single shared state [MHWK16]. It requires the network having the global knowledge of the participants and does not scale to the number of participants.

C. Proof of Stake

To address the energy consumption waste of PoW consensus mechanism, various alternative consensus mechanisms have been proposed, such as Proof of Stake (PoS) [KN18]. The approach aims to replace the useless work of solving puzzles by selecting a leader for deciding the next block according to their stake shares. The probability of generating a block depends on the stake of the nodes in the system, which can result in less electricity consumption and a decreased 51% attack probability [AM+17]. In the case of the few rich stake owners performing malicious attacks, PoS can make use of game theory mechanisms to prevent collusions and centralisation by penalising dishonest behaviours.

Moreover, the maximum transaction rate is a few hundred transactions per second which is low compared with other consensus mechanisms or Visa system [JB17]. The PoS protocol results in lack of consensus finality, which leads to frequent blockchain forks. Though making energy consumption less wasteful, they still require a fair amount of available computation resources. However, PoS-based algorithms can be used in public blockchains and validators could be unknown to perform the consensus process without knowing identity ahead of time compared with PBFT [MXZ+17].

D. Proof of Authority

Proof of Authority (PoA) is designed based on PoS, which is adopted for some private blockchains [DAAB+18]. The protocol predetermines the authority parities in the network, and each authority is assigned with a fixed time slot to be the leader. Network members trust the authorities, and a block is accepted if it receives a majority of approvals from authorised nodes. In this mechanism, it needs to perform Know Your Customer (KYC) to identify the authority ID and background instead of the stake from PoS, where misconduct or manipulation will be publicly revealed [DLZ+18]. As PoA relies on the trusted authorities, it is only suitable for permissioned networks.

E. Proof of Burn

In the Proof of Burn (PoBr) protocol, instead of providing proof of work, a miner sends the coins to "burn" in order to gain the right to mine a new block [NK18]. The miner who burns a larger amount of coins will get a greater chance of being selected by the random selection process. In this way, PoBr protocol does not require the huge hardware cost as PoW; however, the validation process depends on the willingness to burn coins which results in unnecessary waste of resources [KKKT16].

F. Proof of Elapsed Time

Proof of Elapsed Time (PoET) is designed to address the high power consumption (waste), and latency for transaction confirmation in PoW-based consensus protocols and it is first developed by Intel's Sawtooth project [CXS+17]. The protocol aims to replicate a random block generation process without spending valuable resources as PoBr or computation power as Bitcoin. The miner node with the least waiting time is selected to mine the next block by requesting a waiting time from a trusted function in a general-purpose processor. It randomly distributes a leadership election across the entire population of validators; however, this approach is dependent on the environment developed by Intel, where the trust is based on a single-authority [Bal17].

G. Ripple

Ripple is an open-source payment agreement based on the Internet to achieve decentralised currency exchange, payment and liquidation [ZXD+18]. In the Ripple network, the transaction is made by the application and broadcast via tracking nodes or validating nodes. The consensus process of Ripple is run between validating nodes where each node has a pre-configured copy of Unique Node List (UNL), and only the nodes from UNL are capable of voting for the approved transactions. The validating nodes will store the approved transaction with 80% votes from UNL nodes to the local ledger, which is referred to as the last closed ledger [MSZK16].

In the Ripple consensus algorithm, the identities of voting nodes from UNL are known, so the transaction confirmation time is around several seconds, which is more efficient than the permissionless consensus protocol such as PoW. Henceforth, the Ripple consensus protocol is only suitable for permissioned blockchain applications [Pil16]. And the BFT capability is (n -1) / 5, which guarantees a secure consensus process withstanding 20% nodes performing Byzantine faults [BMZ18].

Table 2-B presents the comparison between some mainstream consensus mechanisms including PoW, PBFT, PoS, PoET and Ripple. They are compared in various characteristics such as consensus finality, computation cost, vulnerabilities, and so on. As inferred from the table, all consensus mechanisms have their pros and cons, for example, the PoW consensus protocol performs great in the aspects of security and fairness with high scalability, however, the energy consumption with increasing industrial-scale mining process is critical. The new consensus protocols such as PoS are more environmentally friendly; however, they might be less secure and fair as compared with PoW. Moreover, different consensus protocols adapt to different blockchain types, where the types of blockchain application depend on the use case scenario. In order to adapt the frequent trading demands and consider the global power network delivery quality in the energy sector, an adaptable consensus mechanism is needed.

2.3 Summary

This chapter provides the introduction of the V2G system where the smart grid concept, along with the EV integration, is presented. The adoption of EV in the grid system brings both challenges and opportunities to the network, where it could benefit through scheduling EV charging and discharging load. The EV C&D scheme is a promising solution that utilises the C&D electricity amount to provide ancillary services, where

Table 2-B: Comparison between consensus protocols.

	PoW	PBFT	PoS	PoET	Ripple
Consensus finality	Probabilistic	Instant	Probabilistic	Probabilistic	Instant
Computation cost	High	High (communication complexity/overhead)	Low	Low	Low
Latency in Tx confirmation	High (6 blocks confirmation)	Low (high throughput)	Low (as compared with PoW)	Low (as compared with PoW)	Low (as compared with PoW)
Prone to forks	Yes	No	Yes	Yes	No
Scalability	High	Low (latency increases exponetionally)	High	High	Low (as compared with PoW)
Vulnerability	*Prone to 51% attack	*Vulnerable to faulty nodes $> (n-1)/3$ *Vulnerable to DoS attack	*Prone to 51% attack *Prone to collusion of rich stakeholders	*Prone to developer malicious comprimise	*Vulnerable to faulty nodes $> (n-1)/5$
Type of blockchains	Permissionless	Permissioned	Permissionless and Permissioned	Permissionless and Permissioned	Permissioned
Hardware requirement	No	No	No	Trust execution environment e.g. Intel SGX	No
Use cases	Bitcoin	Hyperledger	Cosmos, Bitshare (DPoS)	Sawtooth Lake	RippleNet

state-of-the-art reviews current C&D schemes from dumb to smart C&D schemes. In order to adapt the decentralised structure of the smart grid, blockchain technology is reviewed where fundamental taxonomies and applications are presented. In addition, relevant technologies such as smart contracts and consensus mechanisms are presented to support the EV participated grid networks.

Chapter 3

User-Behaviour Associated Charging Scheme

3.1 Overview

In order to consider the random characteristic of EV behaviour, the system should be designed with a sufficient number of EV numbers to ensure the reliability of the V2G system. The proposed charging management algorithms in [SES13, ZWM$^+$13] are applied to all estimated parameters, in which the pattern of charging behaviour might be different from the theoretical calculation. In [AAGG14], the residential parking patterns are used to model the parking hours of vehicles, but other related EV user behaviours are not well considered. Furthermore, due to varieties of electricity regulation and standardisation policies, an optimal charging scheme should be adopted.

In this chapter, the user-behaviour associated charging scheme is proposed to accommodate the highly randomised charging patterns. An EV connected SG system is modelled to address the research problem, and the Power Fluctuation Level (PFL) is defined to flatten the overall power profile. The driver behaviour patterns in [JOS$^+$13] are formulated as constraints of SOC and stay-on-line time in the system model. The stochastic features of the charging procedure in a district of London are considered. A charging control strategy is further proposed to minimise the power consumption fluctuation in a typical weekday without interfering drivers' daily routine activities. The GA is applied in the model to determine the optimum charging schedule at every time segment. This is because the use of GA does not require initial input variables and with an acceptable level of computation complexity. Furthermore, the proposed scheme will achieve much lower power fluctuation level than the conventional charging scheme, subject to operational constraints.

3.2 System Model

A residential area is considered where the maximum power capacity of a substation transformer is P_{max}. In this model, the EV is capable of receiving control signals from an aggregator, and the charging process of EV can be realised by programmable charging. This is to enable the instant ON/OFF switching of the power transmission to the EV instructed by the grid operator (assuming a sophisticated design of switches). The system power transmission is illustrated in Fig. 3.1. EV status matrix X is defined in terms of vehicle i at time t as:

$$X_{i,t} = \begin{cases} 1, & \text{if } EV_i \text{ is connected at time } t \\ 0, & \text{otherwise} \end{cases}. \tag{3.1}$$

The power demand of EV ($P_{EV}(t)$) at time t depends on the battery residual (SOC_{ini}) in each EV and the expected SOC (SOC_{exp}) after charging. Hence, it can be formulated as follows:

$$P_{EV}(t) = \sum_{i=1}^{I} \left(X_{i,t} \Big(SOC_{exp}(i) - SOC_{ini}(i) \Big) \right). \tag{3.2}$$

3.2.1 EV Charge Connection Status Model

When considering the charging schedule for EVs, the daily driving pattern should be included to minimise the effect of their routine. By referring to [Li], the vehicle activity profiles are modelled for a typical residential EV charging demand in a day frame. A visible peak charging time from 20:00 to 08:00 (+1) at home is presented in weekdays where irregular and the less strict pattern is depicted during weekends. By combining with the charging duration and energy transfer amount, the individual hourly charging demand pattern during a day with two-time segments can be inferred.

A. Curve fitting

Through examining the character of the EV charging distribution, the amount of power transfer for EV charging $\eta(t)$ at each timeframe t can be modelled as the sum of sine.

$$\eta(t) = [n_1(t),\ n_2(t),\ ...,\ n_j(t)]\,\%. \tag{3.3}$$

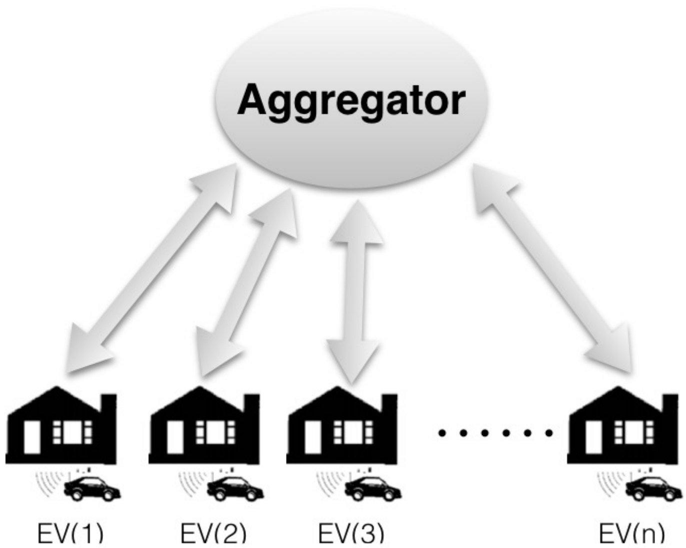

Figure 3.1: Residential EV power and signal transmission model.

where $n_j(t)$ can be written as follows:

$$n_j(t) = \sum_{j=1}^{J} \sum_{t=T_f}^{T_s} \left(a_j sin(b_j t + c_j) \right) + \varepsilon. \tag{3.4}$$

T_f is the first time step, and T_s is second time step elapsed, which enables the formation of a particular fitting in j-th order of sine series. The j indexes the order for the sum of sine series and J is the defined order. The a_j, b_j, and c_j are the parameters in the sum of the sine series, where ε is the error item for the model. As the charging load profile indicates that certain numbers of EVs must stay online in the process, the number of EV $N_{car}(t)$ connecting at the charging point in each time frame t can be reformulated as:

$$N_{car}(t) = \Omega \cdot n_j(t), \tag{3.5}$$

where Ω is the total number of EVs in an area.

B. Parameter Tuning

By implementing curve fitting in MATLAB, the parameter estimation can be obtained for the system model using the data from [oENL]. However, it should be noted that most of the EVs connect to the grid for more than eight hours of duration, at which the charging process usually finishes in around three to four hours [JOS$^+$13]. The parameters are tuned to fit the EV user behaviour. The estimation model is then utilised in the charging process for scheduling, which studies the EV user's behaviour to model the correlation between the behaviour pattern and charging habits.

3.2.2 Battery Capacity

The maximum SOC of the EV is dependent on the battery capacity which is decided by the EV brand and type. It is assumed that the same battery type is applied in this model where the power capacity of the battery $P_c(i)$ of EV i is expressed as follows:

$$P_c(i) = P_{max}, \tag{3.6}$$

where P_{max} is a constant.

3.2.3 SOC Distribution

The transaction count for energy transfer/capacity ratio demonstrates that the battery levels of SOC spread equally at around 5% to 90%. This justifies that most EV drivers adopt routinised behaviour in charging their EV. Hence, the EV battery residual when EV arrives at the charging pile can be formulated as follows:

$$SOC_{ini} = [SOC_1, SOC_2, \ldots, SOC_N] \sim U[\alpha, \beta], \tag{3.7}$$

where α and β are the constant values representing the minimum and maximum boundaries of the SOC value.

3.2.4 Charging Rate

The charging rate controls the completion time of the whole process. The power output $\gamma(i)$ for EV i depends on the regulation of the local charging point.

$$\gamma(i) = \delta, \tag{3.8}$$

where δ is a constant corresponding to the local rate control. After that, the power demand after one time interval will change. Hence the Equation (2) can be reformulated as:

$$P_{EV}(t') = \sum_{i=1}^{I'} \left(X_{i,t'} \left(SOC_{exp}(i) - \left(SOC_{ini}(i) + \frac{P_c(i)}{\gamma(i)} \right) \right) \right). \tag{3.9}$$

Hence, the total residential load can be defined as the sum of EV charging demand and load profile without EV in order to formulate the EV charging problem.

$$P_{total}(t) = P_{home}(t) + P_{EV}(t), t \in T, \tag{3.10}$$

where P_{home} is the power load without EV. The EV charging scheduling problem can be solved by aggregating the above random process (10) with regards to the user charging behaviour.

3.3 Problem Formulation and Algorithm Description

The scheduling of EV load demand is adopted to minimise the impact of adding EV to the grid. In this case, the study focuses on an optimal EV charging strategy through the combination of user behaviour to flatten the load profile of the transformer substation in the distribution network.

3.3.1 Problem Formulation

A half-hourly daily load demand profile of a residential network is applied as the input data in the optimisation problem, where the decision parameters are the EV charging demand for every 24 hours. To decrease the fluctuation level of the whole system, it is necessary to develop an optimal schedule of EV charging to fill the gaps of the residential load profile. To describe the measurement of the fluctuation level of the grid, the overall utility function is as follows.

$$P_{PFL} = \log((\mathrm{Max}(P_{total}) - \mathrm{Min}(P_{total}))/\mathrm{Ave}(P_{total})), \tag{3.11}$$

where P_{PFL} is the overall power fluctuation level in a day of half-hourly temporal resolution, Max(P_{total}) is the maximum substation transformer loading, Min(P_{total}) is the minimum transformer loading, and Ave(P_{total}) and P_{total} are the average and total power in the transformer respectively. P_{PFL} is expressed as the logarithm to increase the stability of the whole system by preventing all EVs from shifting their charging load to the non-peak time.

The optimisation problem for the power grid system can be formulated as:

$$\min_{P_{EV}(t), t \in T} \quad P_{PFL}.$$

S.T.

$$\sum_{t=1}^{T} \sum_{i=1}^{I} \Big(SOC_{exp}(i) - SOC_{ini}(i) \Big) = \sum_{t=1}^{T} P_{EV}(t), \tag{3.12}$$

$$SOC_{exp} = 1, SOC_{ini} \in (0,1), \tag{3.13}$$

$$X_{i,t} = \{0,1\}, \forall i, \forall t, \tag{3.14}$$

$$N_{car}(t)^{'} \leq \sum_{i=1}^{I} \Big(X_{i,t} = 1 \Big), \forall i, \forall t, \tag{3.15}$$

$$P_{total}(t) \leq P_{max}, \forall t. \tag{3.16}$$

The Equation (3.12) constrains the total charging power after schedule optimisation to be equal the power demand from EVs. The constraint (3.13) sets the initial SOC to be within the interval (0,1). Though in practice, this constraint may result in a less flattened power load profile, this is to ensure the user demand are satisfied in the process. The constraint in (3.14) indicates that one EV can only have two statuses, which are connecting and disconnecting to the grid system. Meanwhile, in constraint (3.15), the total number of the utilised EV $N_{car}(t)^{'}$ should be equal or less than the total number of connecting EVs in the system. Moreover, Equation (3.16) limits the total power load in each time interval not to exceed the network transmission line limit.

3.3.2 GA-based EV Charging Scheme

In this section, an algorithm is proposed to solve the above problem with low computational complexity. The EV arrival model $N_{car}(t)$ is used to identify the possible scheduling results. Moreover, the power demand in the next time slot is affected by the previous scheduling results. Hence, it is ensured that the total power charging demand from EV is satisfied while the minimum power fluctuation for the grid system is obtained. The optimal EV charging scheme is shown in Algorithm 1.

Table 3-A: EV Charging Scheme

Input: $P_{home}(t), \forall t$, P_{max}, δ, α, β, $N_{car}(t)$.
Ensure: $P_{EV}(t)$, $N_{car}(t), \forall t$, P_{PFL}=$+\infty$ and determine T_f and T_s
in each jth order of $n_j(t)$ for $N_{car}(t)$,
Calculate: calculate M_1, M_2,...,M_j, $P_{ini} = \sum_{t=1}^{T} P_{EV}$;

WHILE $(P'_{EV}! = P_{ini})$
    FORALL $t \in T$
        FORALL $X_{i,t} = 1$ and $SOC_i < 1$
            STATE Search the optimal schedule EV_i and calculate $P_{EV}(t')$;
            STATE Update SOC_i;
        ENDFOR
        STATE Calculate P'_{PFL} with new input of $P_{EV}(t')$;
        IF $P'_{PFL} \leq P_{PFL}$
            STATE Set $P_{PFL} = P'_{PFL}$;
        ENDIF
    ENDFOR
ENDWHILE

Output: P_{PFL}, $P_{EV}(t), \forall t$.

In the proposed EV charging scheme algorithm, the parameters $P_{EV}(t)$ and $N_{car}(t)$ are initialised according to the input values. Then the initial total power demand from EV charging in the entire time frame of P_{ini} is calculated.

