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Techno-economic Analysis of Peer to Peer Energy Trading with Electric
Vehicles

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Abstract

One of the most promising technologies of reducing greenhouse gas emissions is the application of electric vehicles (EVs). Despite deliberated efforts by governments with various encouraging policies to promote EV uptakes, the numbers of EVs have not increased as quickly as expected. The growth of EV numbers is hindered by cost, accessibility of charging infrastructures and range anxiety.

P2P EV charging might be one of the solutions to mitigate these barriers to promote EV uptakes. P2P EV charging might be able to reduce running costs of EVs, to provide more charging infrastructures via obtaining energy from another individual EVs instead of power grid, and to encourage the installation of P2P charging infrastructures.

However, there have not been much work in the literature on the economic benefit analysis of P2P EV charging. The economic analysis is extremely important at this stage for relevant stakeholders (such as power Distributed Network Operators, EV charging infrastructure planner, Charge Point Operators).

In order to carry out the economic benefit analysis, this thesis took use of the main thought of activity-based model (ABM) to simulate and estimate EV batteries' remaining energy after daily travel, and then modified the supply demand ratio (SDR) P2P pricing model for trading prices calculation. The new combination of above two steps was unique and efficient for the calculation of P2P energy trading with EVs. This work also adopted Monte Carlo method using large number of simulations to reduce errors brought by the randomness of simulation cases. The economic benefits of EV energy buyers and sellers were evaluated at different supply and demand scenarios. The results showed that, with

the consideration of tariff difference between daytime charging and night charging (Economy 7 tariff) only, P2P EV charging is able to bring energy saving for EV energy buyers up to £3,32/month and bring energy income for EV energy sellers up to £5.48/month. Those reduced electricity costs, from P2P energy trading, although limited, would also encourage people's purchasing enthusiasm toward EVs, which would consequently help the uptakes of EVs in UK.

As P2P energy trading is a relevant new research area, this is an initial economic analysis of P2P EV charging. There are some limitations, e.g. the degradation of batteries, adoption of other P2P pricing models and EV charging from local renewable generators, etc. have not been considered. These will be carried out in future work in this area.

Key words: P2P; Electric Vehicles; Techno-Economic Analysis; P2P Trading Prices; Monte Carlo Method

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Chapter 1. Introduction

This Chapter will focus on introducing the basic background of peer to peer (P2P) energy trading with EVs, the aims and objectives of this work and the structure of this thesis.

Electricity is one of the basic needs in a variety of sectors such as communication, agricultural, technological, and any other production companies, leave alone its domestic uses. However, with the problems of global warming and air pollutions caused by traditional energy, the demand for renewable energy in various economic sector increases on a daily basis. Besides, convectional electricity supply of the renewable sources is facing a number of challenges that can only be solved by devolving the supply. Analyzing the challenges associated with the conventional energy supply system would provide the need to adopt new energy supply systems such as P2P. The energy trading using this P2P approach utilizes online platforms such as Piclo to carry out the energy trading activities. The fact that Piclo is relying on online approaches to perform its energy trading proves efficiency of the P2P energy supply. Online trade is one of the modern approaches reducing the drawbacks of physical trade such as time wasting and having to travel long distance to make an order. Through the online P2P trading platform, consumers are able to place their orders at the comfort of their homes, thereby reducing the disadvantages associated with traveling long distances. This shows that P2P is a better approach to energy supply compared to the conventional method. Although there're still large amount of current locomotives use fossil fuels to

propel their engines, changes in energy demand has been seen since the introduction of electric vehicles (EVs), indicating a future increase in the demand for electricity. The current efforts to maintain energy supply to various vehicles' consumers in various localities has necessitated the research of P2P energy trading. P2P energy trading involves buying and selling energy among energy generators and customers with an aim of minimizing the use of intermediaries in the energy supply.

The applicability of this kind of trade will be determined by analyzing advantages associated with the P2P power supply and the benefits that will bring to the EV manufacturing companies and also EV owners. The research will also extend to include economic factors to determine whether the P2P energy supply would be relevant in boosting countries' economies in a way of replacing fossil fuels with cleaner electricity.

Therefore, the aim of this work is to carry out an initial techno-economic analysis of P2P energy trading between EVs, investigating the technical aspects regarding the remaining amount of trading energy from EVs (which are available for P2P trading) and pricing models of P2P energy trading with EVs for economic analysis, as well as the economic benefits for EV energy's buyers and sellers who take part in this process of P2P energy trading.

The objectives of this thesis are as follows:

- 1) To develop a statistical model to mimic and calculate the remaining amount of energy, after daily travel, available for P2P energy trading between EVs.
- 2) To adopt an appropriate P2P energy trading pricing model for evaluating the cost benefit of P2P EV charging.
- 3) To carry out an initial economic analysis of energy bill savings for EV energy buyers and sellers when applying P2P energy trading between EVs, compared to the conventional P2G EV charging.
- 4) To analyze energy bill savings for EV energy buyers and sellers of P2P EV charging at different supply demand ratios (i.e. scenarios with different numbers of buyers and sellers).

The thesis is structured as follows:

Chapter 1: Introduces the background of the thesis as well as the aims and objectives.

Chapter 2: Provides a comprehensive review of correlative literatures, including the overview of EVs, P2P transactive energy trading systems, P2P pricing models, V2G energy trading's development, and P2P energy trading between EVs.

Chapter 3: Develops the methodology followed to activity based model and modified SDR pricing model as approaches to techno-economic analysis of P2P energy trading with EVs.

Chapter 4: Describes the results and findings from simulations, such as the energy demands predicted from SOC conditions, the P2P trading prices between EVs as well as the evaluation of economic profits to participants from this P2P energy trading process.

Chapter 5: Provides a discussion about the results and outlines the future works in the related areas.

Chapter 6: Concludes this study and analyzes the advantages and limitations of this work.

Chapter 2. Literature review

This chapter focuses on the literature review of the topic under discussion. This chapter starts with the overview of EVs and introduces the research questions of this project. Along each research question, this chapter reviews the state-of-the-art of the available models to mimic remaining energy of EVs, presents the literatures with existing P2P pricing models, summarizes the current P2P energy trading research and projects, and then reports the available literatures on P2P energy trading between EVs. The literature review would demonstrate the research background of P2P energy trading topics, and then point out the research gap at the possibility of P2P energy trading directly between EVs, which this work is aiming to solve.

2.1 Overview of electric vehicles

Pollution has been evidenced to cause the environmental effects such as global warming due to greenhouse effect (United Nations, 2015). One of the most promising technologies of reducing greenhouse gas emissions is the application of EVs.

The number of EVs in the world is growing rapidly because of environmental concerns. Economically, international market trends have responded positively to EVs with reports recording that since 2017, the EV stock has increased by 3 million and estimated to reach 125 million by 2030 (Statista, 2017).

Governments are also actively advocating for these eco-friendly vehicles. For example, as regard to the UK Government's Road to Zero strategy (HM Government, 2018), by 2050, almost every car and van in the UK will be zero-emission. In 2021, the UK Government published new deadline for EV uptakes, to support the transition to zero emission road transport and reduce emissions (Committee for Climate Change (CCC), 2021): the sale of new petrol and diesel vehicles will be ended by 2030; and all new cars and vans are expected to be fully zero emission at the tailpipe from 2035. As shown in Fig. 2-1, the number of ULEV (ultra-low emission vehicles) in the UK has increased about 4799% from 2010 to 2020, which shows the ambitious of UK government to encourage the uptake of EVs. The electrification of transport, therefore, presents opportunities for governments and the private sectors to contribute to eco-friendly systems and reduce pollution.

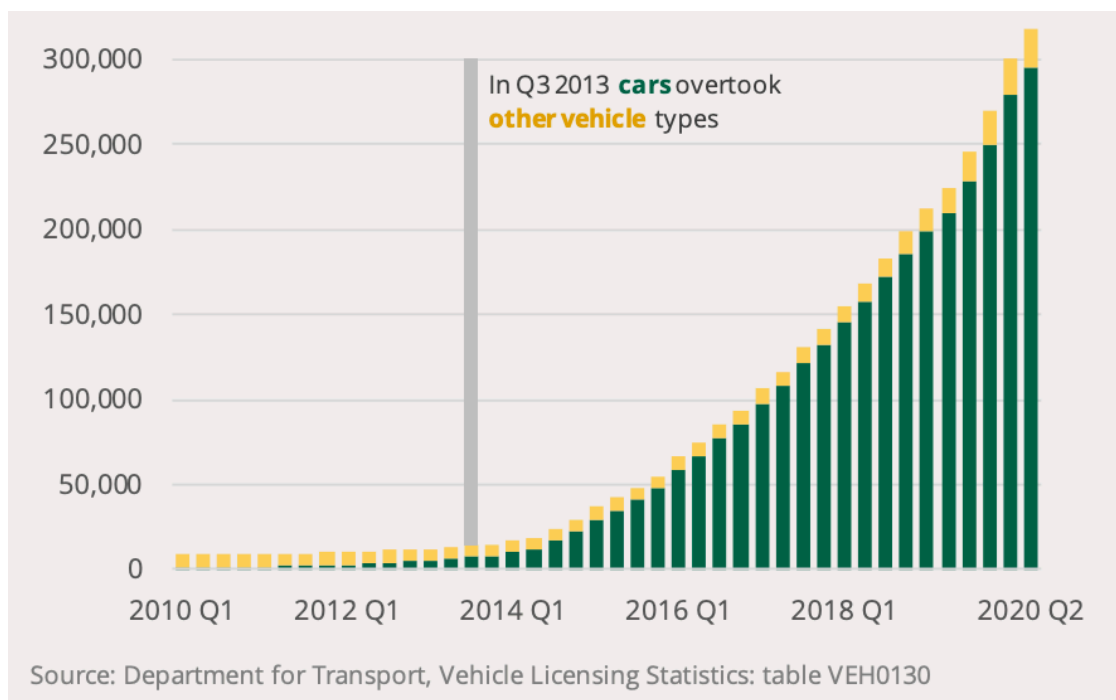


Figure 2-1 Quarterly number of licensed ULEVs in the UK

Despite the widespread campaigns and deliberated efforts by the government and the international bodies, the numbers of EVs have not increased as quickly as expected. The growth of EV numbers is hindered by cost, accessibility of charging infrastructures and range anxiety (Simpson et al., 2019).

P2P EV (Peer-to-peer Electric Vehicle) charging might present opportunities to mitigate these challenges, because P2P EV charging might be able to reduce running costs of EVs, provide more charging infrastructures via obtaining energy from another individual EVs instead of power grid, and encourage the installation of P2P charging infrastructures.

There have been a lot of researches and real-life demonstrations of P2P energy trading. Table 1 below shows some of the typical P2P energy trading pilot and commercial projects these years (Junlakarn S, 2022, etc.).

Table 1 P2P energy trading pilot and commercial projects

Country	Project	Year	Status	Main Contribution	Main technologies used
UK	Piclo (Mujeeb, A 2019)	2015	Completed, Pilot project	Matching the preferences of generators and consumers in the local community.	Online trading platform; Smart meter
USA	Brooklyn Microgrid (Mengelkamp, E. 2018; Brooklyn Microgrid)	2016	Ongoing, Pilot project	Enabling a local energy marketplace of prosumers and consumers by trading excess electricity within a localized area.	Blockchain-based P2P energy trading platform; Smart meter; Simple and easy to participate in electricity trading mobile applications.

