Integration of Electric Vehicles in a Flexible Electricity Demand Side Management Framework

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Abstract

Recent years have seen a growing tendency that a large number of generators are connected to the electricity distribution networks, including renewables such as solar photovoltaics, wind turbines and biomass-fired power plants. Meanwhile, on the demand side, there are also some new types of electric loads being connected at increasing rates, with the most important of them being the electric vehicles (EVs). Uncertainties both from generation and consumption of electricity mentioned above are thereby being introduced, making the management of the system more challenging. With the proportion of electric vehicle ownership rapidly increasing, uncontrolled charging of large populations may bring about power system issues such as increased peak demand and voltage variations, while at the same time the cost of electricity generation, as well as the resulting Greenhouse Gases (GHG) emissions, will also rise.

The work reported in this PhD Thesis aims to provide solutions to the three significant challenges related to EV integration, namely voltage regulation, generation cost minimisation and GHG emissions reduction. A novel, high-resolution, bottom-up probabilistic EV charging demand model was developed, that uses data from the UK Time Use Survey and the National Travel Survey to synthesise realistic EV charging time series based on user activity patterns. Coupled with manufacturers' data for representative EV models, the developed probabilistic model converts single user activity profiles into electrical demand, which can then be aggregated to simulate larger numbers at a neighbourhood, city or regional level. The EV charging demand model has been integrated into a domestic electrical demand model previously developed by researchers in our group at the University of Edinburgh. The integrated model is used to show how demand management can be used to assist voltage regulation in the distribution system. The node voltage sensitivity method is used to optimise the planning of EV charging based on the influence that every EV charger

has on the network depending on their point of connection. The model and the charging strategy were tested on a realistic “highly urban” low voltage network and the results obtained show that voltage fluctuation due to the high percentage of EV ownership (and charging) can be significantly and maintained within the statutory range during a full 24-hour cycle of operation.

The developed model is also used to assess the generation cost as well as the environmental impact, in terms of GHG emissions, as a result of EV charging, and an optimisation algorithm has been developed that in combination with domestic demand management, minimises the incurred costs and GHG emissions. The obtained results indicate that although the increased population of EVs in distribution networks will stress the system and have adverse economic and environmental effects, these may be minimised with careful off-line planning.

Lay Summary

With the anticipated increased penetration of varying renewable energy resources (such as wind, solar and marine) and the introduction of new types of electrical loads, such as electric vehicles (EVs), balancing of generation and demand is becoming an increasingly important issue, especially since there is no matching upgrade or extension of the supply network itself. Electric vehicles not only can be regarded as a transport method, but also as a storage system which provides the opportunity and added flexibility of controllable, bi-directional electrical power flow between the consumer and the power grid.

The thesis presents a bottom-up, stochastic model that captures both the EV usage patterns and the charging profiles within a household, and integrates it with an existing similar domestic electricity demand model. The model simulates the detailed household activities based on the data acquired from the UK Time Use Survey (TUS) and National Travel Survey (NTS) databases. It is then used to generate uncontrolled EV charging demand based on the actual charging specifications of various electric vehicles. Ambient temperature, as an influential factor in battery performance, is also taken into account.

The developed model is then used to investigate the potential impact of a fleet of electric vehicles charging, specifically looking into the cost of electricity generation, greenhouse gas emissions (GHG) and power system demand through low voltage residential demand-side management (DSM). An optimisation algorithm is used to shift electric vehicles charging loads so as to minimize the combined impact of three key parameters: financial, environmental, and demand variability. The results show that it is possible to reshape the power demand and reduce electricity cost and GHG emissions without adversely affecting people's driving patterns.

Finally, a combined household demand side management strategy is developed with the objective of assisting regulation of the supply voltage. Electric vehicle charging demand and domestic “wet load” demand are manipulated in the optimisation algorithm. Network voltage sensitivity is used in the optimisation algorithm to minimise the number of loads that need to be adjusted in order to achieve the desired level of voltage regulation.