After that, in each iteration, the algorithm searches for the optimal schedule for $EV(i)$ according to the EV availability that is presented by $X_{i,t} = 1$. The GA is used in this process as it does not require the initial inputs where the objection function (Equation (12)) is used as the fitness function. Each number of variables in GA is the amount of EV to be charged at each time frame. After each iteration, $P_{EV}(t+1)$ is updated as $P_{EV}(t')$ and the new SOC for each EV i. Hence, there will be a new power fluctuation level, according to Equation (11) for another new EV charging scheduling pattern. During each iteration, the P_{PFL} is updated, and the hourly EV scheduling result $P_{EV}(t)$ is demonstrated.

The computational complexity of the proposed algorithm is denoted as $O|\tau^2|$ in the worst case. Since the proposed EV charging schedule algorithm optimises charging pattern in the day-ahead market. If taking one day for the whole duration of all the time slots, the proposed charging schedule algorithm executes only once a day based upon the previous EV arrival pattern and residential load profile.

3.4 Simulation Results

3.4.1 Parameter Settings

To evaluate the performance of the proposed algorithm, a residential area substation transformer with P_{max}=250kVA power capacity is used, which serves the size of 100 households. This thesis assumes that on average, each household would have owned one EV. For the simplicity of simulations, it models each of the EV with the same battery capacity of 36 kWh, as it is the average battery capacity in the market which holds the applicability of this model. As for the charging rate, there are different charger connector types for different models from manufacturers, where 3kW (16A) and 7kW (32A) charger compatibility are the most common types with Type 1 or Type 2 vehicle inlets according to the London local regulations [zap]. Moreover, the EV charge connection status is modelled as two parts, where the first time segment is from 06:00 to 18:00 and the second time interval is from 18:30 to 05:30 (+1). In this model, the charging rate is set to be a static value, but note that the dynamic charging rate can be controlled by adjusting the parameters.

Table 3-B: Simulation Parameters

Parameter	Value
Time segment(T_{seg})	30 minutes
Scheduling time frame	24 hours
Total number of EV (Ω)	100
EV battery residual distribution	$\alpha = 0.2$, $\beta = 0.8$ [JOS+13]
Expected SOC after charging(SOC_{exp})	0.8 [CJT14b]
EV battery capacity(P_{max})	36kWh
Charging rate (δ)	3.5kW

The summary of other simulation parameters is shown in Table 3-B.

3.4.2 PFL analysis

Fig. 3.2 compares the daily half-hourly resolution of load profile in a residential area without any EV charging scheduling optimisation (Fig. 3.2(a)) and with conventional charging strategy (Fig. 3.2(b)). In simulations, it uses the domestic residential daily profile from the Elexon report [Ele13]. The red dashed line represents the sum of EV charging demand and residential load in each time frame, where the total electricity consumption exceeds the power capacity at hours 17:30–19:00 and 21:30. Furthermore, the maximum power consumption peaks at 329.5 KVA, which are 31.8% over the substation transformer capacity and the lowest power consumption drops to 58.5 KVA at 05:00. This part further evaluates the power fluctuation level according to the performance function where P_{PFL} is computed as 0.56. As in line with [AAGG14], after the conventional charging strategy is utilised, the EV charging load in peak time intervals are shifted to the time period where the electricity consumption is low. This mitigates the maximum power load in the peak time at around 18:00 with a lower power fluctuation level at $P_{PFL} = 0.20$. However, this conventional strategy shifts the loads without considering the state of EV connections and user behaviours in the charging process. Meanwhile, the total EV charging demand is not met in the process.

Fig. 3.3 presents the load profile with the EV charging load optimisation strategy comparing with the EV charging without optimisation. The generation for the selection

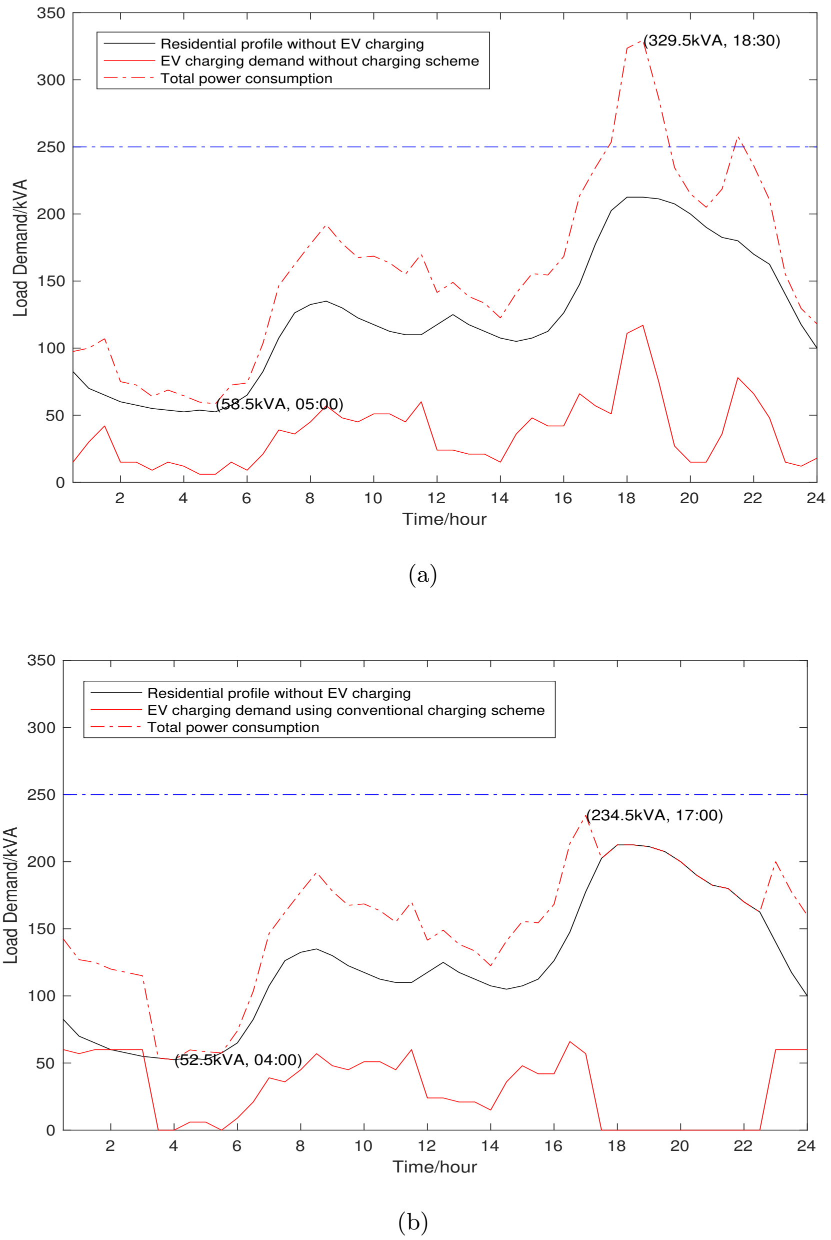

Figure 3.2: Domestic half-hourly load profile without EV charging optimisation. Top panel: Load profile without a charging strategy. Bottom panel: Load profile using a conventional charging strategy.

process is set as 1000. Then the curve for fitness value converges with iterations after the iteration. Moreover, the charging schedule pattern is concentrated in the interval of (3, 10) and the valley of the charging schedule lies at (36, 40), mitigating the high peak-to-average power demand profile. Compared with the conventional charging schedule, the optimised load profile considers the availability of EV in the grid system while achieving lower power fluctuation level such that $P_{PFL} = 0.03$. The logarithm in the objective function also mitigates an extremely charging concentration period in the load profile. Furthermore, Fig. 3.3 illustrates that the overall power load at peak time can be controlled within the substation transformer power capacity by scheduling less EV charging in this period. The P_{PFL} corresponding to different charging strategies is shown in Fig. 3.4.

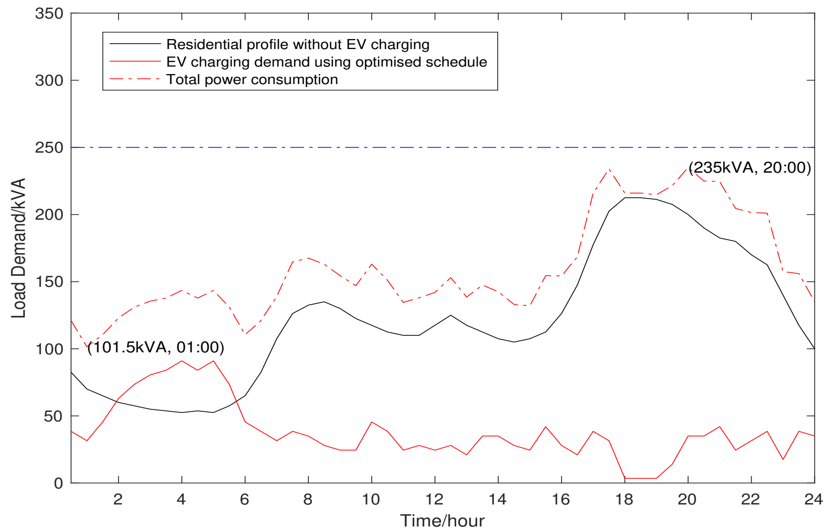

Figure 3.3: Load profile with and without the EV charging optimisation strategy.

Simulation results are satisfied, and further indicated the capability of the proposed algorithm in substantially decreasing the power fluctuation level, as well as ensures the EV charging demand. Both the EV type and charging rate are assumed at a static value in our model.

3.5 Summary

The V2G-G2V concept and the user behaviour of EV drivers are studied to provide direct provision into the EV schedule schemes. The integration of the G2V system into the

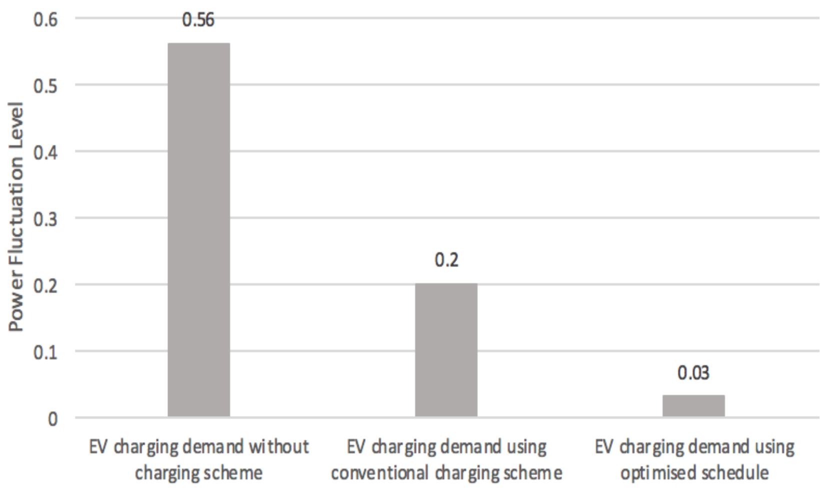

Figure 3.4: Power fluctuation level in comparison to different strategies

distributed network brings potential ancillary services, where peak shaving and valley filling are realised in this work.

Then, it summarises the state-of-the-art in the current research area and describes my previous work to formulate the system model and the research problem. In this part, an optimised EV charging schedule algorithm with user-behaviours analysis is proposed to minimise the power fluctuation level, where the peak and valley loads are mitigated. It models the EV staying-on-line and charging profiles based on the EV driver behaviour: the EV connecting time, battery residual and the expected SOC. To minimise the power fluctuation level of the overall power demand profile, the genetic algorithm is used to find the optimal schedule for the EV users. Simulation results show that the PFL index has decreased tremendously, and the peak power demand is controlled within the substation transformer capacity.

The proposed algorithm provides insight into the structure of the problem, where it can add the day-ahead electricity profile into the model to run the iterative-based algorithm. Moreover, the model can serve as the benchmark for evaluating online algorithms. In the future work, this work will design algorithms incorporated with discharging feature and unpredictable charging rate control which will further improve the power fluctuation level.

Since the proposed charging scheme is based on the randomly generated profile with the constraints in connection status and SOC, the simulation results and algorithm performance might deviate from the scenario in the real world seriously. In order to better model the EV charging and discharging behaviour, a more accurate predictive model should be constructed to improve the performance of the current EV connection model.

Second, the genetic algorithm used in the proposed scheme achieved comparatively low computation complexity. However, the methodologies in searching the optimal EV schedules based on the different dataset and user profile should accommodate the nature of data sources. Moreover, the next topic of my research will be generating an automated schedule for EV drivers, where the methodologies related to deep learning area shall be adopted.

Last but not least, the system structure of the existing research relies on the deployment of an aggregator. However, the objective of promoting the smart grid system is to utilise better the distributed renewable energy sources, where the aggregator re-centralises the distributed system which defies the original intention. So blockchain technology will be considered to further decentralise smart grid system where the data storage of the electricity, market operating, and billing system can be implemented.

Chapter 4

AdBEV participation scheme

4.1 Overview

Uncontrolled EV charging/discharging may lead to instability of the overall grid system operation. This chapter focuses on adaptive EV C&D scheme where the scheduling is dynamic compared with the previous user-behaviour associated scheme. Therefore, it is critical to developing effective charging/discharging scheduling algorithms for efficient grid operations.

The uncertainty of future events is considered, including the charging profiles of EVs arriving, future load demand in the grid, etc. Besides, the large-scale charging of EVs requires low-complexity control mechanisms to reduce the operating delay and the capital cost of equipment investments. In this regard, this part presents an adaptive EV charging/discharging scheduling algorithm based on the blockchain platform, named Adaptive Blockchain-based Electric Vehicle Participation (AdBEV) to execute the information posting and decision-making process.

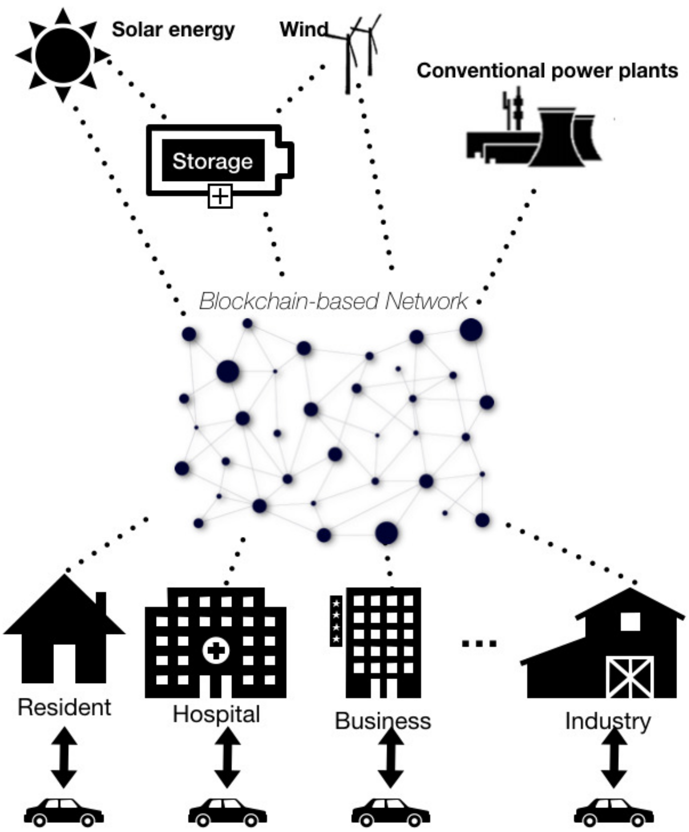

Figure 4.1: The system structure of the smart grid incorporating a public blockchain trading platform where the dotted line indicates the electricity and data/payment exchange.

4.2 System Model

To extend the previously developed system model from [LLCC17], a residential area is considered where the maximum power capacity of a substation transformer is P_{max}. The participants in the grid system include the conventional large power plants, distributed micro renewable generators and storages which compose the electricity provider side. Besides, the consumer power loads, for example, the residential area and hospital, are all connected to the public blockchain power exchanging platform, where the electricity supply and demand information are transmitted, encrypted and saved in the blockchain platform. The electrical grid structure incorporating the public blockchain platform for trading electricity is illustrated in Figure 4.1.

In this model, it is assumed that the EV is capable of publishing and transmitting the charging or discharging order to the smart grid public blockchain trading platform. The charging/discharging process of EV can be realised by a programmable charging installation. This is to enable the instant on/off switching of the power transmission to the EV as instructed by the grid operator (assuming the sophisticated design of switches). The workflow for the transaction to be processed in the blockchain platform is demonstrated in Figure 4.2. The electricity orders which include buy and sell are initiated by the driver owners, and orders are entered to the blockchain-enabled trading platform as soon as the initiator's identity is identified. The orders are then processed using the AdBEV scheme and further to be published to the open order book. The matched orders are transacted and verified by the peers in the network. Orders that are finally confirmed by both parties are saved in a distributed manner.

This system first adopts the EV status matrix X for EV i at time t from the last chapter.

$$X_{i,t} = \begin{cases} 1, & \text{if } EV_i \text{ is connected at time } t \\ 0, & \text{otherwise} \end{cases}. \tag{4.1}$$

The power demand of EV depends on the battery residual (SOC_{ini}) in each EV and the expected SOC (SOC_{exp}) after charging. In the process of scheduling EV charging/discharging, it is important to consider the quantity of the EVs that stay connected to the grid network so that the maximum time can be inferred for order waiting. In order to achieve the low power fluctuation level and user satisfaction, this scheme combines the charging duration and energy transfer amount to infer the hourly charging demand pattern during a day.