Germany	Sonnen (available online)	2015	Ongoing, Commercial project	Stable power supply utilizing batteries and provision of surplus power pool.	Battery technology to store excess electricity for trading within the Sonnen community; Simple and easy to participate in online trading platform.
Netherlands	Vandebron (Dutch Energy Start-up Targets Small Producers, Politico.)	2014	Ongoing, Commercial project	Connecting the RE suppliers, prosumers, and generators via its own platform and establishing a local clean energy community.	Easy method to participate in electricity trading through web and mobile applications.
South Korea	Smart Energy Campus (Korea Smart Grid Association; ByungChul Kim, 2018)	2018	Ongoing, Commercial project	Enabling P2P energy trading model within the microgrid which trading across universities.	Energy storage system to store the energy produced for own use or sell to other consumers.
Malaysia	1st pilot project SEDA (Sandbox project, Yap, Y.H.; Tan, W.S. 2021)	2019	Completed, Pilot project	Enabling a local marketplace in Malaysia for multi microGrids p2p energy trading	Blockchain-based p2p energy trading platform; Smart meter.
Australia	Virtually settled p2p energy trading in existing grid-connected networks (Azim M I, 2020)	2020	Completed	P2P energy prosumers and customers can be benefited compared to the current feed-in-tariff and electricity retail prices, even though p2p traded quantities are regulated by the network operator.	Deploy virtually settled peer-to-peer energy trading in existing grid-connected networks without considering post-trading protection schemes; Test the p2p mechanism on a real low-voltage(LV) distribution network in Australia.
Japan	Blockchain-based p2p energy trading system in Higashifuji with real-life used PHEV and HEMS charge control (Matsuda Y, 2021)	2021	Completed, Pilot project	Combining blockchain-based p2p energy trading to suppressed the over-execution of transactions; demonstrating the possibility of actual energy flow of EVs controlled in Blockchain system.	Blockchain-based p2p energy trading system

However, these P2P energy trading mostly focused on energy trading between residential and business customers, distributed energy generators, battery storage, or a group of energy users in communities or microgrids. There are few research studies nor

demonstrations working on P2P energy trading just between EVs. So that there exists research gaps of studies focusing on the P2P between EVs --- if it's possible to sell the surplus energy in my EV's battery to others? A few research questions need to be addressed: 1) Is there a relevant model to represent the daily energy use of EVs, in order to obtain the remaining energy of EVs available for P2P energy trading? 2) When carrying out P2P EV charging, what P2P pricing models should we use? 3) How much economic benefits would the EV energy buyers and sellers will obtain when they carry out P2P EV charging? 4) What factors will affect the economic benefits of EV energy buyers and sellers?

2.2 Models to mimic the remaining energy of EVs after daily travel

Activity-based models (ABM) are models that are used to develop a predictive assessment of transportation needs through predicting activity schedules (T. Bellemans 2010). In ABM, the calculations of parameters used to develop the predictive analysis are derived from population demographic data of EVs and from periodic dedicative surveys. The application of such surveys incorporates an understanding of transport modes and their features, how to include the data in assessing mobility preferences of the demographic user groups (Matyas and Kamargianni, 2018). After the generation of a synthetic population, an activity schedule should also be generated. An activity schedule model consists of a household member's typical working day activities such as origin intended destination, reason for mobility, when the activity takes place, the mode of transport used among other attributes essential in describing a working schedule. The conglomeration of the data derived from these points of interest, an activity-based

model (ABM) can thus be established. The ABMs are, therefore, established on the simulation on the household members' acts individually.

The foundational concepts underlying the AB model assumes that drivers do not charge their vehicles every day, but rather charge them when they need to. This assumption leads to a predictive element of driver's time of charging and location. It is also observed that the time and location of charging vehicles heavily impact the peak demand for power with higher demand relating to a common time and place of charging. This finding is, however, different from the demands or energy. In fact, the energy consumptions of EVs are statistically similar to the total household energy consumptions. These inferences, for example, time and place are as factors of power demand, are considered in the AB model.

According to Baqueri (2019) the applications of the model can be used to study and analyse transportation demands in large cities. In the application of the project to this sphere, the model can present certain challenges for example overestimating trips within the assigned region hence completely sidelining the residents' activities outside the designated region. On the same note, the model also faces a risk of double representation of residents of a designated location. This is because the travelling patterns and trips can be included in the calculation although different in the sense internal trips and output from external trips can be calculated at the same time hence the double counting effect. The model can also be adjusted to include extensive study

areas that increases the household travel survey, synthetic population and ultimately reflecting on the running of AB model.

A stepwise guide to setting up a P2P energy trading system involves first simulating the mobility pattern of The Flanders region, which is in Belgium, using a model known as FEATHERS (Forecasting Evolutionary Activity Travel of Households and their Environmental Repercussions) model which is agent based (Tom et al., 2010). The FEATHERS model recognizes two main types of users: drivers who could perform all their daily schedules and trips and still have excess energy in their batteries, and drivers who had to have intermediate charging in between their daily schedules and trips.

2.3 Transactive energy trading systems of Vehicle-to-Grid

Transactive energy (TE) management and control involving P2P energy trading have become an increasingly popular topic. TE has a number of advantages as follows. Firstly, existence of a micro-grid created through P2P transaction energy achieves high costs optimization through reduced general costs, transport costs and providing more increased profit maximization (Ikpehai et al., 2016). Secondly, it has created a platform for energy producers to interact and transact energy. As a result, overdependence on the main grid as a source of power is greatly reduced (Chen, Sijie and Nian, 2017). Moreover, TE between peer to peer has the advantage of reduced waste of energy involved in transportation and distribution when energy is transmitted from one producer to another through the close network (Ting et al., 2013).

It is expected that large deployment of Electric vehicles could affect the distribution of the power grid leading to power loss, voltage drops, overloading of distribution cables and transformers and overall degrading the quality of power among other effects. One of the traditional methods proposed to reduce these effects during peak demands is the use of EVs to support the electric grid (known as V2G). V2G can be attained by developing a smart charging algorithm for all EVs that will reduce voltage deviation and power losses by filling electric demand valleys more easily as well as using base-load unit's better.

2.4 Peer-to-Peer pricing models

Some existing literatures mentioned P2P pricing models within a community micro-grid that informs investors and researchers on possible EV P2P energy trading prices (Long et al., 2017). Currently, research on relevant pricing models unique to EV's P2P energy trading prices still needs to be undertaken. More recently during a Power and Energy General Meeting held in Chicago, three representative paradigms of P2P energy trading markets were proposed (Long et al., 2017). These strategies were bill sharing, mid-market rates and an auction based pricing strategy with each one having its unique business model. The business model of the Bill Sharing model required every user pay the same amount for each kWh of energy consumed, and receives a different price for each kWh of energy exported. Concerning the Mid- Market Range (MMR), energy exchange price within participating peers would be at a value mid-way between the

buying price and selling price of electricity thereby simplifying the calculating loads though not sufficiently. The business model of the Auction-based pricing strategy uses existing auction markets for local energy demand and generation. In this strategy, each user provides an offer of their demand and generation of the product that are all collected at the end of bidding and using pre-defined on allocation of prices, the pricing strategy is developed (Long et al., 2017).

Besides the aforementioned methods, a more defined dynamic pricing model was developed for the operation of energy-sharing process founded on Supply and Demand Ratios (Nian, 2017). In this article, the author also considered the willingness of load shifting and a distributed iterative algorithm was set up for calculation of prices. The implementation of this design could easily be executed with normal configuration in the Smart Grid. The results of research showed that consumers in the P2P pricing model could achieve an effective cost saving model compared to dealing directly with the utility grid under the feed-in-tariff. However, the Supply and Demand Ratio method does not put into account power loss during sharing and still remains to be studied and researched.

2.5 Peer-to-peer energy trading with EVs

Peer to peer energy trading process become the more and more popular trend which led to another peer to peer trading system directly between vehicle and vehicle, different

from the previous ones (which only focus on energy trading between communities etc.), such as the vehicle-vehicle energy transfer in a smart grid system by Alvaro et al (2014). The main purpose of this research by Álvaro and colleagues was to decrease the cost of energy witnessed by some EV users who had to charge their vehicles during the day in order to satisfy their daily schedules and travel agendas. The project also sought to help reduce the impacts of charging on the electric grid. As postulated by Alvaro et al., some electronic vehicles with excess supply of energy in their batteries could be able to transfer the energy to other EV units that needed to be charged during the daily trips whereas the other users could actually directly from the main grid or alternatively buy from fellow EV users at a cheaper fee. To facilitate trading, interested buyers and sellers would have to do their own reconnaissance of the EVs around them at the same place and at the same time and collect the necessary information needed to complete a purchase. Since there is a possibility of these two drivers being at the same time and place during the day, it is therefore possible for both sets of drivers enlisted under the FEATHER system to trade the energy directly to one another, reducing interactions with the main power grid while at the same time offer a timely resource at a cheaper price. Results from analysis of this P2P criteria proved that it is possible to conduct cheaper energy trade. The prices of P2P trade mostly depended on the ratio between the buying and selling vehicles. The influence of main grid prices on the price of P2P was experienced at the moment in which the vehicles charge at the main grid.

Based on the above articles, some further extended researches also have done over

the topic of P2P energy trading with EVs. Alvaro-Hermana et al (2016) some extended reversions had been made based on the basic methodology. Firstly, a new consumption model was developed for different EVs, within which the energy consumption of each EV was based on a more realistic data rather than a constant number in (Alvaro et al., 2014). Secondly, the researchers also put into account the charging and discharging efficiencies of the batteries which reduced the benefits of the proposed energy trading systems. Lastly, mathematical calculation which based on travel-agendas from activity-based model to calculate the batteries' conditions during the whole day, could analyses the uniqueness and the efficiency of the P2P system. The results further explained that the proposed P2P energy trading system could affect the prices currently being paid by customers whose vehicle types requires intermediate charging and can also reduce the total daily cost of energy. The mechanisms of optimization of the P2P transactional price still need to be simplified. More explicated improvements need to be conducted on the optimization and evaluation of energy demands based on customers' travel agendas.