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Finally, I would not be able to accomplish this without the support, the encouragement and love of my family. I am grateful to my father and mother and wish them a healthy, trouble-free life from now on. As for my friends, I would like to thank them for the four lovely years in Edinburgh and feel me at home.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

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Chapter 1. Introduction

1.1 Challenges for Future Power System

Power systems are defined as a network of electrical components implemented to generate, transfer and distribute electric power. In the past years, most of the studies are focused on the generation and transmission level such as increasing the power generation capacity, reducing power generation and transmission cost, stability and security of power network, maintenance of network equipment, etc. However, with the development of technology, the traditional power system issues are not dominated in the future power system. Some new challenges such as better customer services, environmental protection and more social responsibility. [1]- [5]

There is a growing tendency that a large number of generators are connected to the power system network includes renewable (such as solar PV, wind turbines and biomass) and grid-scale battery storage. These are the power input to the grid which are unpredictable and unstable compared with the conventional and nuclear power plant. From the aspect of consumption, increasing number of new electric appliances are connected to the network, especially a higher penetration level of electric vehicles. [6]- [9]

The user's activities patterns are changing all the time, and are challenging to predict. Therefore two-way power flows are presented rather than the previous one-way power network. The vast uncertainties and instabilities in both generation and consumption sides are dramatically increasing the difficulties in balancing generation and demand.

Furthermore, the delivery of electricity is not the only target for future distribution network operators. Distribution network operators are not merely the energy supplier but also should act as the company and thus take more social responsibility. Therefore, customer services and environmental protection should be considered two priorities for the future. How to provide better customer service and how to, meet our customers' future needs and thus increase the satisfaction of each customer are essential questions. So too is how to lead all of society towards more low-carbon energy consumption behaviours. These problems cannot be ignored and will become the main challenges for the future.

1.2 Research objectives and scope

The research presented next in this PhD thesis can be divided into three primary objectives. The first objective is to create a bottom-up household electric vehicle charging activity profiles and demand model. This model introduces a Monte Carlo – Markov chain (MCMC) to simulate the detailed household activities based on the data acquired from the UK Time Use Survey (TUS) and National Travel Survey (NTS). These driving activity profiles are converted into electric vehicle charging power demand by developing the electric vehicle charging model. The second objective is to minimise the combined cost of low voltage distribution power network from aspect of finance, greenhouse gases emissions and power demand variations by using the multi-objective functions. The third objective is to develop a combined household demand side management to control household voltage level. Electric vehicle charging demand and wetload demand will be manipulated in the optimisation algorithm. Voltage sensitivity are used in the optimisation algorithm to maximise the influence of active power demand on the voltage level and minimise the disturbance of demand side management.

The specific research objectives can be summarised as follow:

1. The developed household user driving activity profiles can provide the detailed travel information for each household which shares the strong correlation with other daily activity profiles.
2. The electric vehicle charging load can model the accurate daily power consumption of each electric vehicle which takes into account external factors such as local temperature.

3. The impact of uncontrolled electric vehicle charging on the low voltage distribution network will be investigated. Various electric vehicle penetration levels and different generic distribution network will be implemented in the simulation.
4. An assessment of the influence of electric vehicle charging demand side management on low voltage distribution network will be carried out by multi-objective function optimisation algorithm calculating financial, environmental and energy system cost.
5. The household demand optimisation algorithms are developed based on voltage sensitivity to maintain the voltage level in the low voltage distribution network.
6. The comparison and analyst are conducted between electric vehicle charging demand management and combined household demand management; they operate, also between two proposed optimisation algorithms based on bus voltage and voltage sensitivity.

The scope and boundaries of this research are defined as follow:

1. The household electric vehicle charging model is based on the previously developed load mode in our research group. This is a supplement and perfection of previous work.
2. The network used in the simulation is a typical generic UK low voltage residential and highly urban network; all of the customers are domestic.
3. The OpenDSS is used to model the power flow analysis in all cases. Furthermore, Matlab is implemented as COM Interface of OpenDSS to achieve demand side management.

1.3 Thesis statement

A bottom-up, user-inclusive electric vehicle charging model can provide accurate aggregated demand profiles, which can then be used to develop charging management strategies that can improve voltage regulation, generation costs and environmental impacts within the future electricity.