This scheme models the vehicle activity profiles for a typical residential EV charging demand in a day frame referring to [oENL]. By combining this with the charging duration and the amount of energy transfer, the charging demand pattern can be obtained during

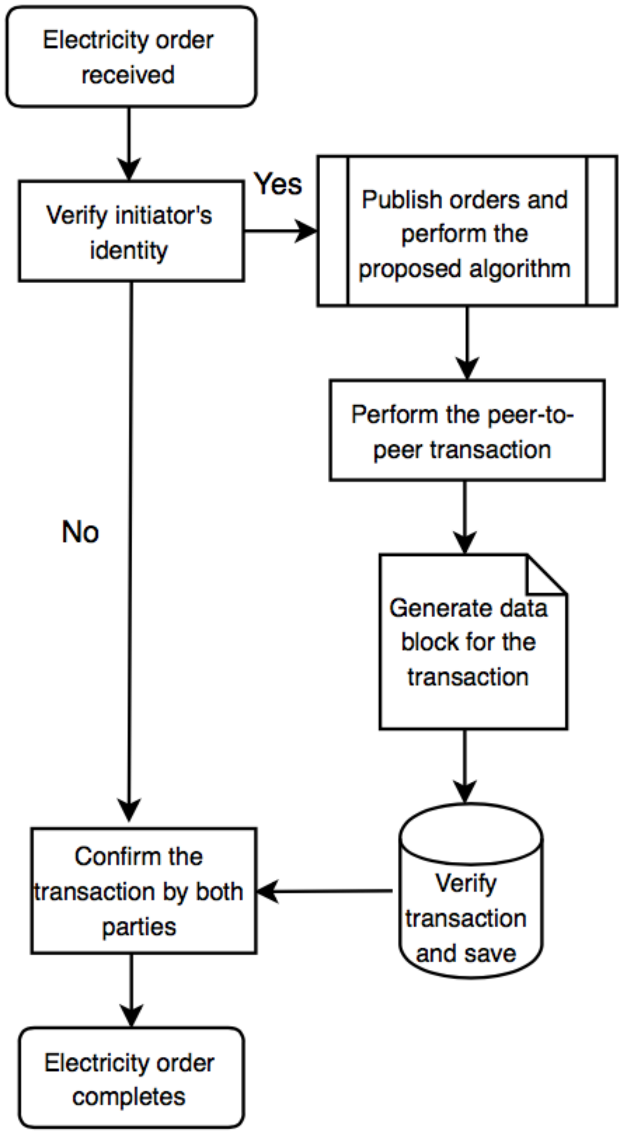

Figure 4.2: The work flow for transaction execution in the blockchain-enabled smart grid system.

a day. Through examining the characteristic of the EV charging distribution, the amount of power transfer for EV charging can be modelled as the sum of sines considering the balance between model accuracy and complexity, and it can be represented by a time segment vector $\eta(t)$ composed the percentage of stay-on-line EV.

After each iteration of order execution, the power demand after one time segment $P_{EV}(t')$ will change accordingly. Hence, it can formulate the Equation (4.2) with the amount of power exchange Q_i as follows corresponding to the order category:

$$P_{EV}(t') = \sum_{i=1}^{I'} (X_{i,t'} Q_i) \tag{4.2}$$

Then, the total residential load as the sum of EV charging/discharging demand can be defined and load profile without EV in order to formulate the EV charging problem.

$$P_{total}(t) = P_{home}(t) + P_{EV}(t), t \in T, \tag{4.3a}$$

$$P_{total}(t) + \varsigma(t) \leqslant P_{sub}, \forall t, \tag{4.3b}$$

$$V_{min} \leqslant V(t) \leqslant V_{max}, \forall t, \tag{4.3c}$$

where P_{home} is the residential power load without EV. The EV charging/discharging scheduling problem can be solved by aggregating the above random process (4.3a) with the proposed algorithm. To improve the power system operation, the peak transformer substation load demand must not be exceeded after implementing EV charging/discharging energy to the residential electricity demand. In constraint (4.3b), the error item $\varsigma(t)$ denotes power losses or branch overloaded plus the total power load shall not exceed the substation power capacity P_{sub}. Hence, there is a maximal number of EV $\max(N_{car}(t))$ that can be adopted in the grid network to avoid exceeding the substation capacity. Furthermore, it constrains the voltage levels $V(t)$ in buses are not allowed to fall outside the maximum and minimum limits in constraint (4.3c).

4.3 Problem Formulation and Algorithm Description

The scheduling of EV charging/discharging demand is adopted to minimise the impact of injecting or consuming the excess amount of power to the grid. In this case, the study focuses on an adaptive charging/discharging strategy for various types of EV to flatten the load profile of the transformer substation in the distribution network.

4.3.1 Problem Formulation

A half-hourly daily power exchange order book profile of a residential network is applied as the input data in the EV scheduling problem, where the decision parameters are the EV charging/discharging demand for each 24 hours. To level the fluctuation level of the whole system, it is necessary to develop an adaptive schedule to fill the gaps of the residential load profile. To describe the measurement of fluctuation level in two consecutive time segments of the grid, the overall utility function is as follows:

$$P_{PFL} = \sum_{t=1}^{T} \|P_{total}(t) - P_{total}(t-1)\|, \tag{4.4}$$

where P_{PFL} is the overall power fluctuation level for a day with half-hourly temporal resolution, $P_{total}(t)$ and $P_{total}(t-1)$ is total power in the transformer at hour t and $t-1$.

The objective of the system is to minimise the power fluctuation level index P_{PFL} of the overall power grid system with the collections of variables to be optimised for corresponding i and its corresponding SOC_{exp}, which can be formulated as follows:

$$\min_{\forall SOC_{exp}(i) \in I} \quad P_{PFL}. \tag{4.5a}$$

S.T.

$$\sum_{t=1}^{T} \sum_{i=1}^{I} \Big(SOC_{exp}(i) \pm SOC_{ini}(i) \Big) = \sum_{t=1}^{T} P_{EV}(t), \tag{4.5b}$$

$$SOC_{ini} \in (0,1), \forall i, \tag{4.5c}$$

$$SOC_{exp} \leqslant P_{max}, \forall i, \tag{4.5d}$$

$$X_{i,t} = \{0,1\}. \forall i, \forall t, \tag{4.5e}$$

Equation (4.5b) limits the total charging and discharging power equal to the order demand from EVs with respect to the available EV number i and the achieved $SOC_{exp}(i)$. Equation (4.5c) sets the initial SOC to be within the interval (0,1). Though in practice, this constraint may result in a less flattened power load profile, this is to ensure the user demands are satisfied in the process. Constraint (4.5d) are imposed to guarantee that the maximal SOC after charging does not exceed the EV battery capacity P_{max} for each EV i. The constraint in (4.5e) indicates that one EV can only have two statuses, which are connecting and disconnecting to the grid system.

The formulated problem is a mixed combinatorial non-convex problem due to the binary constraint for EV connection status $X_{i,t}$ in Eq.(4.5e). In general, there is no systematic and computationally efficient approach to solve this problem optimally. As can be observed, the optimisation problem is to designate the optimal number of EVs to execute power transfer (charging/discharging) thus to minimise the overall power fluctuation level.

4.3.2 AdBEV Scheme

In this section, the AdBEV scheme is proposed to solve the above problem by using the electricity exchange book for power trading system. Moreover, the power demand in the next time slot is affected by the previous scheduling results. Hence, it is needed to ensure that the total power charging demand from EV is satisfied while the minimum power fluctuation for the grid system is obtained.

When considering the charging/discharging schedule for EVs, a distributed power exchange system should rely on a competitive price market in order to provide participants with the incentive for maximising their benefits. If participants wish to meet their instant power demand, they have to initiate a high bid price order or a low ask price order. In the meantime, a large iceberg order that exceeds the grid network capacity (threshold) should be split into smaller orders according to the order specifications, which in this case the offloading balance can be achieved by tranching the large power demands in a fast, responsive manner. In this algorithm, for simplicity, it assumes the order initiator can only send out one order until it is being executed.

4.3.2.1 Normal Electricity Exchange Order

For an electricity exchange order $\overrightarrow{O_i}$ with a small quantity, the demand is formatted as an input to send to the electricity exchange stand book Std_{in} in the form of a vector which can be denoted as follows:

$$\overrightarrow{O_i} = (\gamma, Id_i, \sigma_i, Q_i), \tag{4.6}$$

where the Id_i is the unique identifier for the charging/discharging initiators (EVs or other components). The σ_i is the agreed unit price for the electricity order, the Q_i is the electricity demand quantity of this order, and γ is a matrix indicating whether it is a electricity charging or discharging order:

$$\gamma = \begin{cases} 1, & \text{charging order} \\ 0, & \text{discharging order} \end{cases}. \tag{4.7}$$

Then for each inserted order message, the solution should be applied to the current book Std_{in} to generate any matched trades in the order of matching the precedence. And all non-error output (each matched trade order) should be directed to the Std_{out}.

The trade information format is expressed as follows:

$$\overrightarrow{T_i} = (Id_{sell}, Id_{buy}, \sigma_m, Q_m), \tag{4.8}$$

where the Id_{sell} and Id_{buy} are the matched electricity sell and buy order identifier respectively, the σ_m is the matched price in pence, and the Q_m is the matched quantity for the order. Following the receipt of an order message, and after receiving any matches in the book and outputting any generated trade messages, the solutions should display the current full order book in the above format.

4.3.2.2 Iceberg Electricity Exchange Format

To tackle the problem to be formulated, the Iceberg order management algorithm which has been extensively used in the digital financial trading market is adopted to manage the EV charging and discharging demands [EM07]. The analogy between the energy market and the financial sector is strongly correlated for energy balancing mechanism in the electricity market, where the impact of placing a large order in the market is similar to demanding a large volume of electricity or injecting too much electricity to the grid network.

Assuming that a participant with huge electricity demands holds total power demand (ϕ_0) for exchange and it should be liquidated before time T_{max}, then it assigns a peak size ϕ_p and a limit $\bar{S}$ to this iceberg exchange demand. For the charging demand side, latter is strictly higher than the initial best bid price S_0 which is denoted as:

$$S_0 < \bar{S}, \tag{4.9}$$

such that the first proportion of the order is not immediately executable, and vice versa.

In order to process the iceberg power exchange smoothly and ensure the benefit gained from participants, it is crucial to choose the price for this demand. According to [EM07], the best charging price S_t can be modelled by a jump-diffusion process. Since the scheme aims to build a power exchange market for EV users, in order to obtain the guide price for each time interval, for $S_t < \bar{S}$, it adopts the widely used geometric Brownian motion for stock price to model the real-time electricity price variation in one day:

$$\mathrm{d}S_t = \mu S_t \mathrm{d}t + \sigma S_t \mathrm{d}W_t, \text{with } S_0 < \bar{S}, \tag{4.10}$$

where the percentage drift μ and the percentage volatility σ can be set to constants, and the W_t is a Wiener process. Thus, for a given highest price value S_0, the best iceberg price S_t can be obtained according to the following equations.

$$S_t = S_0 \exp\left((\mu - \frac{\sigma^2}{2})t + \sigma W_t\right), \tag{4.11}$$

$$E(S_t) = S_0 \exp(\mu t). \tag{4.12}$$

Then, the iceberg format can be formulated as the vector in Equation (4.12) which integrates the order best price σ_{S_t} and the total demand ϕ_i. And the Q_{pi} is the peak size for one trading period which is never greater than ϕ_i theoretically.

$$\overrightarrow{O_i} = (\gamma, Id_i, \sigma_{S_t}, \phi_i, Q_{pi}), \tag{4.13}$$

Both the normal and icerberg electricity exchange should be displayed in the order book according to the following function to rank their priorities:

$$f(P_{1p}(n), P_{2t}(n)) = \alpha Rank(Pr) + \beta Rank(T), \tag{4.14}$$

where $Rank(Pr)$ and $Rank(T)$ are defined as the rank for price and generation time respectively, and $\alpha = 10\beta$ in order to build a price-competitive market.

Table 4-A builds the trading system where the proposed algorithm first initialises the electricity charging and discharging demand and identify the normal and iceberg orders.

Then it sorts all orders with respect to the ranking function $f(P_{1p}(n), P_{2t}(n))$ in order to match those orders for exchange. After executing all orders within each trade frame interval, it gives the respective response for those orders.

Table 4-A: Electricity Trading System with Order Book Initialisation

Step 1. Initilisation
Initialise the EV electricity exchange order in the Std_{in} and identify the iceberg order whose place order exceeds the market capacity.
Set the order peak size $P_{max}(t) = Q_{pi}$.
Step 2. Sort the orders
Sort all orders according to $f(P_{1p}(n), P_{2t}(n))$.
Step 3. For orders n = 1, ... , N-1 at $t \in T$
Match the charging and discharging electricity order according to the adaptive EV charging/discharging algorithm.
Send the output orders to the Std_{out} and calculate the $P_{EV}(t)$.
end
Step 4. Generate full order book
If the order is placed:
Generate the receipt for the order message;
Otherwise:
Update the buy/sell order according to the new order book;
Set the order $P_{2t}(n) = P_{2t}(n) + 1$, and go back to step 2.

In Table 4-B, it proposes a best order strategy to match the electricity charging demand and discharging supply where three cases are considered. If the power demand is satisfied while maintaining a minimised power fluctuation level, then the algorithm executes all matching orders in the order of price rank. If the total quantity of electricity selling orders is smaller than the buying orders, it first executes the orders with the highest priority values. Then for the unmatched power demand orders, an aggressive iceberg execution strategy is adopted to match the orders in one time frame ($t \in T$). If the number of iceberg orders equals to 1 ($N_{Q_i} = 1$), it waits until the next cycle with the same priority value; otherwise, they will be assigned with new priorities. In the case of more sell orders occurring, the passive iceberg execution is used where orders are passively waiting for the next cycle execution. For each time frame ($t \in T$), the order book is built and updated.

Since the AdBEV scheme optimises the charging pattern in the day-ahead market, if

Table 4-B: Adaptive Blockchain-based Electric Vehicle Participation (AdBEV) Scheme

Step 1. Initialise the priority setting
For order n = 1, ... , N-1
Assign the $P(n)$ according to $f(P_{1p}(n), P_{2t}(n))$.
end
Step 2. Best order strategy
If the $P_{EV}(t)$ in the time frame t in T is satisfied:
Execute all matching orders;
else if $\left(\sum_{i=1}^{I} \overrightarrow{O_i}(S=0)\right) < \left(\sum_{i=1}^{I} \overrightarrow{O_i}(S=1)\right)$:
Execute the order according to the priority value $P(n)$, and go to step 3;
else:
Execute the order according to the priority value $P(n)$, and go to step 4;
Step 3. Aggressive iceberg execution
If the order is a normal buy order:
Fill the order from the main grid electricity input;
else:
if $N_{Q_i} = 1$:
Wait for the next cycle until reaching the time limit WT_{max};
else:
In single price level, old iceberg retains a higher priority;
In multiple price level, a higher price retains a higher priority.
Step 4. Passive iceberg execution
If the order is normal sell order:
Push the order into the next order period and remain the priority until being killed;
else:
Go back to step 1.
Step 5. Repeat
Update the order book in Table 1 and execute.

a single day for the whole duration of all the time slots is taken, the proposed scheduling scheme executes only once a day based on the previous EV arrival pattern and residential load profile.

4.4 Simulation Results

4.4.1 Experiment Setup

To evaluate the performance of the AdBEV scheme, a residential area substation transformer with P_{max} = 250kVA power capacity is used, which serves the size of 100 households. It assumes that on average, each household would have owned one EV. In order to adapt the various types of EV in the market, it chooses two types of the most popular EV battery capacity of 8.8kWh (Toyota Prius) and 60kWh (Tesla model S) respectively. As for the charging rate, there are different charger connector types for different models from manufacturers, where 3kW (16A) and 43kW (63A) charger compatibility are the typical ones for slow charging and fast charging inlets according to the London local regulations [LSL+17]. In the simulation process, the number of EVs for slow and fast charging is set with a ratio of 4:1 according to the availability of the charging ports [zap]. Moreover, the EV charge connection status is modelled as two parts, where the first time segment is from 06:00 to 18:00 and the second time segment is from 18:30 to 05:30 (+1). In this model, the initial battery residual (SOC_{ini}) for EVs is randomly generated and the battery level (SOC_{exp}) after charging is set to be 80% for protecting batteries, where the SOC after discharging is set to be 50% for the convenience of EV use.

Considering the distributed trading platform for electricity exchange market, this scheme adopts the Ethereum platform to implement the designed algorithm. The Ethereum platform is a decentralised platform which gives users to run distributed applications in the public blockchain [AT17]. The Solidity language with version 0.4.0 is used to deploy our smart contract to execute the AdBEV scheme. Henceforth, the gas consumption mechanism from the Ethereum platform provides a direct inspection of the operational complexity in the designed algorithm. In the public blockchain platform, the users have to pay the *GAS* cost in Ethereum platform in order to execute the commands in the smart contract [LCO+16]. With the increase in the number of peers in the network, the cost for executing a complex algorithm will largely increase the trade price for the electricity [ATDM17].

There are two types of orders set in the simulation: normal orders and iceberg orders according to Equations (5) and (10). The aim of using iceberg orders is to reduce the power load fluctuation triggered by the orders with large trading quantity. In our simulation, the ratio of the conventional orders and the iceberg orders is around 1:1. In addition, the peak size of the trading quantity (Q) in each order is fixed at 4 kW in the simulation. In Table 4-C, it demonstrates the partial order book in our simulation. The data structure is determined by the system model (see Section II). The buying side orders are ranked in ascending order according to the price where it is in descending order in the selling side, which resembles the stock exchange market with price-competitive features. Note that for the iceberg orders, it highlights them with bold figures in quantity (Q) column. Then the system simulates the exchange process with the order input to calculate the overall price fluctuation concerning the real-time price.

Table 4-C: Power Exchange Order Book

S(Buy/Sell)	Id	Price(pence)	Q(kW)
Buy	12	11	1.07
Buy	***70***	***12***	***4***
Buy	0	13	2.14
		...	
Sell	***48***	***14***	***1.80***
Sell	18	15	0.44
Sell	***0***	***17***	***4***

The price of the electricity exchange market is fluctuated according to the iceberg order execution algorithm where the drift of the best bid price has been assumed to be a constant. To keep the setup tractable for exposition, it assumes a simplified scenario: the best bid price exhibits a zero-drift $\mu = 0$ prior to the submission of the iceberg order. The original price fluctuation interval is set to be $\sigma_i \in (10, 30)$ subject to the local area, henceforth, the order price σ_t is modified for certain hours during the day to simulate the retail electricity prices in distribution networks, which are displayed in Figure 4.3. The price in each hour is calculated from the average price of all the deal orders in each time frame from the order book. As seen from the figure, the electricity price is higher during 6:00 to 8:00, 11:00 to 13:00 and 17:00 to 19:00, which conforms to the higher power demand P_{EV} for EV charging period as depicted in Figure 4.3.