Besides, the emergence of blockchain-technology application in peer to peer electrical-energy trading also encourages the development of applying P2P process into energy trading (TM Kumar, 2021). Combined with smart contracts, blockchain-technology could provide secure tamper-proof records of energy trading transactions. According to report published by the International Renewable Energy Agency (IRENA, 2020), crucial enabling technologies that should be focused on to realize P2P energy trading include

renewable mini-grids, artificial intelligence and big data block-chain. In terms of appropriate business models, the agency presents community ownership models, pay-as-you-go models, and energy-as-a-service working models. These models have been shown to work in some countries for example community ownership in the SoLshare P2P trading platform in Bangladesh (UNCC, 2021) where SoLshare has installed small mini-grids that connects consumers allowing them to share electricity within the locality. The research finding of applications of these strategies presents viable opportunities for the EV sector towards developing P2P frameworks. Ahmed and Kim (2018) even conducted experiments in developing P2P trading systems in campus parking lots using frameworks composed of four main pillars: available energy, data acquisition and interpretation, communication systems and a market layer. Calculation algorithms were included in the research which realized that the profits realized through the trading depended on availability of trading vehicles, time of day and number of parking lots (Ahmed and Kim, 2018). Alexandros and Emmanouil (2020) proposed an offline and online scheduling algorithms for the charging of electric vehicles (EVs) in a single charging station (CS), which has available cheaper but limited energy from renewable energy sources (RES). In their scheme, vehicles are able to participant in vehicle-to-vehicle (V2V) energy transfers that are used to reduce the charging cost and increase the RES utilization. Moreover, Mohamed and Ahmed (2021) proposed a privacy-preserving vehicle-to-vehicle (V2V) energy trading scheme based on blockchain technology, in which scheme the privacy of both charging and discharging EVs could be protected. In this work, leveraging blockchain technology, they also carry out a privacy-preserving charging-station-to-vehicle (CS2V) energy trading scheme which are stated

to provide security and transparency without the need for a trusted third party. However, those application of blockchain based P2P energy trading technology has not considered for the aspect of EVs' energy trading, with most of them still limited to the trading between smart communities with devices, rather than EVs themselves.

2.6 Summary

Since one of the most promising technologies of reducing greenhouse gas emissions is the application of EVs. Despite deliberated efforts by governments and the international bodies with lots of encouraging policies to promote EV uptakes, the numbers of EVs have not increased as quickly as expected. The growth of EV numbers is hindered by cost, accessibility of charging infrastructures and range anxiety.

P2P EV charging might be the solutions to mitigate these barriers to promote EV uptakes. P2P EV charging is expected to be able to reduce running costs of EVs, to provide more charging infrastructures via obtaining energy from another individual EVs instead of power grid, and to encourage the installation of P2P charging infrastructures.

There have been a lot of research and real-life demonstrations of P2P energy trading. However, these P2P energy trading mostly focused on energy trading between residential and business customers, distributed energy generators, battery storage, or a group of energy users in communities or microgrids, few works are working on the direct

energy trading with EVs. Our research work is going to explore the possibility of applying peer to peer energy trading between EVs, trying to fill the above research gap to some extent.

Chapter 3. Methodology

This chapter will demonstrate the overall research methodology as shown in Figure 3-1, and then separately introduces each techno module to show how we modify and apply those models in order to analyze the economic benefits of P2P energy trading with EVs.

As shown in Figure 3-1, in our work, we would firstly apply the activity based model to develop a predictive assessment of transportation needs through predicting activity schedules of EV samples. Activity-based model is a tool to predict the travel agenda for each P2P participants, which would be a straightforward and intuitive approach to predict the activities agendas by directly mimic their daily travel time, distance and targets etc. In these part, firstly, the input parameters in the calculation are derived from population demographic data of EVs and from periodic dedicative surveys in UK, and the outputs would be state-of-charge of EVs batteries as well as energy demands and supply provided for P2P trading between EVs. Secondly, we would apply the P2P energy trading model for our case of study. The Supply-and-Demand Ratio (SDR) method would be modified and used in our study case, leading to the results of relationship between SDR with P2P trading prices. Thirdly, in the dashed box in Figure 3-1, we would carry out the calculation process of economic analysis of energy bill savings for EV participants who take part in the P2P energy trading process. We would first classify the EV samples as energy sellers, energy buyers and non-participants based on the results of energy demands which we get from previous activity based model. Next step we would assume that sellers and buyers would directly trade energy

with each other in the process of P2P with trading prices got from modified SDR pricing model. And then we would calculate the energy bills that sellers gained and buyers saved, with adopting Monte Carlo method to do large numbers of simulations to reduce random errors. Details of illustrations would be stated in Chapter 3.1 to 3.6.

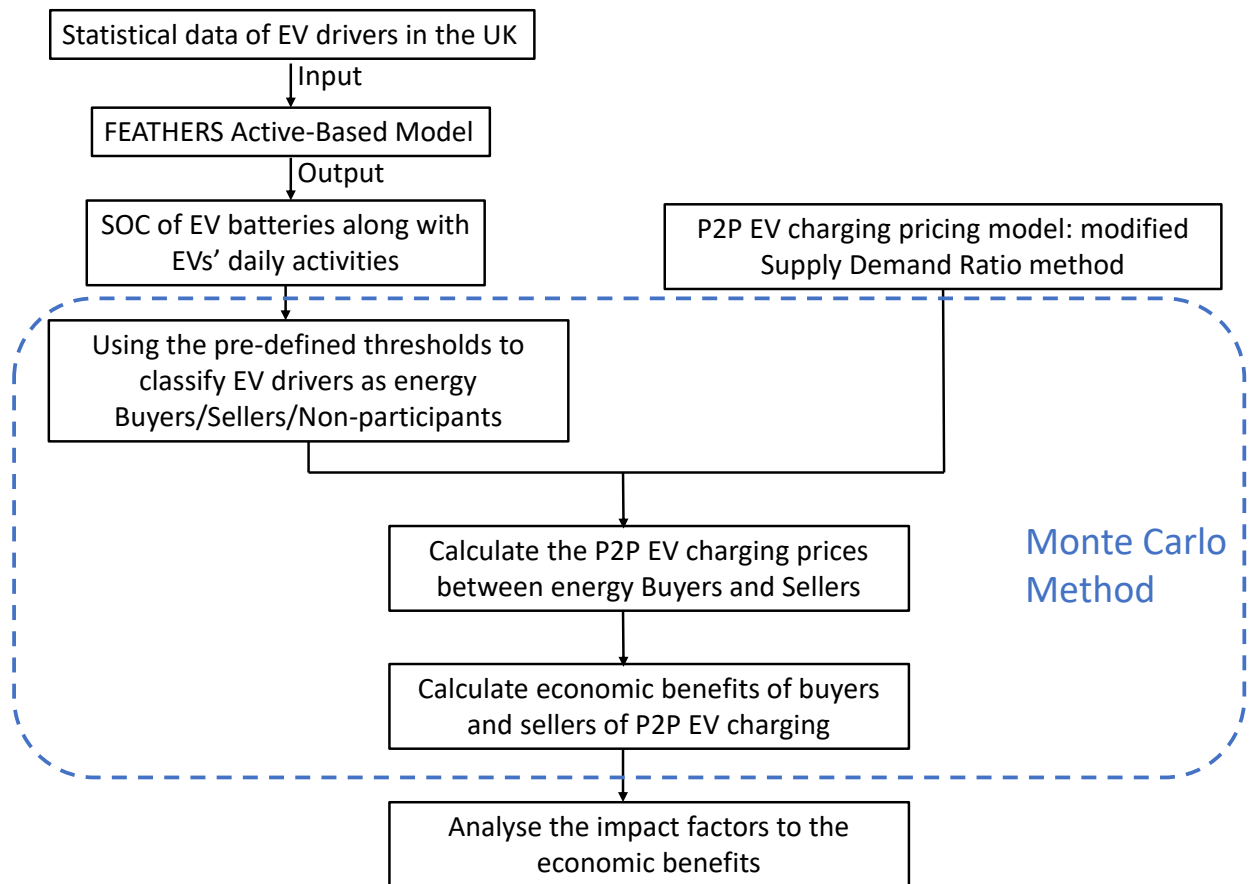


Figure 3-1 Framework of the techno-economic analysis of the P2P EV charging

3.1 FEATHERS activity-based models

Activity based models (ABM) are models that are used to develop a predictive assessment of transportation needs through predicting activity schedules. In ABM, the calculations of parameters used to develop the predictive analysis are derived from population demographic data of EVs and from periodic dedicative s surveys. To model medium size regions (Traffic Analysis Zones with an average area of 5 km^2) and external regions which in this case can be cities in the United Kingdom, the FEATHERS framework is most preferred for an activity-based model. The FEATHERS framework includes external origins of trips, establishment of a study area within the model, inclusion of a study area within the chosen destination (Baqueri et al., 2019).

In our work, we would like to use the basic scheme of FEATHERS activity-based model (ABM) in order to mimic and simulate the daily activities of EVs in UK. The flowchart of using FEATHERS ABM in our study case is shown in Figure 3-2. The inputs are based on averaged statistical data of EV drivers in the UK, and the expected output are state-of-charge (SOC) of EV batteries along with EVs' daily activities.

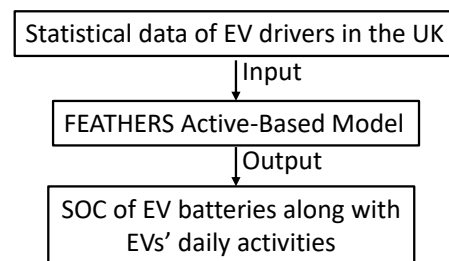


Figure 3-2 Flow chart of using FEATHERS activity-based model

Then we take two scenarios into consideration to calculate the amount of energy supplied and demanded, as well as generate SOC figures. The activity-based model avails sufficient information on specific individual schedule activities and trips such as motives and timing. For each scenario, we set the daily travel agendas for EV owners, as shown on Figure 3-3, based on activity-based model, and then calculate the following statistics of state-of-charge according to the above assumptions. As to Figure 3-3, one of the possible travel agenda shows here including charging/discharging activities with time and distances setting which based on activity-based model. To calculate the peak demand from the ABM model, two scenarios can be developed. These are:

- Scenario 1: people tend to charge immediately at low tariff period (12:00 midnight – 7:00am)
- Scenario 2: people tend to charge at distributed times so as to avoid the peak time, and maximum charging during the low tariffs.

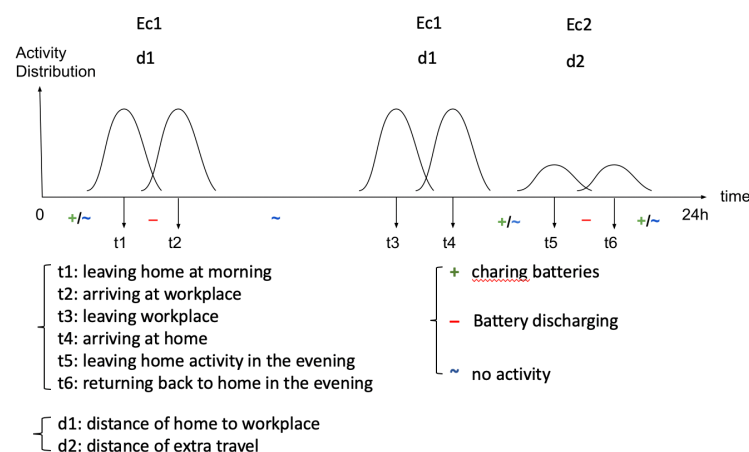


Figure 3-3 Travel Agenda based on Activity-based model

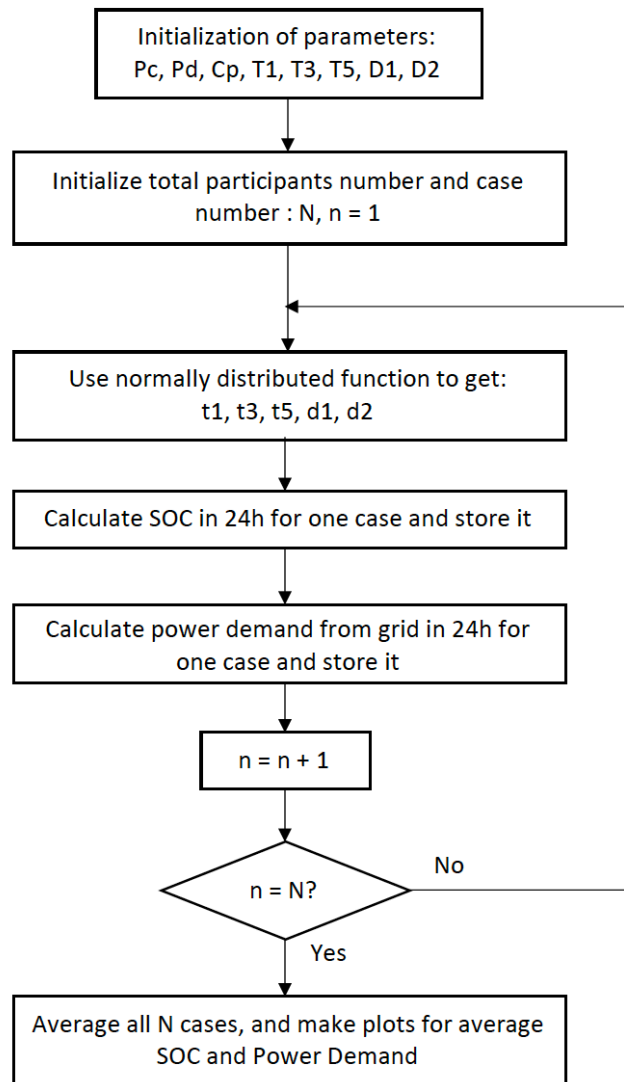


Figure 3-4 Flowchart of activity-based model's implementation in Matlab

For each scenario, we could put the activity-based model into MATLAB implementation as the flow chart shown in Figure 3-4. In the above cases, the charge time is assumed to be uninterrupted, and that the people within the study area will charge their EV

batteries as a result of range anxiety. Moreover, because the model is designed as a microsimulation, the framework of choice only interprets individual data and not collective data hence putting into perspectives the individual preferences and scenarios. For this project, several factors were considered during calculation:

- A. The categories of vehicles: each vehicle has a specific energy demand and electricity consumption rate. Based on the information from existing electric vehicles' reports on markets, we choose one common type of electric vehicle with 20kWh battery capacity (Average Car Mileage UK, 2020) and 0.15kWh/km energy consumption rate as study objects.
- B. The types of chargers are also considered in this experiment. As the benchmark experiment of the FEATHERS framework, vehicle chargers are set to be 3.3 kVA at home or 7.2kVA at work station.
- C. Applications of the FEATHERS framework in the daily activities and trips. Under this framework, the possibilities of a vehicle being charged can be calculated and feasibility indicator postulated. The results derived from these calculations can be comparatively used to determine the electrification scenarios, electrification feasibility and the market share of the vehicles in each successful trip.
- D. In this research, the ownership of vehicle is determined by the usage of cars for trips. Cars that are not used for work trips are assumed to be privately owns.

3.2 P2P pricing model for P2P EV charging

Based on the above results from activity-based model (State-Of-Charge, energy demands for buyers and sellers, travel agendas etc), we'd like to choose SDR (Supply and Demand Ratio) pricing model (Liu, et al.,2017) to estimate prices of P2P energy trading process because of its concise and non-tedious computation. However, SDR pricing model in Liu.2017 required the participating of Energy Sharing Provider (ESP) as a middle operator to control and adjust the prices respectively for sellers (EV owners who want to sell the spare battery energy) and buyers (who need to buy electricity from other EV owners or grids). The prices for sellers and buyers are based on the ratio of supply and demand as shown below in Eq.(3.1) Eq.(3.2) and Eq.(3.3).

$$SDR^h = \frac{TSP^h}{TBP^h} \quad Eq.(3.1)$$

$$Pr_{sell}^h = f(SDR^h) = \begin{cases} \frac{\lambda^{sell} \cdot \lambda^{buy}}{(\lambda^{buy} - \lambda^{sell}) \cdot SDR^h + \lambda^{sell}}, & 0 \leq SDR^h \leq 1 \\ \lambda^{sell}, & SDR^h > 1 \end{cases} \quad Eq.(3.2)$$

$$Pr_{buy}^h = f(SDR^h) = \begin{cases} Pr_{sell}^h \cdot SDR^h + \lambda^{buy}(1 - SDR^h), & 0 \leq SDR^h \leq 1 \\ \lambda^{sell}, & SDR^h > 1 \end{cases} \quad Eq.(3.3)$$

Eq.(3.1) indicates that supply and demand ratio (SDR) at one time h, is equal to the ratio of total selling energy power at time h (TSP^h , kWh) and total buying energy power at time h (TBP^h , kWh). Based on that, the P2P trading price to sellers (Pr_{sell}^h , £) and

P2P trading price to buyers ($Pr_{buy}^h, \text{£}$) at time h shows as Eq.(3.2) and Eq.(3.3). So that we could get that the P2P trading prices are related to electricity grid price at time h ($\lambda^{buy}, \text{£}$) and feed-in-tariff at nighttime ($\lambda^{sell}, \text{£}$), which we could get from official database.

In this work, since we require the direct trading process between sellers and buyers, we don't need the participant of ESP. So that we could assume that, the amount of electricity traded during the P2P energy trading (ET) process is based on the demand from buyers, and the price of P2P energy trading is based on the Supply/Demand Ratio which would be modified from the method in Liu.2017.

As regard to the calculation of energy supply and demand, matching the demand and supply in a P2P market system not only enhances the liquidity of the system but also create more opportunities for the system to grow owing to the foundational concept of "you have what I need, that you don't need that much. Let's share". Even in such a case, it is more necessary to acknowledge the following situations in the SDR mechanism:

1. Resources and needs are heterogeneous because of the diversity of customer groups, and a blur supply and demand line.

2. Diversity of needs in the P2P channels creates a diversity in peer preferences since preferences are indicators of supply, a product of a customer's willingness and expectations based on current need or transaction history
3. The diversification of customer preference and the heterogeneous needs means that fair matching is not attainable
4. It is difficult to motivate prosumers to engage in P2P trading because of existing problems in EVs themselves such as battery's charge-discharge loss, range anxiety limitation etc. So that only when the economic benefits existed can P2P energy trading process be accepted more possible.

In this thesis, our major objective is to get a basic scheme of whether P2P energy trading is an economical process for participants (sellers and buyers). Consequently, we would like to make a basic assumption that the P2P energy trading could happen between EV owners, and energy supply would meet the demands of buyers. In our case, when the seller is only one EV, and buyer is also only EV (under this condition all the demands from buyer would be satisfied by seller, and the energy trading process would be possible to happen), the price of the P2P energy trading is set to be the middle of λ^{buy} (price from grid at noon, which is high, £) and λ^{elt} (price from early low tariff at midnight, £) as shown in Eq.(3.4) below.

$$Pr = \frac{(\lambda^{buy} + \lambda^{elt})}{2} \quad Eq. (3.4)$$

Consequently, when sellers are n vehicles, and buyers contain m vehicles, we could infer that energy supply is n kWh, energy demand is m kWh and the SDR equals to n/m . Combined with λ^{elt} , λ^{buy} , and SDR, the P2P energy trading price (Pr , £) could be derived out as Eq.(3.5) below --- the p2p energy trading price between EVs is related to λ^{buy} , λ^{elt} , and SDR.

$$SDR^h = \frac{\text{Number of Suppliers}}{\text{Number of Demanders}}$$

$$Pr = \frac{(\lambda^{buy} + SDR * \lambda^{elt})}{1 + SDR} \quad Eq. (3.5)$$

Since there are no middle operator (like ESP), the P2P price would be same to both sellers and buyers as Eq.(3.5) shows. So that we would like to base on Eq.(3.5) for our calculation in this work.

3.3 Classification of P2P EV energy sellers and buyers

In this work, we are going to classify each of the 1000 EVs samples into separate sets of: sellers, buyers and non-participants based on their remain SOC levels when back at home after one day's activities. Sellers are EVs which remain surplus energy when they

arrive at home, indicating that they have enough energy in their batteries and are more likely to be willing to sell energy in the process of P2P energy trading with EVs. Buyers are those EVs which don't remain enough energy in their batteries or their SOC levels are too low to be not healthy to battery life. Buyers have the need to buy energy during daytime and sellers are available to supply surplus energy during daily activities, so that the P2P energy trading with EVs could happen between those two sets of participants. The rest of samples which remains safe-level of SOC but don't have enough spare energy to sell are non-participants. In order for clear classification, we are going to let them be:

- 1) Set A: sellers(EVs) who are available sell energy at daytime;
- 2) Set B: non-participants(EVs) who don't participate in the process of P2P energy trading with EVs;
- 3) Set C: buyers(EVs) who are keen to buy energy at daytime.

In order to clarify, we would use "level of SOC" as the standard of classifying set A, B and C. For example, if the remaining SOC's are between 0% and 20% of battery capacity, then those EV samples are set to be "Set C" as buyers who need to buy energy at daytime; and if the remaining SOC's are more than 80% of battery capacity, then they could be set as "Set A" as sellers who have surplus energy to sell. Consequently, all the rest of samples are going to be "Set B" as non-participants. By the way of changing the "level of SOC", energy supply and demand ratio could also be

determined because the “supply” only relates to Set A, and “demand” only relates to Set C. As a result, we would use this way of classification in the following sections of calculation.

3.4 Economic benefit analysis

3.4.1 EV energy sellers:

In the calculation of daily profits for sellers and buyers, due to the amount of our samples, for each SDR, we choose 5 pairs of sellers and buyers, let them do the peer to peer trading with each other and then get the average of profits for each of them. Since the stochastic errors due to limited extraction of samples, we would also need to combine the Monte Carlo method to randomly repeat the extractions, in order to get a more accurate average results (Detailed working on Monte Carlo method would be introduced in following chapter 3.5). For sellers, the daily gaining from P2P energy trading process (compared to non-P2P engaging process) should be $Profits_{seller}$ as shown in Eq.(3.6). λ_{elt} is the early-low-tariff at midnight, P_r represents the P2P trading price, and the ED represents the quantity of energy traded through P2P process which is decided by energy demands.

$$Profits_{seller} = (P_r - \lambda_{elt}) * ED \quad Eq.(3.6)$$

3.4.2 EV energy buyers

And for buyers, the daily saving from P2P energy trading process $Profits_{buyer}$ as shown in Eq.(3.7). λ_{buy} represents the grid price at noon.

$$Profits_{seller} = (\lambda_{buy} - P_r) * ED \quad Eq. (3.7)$$

3.5 Monte Carlo method

This work also adopted Monte Carlo method using large number of simulations to reduce error brought by the randomness of simulation cases. The scheme of how Monte Carlo Method is engaged in the calculation is shown in the dashed box in Figure 3-5 below.