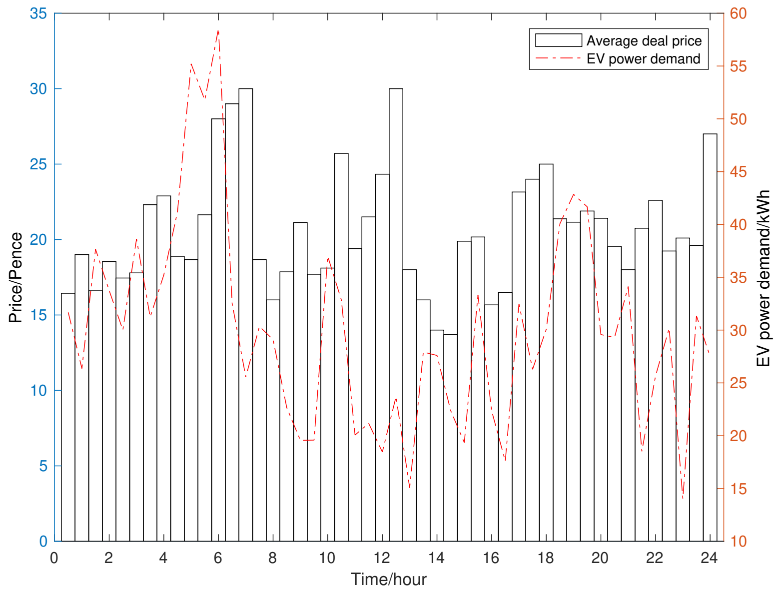

Figure 4.3: Average generated trading price in a day.

4.4.2 Power Fluctuation Level Minimisation

The simulation result shows the optimising effect of the algorithm to the power load fluctuation in Figure 4.4. It compares the daily half-hourly resolution of load profile in a residential area without any EV charging scheduling optimisation (top panel) and with the scheduling strategy using GA (bottom panel). In the simulation, it uses the domestic residential daily profile from the Elexon report [Ele13]. The red dashed line represents the sum of EV charging demand and residential load in each time frame. The total electricity consumption exceeds the power capacity at 20:30 due to large volume charging demands during this period in this case, with $P_{PFL} = 1.15$ through Equation (7). As in line with [LLCC17], after utilising the scheduling algorithm using GA, the EV charging load is shifted to the off-peak time, and the discharging features are considered.

It can be seen that the GA scheduling algorithm mitigates the peak time electricity consumption with a lower power fluctuation level at $P_{PFL} = 0.85$. Compared with the P_{PFL} index without any scheduling algorithm, the index decreases by 26.1% and the load at substation transformer during the peak period is mitigated.

With the proposed AdBEV scheduling scheme, EV can generate charging or discharging orders to the market with respect to their connection statuses, battery capacity and charging/discharging constraints. This enables the reduction of the overall power demand fluctuation level where the optimised result P^*_{PFL} with the proposed algorithm is 0.63, calculated by the Equation (7) which is reduced by 25.9 compared to the P_{PFL} using the GA scheduling algorithm. Using the optimised EV charging scheme in [LLCC17] as the benchmark, the index P^*_{PFL} is proved to be capable of better flattening the consumption loads which is depicted in Figure 4.5. Furthermore, when trying to increase the number of EVs in the network, the $P_{EV}(t)$ will increase linearly as it assumes the SOC to be normally distributed [ZWM+13]. Refer to the overall utility function Eq. (4,4), the power fluctuation level P_{PFL} is aggregated with the absolute value of the power consumption difference in two consecutive hours, wherewith the increase of $P_{EV}(t)$ the ability to minimise the power fluctuation level is linearly increased.

4.4.3 Computation Cost Analysis

The computation complexity should be noted as the computation cost is related to the exchange efficiency and cost. The calculation of the *gas* corresponds to the low-level operation in the Ethereum Virtual Machine, where each opcode has a *GAS* related to it. For example, according to [W+14], the operators *add* uses 3 *gas* as while mul (for two integers) uses 5 *gas*. Also, it is important to note that all transactions cost 21000 *gas* as a base even not interacting with a contract, where the total *gas* is the 21000 *gas* plus any *gas* associated with running the contract if you are interacting with a contract.

In Ethereum, it models the theoretical computation cost with respect to the number

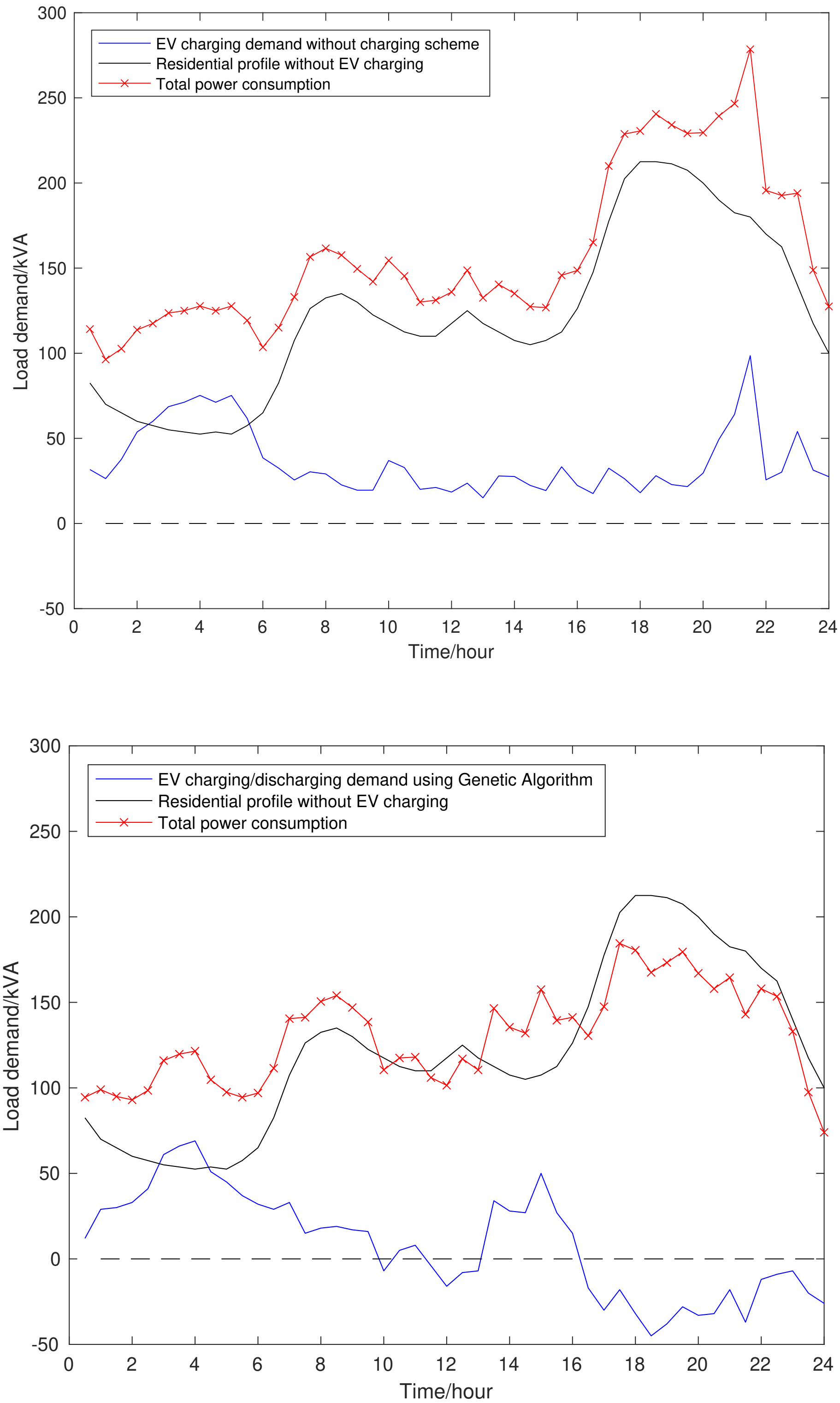

Figure 4.4: Comparisons of the domestic half-hourly load profile. Top panel: Load profile without charging strategy. Bottom panel: Load profile using charging/discharging algorithm.

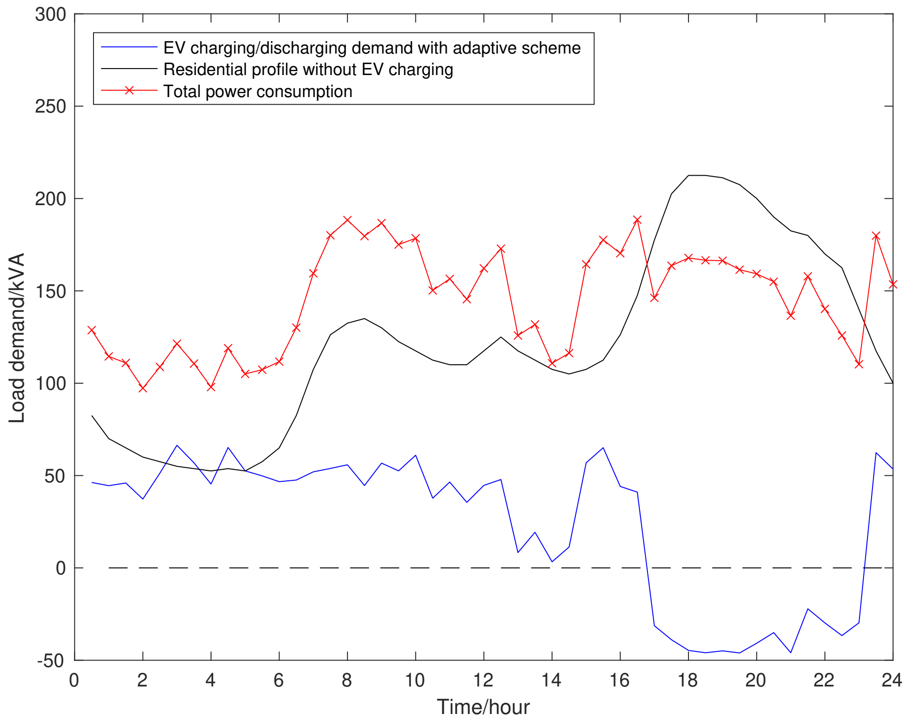

Figure 4.5: Domestic half-hourly load profile using the proposed adaptive EV charging/discharging demand matching algorithm.

of peers in each network as in Figure 4.6. Note that the actual cost for *gas* of a transaction cannot be determined before the transaction is completed as the transaction in the same block may alter the result. However, in most scenarios, providing the estimate is sufficient to refer to the algorithm complexity. The benchmark scheduling scheme using GA costs more *gas* than the proposed AdBEV scheme. With the increase in the peer quantity in the network, the total cost for the transaction will undermine the overall power exchange performance.

4.5 Summary

In this chapter, it proposes an AdBEV scheduling scheme to minimise the power fluctuation level, which enables an autonomous and secure trading platform for the energy

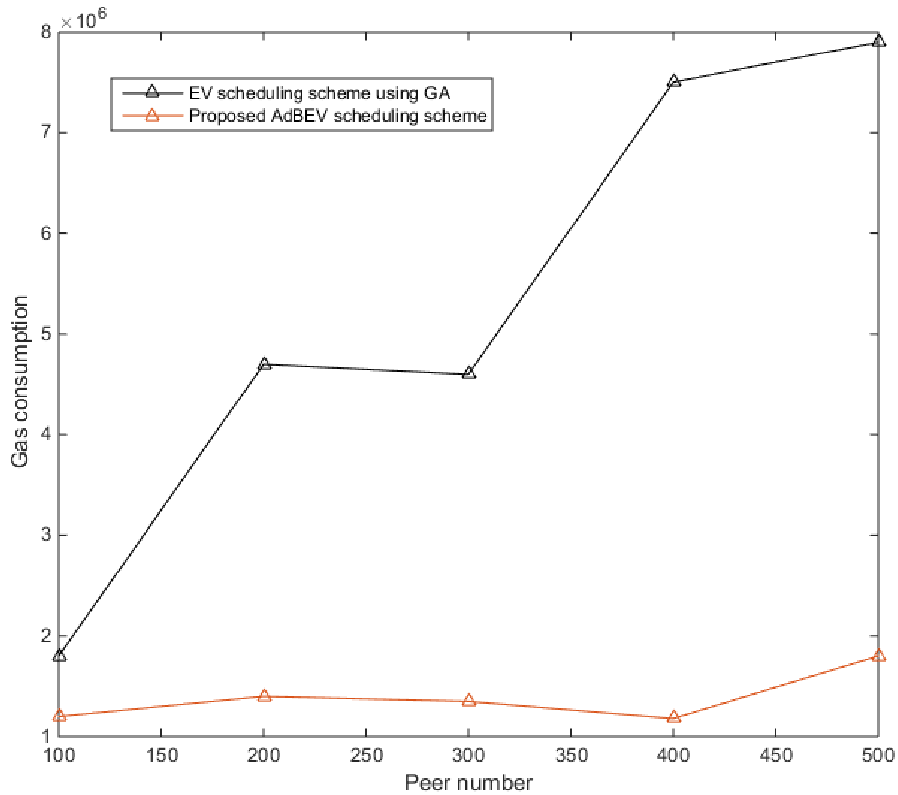

Figure 4.6: Computation cost comparison between the EV scheduling scheme using GA and the AdBEV.

industry. The EV stay-on-line model is adapted to control the availability of the charging/discharging amount. The iceberg order execution algorithm is adapted to process the great demand for scheduling. Simulation results imply the capability of the proposed algorithm in substantially decreasing the power fluctuation level, as well as maximising the EV driver benefits.

The trendiest EV battery types and charging rate are adapted to control the charging and discharging process dynamically. The AdBEV scheme provides insight into the structure for buildings in the transactional energy market into the blockchain technology to further decentralise the smart grid system. The proposed algorithm has a lower *gas* consumption in the execution process and thus maximises the order trading efficiency. Hence, in the future, it is required to find the balance between the on and off-chain complexity, while still leveraging the decentralised capabilities of a blockchain.

Chapter 5

P2P Electricity Trading System

5.1 Overview

In the traditional energy trading system, it involves typically order generation, broker-dealer, trade compliance, order management, price delivery, exchange execution and settlement accounting, which are time-consuming and lack flexibility. Applying the market-based electricity trading system to the grid network is envisaged to reduce the dependency of agents on the aggregator, wherein the existing energy management architectures lack coordination among actors which limits the capability of peer-to-peer trading.

Motivated by this, this chapter exploits the feasibility of applying blockchain technology to the electricity trading market to develop a transparent and stable power system. A Peer-to-Peer Electricity Blockchain Trading (PEBT) system is proposed to support P2P electricity trading for EVs. A PoB consensus protocol is designed to accommodate the EV C&D scenario, where it chooses the winning block based on the maximal benefit included in this block transactions. It is unveiled that the proposed blockchain-enabled electricity system could ensure the overall system benefit with minimised power fluctuation level.

5.2 Peer-to-Peer Electricity Blockchain Trading System Model

The revolution towards the P2P power exchange system can be achieved predicated on the diminutive-scale energy generators and EVs, where they may produce, consume, and sell excess electricity capacity like a commodity. Energy transactions and agreements instead replace the hierarchical structure. In this way, power loads, including domestic and business users, can connect to both the retail for end-users and wholesale market from the conventional power generators. This part proposes a peer-to-peer electricity trading system that sanctions prosumers to trade energy while ensures the overall network quality with its designed consensus mechanism.

5.2.1 Overview of PEBT System

As shown in Fig. 5.1, in the traditional power grid system (Figure 5.a), the electricity flow is hierarchical, and the electricity exchange process relies on the retailers to participate in the price negotiation process. In order to adapt the existing conventional power system, refer to Figure 5.b that it reserves the conventional power delivery system. The system reformation lies on the middle to the low voltage level where the power loads are delegated to microgrid containing renewables, small power storage, and EV. Furthermore, providing the wholesale market in the conventional grid system, transactional energy enables coordination of retail customers utilising frequent tranching transactions to be executed automatically by blockchain embedded system, consequently reducing the centralised features of the next-generation grid system [PG16].

In the PEBT system, all components in the microgrids such as domestic users, batteries, solar panels and EVs are capable of drawing and injecting electricity into the power network. Electricity is defined as a smart property as ownership of this asset can be controlled by smart contracts. The advantage of treating electricity as the smart property is that it can be controlled via digital devices, and the asset ownership transfer can be achieved at low cost. For EVs, the charging and discharging process can be realised by

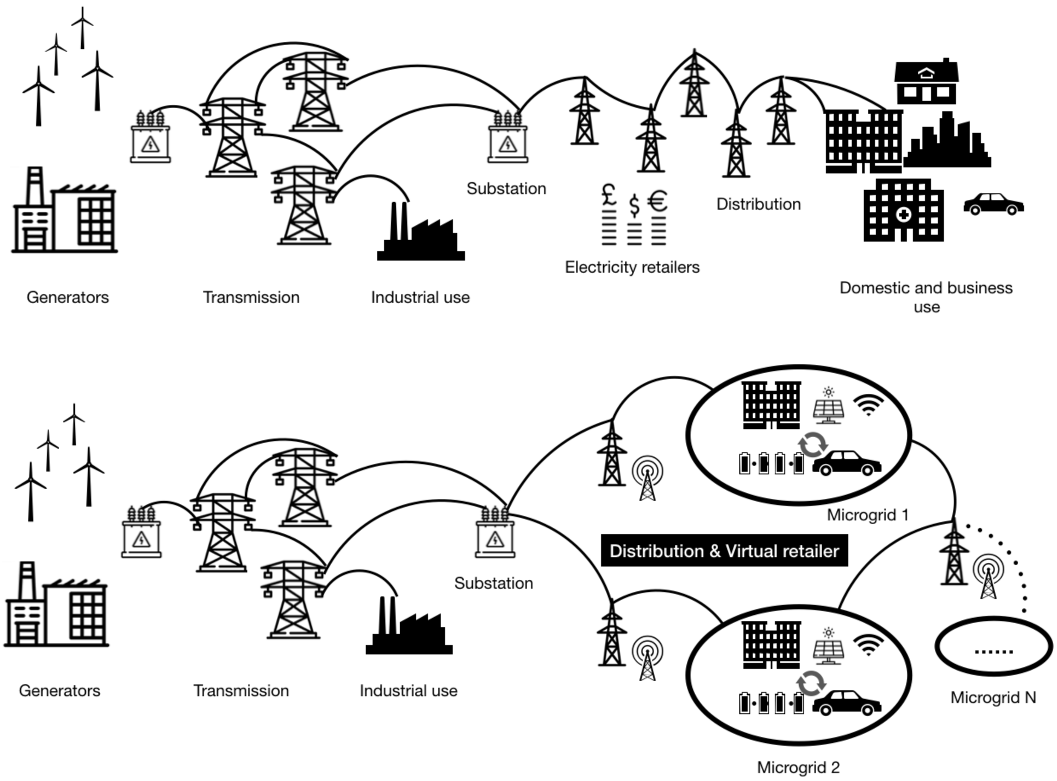

Figure 5.1: Electricity trading system model comparison. Figure 5.1.a. Traditional hierarchical power distribution system. Figure 5.1.b. Proposed decentralised power exchange system with microgrids.

a programmable charge installation which enables the instant on/off switching the electricity flow as instructed by EVs (assuming the sophisticated design of switches). The demands for buying and selling electricity is defined as transactions, in which the information is broadcast in the grid system via an appropriate wireless network [Pil16]. The transactions can also be executed between retail and wholesale markets which equalises the opportunity for all components. Moreover, the exchange procedure must account for the transmission and distribution limits and other physical constraints on the grid.

As discussed above, the PEBT system conforms the following rules:

1. **Adaptable -** The fundamental components of the PEBT system is taken as the reference to the current market compositions, which also have been modified to

adopt the blockchain technology. PEBT system supports the integrity of the traditional model and complies to the market rules.

2. **Efficient -** The transaction process eliminates the involvement of the third party comparing to the traditional retail process, thus the amount of time consumed is decreased while the efficiency is improved in a transparent exchange way.

3. **Flexible -** The proposed model deploys an open trading platform which allows more energy prosumer types to enter the exchange market in a more flexible manner.

4. **Cost Effective -** The new electricity system builds a direct connection between buyers and sellers while ensuring the overall power network stability, which maximises the economic return for both the grid system operators and individual users.

5.2.2 P2P Trading Model in PEBT System

As depicted in Fig. 5.2, the microgrid components are the nodes in the PEBT system, and they can publish transactions according to their demands. The demands of buying and selling electricity are encapsulated as transactions in the PEBT system, where each transaction period is defined as T_{round}. T_{round} is the time for mining a new block in the blockchain, which is defined by the consensus primitives. Moreover, each node is capable of setting the price for the electricity transaction to incentivise users to balance the supply and demand, in the meantime, to reduce the power generation and consumption peaks. For each transaction in the PEBT system, it is formatted as Equation (5.1) in the form of a vector.

$$\overrightarrow{TX_i} = (\gamma, Id_i, \sigma_i, Q_i), \tag{5.1}$$

where the Id_i is the identifier for the transaction initiators, the σ_i is the unit price for

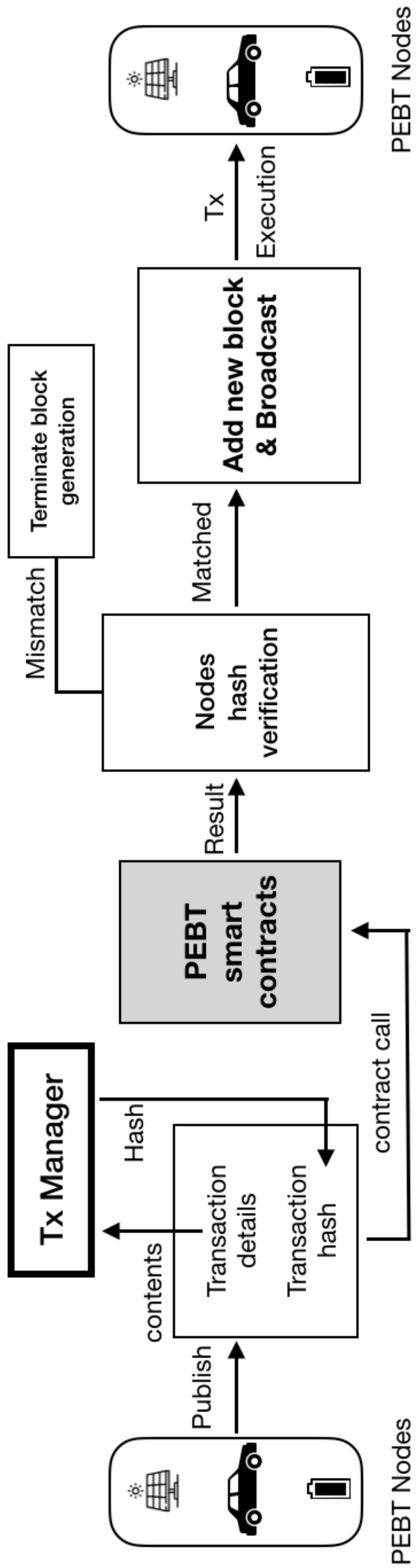

Figure 5.2: Structure of proposed PEBT system transaction process.

the electricity transaction, the Q_i is the transaction quantity, and γ is a status matrix:

$$\gamma = \begin{cases} 1, & \text{buy order} \\ 0, & \text{sell order} \end{cases}. \tag{5.2}$$

1) Transaction initialisation: In order to protect users' privacy, the transaction payload is encrypted by the transaction manager where the actual contents of the transaction are presented by hash. In PEBT, the transaction details can only be accessed by the deal nodes and the real contents can be revealed by identity registration with the transaction manager.

2) Transaction aggregation: After completion of order preparation, all transactions are aggregated, including the amount of electricity and expected time for transaction completion. The system will count the total electricity demands and call smart contracts to execute energy trading.

3) Consensus commitment: The consensus mechanism is applied to the transactions to select a leader of the current process. The leader broadcasts block data and its PoB to other authorised nodes. The nodes then audit the block data to see if the hash matches its local records in the nodes hash verification process. If the hash results are matched, nodes will accept the new data block and proceed to the next step. If not, then the new block generation process will be terminated, and the system waits for the next round. More details of the PoB mechanism will be given in Section 5.3.

4) Block Generation: The agreed transaction data is then broadcast to the whole network and only participants being selected in the new block are able to decrypt the block contents to execute the transactions. Then the encrypted block contents can be executed in the network.

5.2.3 Problem Definition for Electricity Trading

In this section, it presents the problem definition for the EV's electricity amount in the PEBT system to charge and discharge to minimise the overall power fluctuation in a grid system composed of microgrids. It defines that the component in the PEBT node with the characteristics of EV that is capable of both drawing and injecting energy into the same entity, and they will be referred to as EVs for simplicity. The components in the PEBT node are defined that can draw and inject energy into the grid. In this part, it assumes all components are EV with the capabilities of drawing and injecting energy into the grid. Within and between each microgrid, the prosumers including EV are denoted as nodes, and they can draw or inject electricity into the grid. A set of microgrids (denoted as M_n) is indexed by n, where $n \in \omega := \{1, 2, ..., n\}$. Denoting that a set of charging EVs in M_n as $\chi := (CV_i^n | i \in \mathbb{Z}, n \in \omega), \mathbb{Z} = \{0, 1, 2, ..., I\}$, where I denotes for the total number of charging EVs. The discharging EVs in M_n denoted as $\psi := (DV_j^n | j \in \mathbb{Z}, n \in \omega), \mathbb{Z} = \{0, 1, 2, ..., J\}$, where J is the total number of discharging EVs. $\chi_i^{n,min}$ and $\chi_i^{n,max}$ are the minimum and maximum electricity charging demands in M_n, which correspond to the minimal energy for EV normal use and battery capacity respectively for CV_i^n.

Then, the system defines χ_{ij}^n is the power demand of CV_i^n for directly obtaining electricity from the EV DV_j^n in M_n. The electricity demand vector of CV_i^n is $X_i^n := \{\chi_{ij}^n | j \in \mathbb{Z}\}$. Considering that it needs to satisfy the minimal charging demand for EV, the energy demand (C_i) function at round time $t \in [1, 2, ..., T]$ is defined as follows:

$$C_i\big(X_i^n(t)\big) = \upsilon \sum_{j=1}^{J} \chi_{ij}^n(t) - \chi_i^{n,min}(t), \tag{5.3}$$

where υ is the electricity charging efficiency in the power exchange process.

For the discharging EV in PEBT system, the amount of available electricity supply is o_j^n from discharging EV DV_j^n in M_n. And the corresponding electricity supply vector is

$O_j^n := \{o_j^n | j \in \mathbb{Z}\}$. Then the maximum electricity supply (H_j) from discharging devices at round time $t \in [1, 2, ..., T]$ is defined as follows:

$$H_j\big(O_j^n(t)\big) = \varpi \sum_{j=1}^{J} \big(o_j^n(t)\big), \tag{5.4}$$

where ϖ is the discharging efficiency taking into account of transmission line loss.

Furthermore, it defines the electricity consumption from the microgrid M_n at round time t as $P^n(t)$. Since the system aims to minimise the overall electricity consumption fluctuation to increase the smart grid stability, the consumption curve of a day should be as gentle as possible to achieve power balance. The objective function is to minimise the variance of slope for a period of electricity exchange thus to achieve the network power balance. It first defines the power fluctuation amount with respect to time in microgrid n as follows:

$$\begin{aligned}
\Theta_n(t) &= \sum_{i=1}^{I} \big(C_i(X_i^n(t)\big) - \sum_{j=1}^{J} H_j\big(O_j^n(t)\big) + P^n(t) \\
= \upsilon\big[\sum_{j=1}^{J} \chi_{1j}^n(t) + \sum_{j=1}^{J} \chi_{2j}^n(t) + ... + \sum_{j=1}^{J} \chi_{Ij}^n(t)\big] &- \big[\chi_1^{n,min}(t) + \chi_2^{n,min}(t) + ... + \chi_I^{n,min}(t)\big] \\
&- \varpi \sum_{j=1}^{J} o_j^n(t) + P^n(t) \\
&= \upsilon \sum_{i=1}^{I} X_i^n - \sum_{i=1}^{I} \chi_i^{n,min}(t) - \varpi \sum_{j=1}^{J} o_j^n(t) + P^n(t)
\end{aligned} \tag{5.5}$$

then the slope of the power fluctuation curve is the derivative of the function $\Theta(t)$ which can be represented as follows:

$$l(t) = \frac{d}{dt}\Theta(t) \tag{5.6}$$

Finally, the objective can be represented as the variance of the slope function $l(t)$ as follows:

$$PF : \min_{C_i,H_i} \left\{ \frac{1}{T} \left[\left(l(t_1) - \overline{l(t)}\right)^2 + \left(l(t_2) - \overline{l(t)}\right)^2 + \left(l(t_T) - \overline{l(t)}\right)^2 \right] \right\} \tag{5.7}$$

$$\text{S.T.}$$

$$\begin{gathered} \upsilon \sum_{j=1}^{J} \chi_{ij}^{n}(t) \geqslant x_i^{n,min}(t), \forall i \in \mathbb{Z}, \\ \chi_{ij}^{n}(t) \geqslant 0, \forall i \in \mathbb{Z}, \forall j \in \mathbb{Z}, \\ \sum_{j=1}^{J} \left(o_j^n(t)\right) \leqslant \sum \left(Q_i(t) | \gamma = 0\right), \forall j \in \mathbb{Z}, \\ \varpi O_j^n(t) = \chi_{ij}^{n}(t), \forall i \in \mathbb{Z}, \forall j \in \mathbb{Z}. \end{gathered} \tag{5.8}$$

The first constraint ensures that there is sufficient amount of charging electricity for EV to use. Then it constrains that all EV power demands shall be considered so that the charging amount is greater than 0. In the third constraint, the amount of discharging power to be optimised shall not exceed the electricity amount from the transaction records. At last, it sets the amount of discharging power from EV are fully transmitted to the charging EVs to guarantee energy efficiency.

By taking the second derivative of the objective function, the following functions can be obtained:

$$(PF)^{'} \coloneqq \frac{2}{T} \left[l(t_1) + l(t_2) + ... + l(t_T) - T\overline{l(t)} \right] \tag{5.9}$$

$$(PF)^{''} \coloneqq \frac{2}{T} \sum_{t=1}^{T} l^{'}(t) \tag{5.10}$$

The objective function in (5.10) is strictly convex with the constraints, thus there exists a unique optimal solution as the result of the second derivative is greater than 0. The optimal solution for the objective function is denoted in the Equation (5.11), where T is defined by the total round number for the electricity exchange and $P^n(t-1)$ is the last round electricity consumption by other loads in the microgrid. Also, the reciprocal of the solution is used as the benefit for this transaction λ.

$$[C_i, H_i] \coloneqq T\overline{l(t)} - P^n(t-1) \tag{5.11}$$

5.3 Proposed Proof-of-Benefit Consensus Mechanism

In this section, a proof-of-benefit consensus mechanism to proceed the transactions for the PEBT system in order to minimise the objective function. In this consensus mechanism protocol, participants are the main principals who are required to perform routines to maintain and extend the blockchain. Participants of the trading system rely on the blockchain to execute the transactions matching, and the execution process is implemented via the grid infrastructure settings. According to the proposed PEBT system, the charging and discharging EVs need to submit the transactions with the required inputs. The calculation process of solving the overall benefit problem is completed in each node's local network, where the result is then uploaded along with the launch of the proposed blockchain protocol.

As described in Algorithm 1, there are two parts of functions which are the round preparation and mining execution, respectively. At the beginning of each round, peers in the network prepare to mine on a particular chain by calling the function $PoBRound$ and pass the latest block in the network. The mining process is executed after waiting a specified round time when the nodes call the function $PoBMine$ to mine a new block. The node passes the header of the latest block and last block to be extended ($previousBlock$). In this process, the system has to make sure that the $previousBlock$ and the $roundBlock$ have the same parent and each node waits for mandatory $ROUNDTIME$ for choosing the most beneficial block for the grid system. Then a benefit value is generated in the local network based on the benefit generation function in Section 3, which is then used to determine the winning block with transactions to be executed in the next round. A higher benefit value means that the charging and discharging schedules have a more positive impact on the overall grid performance. Furthermore, a monotonic counter is used to prevent concurrent invocations between the network peers.

Algorithm 1 Proof of benefit primitive

$counter \leftarrow MonotonicCounter()$
$roundBlock \leftarrow$ **null**
$roundTime \leftarrow$ **null**

function PoBRound($block$)
  $roundBlock \leftarrow block$
  $roundTime \leftarrow GetLocalTime()$
end function

function PoBMine($header, previousBlock$)
  assert $header.parent = Hash(previousBlock)$
  assert $previousBlock.Parent = roundBlock.parent$
  assert $Time.now \geq roundTime + ROUNDTIME$

  $\lambda \leftarrow GetBenefit()$

  //Restart the next mining cycle
  assert $counter = MonotonicCounter()$
  return(λ, **null**)
end function

In the Algorithm 2, the details to execute transactions are described. Each node in the network receives transactions from other nodes and maintains a copy of the current chain with labelled blocks. In every round, nodes call the function $IMPLEMENT$ to proceed the pending transactions into a new block and generate a proof along with it. Then the new chain is broadcast to the network peers, in the meantime, where the chain with more benefits will be accepted if received.

The nodes will return an updated chain with the new block from the set of new transactions after executing function $IMPLEMENT$. The $newBlock$ contains the hash

Algorithm 2 Transactions Execution

```
function IMPLEMENT(newTXs, chain)
    previousBlock ← LastBlock(chain)
    parent ← Hash(previousBlock)
    header ←< parent, newTXs >
    proof ← PoBMine(header, previousBlock)
    newBlock ←< parent, newTXs, proof >
    returnAPPEND(chain, newBlock)
end function

function BENEFIT(chain)
    benefit ← 0
    for block in chain do
        benefit ← benefit + blockchain(proof).λ
    end for
    return benefit
end function
```

value of root (*parent*) blocks, the new block made from $newTXs$ and proof of benefit ($proof$). In the function $BENEFIT$, it computes the overall benefits of the chain by summing up the benefit value ($proof$) so that it can be used to determine the correct blockchain with the highest benefit value. In this way, it will incentivise the system nodes to act more desirably to contribute to the overall grid performance.

In a complete execution process, each node starts with an empty blockchain, a set of pending transactions and an initial empty *roundBlock*. After initialising the states, nodes listen for the transactions from the network. When receiving transactions from the network, the node adds them to the block and broadcasts this to the network peers. Before the start of each new round, the node calls again the function $PoBROUND$ to bind mining to the current, up-to-date chain and start the next round after waiting the required timeframe $roundTime$.

5.4 Analysis

In this section, it presents the security analysis of the proposed PoB consensus mechanism used in the PEBT system and numerical results for the power fluctuation performance after applying our electricity trading strategy.

5.4.1 Security Analysis

PEBT system is designed to adapt to the electricity trading demands, where transaction and processing time should be controlled. In the meantime, the system needs to ensure the privacy of nodes so that the transaction data cannot be accessed by the third party. Furthermore, the system has the ability against potential traditional security attacks via standard cryptographic primitives. Hence, the security aspect of our PoB consensus-based PEBT system is analysed.

1. Control of blocks: Consider a set of participants $\alpha \in (CV_i^n, DV_j^n)$, all the charging and discharging vehicles in microgrids $CV_i^n, DV_j^n \in M_n$. The well-behaved nodes will act according to the PoB consensus mechanism where they are supposed to append the longest chain, and the new chain with the largest benefit value λ will be chosen as the newly added block. During each round, each node will obtain the $proof$, which includes the benefit value based on the pre-defined algorithms. Hence, the number of new blocks that are mined by a set of nodes α is proportional to the number of nodes in α.

2. Round and processing time: It proposes a $ROUNDTIME$ of 5 minutes, where the block confirmation time is slightly larger than 5 minutes. Compared to the Bitcoin blockchain, the block confirmation time is 10 minutes which cannot meet the requirement for frequent trading commands from participants. Furthermore, the confirmation time is longer than the Ethereum network, which is usually 15 seconds to ensure the minimal time frame for the charging and discharging process.

Thus, the system has chosen this value based on an evaluation of block propagation time in those networks. In the block processing time, the selection of the winning block with maximal benefit can be implemented without transmitting the complete block, and only after the winner is determined should the whole block be transmitted.

3. Data integrity: In the PEBT system, it relies on the transaction manager to encrypt the transaction contents into the hash value so that the transaction contents cannot be accessed by the third party. Without corresponding keys for the hash value, a potential attacker cannot alter the contents of the transaction. The decentralised nature of the blockchain features on the data unforgeable as all transactions require digital signatures and the only way to corrupt the network is to gain the majority (51%) computing power of the system resources.