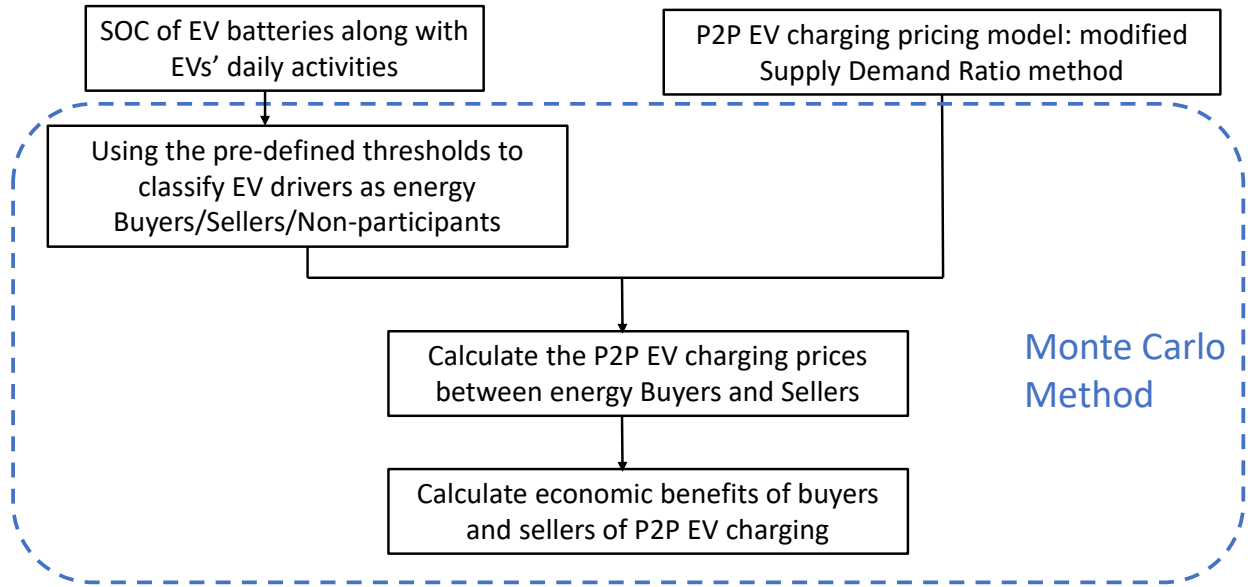


Figure 3-5 Monte Carlo method for the economic benefit analysis

Based on Monte Carlo method, we do randomly sampling simulations to calculate economic profits for P2P energy trading participants. The Monte Carlo simulations are statistical tools that model the outcomes of processes that, due to random variables,

cannot be predicted. As an analytic tool, the simulations are critical in understanding the impacts of risks and uncertainty of an intended forecast model.

Principally, the simulation uses a list of multiple values that are assigned to uncertain variables and then the results are averaged to obtain a statistical estimate. So that in this work, we will choose different EVs pairs of samples as variables in Monte Carlo method, combined with the corresponding P2P trading prices from modified SDR pricing model, and then calculate the average profits for P2P energy trading's participants per day to ensure the calculation's accuracy and robustness.

3.6 Case study

This Chapter will introduce the set-up of simulation samples, concluding the input parameters and simulation scenarios. We would build a set of samples of EVs, and let them take part in the process of P2P energy trading with each other. As we stated before, firstly, we use activity-based model to simulate SOC(State-Of-Charge) of EVs' batteries. Samples are set to be 1000 EVs. And the initialization of charger type is set to be 3.3kW at home and 7.2kW at car park. The discharging rate is set to be 0.15 kWh/km. The average battery's capacity is set to be 20kWh. Travel distances take two basic 20 miles (Average Car Mileage UK, 2020) and 10 miles. Timelines of travel agendas are also set properly based on activity-based model.

And then, we would take two common scenarios of people charging their EVs' batteries:

- 1) We expect that people tend to charge their EVs immediately, during low tariff period at midnight;
- 2) We assume that people charge their EVs' batteries immediately after last arrival at home. Detailed analyzations are as follows.

For each scenario, we would apply the activity based model to calculate EVs' batteries state-of-charge (SOC), and furthermore calculate the energy demands available for P2P energy trading process. Then we would compare and choose one suitable scenario as our case of economic analysis, and let the EV samples trade with each other in the direct P2P process in which trading prices would be derived from the modified SDR pricing model. Furthermore, we expect to calculate the economic profits for those participants, and then study the influences of different supply-demand ratios toward the economic benefits. We expect to establish such kind of hypothetical framework to mimic the real situation of P2P energy trading in the future. Details of calculations and results are shown in Chapter 4.

3.7 Summary

To sum up, this chapter express the overall methodology of this research project.

Firstly, we developed a statistical activity based model (ABM) to mimic and calculate the

remaining amount of energy in EV batteries after one day's activity. Part of those energy is expected to be available for P2P energy trading between EVs. Secondly, we modify the supply-demand ratio method (SDR) to let it be more concise and suitable for calculating the P2P trading prices. After we got the above results from ABM and pricing model, we would then carry out calculation of economic benefits for both energy sellers and energy buyers, adopting Monte Carlo method to ensure the calculation's robustness and accuracy.

Chapter 4. Results and findings

This chapter will show the calculation processes, results and findings of the research. We would firstly show the calculation results of SOC and remaining energy in Chapter 4.1, which derived from combining activity based model. Then we would show the results of modified SDR pricing model in Chapter 4.2. Thirdly we would illustrate the results of EV participants' economic profits during the process of P2P energy trading and furthermore explore the influence of different SDR toward the economic benefits in Chapter 4.3.

The flow chart of overall calculation process is shown on Figure 4-1. According to the results of travel agendas generated by FEATHERS activity-based model in Chapter 3.1, we will firstly compute out the State-Of-Charge (SOC) of EV's battery condition in one day for each sample. Secondly, based on the modified SDR pricing model in chapter 3.2, we would get P2P energy trading prices at different SDR conditions. Lastly, we could combine the results of SOC scenarios with P2P trading prices to generate daily economical profits(benefits) separately for sellers and buyers. Combined the Monte Carlo method, we run through randomly combinations of P2P energy trading pairs for the accuracy and robustness of calculation results. Consequently, the economic benefits of applying P2P energy trading process with electric vehicles could be inferred properly.

Analysis of Peer-to-Peer Energy Trading process among Electric Vehicles

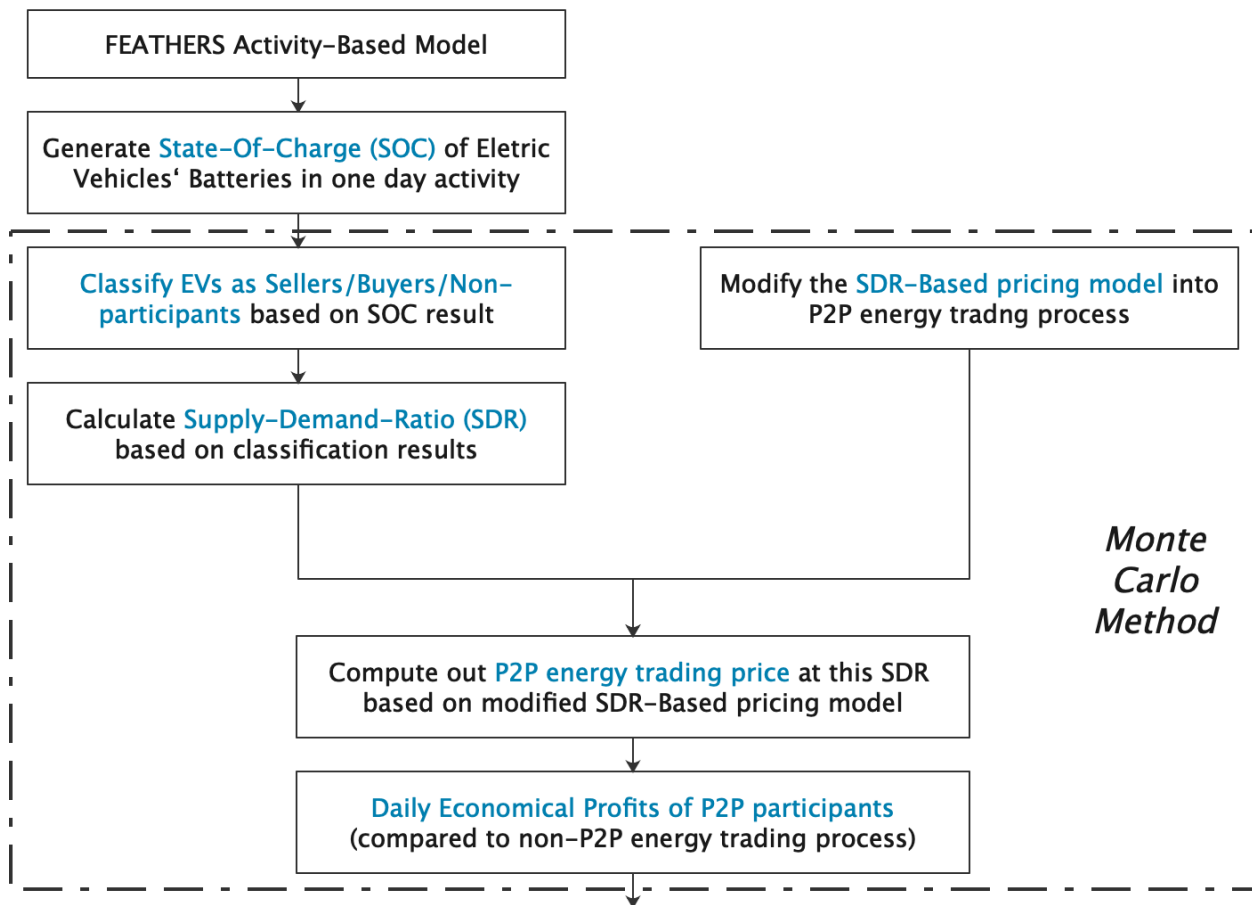


Figure 4-1 Calculation Flow Chart

4.1 Calculation results of SOC and remaining energy of EVs

For scenario 1, that people tend to charge their EVs immediately during low tariff period at midnight. In this condition, we need to take several assumptions in order to simplified the simulation:

- 1) People only charge their batteries at 24:00 when low-tariff period starts;

- 2) For each activity of all samples, points of time and distances obey normal distribution to all participates;
- 3) Only when the remain energy in battery is more than 20% of the total capacity can we use the spare energy in the battery.

So that the simulation results of SOC of scenario1 are shown on Figure 4.2 as below:

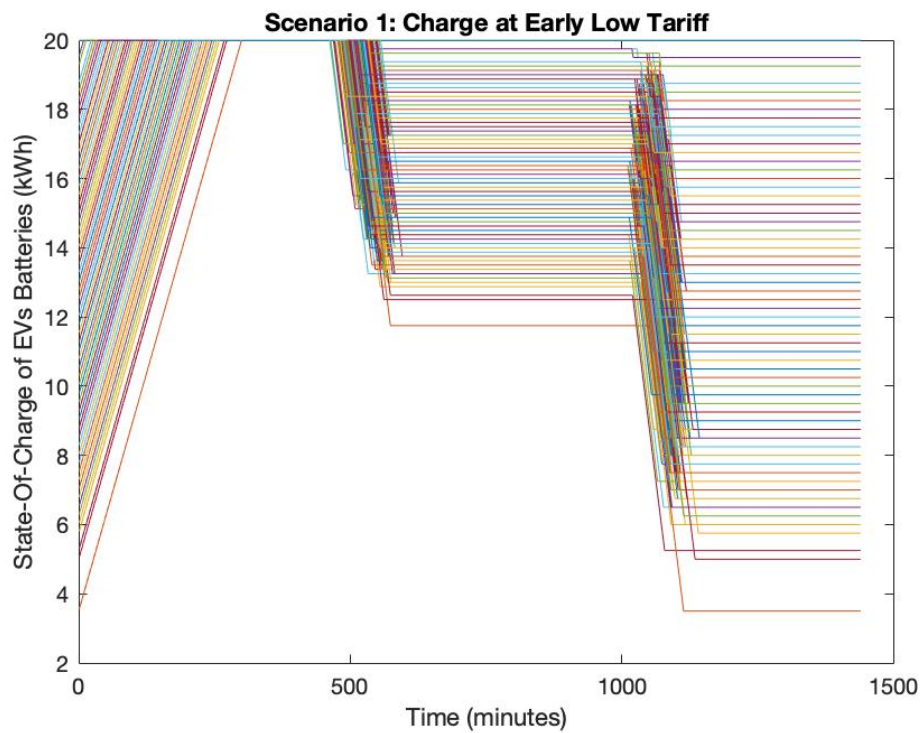


Figure 4-2 SOC of samples in scenario 1

In Figure 4.2, the abscissa axis means the time from 0:00 to 24:00 in one day, united by minute; the ordinate axis represents the SOC of EVs batteries. As time going, it is showed that part of EVs still have enough remaining electricity energy within their cars

when they arrive at home at night, however, SOC of other EVs are going to running out or left at a low-level (less than 20% of total capacity) when they get home, which means they are more likely to charge their EVs during daytime. Participants with surplus electricity could be the potential energy suppliers, and participants with lack of electricity arriving at home are likely to become demanders. P2P energy trading of surplus electricity between those suppliers and demanders would be possible to happen.

For scenario 2, people charge batteries immediately after last arrival at home. We also take several assumptions as follows:

- 1) People charge batteries immediately after last arrival at home regardless of how high or low of the grid price at that time;
- 2) They don't charge at daytime, also in order for easy simulation;
- 3) For each activity, points of time and distances are normally distributed to all participants;
- 4) Only when the remain energy in battery is more than 20% of the total capacity, can we use the spare energy in the battery.

Then the simulation results of SOC of scenario2 are shown on Figure 4-3 as below:

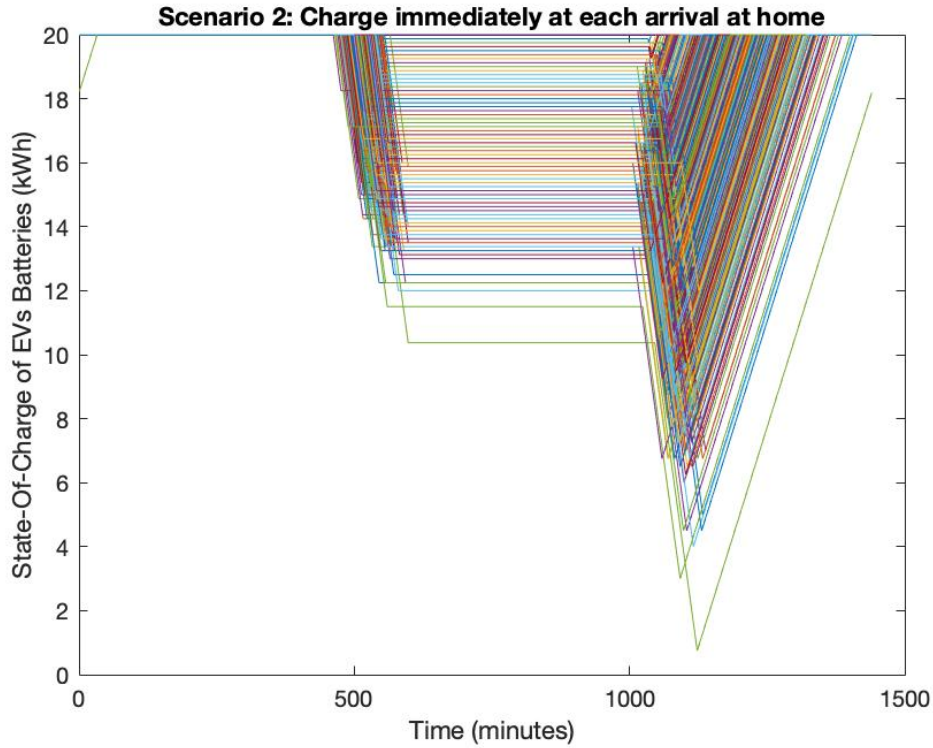


Figure 4-3 SOC of samples in scenario 2

In this scenario, some EVs contains surplus energy when they get home and some EVs don't contain enough energy arriving at home, and the P2P trading process seems to be able to happen. However, since the charging time of all cars cannot be ensured at the lowest price at low tariff period, the charging prices at home of each cars could not be ensured to be the lowest one, so that the P2P trading price has the possibility to be less than charging price at home which makes sellers to sell energy at a lower P2P trading price than which could make sellers to get profits during P2P trading process.

Consequently, in this condition of scenario 2, the P2P trading process could not ensure both "buyer" and "seller" to get profits compared to non-P2P energy trading. So that this

scenario is not suitable for our study. So that in this work, we would only study about the first scenario.

4.2 Results of average P2P trading price from modified SDR pricing model

Based on the above results, we would like to choose scenario 1 as our study case for P2P energy trading. According to Eq.(3.5), SDR pricing model is based on the ratio of supply and demand, as well as λ^{buy} and λ^{elt} . As stated in Chapter 3, P2P energy trading price is set between the highest grid prices at daytime and the lowest feed-in price at midnight. For sellers who have surplus energy to sell, they can charge their batteries at a low price at midnight and then sell them at a higher P2P price which could gain some profits for them during the trading process. And for buyers who would like to charge their EVs at daytime, before P2P energy trading, they need to charge at a higher grid price at daytime, but during P2P energy trading, they could be able to charge at a lower P2P trading price at daytime, which also could reduce costs for them. To concluded, P2P energy trading process aim to benefit both sellers and buyers in this condition. So that we could get the average prices of P2P energy trading process as following figure:

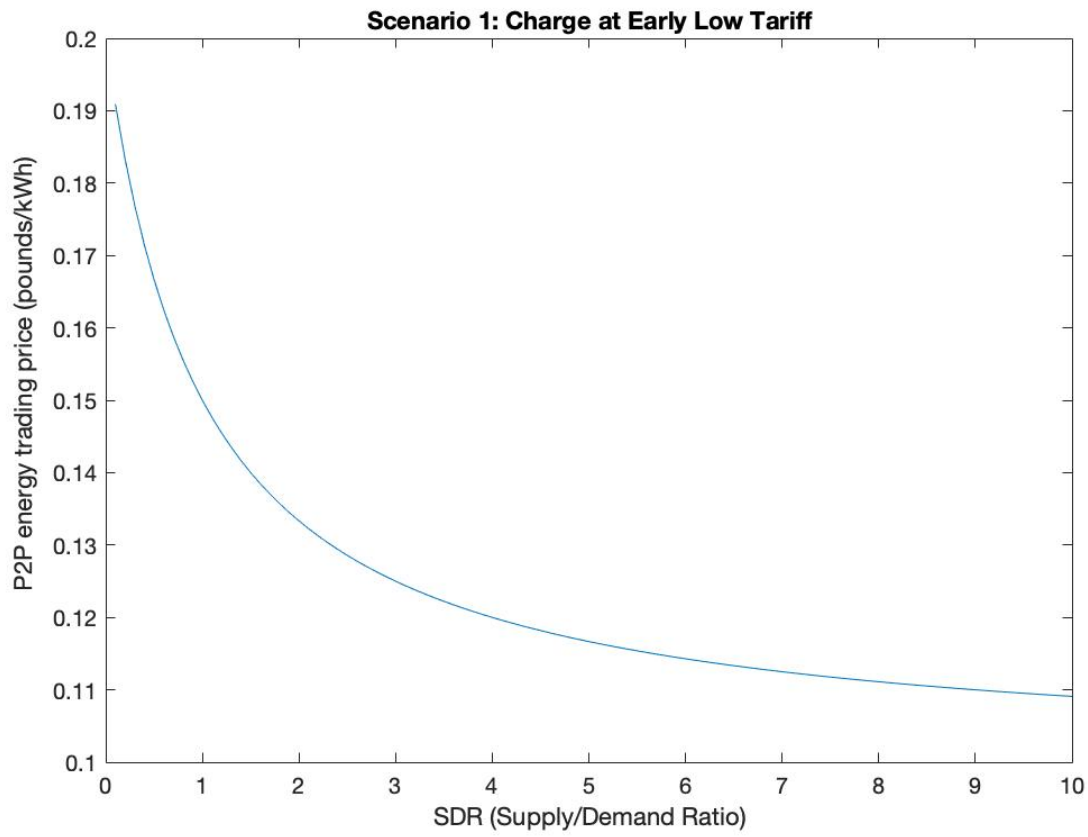


Figure 4-4 P2P trading price

The results of figure above indicate that, under the SDR pricing model and combined with Monte Carlo method, P2P trading prices are changing with SDR's change. When supply energy is more than demand energy, SDR goes to higher and P2P trading price goes down with infinite approach to Grid's feed-in price; when supply energy is less than demand energy, SDR goes down and the P2P trading price grow higher with infinite approach to peak electricity price at noon.

4.3 Economical profits to participants during P2P energy trading process with EVs

According to SOC figures in Chapter 4.1 and the results of P2P trading prices in Chapter 4.2, we aim to combine them to compute daily profits for all participants. Since not all the sample EVs have needs to sell or buy electricity during daytime, we need to firstly make classification of participants, and then only let the sellers and buyers to trading energy and calculate economic benefits for them.

4.3.1 Classification of sellers, buyers and non-participants

According to the SOC levels on Figure 4-2 in the early-low-tariff scenario, the classification assumptions could be shown as below on Table 2.

Table 2 Classification of Sellers, Non-participants and Buyers based on the remain levels of SOC

	Sellers	Non-Participants	Buyers
1	85%-100%	30%-85%	0%-30%
2	80%-100%	30%-80%	0%-30%
3	75%-100%	30%-75%	0%-30%
4	70%-100%	30%-70%	0%-30%
5	65%-100%	30%-65%	0%-30%
6	60%-100%	30%-60%	0%-30%
7	60%-100%	27.5%-60%	0%-27.5%
8	60%-100%	25%-60%	0%-25%
9	60%-100%	20%-60%	0%-20%

As shown in Table 2, we take 9 kinds of classification assumptions, and for each condition, we are going to calculate the corresponding P2P trading price and the economical profits for separately for sellers and buyers. For example, for the first case of classification, set A (energy sellers) are EVs who remain 85%-100% SOC of battery when back home, set B (non-participants) are EVs who remain 30%-85% SOC of battery when arriving at home, and set C (energy buyers) are those who remain only 0%-30% SOC of battery when arriving at home. So that we could calculate the SDR and P2P energy trading price forward different kinds of classification, and then analyse the economical profits for both sellers and buyers.