5.4.2 Numerical Results

This thesis evaluates the performance of the proposed PoB consensus mechanism for PEBT system based on the Austrian residential power consumption data from Europe Network of Transmission System Operators for Electricity [ENT15]. A residential area with 200 households is considered to simulate the EV-integrated electricity trading system. The system assumes that the initial number of EV in the area to be 100. According to [LSL+17], there are mainly three charging types, up to 3 kW for slow charging, 7-22 kW for fast charging points, and 43, 50, or 120 kW for rapid charging units, where the charging speed depends on the connector types. It randomly generates the transaction demands according to the distribution of charging unit types and assign them to the charging and discharging transactions. The transactions are in chronological order in which the older transactions have a higher priority in the execution process.

Moreover, the EV charge connection status is modelled into two parts in a half-hourly manner according to the charging demand distribution throughout a day [oENL]. Then it randomly generates the EV connection profile where the number of transactions is the total number of connected EVs in each time slot. Moreover, the number of charging and discharging transactions are set to be 2:1.

The daily residential power consumption served as an input to the PEBT-enabled system with PoB consensus mechanism for simulation; more precisely as the consumption forecast for each round calculation. In each round iteration, PEBT system refers to the power consumption quantity from the last time slot and calculates the overall power consumption curve slope accordingly. In Fig. 5.3, it demonstrates the charging and discharging electricity demand changes after applying the PEBT system, where the system ability is inferred to optimise the 24-hour electricity flow. The blue bars are the charging and discharging demands sent from the EVs in each time slot respectively, where the green bars are the demand quantity after optimisation in the PEBT system.

The results are shown as aggregation quantity in each time slot (1 hour) in a day with arbitrarily generated power demands. For example, in hour 1, the simulation result shows the effect of the PoB consensus mechanism on the electricity transaction execution. Note that it is assumed that each transaction has a maximum waiting for two rounds which means that the transaction will be enforced to execute after two rounds to ensure that the system does not intervene EV owner's daily routine, so the total amount of transaction quantity is ensured in this process. The darker blue and green bars represent the demands before optimisation, where there are clear peaks at 07:00 - 09:00 and 18:00 - 21:00 corresponding to the work hours, reflecting market consistency.

As shown in Fig. 5.4, it depicts the objective function PF value from Section 3 to quantify the power fluctuation level with and without PEBT system. The black line with circle mark is the PF value without the PEBT system, where the value is calculated from the last 24-hour power consumption profile with the electricity demands from EV charging and discharging. The red dashed line with asterisk mark is the PF value in a day which the value changes based on the different charging and discharging demands fed from the EV users. The PF value with the PEBT system is more stable and shows

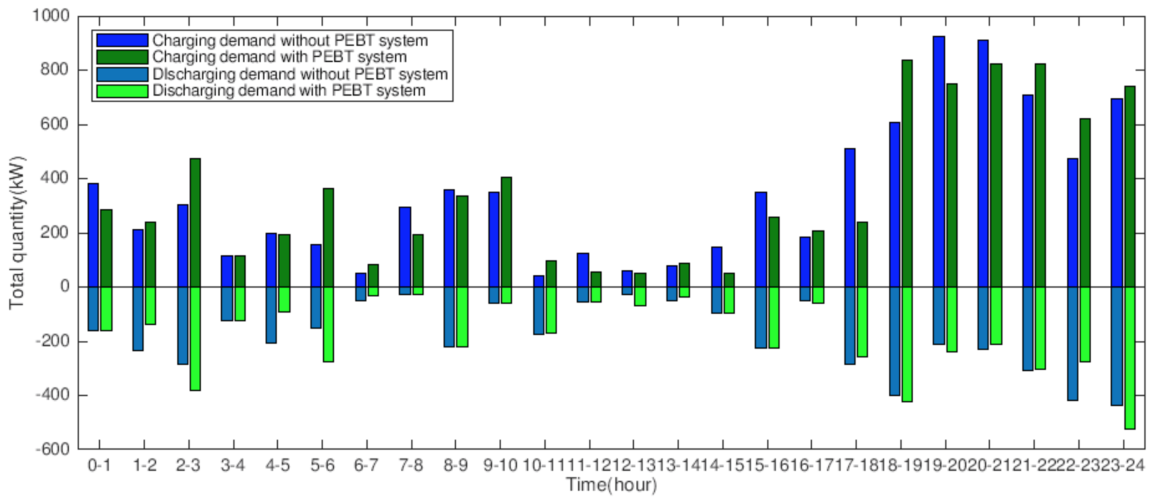

Figure 5.3: Charging and discharging demands collected from EVs in 24 hours.

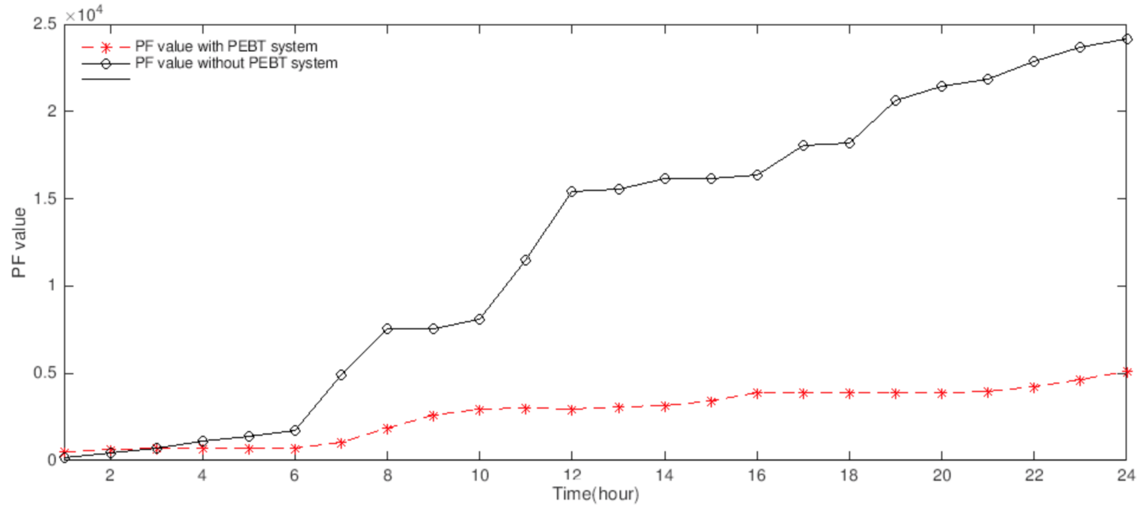

Figure 5.4: PF value of the overall power grid with and without PEBT system.

a much lower PF value by the end of the day. Moreover, the trend of the PF value change is generally growing as the number of EVs in the microgrid has limited capability to stabilise the system.

In the Fig. 5.5, it shows the overall power consumption, including the charging transactions that consume electricity, discharging transactions that inject electricity back to the grid and the residential power loads. According to Equation (5.7), the cube root of the PF value can be calculated, which is 48.5. With the proposed PoB consensus mech-

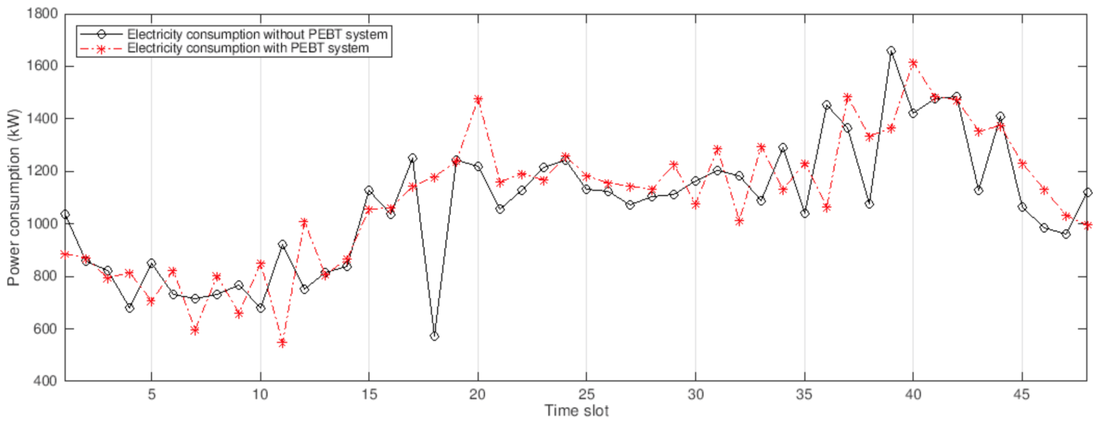

Figure 5.5: Power consumption profile in a residential area.

anism enabled the PEBT system, EV can trade electricity through placing charging or discharging transactions to the market concerning their connection statuses, charging connector types and charging/discharging constraints. This enables the reduction of the overall power consumption fluctuation level where the optimised result PF with the proposed system is 32.4, which is 33.2% lower compared to the result without optimisation. The system uses the last time slot electricity consumption data to schedule the charging and discharging transactions have significantly flattened the overall power consumption curve, which will increase the stability of the smart grid. In this case, the cost for starting the subsidiary generators (power generators with less response time) to supplement the power consumption can be reduced.

5.5 Summary

The electricity industry is undergoing major evolutions that works far more than the infrastructure upgrade, where people focus more on renewable and sustainable energy. In this part, this thesis proposed a proof-of-benefit consensus protocol in the blockchain system and further presented the PEBT system that works with EV in the electricity market to minimise the power fluctuation in a day. By achieving the objective, the stability is enhanced with more flattened power consumption and the operation cost is accordingly reduced corresponding to the emergent situation operation. The state-of-art blockchain technology and the consensus mechanisms, including proof-of-work and proof-of-stake, are analysed so that the suitable application scenarios are identified. Then, the PoB is proposed along with the PEBT system to support EV participating in the electricity trading with local peers. Security analysis has shown that the proposed mechanism is capable of protecting the transaction execution against potential attacks and adapting to the electricity trading scenario. Simulation results present the charging and discharging demand changes using the PEBT system and further implies the capability of the proposed system in substantially decreasing the PF value.

The real dataset is used from Austrian households to analyse the customer electricity consumption behaviour and currently available charging speed types are adapted to simulate the proposed system. The PEBT system provides a brand-new way to practice the transactional energy market, and the blockchain technology not only decentralises the hierarchical power grid system but also increases the system security. In the future, it is necessary to implement the system in the blockchain platform to feed with real-time data in order to test its scalability and performance.

Chapter 6

Consensus Mechanism-Driven EV C&D Scheme

6.1 Overview

Various EV charging/discharging schedule optimisation strategies have been proposed to minimise the power grid load fluctuation level [WW13], which considers the load demand and V2G constraints to meet the pre-determined load target. In practice, the critical challenge in designing charging/discharging algorithm lies in the randomness and uncertainty of future events. It is necessary to develop online charging/discharging algorithms to deal with uncertain future events and make real-time decisions.

This chapter introduces the consensus mechanism-driven EV C&D scheme, which utilises the consensus protocol in the blockchain system to support automated and efficient scheduling. To realise power transactions between EVs and grid system, the market-based electricity trading system is envisaged to reduce the power agency dependency and realise the capability of peer-to-peer trading [LCLC18b]. Instead of directly applying an EV charging/discharging strategy to a central controller in the traditional power grid system, the blockchain-enabled power exchange system controls the electricity transaction using smart contracts which supports public audit and transaction execution. The proposed ePoB demonstrates that it achieves higher scalability while withstanding the Sybil attack.

6.2 Overall System Design

6.2.1 Design Principles

In a distributed environment, the infrastructure is supposed to provide transparency, accountability as well as scalability for the participants, where the multi-layered participants in the electricity trading process include power generators, electricity brokers, dealers, residential and business electricity buyers and sellers. In order to accommodate the EV charging scenario, the electricity exchange platform demands a huge volume of participants to trade independently. Thus, a permissionless blockchain is proposed to enable an accountable infrastructure for electricity exchange. To summarise, the distributed charging scheme should maintain an accountable source of transaction records and adapt to the constraints in the existing electricity exchange scenario in terms of both functional and non-functional requirements. The consensus mechanism enables an automated transaction process without a centralised authority to supervise the business conduct while ensuring the privacy of the transaction data, and if a dispute arises between buyers and sellers, the infrastructure should uphold accountability and fairness. Therefore, the design principles for a privacy-preserving electric vehicle charging scheme is outlined as follows.

1. *Scalability:* The consensus protocol should be able to support millions of participants to freely trade electricity in low latency and high throughput manner. For example, the Paxos-based consensus and BFT algorithms normally lack scalability. When the number of network nodes increases, the performance of the consensus process will decrease exponentially and crush potentially.

2. *Reliability:* The distributed system must be able to manage unfaithful actions and withstand malicious attacks. The process of transactions exposes the issues of single-point failure, hacking and regulatory policies. Thus trade-offs need to be made to build a reliable infrastructure.

3. *Confidentiality:* The protection against electricity data is crucial for preserving user privacy and enhancing system security. The transaction data should be carefully aggregated and encrypted in order to be transmitted in a secure and efficient way.

6.2.2 Network Model

An architecture overview of the EV charging process is proposed on the blockchain platform, as shown in Fig. 6.1. The upper block represents the public electricity exchange service network where external participants, including EV electricity buyers, sellers, electricity trading brokers, and deals are allowed to register for the transaction service. All the exchange demands (transactions) are sent to the validation nodes to perform the identity and validity checks for the transaction and order issuers. Then the transactions are encapsulated into blocks in the time stamp manner, where each block contains all transactions submitted in one confirmation time slot. All the transactions data are transmitted to the demilitarised zone, where each network in the distributed system has a gateway to communicate with the validator nodes.

The gateway nodes situate between the web-based transaction interface and the demilitarised zone, which provides protection of the data security where the encryption algorithm will be applied. Furthermore, the gateway isolates the blockchain network from the open-source Internet environment, where the telecommunication company provides the gateway service. In the network within the demilitarised zone, network peers proceed with the consensus protocol to choose the block with the highest benefit value and generate the new block, which is then broadcast to the network. Moreover, the consensus results will pass over back to the gateway nodes which sends to the public

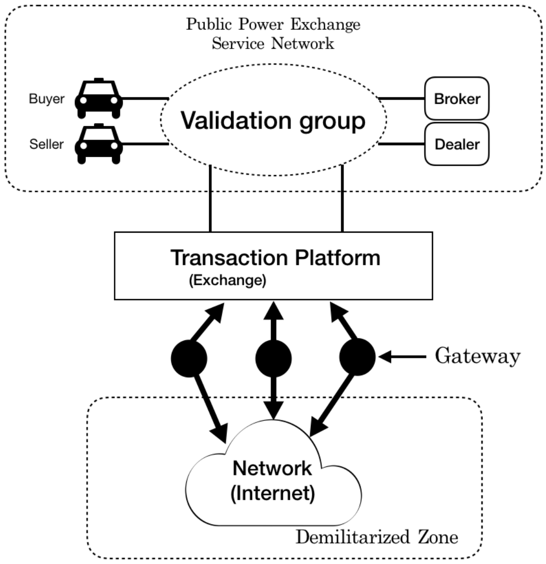

Figure 6.1: An overview of the distributed EV charging scheme with gateway date aggregation.

trade platform.

6.2.3 Enhanced Proof-of-Benefit Consensus Protocol

The Enhanced Proof-of-Benefit (ePoB) consensus protocol provides an efficient EV charging/discharging control on the blockchain platform. The participants in the consensus process are a tuple of $\langle U, G, P, A \rangle$, where U is a set of public nodes to submit buy/sell electricity orders; G is a set of gateway nodes, and P is a set of decentralised network peers to execute the consensus process. A is the public blockchain network consists of the components $U \cup G \cup P$. The completion of transaction execution in the ePoB consensus protocol is that the confirmed block is replicated to the distributed network. Transactions are broadcast across network peers P, and all the transactions submitted to or read from the network pass through gateway nodes G for encryption.

The algorithm assumes that all participants who need buying or selling electricity are required to perform ePoB consensus protocol to maintain and extend the blockchain. The matching and execution processes are implemented via grid network infrastructure

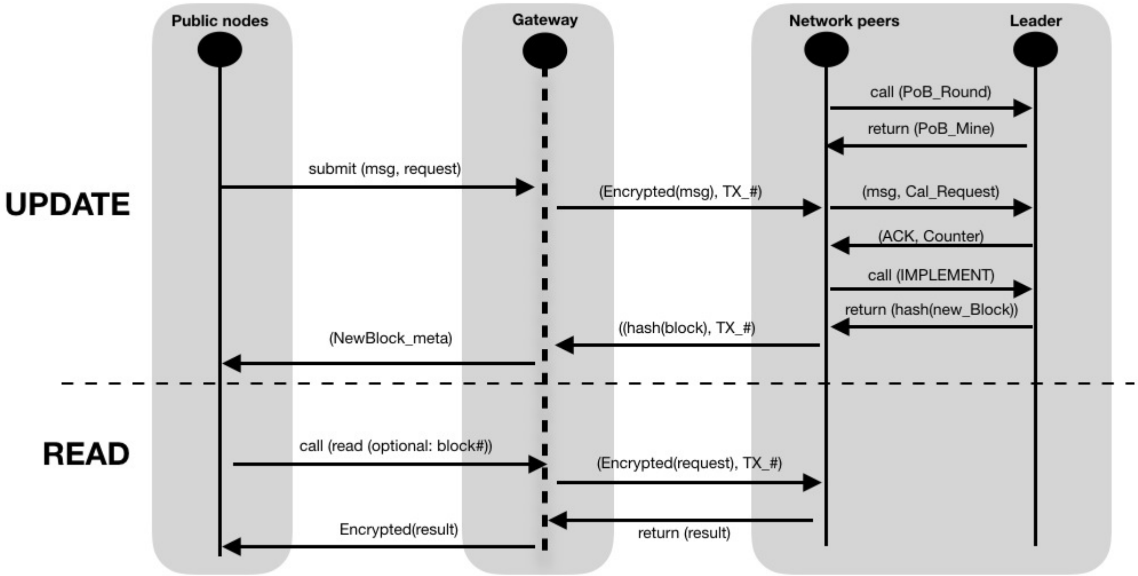

Figure 6.2: An overview of the distributed EV charging scheme with gateway date aggregation.

settings. A complete working logic can be concluded, as shown in Fig. 6.2. There are generally two types of operation on the blockchain-enabled electricity transaction platform, which are updated and read operations. The update operation requires the network choosing the leader for block confirmation to extend the blockchain, which will be discussed in detail in the subsection 6.4.2. For the read operation, any public node can look up information from the blockchain system by calling the *read* function, and it can access a particular block with its block ID. In the meantime, all the information will be encrypted via the gateway nodes to provide privacy for both the public nodes and transaction platform.