4.3.2 Calculation of SDR and P2P trading price during P2P energy trading process combined with Monte Carlo method

Based on the classification of sellers (set A), buyers (set C) and non-participants (set B) above, in this section, we are going to combine different classification levels, resulting in the change of SDR (supply/demand ratio), in order to study how the economical profits change separately sellers and buyers during P2P energy trading process. The calculation would base on the following assumptions:

- 1) Only EVs from set C have the needs of trading energy during daytime;
- 2) Only EVs from set A are available to sell energy to set C;

- 3) Set A and Set C are willing to trade energy at noon by P2P process;
- 4) The P2P trading process is not constrained by charging period, but constrained by quantity of energy demands;
- 5) No limitation on minimum charging capacity no matter how slight you need to charge.

The calculation results of SDR and P2P trading prices are shown on Table 3 as below. According to samples' information on Chapter 3.1, samples are set to be 1000 EVs. And the initialization of charger type is set to be 3.3kW at home and 7.2kW at car park. The discharging rate is set to be 0.15 kWh/km. The average battery's capacity is set to be 20kWh. We run the simulation for each condition of classification and get the SDR specially at that circumstance. Among the simulation, we would also need to adopt the Monte Carlo Method using large number of simulation loops to reduce the random errors brought by the limited number of samples. Then combined with SDR pricing model on Chapter 4.2, according to Eq.(3.5), we could compute out the averaged P2P trading price at noon for each classification circumstances as follow.

Table 3 SDR and P2P energy trading prices for different classification conditions

	Sellers' SOC	Non-Participants' SOC	Buyers' SOC	SDR	P2P Price (£/kWh)
1	85%-100%	30%-85%	0%-30%	0.2679	0.1789
2	80%-100%	30%-80%	0%-30%	0.5366	0.1651
3	75%-100%	30%-75%	0%-30%	1.0794	0.1481
4	70%-100%	30%-70%	0%-30%	2.1818	0.1314
5	65%-100%	30%-65%	0%-30%	3.0857	0.1245
6	60%-100%	30%-60%	0%-30%	5.0615	0.1165
7	60%-100%	27.5%-60%	0%-27.5%	6.1702	0.1139
8	60%-100%	25%-60%	0%-25%	10.8	0.1085
9	60%-100%	20%-60%	0%-20%	21.8571	0.1044

As indicated in Table 3, with different kinds of classification, SDR shows different values. Besides, with the grow of SDR, the P2P energy trading price goes downstairs which follows the same rule shown in Figure 4-4.

4.3.3 Calculation of economical profits for sellers and buyers during P2P energy trading process combined with of Monte Carlo Method

In order to reduce the stochastic errors, we again need to apply the Monte Carlo method to randomly select the sampling pairs for multiple times and then get the average of their results for each classification condition. After the calculation of Monte

Carlo method, the average daily profits for each seller and buyer are shown on Table 4.

And the average profit per month for each seller and buyer are shown on Table 5.

Table 4 Calculation of economical profits for sellers and buyers per day

	SDR	Seller's average gaining (£/day)	Buyer's average savings (£/day)
1	0.2679	0.1124	0.0301
2	0.5366	0.1036	0.0556
3	1.0794	0.0777	0.0838
4	2.1818	0.05	0.109
5	3.0857	0.0361	0.026
6	5.0615	0.1114	0.1315
7	6.1702	0.0219	0.1353
8	10.8	0.0133	0.1432
9	21.857	0.0084	0.1826

Table 5 Calculation of economical profits for sellers and buyers per month

	SDR	Seller's average profits (£/month)	Buyer's average savings (£/month)
1	0.2679	3.37	0.90
2	0.5366	3.11	1.67
3	1.0794	2.33	2.51
4	2.1818	1.50	3.27
5	3.0857	1.08	3.34
6	5.0615	0.78	3.95
7	6.1702	0.66	4.06
8	10.8	0.40	4.30
9	21.857	0.25	5.48

As shown on Table 4, in the first case of classification, SDR is calculated out as 0.2679, and the corresponding P2P trading price at noon is 0.1789 £/kWh. And consequently based on Eq.(3.6) and Eq.(3.7), seller's average gaining per day is 0.1124 £/day during the process of P2P energy selling, and each buyer will averagely saves 0.0301 £/day in the process of P2P energy trading, compared to buying those energy through power grid. With the grow of SDR, seller's average gaining is decreasing, however the buyer's average savings are keep growing. In order to show the analysis of the macroscale income of participants, we would like to calculate the profits for one month, 30 days, for both sellers and buyers. The results of monthly profits are shown in Table 5. For directly observation, we draw the figure of monthly profits with the change of SDR as shown in Figure 4-5 below.

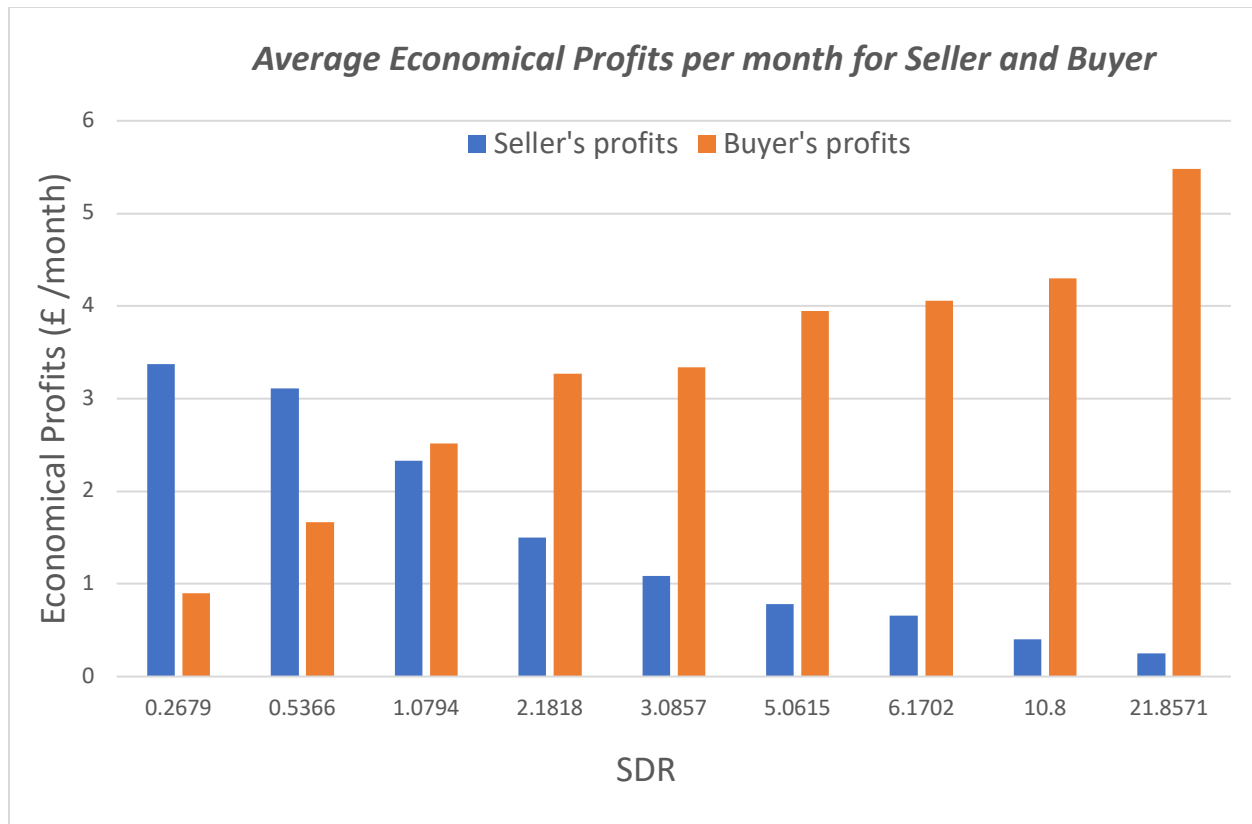


Figure 4-5 Economical profits for sellers and buyers in one month

Figure 4-5 visually shows the money that one seller gained from P2P energy trading process in one month, and the costs that one buyer saved from P2P energy trading rather than directly traded from power grid. With the increase of SDR, the seller's profits go downward from nearly 3.5 £/month at 0.268 SDR to 0.25 £/month at 21.857 SDR, which shows that when the supply are growing and the demands are relatively dropping, one seller would get less market share due to the competition of lots of suppliers, consequently, the profits that sellers averagely gained from this P2P trading process would decreasing. As to buyers' benefits, it is indicated that with the increase of SDR, buyers' profits would go upstairs steadily from 0.90 £/month at 0.268 SDR to 5.48

£/month at 21.857 SDR. An interesting point shows that when SDR nearly equals to 1, in which condition energy supply equals to energy demands, sellers and buyers share nearly the same amount of economic profits for each one of participants. When SDR is smaller than 1, sellers economically gain more than buyers; but when SDR is larger than 1, buyers' profits are larger than sellers' profits share.

Moreover, in order to directly show how the buyers and sellers gain profits, we choose an example of a pair of seller & buyer to study their cost and profits during the activity of one day at Table 6.

Table 6 Seller and Buyer's costs/day before and after P2P energy trading

	Before P2P Energy Trading	After P2P Energy Trading
Seller	Charging at home(morning): -80 pence(8kWh, 10p/kWh)	Charging at home(morning): -100 pence(8kWh, 10p/kWh)
	No charging at daytime	Selling P2P energy at daytime: +28 pence(2kWh, 14p/kWh)
	Total costs: 80 pence	Total costs: 72 pence
Buyer	Charging at home(morning): -160 pence (16kWh, 10p/kWh)	Charging at home(morning): -160 pence(16kWh, 10p/kWh)
	Buying Grid energy at daytime: -30 pence(2kWh, 15p/kWh)	Buying P2P energy at daytime: -28 pence(2kWh, 14p/kWh)

	Total cost: 190 pence	Total costs: 188 pence
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According to above example of one pair of seller and buyer, we could find that the process of P2P energy trading could reduce both buyer and seller's cost under some conditions. The cost of seller is reduced 8 pence, and the cost of buyer is reduced 2 pence. It is economically feasible in this case. This is only one example of a pair of buyer and seller within the process of P2P energy trading.

Based on all the results above, we could find that our framework of calculating economic profits could work well on conducting the amount of economic benefits for sellers and buyers, and the amount of profits they get could be influenced by the supply and demand ratio. However, we could also find that the amount of profits are not considerable to attract more potential EV users taking part into this P2P trading process. We would discuss about the reasons of those limited benefits and provide some potential improvements and future research points in Chapter 5.