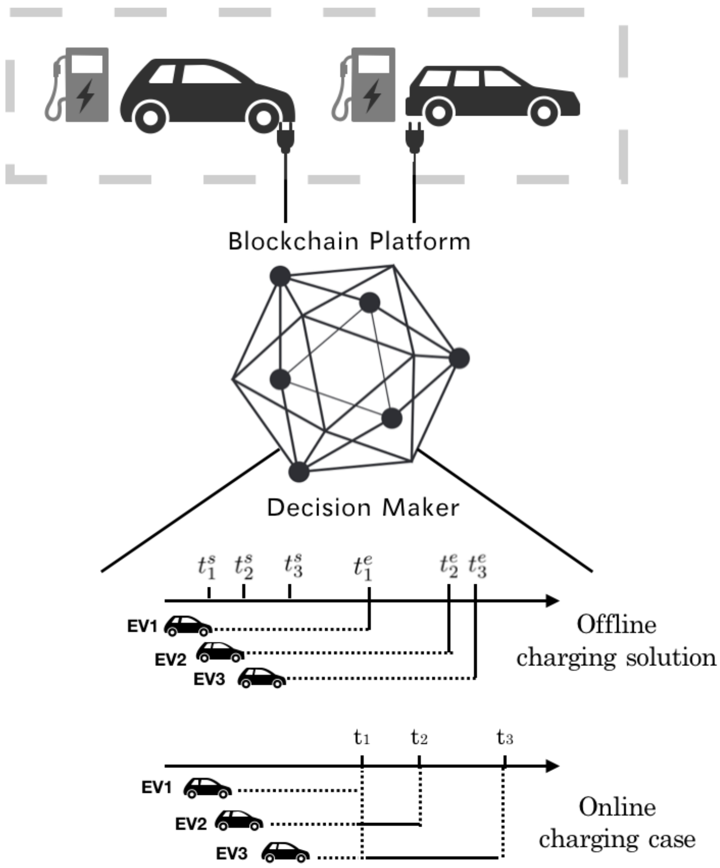

Figure 6.3: An illustration of electric vehicles charging and discharging on blockchain platform with offline and online charging/discharging solutions.

6.3 Problem Formulation

6.3.1 System Model

A blockchain-based power grid system is considered where EVs are required to submit charging or discharging demands to the blockchain platform, as illustrated in Fig. 6.1. A programmable charging installation can realise the charging/discharging process of EV, and the power transmission is instructed by the consensus mechanism executed by the smart contract, where more detailed blockchain operation can be found in [LCLC18b]. Suppose there are N EVs arrive during a time period T, which is considered to be 24 hours of a day in the model. It is denoted that the total charging rate C_t with respect to the charging rate (x_{it}) for each EV_i at time t:

$$C_t = \upsilon \sum_{i \in I_t} x_{it}, \tag{1}$$

where υ is the electricity charging efficiency in the power exchange process, and I_t is a set of charging EVs connecting to the charging port at time t. Similarly, the discharging rate of D_t is defined at time t:

$$D_t = \varpi \sum_{j \in J_t} x_{jt}, \tag{1}$$

where ϖ is the discharging efficiency taking into account transmission line loss and J_t is a set of discharging EVs connecting at time t. Due to the charging connecting port types and battery constraints, the charging rate (x_{it}) control is limited to the interval $x_{it} \in [0, U_i]$ and the discharging is set to be at a constant power emission O_j.

To formulate the EV charging/discharging problem, the EV_i starts charging/discharging is denoted at t_i^s and finishes at time t_i^e as in Fig. 6.3. It also needs to constrain the charging demand $CV_i \leq \min\left(U_i(t_i^e - t_i^s), B_{max}^i\right)$ where B_{max}^i is the battery capacity of EV_i and DV_j is the battery level for discharging EVs. Then the overall power consumption ($P_C(t)$) is defined considering the base load of the area as the following equation:

$$P_C(t) = \int_{t \in T} (C_t - D_t)\mathrm{d}t + P_{BL}(t), \tag{3}$$

where $P_{BL}(t)$ is the base residential power consumption excluding the electricity charged to or discharged from EVs. Accordingly, the optimisation problem for minimizing the PFL to achieve load flattening is then be formulated as follows:

$$\min_{x_{it}, x_{jt}} \int_0^T \Big(P_C(t) - P_C(t-1)\Big)^2 \mathrm{d}t \tag{4}$$

$$\text{s.t.} \quad \int_{t_i^s}^{t_i^e} x_{it} \geq CV_i, i = 1, 2, ..., N, \tag{4a}$$

$$\int_{t_j^s}^{t_j^e} x_{jt} \leq DV_j, j = 1, 2, ..., N, \tag{4b}$$

$$0 \leq x_{it} \leq U_i, i = 1, 2, ..., I, t \in [t_i^s, t_i^e]. \tag{4c}$$

If the EV profiles such as t_i^s, t_i^e, CV_i, and DV_j are submitted to the blockchain platform non-causally before each round time, the above formulated can be approved as a convex optimisation problem which can be solved using interior point method [Gra94]. However, the complete EV profile cannot be fully revealed until the EV has connected to the charging port, which is the randomness in this process. In order to make a real-time decision, an online algorithm will allocate power transmission rate for EV charging and discharging with the causal information.

6.3.2 Online EV power transmission model

As the discussion above, if the decision-maker (scheduler) has the full knowledge of EV non-causal information, the system can achieve optimised objective value. In an online EV charging/discharging mode, the scheduler only possesses the charging profile of EVs which arrive upon or before time t, and it does not respond to any future information. Based on the current EV profiles, the scheduler can make a real-time decision on the charging rate x_{it} and the discharging EV profiles corresponding to x_{jt}. It denotes Υ_{ON} as the overall PFL obtained from the online EV charging/discharging algorithm, and Υ^*_{OFF} as the PFL calculated from the optimal offline solutions with all noncausal information. Intuitively, it can infer that the PFL value from the online algorithm $\Upsilon_{ON} \geq \Upsilon^*_{OFF}$ as Υ^*_{OFF} is the theoretical optimum of this minimisation problem. In order to achieve an efficient charging/discharging scheme to benefit the overall grid system, the performance is guaranteed compared with the optimal solution by introducing the competitive ratio.

The competitive ratio is the worst-case performance measure which demonstrates the worst-case performance of an online algorithm compared with the available optimal solution [BCPK09]. The proposed ePoB is a c-competitive optimisation problem if the following equation holds with a constant ε.

$$\Upsilon_{ON} \leq c * \Upsilon^{*}_{OFF} + \varepsilon. \tag{5}$$

6.4 ePoB Algorithm

6.4.1 Model transformation

When considering an online charging case as illustrated in Fig. 6.3, instead of considering the charging/discharging start and end time (t_i^s and t_i^e) in sequential order, the time instants are relabelled to transform the offline charging solution into an event-driven online scheduling algorithm. Each time instant represents either arrival or a departure of EVs, where each event during time T generates a time label. The scheduling time interval is divided into two types where the first is all the current and past EV charging profile known by the scheduler and the second is the time for receiving causal information. Let κ be the entire set of time intervals' indices from total time period T, and δ_k be the length of the k^{th} interval. Also, it is assumed that the charging rate of each EV i remains constant in k^{th} interval, which is denoted by x_{ik}. Also, let $\phi(i)$ be the set of indices of time intervals that EV i connects to the charging port.

It considers a specific time instant t_θ when the scheduler has the information of all current parked EVs, i.e. I_{t_θ}. The departure time of EV $i \in I_{t_\theta}$ is represented by a sequence of its departures, which is denoted by $t_{\theta 1}$, $t_{\theta 2}$, ... Then at the point of time t_θ, it has the following definition to formulate the online scheduling problem. Let $\overline{\kappa}(t_\theta)$ be the total set of indices of intervals, $\overline{\delta}_k(t_\theta)$, $k \in \overline{\kappa}(t_\theta)$ as the length of k^{th} interval.

And $\overline{I}(k, t_\theta)$ denotes a set of EVs that are already connected before time instant k and will still connect to the charging port at interval k, $k \in \overline{\kappa}(t_\theta)$. $\overline{\phi}(i, t_\theta)$ denotes the set of indices of time interval that EV i will connect to the charging port. This algorithm still adopts the charging rate x_{ik} of EV i in the interval $k \in \overline{\kappa}(t_\theta)$, then the problem (4) can be transformed to the following discrete time optimisation problem:

$$\begin{aligned}\min_{x_{ik}, x_{jk}} \sum_{k \in \overline{\kappa}(t_\theta)} \Bigg[& \sum_{k \in \overline{\kappa}(t_\theta)} \big(\upsilon \sum_{i \in \overline{I}(k,t_\theta)} x_{ik} - x_{i_{k-1}}\big) - \\ & \sum_{k \in \overline{\kappa}(t_\theta)} \big(\varpi \sum_{j \in \overline{I}(k,t_\theta)} x_{jk} - x_{j_{k-1}}\big) + \\ & \big(P_{BL}(k) - P_{BL}(k-1)\big)\Bigg]^2 \overline{\delta}_k(t_\theta),\end{aligned} \tag{6.6}$$

$$\text{s.t.} \qquad \sum_{k \in \overline{\phi}(i,t_\theta)} x_{ik} * \overline{\delta}_k(t_\theta) \geq \overline{CV}_i(t_\theta), i \in I_{t_\theta}, \tag{6a}$$

$$\sum_{k \in \overline{\phi}(j,t_\theta)} x_{jk} * \overline{\delta}_k(t_\theta) \leq \overline{DV}_j(t_\theta), j \in I_{t_\theta}, \tag{6b}$$

$$0 \leq x_{ik} \leq U_i, i = 1, 2, ..., N, k = 1, 2, ..., \overline{\kappa}. \tag{6c}$$

$\overline{CV}_i(t_\theta)$ is the residual demand to be satisfied for EV i at the time instant t_θ and $\overline{DV}_j(t_\theta)$ is battery requirement for discharging its power from the EV j. Based upon the above formulated online optimisation problem, it is assumed that $\widehat{x_{ik}}(t_\theta)$ and $\widehat{x_{jk}}(t_\theta)$ are the optimal solutions from the current available EV profiles. However, the formulated problem dismisses the future demand by assuming no future arrivals, where the PFL calculated tends to be smaller than the optimal offline solution. Hence, in the proposed ONPoB consensus mechanism, it improved the performance of the scheduler by setting an appropriate value of the competitive ratio.

6.4.2 Proposed ePoB Consensus Mechanism

ONPoB consensus mechanism accepts the charging and discharging demands from EVs and generates the benefit number λ for the blockchain system. Participants who are the EV drivers are required to perform the standard routine to maintain and extend the blockchain. The calculation process for solving the overall benefit problem is completed in each node's local network, and the result is uploaded along with the proposed consensus mechanism protocol. As described in Table 6-A, the mechanism composes of mining round preparation and mining execution process. Each node in the network prepares to mine on a specific chain by calling the function $ONPoBRound$ and passes the latest block in the network. The mining process is executed after waiting for a specified round time when the nodes call the function $ONPoBMine$ to mine a new block. The node passes the header of the latest block and the last block to be extended ($previousBlock$). Then a benefit number is generated based on the proposed scheme with online optimisation process in the local network, which will be used to determine the winning block with transactions to be executed in the next round.

A higher benefit number means that the charging and discharging schedule results have a more positive effect on the load flattening. Furthermore, a monotonic counter is used to prevent concurrent invocations between the network peers. In the benefit calculation process, it denotes $\widehat{S_t}$ as the sum of charging rate and $\widehat{DS_t}$ as the sum of discharging rate at time t_θ. As future events need to be considered for EV arrivals and departures, the algorithm updates the charging profiles ($\overline{I}(k, t_\theta)$, $\overline{\phi}(i, t_\theta)$) of the current EVs and re-calculate the charging rate due to the change of constraints. Then it can obtain a new charging/discharging schedule by solving the updated problems corresponding to the change of EV profiles. Moreover, the network peers adopt the generated benefit value to continue mining the block.

The blockchain is extended via the consensus protocol that ensures a common and unambiguous ordering of transactions and blocks. Furthermore, the consensus proto-

Table 6-A: ONPoB consensus mechanism primitives

Parameter initialisation

$counter \leftarrow MonotonicCounter()$
$roundBlock \leftarrow$ **null**
$roundTime \leftarrow$ **null**

end function

---

function ePoBRound($block$**)**

$roundBlock \leftarrow block$
$roundTime \leftarrow GetLocalTime()$

end function

---

function ePoBMine($header$**,** $previousBlock$**)**

$t_\theta = previousBlock.time$, and calculate $\overline{\delta}_k(t_\theta)$
Update $\overline{I}(k, t_\theta)$, $k \in \overline{\kappa}(t_\theta)$, $\overline{\phi}(i, t_\theta)$, $\overline{CV}_i(t_\theta)$,
$\overline{DV}_j(t_\theta)$, $\forall i \in \overline{I}_{t_\theta}$.
Solve problem (6) for the optimal solution $\widehat{x_{ik}}(t_\theta)$ and $\widehat{x_{jk}}(t_\theta)$,
$\forall i, j \in \overline{I}_{t_\theta}$.
Set $\widehat{S_t} = \min\left(c * \sum_{i \in \overline{I}_{t_\theta}} \widehat{x_{i1}}(t_\theta), \sum_{i \in \overline{I}_{t_\theta}} U_i\right)$,
$\widehat{DS_t} = \max\left(c * \sum_{j \in \overline{I}_{t_\theta}} \widehat{x_{j1}}(t_\theta), \sum_{j \in \overline{I}_{t_\theta}} (\overline{DV}_j / O_j)\right)$,
$\widehat{x_{i1}}(t_\theta) \geq 0$, $\forall i \in \overline{I}_{t_\theta}$.
$\lambda = \frac{1}{\sum_{k \in \overline{\kappa}(t_\theta)} (\upsilon(\sum_{i \in \overline{I}(k, t_\theta)} x_{ik} - x_{i_{k-1}})) - \ldots}$
$\frac{1}{\sum_{k \in \overline{\kappa}(t_\theta)} (\varpi \sum_{j \in \overline{I}(k, t_\theta)} x_{jk} - x_{j_{k-1}}) + (P_{BL}(\theta) - P_{BL}(\theta - 1))}$
Restart the next mining cycle
$counter \leftarrow MonotonicCounter()$
$return(\lambda, null)$

end function

---

col also guarantees the integrity and consistency of the blockchain across distributed nodes. The consensus mechanism is evolved with application requirements, and poor choice/design of a consensus mechanism will inevitably render the blockchain platform useless, thereby compromising the performance. The proposed ePoB consensus protocol is deployed on the public Ethereum blockchain by executing the Ethereum virtual machine on the QuorumChain. The smart contract on the blockchain is implemented by open-source agreements, which is used by the ePoB consensus protocol to validate blocks. In Table 6-B, it presents a comparison of consensus protocols regarding the features of the performance.

Table 6-B: Comparison of blockchain consensus mechanisms

	PoW	PBFT	ePoB
Blockchain type	Public	Private	Both
Transaction finality	Probabilisitic	Immediate	Probabilistic
Transaction rate	Low	High	High
Trust model	Untrusted	Trusted	Semi-trusted
Cost of participation	Yes	No	No
Nework scalability	High	Low	High
Adversary Tolerance	$\leq 51\%$	$\leq 33\%$	$\leq 51\%$

The ePoB consensus protocol is designed for EV charging and discharging that the blockchain type is governed by the EV drivers. To extend the usability of the protocol, this protocol considers the user type of prosumers in the future. Hence, the blockchain type is set to be both permission, and permissionless depends on the application level. The transaction finality indicates whether the transaction once added to a block is considered as a confirmed transaction in the blockchain. The PoW and ePoB consensus model compete for the leader election by solving the puzzles where it is to find the best benefit number λ in the ePoB. This leads to a probabilistic transaction finality model where blocks need to wait for being confirmed and finalised. As for the transaction rate, the PoW has to spend a significant amount of time to solve the cryptographic puzzle so that the transaction rate is comparative low, where the PBFT and ePoB follow the standard consensus reaching algorithm so that the transaction confirmation is expected to support high transaction rates.

The trust model determines if the participating nodes in the blockchain have to be trusted or not. In PoW and ePoB, nodes can be untrusted as long as the mechanism reaches the consensus based on computational work where peering nodes have to be known and registered to be involved. The consensus will not be affected if there are 51% nodes are not adversarial in the PoW. In the PBFT, each node should make sure bugs in the network are less than 33% to maintain the consensus process integrity. Henceforth, regarding the network scalability, the PBFT consensus mechanism is not scalable due to the massive amount of overhead where the largest peer number is 20 in the theoretical sense.

6.5 Simulation results

6.5.1 System Analysis

This part analyses the blockchain-based privacy-preserving charging/discharging system based on the distributed system properties, gateway encryption performance and grid network performance in general.

6.5.1.1 Validity

The consensus protocol is designed for EV charging and discharging scenarios which ensure the high performance of block extension and low delay for transaction execution. This subsection will analyse the validity of the consensus protocol and the performance under different parameters.

In our privacy-preserving EV charging scheme, the ePoB consensus protocol chooses the leader to proceed blockchain extension. Before generating a new block, the network peers in the demilitarised zone prepare the mining process which awakes the idle nodes. Therefore, the *validity* property lies on the leader selection and network mining process.

Each network node selects the transactions in its buffer after receiving the return result from the function PoB_Mine. The network validator's (node's) selected transactions are capsulated into a block without revealing its transaction contents to peer validators. Each network validator also checks each transaction against its transaction buffer. If it finds the same benefit number generated from the transaction block, it puts a count on the transaction block. Then it broadcasts the transactions and the counts to the network from which the leader is the validator with the highest count.

Assume that the faulty nodes are less than 50% of the total n nodes in the demilitarised zone. As the validators are selected based on the highest benefit value, which is higher than the probability of picking a random non-fault node, the majority of counts from the validator group can ensure the correctness of the selected transactions with an overwhelming probability. Suppose the number of network validators is N_p. The system and blocks are safe and legitimate as long as there more than $N_p/2+1$ peers are working effectively.

Proof: Assume that illegitimate blocks can be approved and signed. As a leader must obtain more than $N_p/2+1$ counts to produce a valid block, under the circumstances that the number of the legitimate validator is greater than $N_p/2+1$, the legitimate validators will not sign the invalid block. Thus, the number of signatures of illegal block is at most $N_p-(N_p/2+1)=N_p/2-1$. Therefore, the result is contradicted to the assumption, and the original proposition is correct.

6.5.1.2 Protocol performance

The ePoB consensus protocol is implemented with privacy-preserving gateway encryption in Python and Java code. The consensus process is stimulated by deploying smart contracts on the Ethereum platform, and the transactions are auto-generated data entry with electricity demand-type, price, and quantity. In order to evaluate the performance of the implementation of the electricity exchange system, the simulation program sent transactions to the network from the public power exchange service network on EC2 virtual machine. Then the protocol performance evaluation is based on each block validation time and the final transaction confirmation time. Furthermore, the analysis of the processing speed of the consensus protocol is presented by comparing the perceived latency by clients with different consensus protocols.

The proof-of-benefit consensus protocol is designed to accommodate a large volume of electricity orders from the public and confirm the transaction to extend the blockchain.

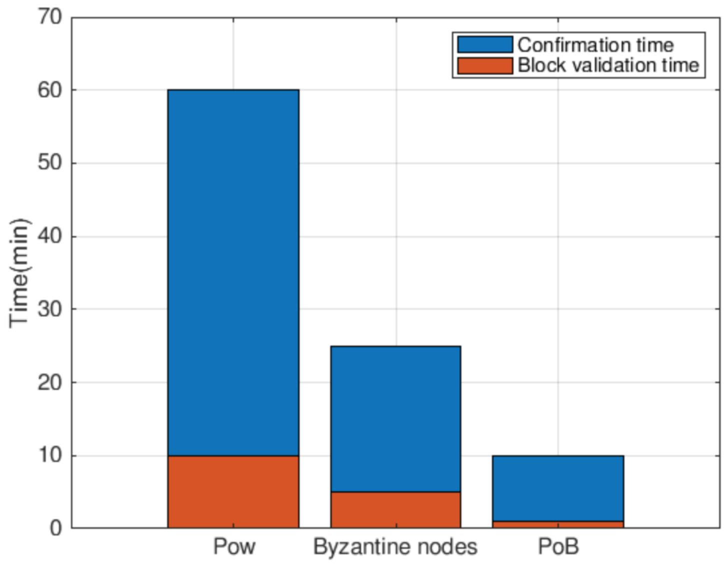

Figure 6.4: Transaction validation time comparison between PoW nodes, Byzantine nodes, and ePoB network peers.

Based on the evaluation information in the Bitcoin network, it uses PoW consensus protocol to mine a new block where each block is generated around 10 minutes based on the current network capacity as shown in Fig. 6.4. Also, the transaction to be confirmed within the whole network takes about six blocks generated and confirmed, which is around 60 minutes. The Byzantine nodes from the PBFT consensus protocol use a transaction pipeline to exchange transaction message, where the block confirmation time is highly dependent on the number of validators. Henceforth, the comparison is based on the same number of validators (15) with a constant transaction throughput which is 120 per second. In the ideal case of ePoB, the limited time for each block generation is set to be $ROUNDTIME$ of 60 seconds. Theoretically, the ePoB is based on the public blockchain where a valid block can be propagated to the whole network within 10 minutes to avoid soft fork with reference to the public PoW consensus protocol. In summary, the ePoB achieves a lower system transaction confirmation time which increases system throughput of the public electricity exchange system.

6.5.1.3 Security analysis

In order to evaluate the security of the enhanced ePoB consensus protocol in the electricity exchange system, the analysis process assesses the system performance against the commonly seen attack scenarios. First, the Distributed Denial of Service (DDoS) attack targeting the blockchain infrastructure is analysed. The DDoS attack is that the adversaries broadcast a large volume of transactions in order to flood the network. In the ePoB-enabled system, the gateway nodes can filter out the flooding messages based on the signature of the message senders, so that the network peers in the demilitarised zone are able to receive the filtered messages.

Then the Sybil attack against the system is analysed, where Sybil attack is a typical security attack that is common on the public blockchain platform. The adversary establishes many nodes in the blockchain network to participate in the consensus process so as to control the consensus result. Since the validators in our protocol choose the block based on the overall benefit number, the probability of the attacker to succeed is quite small unless they gain up to 51% nodes. In Fig. 6.5, it plots the accuracies of the consensus result with the different number of attackers in the system under Sybil attack. It can be observed that the consensus result accuracy is approximately 100% when there is no attacker. With the increasing number of the attacker, the accuracy achieves relatively high if the number of attackers is smaller than the number of validators in the network. Henceforth, it can obtain that the ePoB-based system effectively prevents most of the Sybil nodes from becoming validators.

6.5.2 Competitive ratio analysis

Our objective is to minimise the power fluctuation level to achieve load flattening by scheduling EV charging and discharging. In order to achieve a smart scheduling strategy, this part introduces the c-competitve optmisation problem where a proper c value should be set to improve performance with consideration of future events. In the subsection,

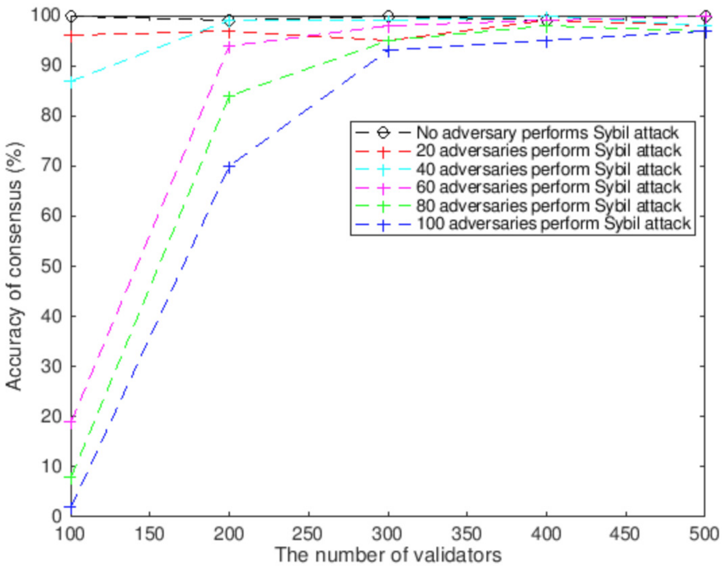

Figure 6.5: Consensus result accuracy comparison with respect to different number of attackers performing Sybil attacks.

it shows that the ePoB is 2.39-competitive using an amortised local competitiveness analysis with a potential function Ξ with respect of time t. The current time is denoted as τ_0. From the last section, the sum of charging and discharging rates are denoted by $\frown{S}$ and $\frown{DS}$ respectively. Then the optimal offline solution for the current total charging and discharging rates are S^* and DS^* respectively. In order to make the ePoB c-competitive, it is sufficient to prove the following inequality holds:

$$\begin{aligned} &2\Big[\upsilon(\frown{S}_\tau - \frown{S}_{\tau-1}) - \varpi(\frown{DS}_\tau - \frown{DS}_{\tau-1}) + \big(P_{BL}(\tau) \\ &- P_{BL}(\tau-1)\big)\Big] + \frac{\mathrm{d}\Xi}{\mathrm{d}\tau_0} \leq 2c\Big[\upsilon(S^*_\tau - S^*_{\tau-1}) - \\ &(DS^*_\tau - DS^*_{\tau-1}) + \big(P_{BL}(\tau) - P_{BL}(\tau-1)\big)\Big] + \varepsilon^*, \end{aligned} \tag{6.7}$$

where $\forall \tau_0 \in [0, T]$ and ε^* is constant. Take the above inequal integral over the whole considered time period T on both sides, it can be seen that the LHS is the power fluctuation amount produced by the proposed ePoB consensus mechanism and the RHS is the PFL produced by the offline algorithm with a constant $c * T\varepsilon^*$, which is consistent with definition for c-competitive optimisation problem.

In order to perform the competitiveness analysis, it is obvious that the values of $\widehat{DS}$ and DS^* are the absolute values of the charging rates from the proposed ePoB algorithm and optimal offline solution. Without losing the generality, it denotes $\widehat{S}$ and S^* in the following context for the sum charging and discharging rates to complete the analysis. For any $t_0 \leq t^{'} \leq t^{''}$, let $d(t^{'}, t^{''}) = \max(0, \widehat{S}(t^{'}, t^{''}) - S^*(t^{'}, t^{''}))$, where $\widehat{S}(t^{'}, t^{''})$ and $S^*(t"', t^{''})$ are the total remaining demand of EVs whose scheduling deadlines are between $[t^{'}, t^{''}]$ and $d(t^{'}, t^{''})$ denotes the amount of additional demand left for the ePoB algorithm to schedule with deadline in $(t^{'}, t^{''}]$. Then a sequence of critical times $t_0 < t_1 < t_2 < t_n$ is defined, where t_1 is the latest time such that $\frac{d(t_0,t_1)}{(t_1,t_0)}$ is maximised. Hence, if t_i is earlier than the latest deadline, let $t_{i+1} > t_i$ be the latest time that maximises $\frac{d(t_i,t_{i+1})}{(t_{i+1}-t_i)}$ and it refers to the interval $[t_i, t_{i+1}]$ as the critical intervals. Let g_i denotes:

$$g_i = \frac{d(t_i, t_{i+1})}{(t_{i+1} - t_i)}, \tag{8}$$

where the physical meaning of g_i is the power exchange (charging/discharging) intensity. Note g_0, g_1, ..., g_T is a non-negative strictly decreasing sequence, $g_i \geq g_{i-1}$, and the quantities of t_i and g_i depends on the current time t_0 and might change overtime. Based on the above definitions, it can be obtained with the following inequality:

$$cg_0 \leq \widehat{S} \leq c(g_0 + S^*). \tag{9}$$

Henceforth, the potential function Ξ can be defined as:

$$\Xi = \beta \sum_{i=0}^{T} (t_{i+1} - t_i) * g_i^2, \tag{10}$$

where β is a constant to be optimised. And notice that $\Xi(0) = \Xi(T) = 0$ holds since the load is zero before any EV arrives and after the last deadline. From Equation (10), considering $\widehat{S}(\tau_0, \tau_1) \geq S^*(\tau_0, \tau_1)$, it can obtain that the upper bound for $\frac{\mathrm{d}\Xi}{\mathrm{d}t_0}$ is $\beta\Bigg(2g_0(S^* - \widehat{S} + g_0^2)\Bigg)$. Then take the result of $\frac{\mathrm{d}\Xi}{\mathrm{d}t_0}$ back to inequality (7), it therefore suffices to show the formulated online problem holds. Then using the numerical method in [BCPK09], it can obtain with a competitive ratio of 2.39 where β is 2.7.

6.5.3 PFL comparison

This part evaluates the performance of the proposed ePoB consensus mechanism by observing the power fluctuation level comparisons. The baseload is inferred from the Austrian residential power consumption data from Europe Network of Transmission System Operators for Electricity [ENT15]. The EV arrival pattern and charging connection status are modelled as two parts according to the charging demand distribution in system time of 24 hours [oENL]. A residential area with 200 households with an initial number of EV of 100 is considered. Furthermore, the length between two consecutive decision-making times is set to be 10 minutes which is also the block confirmation time of the proposed ePoB consensus protocol. The maximum charging rate U_i is set to be 50 kW for rapid charging units, and the discharging rate is set to be a constant of $15kW$ according to the charging port types [LSL+17]. In our proposed system, EV acts as a customer that drains energy from the system to satisfy charging demand but also a power supplier to discharge electricity back to the grid. The objective is to utilise the algorithm to minimise the power fluctuation level so that it can serve as an ancillary service of load flattening. It chooses the following algorithms to compare the performance of load flattening:

Offline Optimal: Assuming having complete knowledge of historical and current EV charging/discharging profiles and the future random data is also known for PFL computation.

Online Algorithm without Future Knowledge: Assuming that there are no future arrivals of EVs, it makes a decision purely based on the historical and current EV charging/discharging profiles.

Offline AdBEV: The expected values of future EV arrival are assumed to be known to make decisions [LCZ+18].

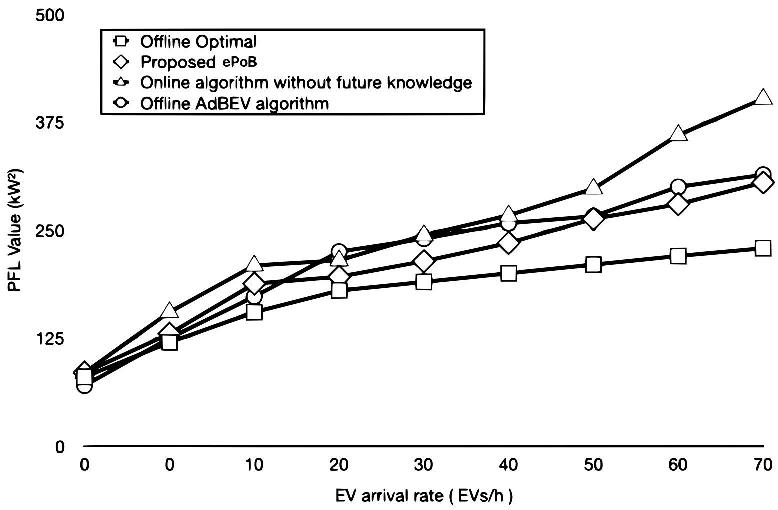

Figure 6.6: Power fluctuation level comparison with EV charging/discharging scheduling strategies.

As depicted in Fig. 6.6, the optimal offline algorithm produces the best performance for minimizing the power fluctuation level, which is consistent with theoretical analysis, because the optimal offline algorithm has the complete knowledge of EV profiles. The online algorithm has the worst performance in general as it does not consider non-causal information of future random data. Thus, the slope for the PFL value gets larger with the number of EVs arrival increasing since unexpected EV loads will further burden the grid system. As for the comparison between the proposed ePoB and the offline AdBEV algorithm, the ePoB outperforms the AdBEV algorithm in general by 3.5% with respect to the PFL value, especially under higher EV arrival rates. In summary, the ePoB consensus protocol is capable of scheduling EV charging and discharging as energy storage to flatten the system load.

6.6 Summary

This thesis proposed an ePoB consensus protocol for blockchain system, which is based on an online algorithm for scheduling EV charging and discharging to minimise the power fluctuation level. The analysis result has shown that the ePoB consensus protocol is more suitable than the existing consensus protocols in the scenario of EV scheduling to achieve load flattening. Furthermore, the simulation result demonstrated that ePoB protocol has better performance in minimizing the PFL value with increasing EV future arrivals. It is believed that the advancement of online EV scheduling algorithm and integration of blockchain technology will greatly improve the efficiency and resilience for our future grid system.

Chapter 7

Conclusions and Future Work

7.1 Conclusions

This thesis is dedicated to the EV charging and discharging scheme to flatten the power consumption profile in the smart grid. The proposed C&D schemes aim to minimise the power fluctuation level and enhance the resilience of the smart grid by providing ancillary services from discharging excess electricity to the grid. In order to improve the performance of the proposed schemes, blockchain technology is applied to enable a decentralised and secure electricity exchange platform for EV charging and discharging.

An optimised EV charging schedule algorithm with uncertain user-behaviours is proposed to minimise the power fluctuation level, where the peak and valley loads are mitigated. It models the EV staying-on-line and charging profiles based on the EV driver behaviour where EV connecting time, battery residual and SOC are analysed to schedule EVs. The simulation result demonstrates that the proposed algorithm substantially decreases the PFL index and ensures EV charging demand at the same time.

In order to deal with large volumes of EV C&D demands and frequent transactions, this thesis studies the blockchain technology and exploits the blockchain applications in the energy sector to decentralise the current grid system. This thesis develops a novel EV participation scheme on a blockchain-enabled smart grid system, and an AdBEV scheduling scheme is proposed to minimise the power fluctuation level which enables an autonomous and secure trading platform for the energy industry. The iceberg order execution algorithm is adopted from the financial sector to process the massive demand for scheduling EV charging and discharging. The AdBEV scheme also provides insight into the infrastructure of the transactional energy market with the blockchain technology, which further decentralises the smart grid system.

A novel peer-to-peer electricity trading system is further proposed for EV to optimise the charging and discharging schedule. This thesis proposed a proof-of-benefit consensus protocol in a blockchain system to stabilise the smart grid and presented the PEBT system that works with EV in the electricity market to minimise the power fluctuation in a day. By achieving the objective, the stability is enhanced with more flattened power consumption, and the operation cost is accordingly reduced in an islanding operation mode. Simulation results present the charging and discharging demand changes via using the PEBT system and further implies the capability of the proposed system in substantially decreasing the PF value.

A public power exchange service network that enables EV P2P electricity trading to charge and to discharge from the power grid is designed. Moreover, an ePoB is proposed to improve the protocol security and performance of the electricity exchange system. An online benefit generating an algorithm for choosing the winning block is proposed on the blockchain platform to handle the EV C&D loads to flatten the overall power load fluctuation. The simulation and analysis demonstrate that it achieves higher scalability than PoW and BFT-based consensus protocols. Also, the consensus protocol can withstand the Sybil attack while achieving lower power load fluctuation level.

7.2 Future Work

The potential areas for future works include:

- The current blockchain system supports a secure and distributed ledger, and the consensus mechanisms are designed for different types of applications. However, the security of the system relies on secure data transmission and management, where improvement could be made for data encryption in the network layer and authentication mechanisms for user identity detection. Integration with user identification with access priorities would further improve system security and flexibility.
- Besides the drawback as mentioned earlier in the public blockchain system, adaptability for multiple P2P trading systems should also be addressed. It is envisioned that the P2P trading electricity platform will rise in different regions and business sectors to support various scenarios from industrial to residential scale, where they might use public, private, consortium or hybrid blockchains. In this case, the interaction interface on cross-platforms should be carefully designed to accommodate different protocols and standards so that the trading system could be more operationally efficient.

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