4.4 Summary

According to the results shown from Chapter 4.1 to Chapter 4.3, we could find that the use of FEATHERS activity based model and modified SDR pricing models works good for setting up the basic framework of P2P energy trading cases. We successfully calculate out the remaining energy available for P2P trading as well as the related

trading prices. Then we find that our module of simulating P2P energy trading between EVs also comes out reasonable results of economic profits for both energy sellers and energy buyers, which means that the process of P2P energy trading with EVs is able to get benefits for participants in some conditions. Moreover, we find that the amount of economic profits are not much too profitable with only a few pounds per month which in this stage might not be enough to stimulate more participation of potential EV users.

Chapter 5. Discussions

This project carried out an initial techno-economic analysis of the economic benefits of EV drivers by P2P EV charging. The remaining battery energy of EVs after daily travel was estimated by using a FEATHERS activity-based model, and the pricing model adopted the supply demand ratio method. The economic analysis was carried out by using Monte-Carlo method. Nevertheless, there are some factors affecting the results and also some limitations of this current work. These discussions are presented as follows.

5.1 Variations of daily travel data and vehicle types

This work provides a framework to estimate EVs' remaining SOC after daily travel by using activity-based model (ABM). The types of EVs and the EV drivers' activities data are the inputs to the framework/model. These activities include the travel journey start and end time, travel distance, type of territory of driving, etc. For a study of a particular community, these data should be obtained as the input for the FEATHERS ABM. In this work, due to the lack of real-life data, the UK statistic data of EV drivers were used. For example, the daily travel distances were taken two scenarios, i.e. 10 miles/day or 20 miles/day. Also, one vehicle type of the average amount of battery capacity (i.e. 20 kWh) and energy consumption per mile (i.e. 0.15kWh/mile) was considered in this work. These average data of the battery capacity and energy consumption per mile were taken from report of UK Government. Although there existed some researches working on the study of EV peer to peer energy trading such as Alvaro-Hermana et al (2016),

however, one of the advantage of our work is that we here made a more flexible framework covering the whole process of activity-tracing, price-setting mechanism as well as the estimation of profits and loss, rather than only focus on a particular region as shown in Alvaro-Hermana et al 2016. Once we get the real-life data of EV's travel activities in the future, we can directedly put them into the framework and get the assessment of economic benefits during P2P energy trading process with EVs. So that with the framework set up in this project, when carrying out a simulation of real case study of community or city for P2P EV charging, these data of vehicle types, EV daily travel data will be updated to carry out the techno-economic study.

5.2 P2P pricing models

As discussed in the literature in Section 2.4, there are a few different P2P pricing models (Long, 2017) which can be used as the pricing model for P2P EV charging. However, those models' set-up lacks of the calculation of economic profits for participants and mostly provide theoretical methods. So that in our work, we modified one kind of P2P pricing model and combined it into the following calculation of economic benefits. The SDR method was modified in this work as a result to be more suitable for P2P energy trading directly between EVs rather than having a middle operator in the original SDR model. The pricing model is used to calculate the EV energy selling and buying prices between EV energy buyers and sellers. Different pricing models affect the amount of energy bill savings for EV energy buyers and sellers. For this work, regardless the pricing model adopted, the P2P EV charging prices

will be between off-peak and peak electricity prices, i.e. the EV energy buyers EV charging bills will be reduced and the EV energy sellers will obtain income by selling energy to others. Since the price gap between off-peak and peak prices is limited, so that the consequently calculations of economic benefits are not expected to deviate on too much scales. Future work can be carried out to compare the impact of different P2P pricing models (such as MMR, SDR, BSM, etc.) to the economic benefits.

5.3 Electricity tariffs and renewable energy used for EV Charging

This project considered Economy 7 tariff for EV charging and the economic gains obtained by the sellers and buyers are from the tariff difference between daytime charging and night charging. In other words, the EV energy sellers obtain income by selling a higher price in peak time of the energy that they obtained at the off-peak time. £0.10/kWh was considered as the price for off-peak time and £0.20/kWh was considered as the price for peak time. So that this is one of the reasons that, only a few couple of pounds of economic benefits were obtained by the sellers and the buyers in the case study carried out in this work.

Besides, in this work, we haven't considered the economic impacts of using renewable energy for charging EVs such as solar energy. In UK, there are three main markets of solar energy as 1) large-scale solar; 2) commercial rooftop; 3) domestic PV. Firstly, large scale solar farms, which refers to ground-mounted capacity systems (at least

1MW), are the primary source of energy with around 48% of total UK solar energy (Al-Ezzi A. 2017). However, they typically provide power to grid instead of directly to end-users. Secondly, as regard to commercial rooftop, this group is usually installed on the non-domestic buildings and frequently larger than domestic arrays --- capacity typically varies from 10 to 250 kW and also can be large as 5MW (which provide industrial customers such as commercial building with a considerable level of self-generated power). Thirdly, the domestic or private group consists of small-scale building-mounted installations on residential rooftops --- providing free electricity with a capacity of 3-4 kW, or up to 10kW on larger homes which allowing reductions in electricity bills (Al-Ezzi A. 2017).

As to our study point related to energy charging towards personal EVs, the large-scale solar arrays and commercial rooftops solar panels might not be usable for our end-users like private EVs. However, the domestic PV energy from residentials' rooftops might be a possible way to charge EVs cheaper. For example, for one resident who would like to sell his surplus energy during the P2P energy trading process V2V, if parts of the energy charging to his EV are provided by solar panels (5 panels of 200W/panel, with total capacity of 1 kW) on his rooftops and daily sunshine hours available for PV panels fully working is 4 hours in the UK, the resulting available solar energy charged to EV in this day is 4 kWh. If all those 4 kWh energy is sold out during the process of P2P energy between EVs, that means to sell the 4 kWh energy to P2P energy buyers at the P2P trading prices such as 14 pence/kWh, the gaining of this seller in this day is 0.56

£ --- which is higher than the non-solar-energy-charging results of 0.1124 £/day in Table 4. In the above hypothetical deduction, the seller can charge his EV with nearly no cost for 4 kWh energy, consequently his economic profits during P2P energy trading process would be higher. More detailed calculation and more comprehensive analysis would be expected for the future studies discussing about whether and how much the rooftop solar energy could bring economic benefits in P2P energy trading process.

5.4 Energy losses and battery degradations

For vehicle to grid (V2G) applications, there are round-trip energy losses in the process of battery charging and discharging. The energy losses in the process are normally around 80-90%. The energy losses mostly come from the converter with conversion from AC to DC, and DC to AC for V2G. However, for P2P EV charging, it is DC battery energy from one EV to DC energy on another vehicle. The energy losses are marginal compared to the AC and DC conversions. For simplicity, in this study the energy losses in the P2P trading process were not considered. And future studies are expected to carry out more precise calculation about the energy-loss influence toward the P2P energy trading process.

Besides, batteries are degraded over per use and over calendar time. The influencing factors on EV battery's degradation process are various, and it's also difficult to quantify how much the battery degradation per cycle or per day (Wang D, 2016). There are four

main parameters affecting battery's degradation (Lacey G, 2013): 1) battery temperature; 2) charge/discharge rate (C/D rate); 3) average state of charge (SOC); 4) depth of discharge (DOD) --- the change in SOC. Among the above factors, the battery temperature, which related to environment temperature as well as the charging current rate (the amount of charging power), is the most significant factor for battery degradation. But as to our study focusing on P2P energy trading with EVs, battery temperature would not be affected compared to non-P2P charging process. Besides, as to our work in this thesis, in order to make sellers gain economic benefits, we made requirements that they charge their EV batteries at midnight where Economy-7-Tariffs works. Since this requirement made the SOC of EVs to be kept at a low level for more time, so that generally our condition has the effect of reducing the average SOC of the battery (the averaged SOC that the battery maintained during its total life) and consequently slow down the battery aging (Millner A. 2010). Furthermore, compared to the effect from battery temperature, the change of DOD level has less effect on battery resistance increase (Gailani A, 2020).

According to the above analysis, the cost of battery degradation could not be considered in this current study since the addition of P2P trading process would not significantly change the battery degradation theoretically, moreover, in this work we only aim to provide a basic framework for general development of how EVs trading energy with the process of P2P. However, it is still worth doing for further study to carry out the

more accurate and comprehensive results of the impacts on battery degradation from P2P trading process between vehicles.

5.5 Summary

To sum up, in this chapter, we mainly talk about 4 potential factors that might influence the results of economic profits. Since our study aims to provide just an initial framework of P2P energy trading between EVs, although the variation of daily travel agenda and vehicles types is limited in our case of study, we could still get reasonable results of the economic benefits for participants. Besides that, in our work, although we only choose one kind of P2P pricing model as the base of trading price, we are convinced that the scale of outcomes for economic profits would not deviate too much. However, in this work, we haven't taken into account of the influence of energy losses and battery degradation, which are expected to reduce the potential gaining in some extent. So that we expect them to be interesting topics for future study. Furthermore, we also put forward an promising point for future work which would consider the use of renewable energy sources such as the combination of solar panel, which is expected to reduce the cost of energy sellers, leading to a more attractive outcome of economic benefits.

Chapter 6. Conclusions

This chapter will focus on conclusions as well as prospect of future research work.

Based on the results and discussion sections stated before, we could get some conclusions as to our initial work on techno-economic analysis of P2P energy trading with EVs as follows:

- 1) This project set up a statistical activity based model specifically for the P2P energy trading process between EVs (referred to the train of thought of FEATHERS model) to estimate the remaining SOC. This is a framework model which is able to produce EV SOC profile along daily activity of EVs. Once the data of vehicle type and daily trading data is provided, the framework generates remaining SOC profiles. With predefined percentage values, this will classify the EV drivers as buyers, sellers and non-participants.
- 2) This work made improvement by modifying the original SDR method to be suitable for the condition of P2P trading directly between vehicles, rather than using a middle operator for operating P2P process. More kinds of P2P pricing models are expected to carry out in the calculation of P2P trading prices in the future.
- 3) This project successfully carried out an economic benefit analysis calculating the energy bill savings for EV energy buyers and income for EV energy sellers. It is found that P2P EV charging is able to bring energy saving for EV energy buyers up to £3,32/month and bring energy income for EV energy sellers up to

£5.48/month. The economic benefits carried out in this work seem not substantial but we expect that the consideration of renewable energy resources in the future study will improve the performance of the using of P2P energy trading process.

- 4) This project also carried out the economic analysis at different supply and demand ratios scenarios and compare the economic gains between them.

Furthermore, according to the limitations stated in Chapter 5, future study might focus on the following aspects:

- 1) When we have the practical real-life data of the EV users of a studied community, these data will be richer inputs into the FEATHERS ABM. With the framework set up in this project, when carrying out a simulation of real case study of community or city for P2P EV charging, these data of vehicle types, EV daily travel data will be updated to carry out the techno-economic study.
- 2) Comparison of more different P2P price models such as MMR, BSM, Auction-based model, etc might help us to improve the final economic benefits.
- 3) The consideration of some EV energy sellers who obtain energy from local renewable generation might also be an interesting topic of studying the outcomes of economic benefits study.
- 4) Consider the energy losses and battery degradation.

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