1.4 Acknowledgement of the thesis contributions

The main contribution of this research can be summarised as

1. Development of household users' driving activity profiles and electric vehicle charging model.
2. The investigation into the influence of uncontrolled electric vehicle charging demand on financial and environmental cost and low voltage distributed power networks.
3. Development of multi-objective optimisation algorithm to minimise the combined cost including finance, environment and energy system.
4. Development of an optimisation algorithm to implement the demand side management of combined household demand based on voltage sensitivity.

1.5 Thesis structure

This thesis is divided into seven chapters. Chapter 1 includes an overview of the whole research area, highlighting the contributions of this project and forming the introduction of this doctoral thesis.

Chapter 2 reviews available literature published on the two main subjects, electric vehicle charging model and control voltage regulation. In the section detailing the electric charging mode, various electric vehicle charging demand methods and models will be analysed and compared. Of first importance is how to model people's travelling activities; secondly, we consider how to simulate the electric vehicle charging model. The accuracy of the results of these two parts serves as the input data of the whole model and is critical to both the further assessment of the influence of uncontrolled charging and implementing the optimisation algorithm. As the foundation of this research, electric vehicle policy will play an essential role in the future development of vehicle-to-grid technology. Global electric vehicle policy will be summarised and analysed, particularly policy in place within the UK. The knowledge of low-voltage distribution networks is also introduced to show the reason why demand side management is necessary and essential for the current distribution network operator.

Chapter 3 demonstrates the methodology for developing the household users' travelling activity profiles and the electric vehicle charging demand model. For household users' travel activity profiles, the detailed processing steps will be presented and explained from a large body of raw data taken from the UK Time User Survey (TUS) and National Travel Survey (NTS) in the final mathematical model which could generate the complete highly-correlated, household activity profiles. [10]

For the electric vehicle charging demand model, it will generate the uncontrolled charging demand based on various specifications of electric vehicles. Ambient temperature, as an influential factor in battery performance, will also be taken into account.

Chapter 4 presents a demand side management optimisation algorithm based on the voltage sensitivity in order to solve voltage variation issues in the low-voltage distribution networks. Firstly, the effect of uncontrolled charging demand with various penetration levels will be analysed. The methodology of calculating voltage sensitivity is also demonstrated step-by-step. Subsequently, another optimisation algorithm based on bus voltage will be compared to the algorithm proposed herein. Four defined parameters are employed to measure the performance of optimisation algorithms.

Chapter 5 shows demand side management of wetload demand in the household. The detailed household wetload demand profiles are demonstrated and analysed. Combined household demand side management is then implemented, based on voltage sensitivity including electric vehicle charging and wetload demand. Finally, comparisons are conducted between combined household demand side management and electric vehicle charging demand management.

Chapter 6 investigates the potential impact of a fleet of electric vehicles uncontrolled charging on the cost of electricity generation, greenhouse gas emissions (GHG) and power system demand. In order to decrease the negative impact of uncontrolled charging, the multi-objective optimisation algorithms are proposed through low voltage residential demand-side management (DSM). However, optimisation algorithms proposed in this chapter are based on the energy aspect which doesn't include power system issues such as voltage variation. Therefore, the next chapter will discuss and solve this problem regarding power system.

Chapter 7 is a summary and overview of all contributions to the research made in the previous chapters from generating users' activity profiles to combined demand side management. Furthermore, some limitations and reflections on the research are discussed. Finally, a future trajectory for the improvement of this research will be offered as a conclusion.

Chapter 2. Literature Review

2.1 Introduction

This chapter presents the background and literature review of the relevant research topics of this thesis. The summary of global electric vehicle policy and power system network status are presented, and discussion of current electric vehicle driving behaviours and charging models will be conducted. Furthermore, demand side management, vehicle-to-grid technology and voltage control regulations are the core optimisation method for this research and will thus be demonstrated in detail.

2.2 New Electric Vehicle Policy

According to electric car market statistics from April 2018, there are almost 145,000 plug-in vehicles on the road in the UK, which includes pure-electric vehicles (EVs), plug-in hybrid electric vehicles (PHEVs) and hydrogen fuel cell electric vehicles (FCEVs) [11], [12].

Compared with 3,500 cars in 2013, the demand for electric vehicles is experiencing dramatic growth. The following infographic provides detailed information on the UK electric vehicle market and ancillary equipment.

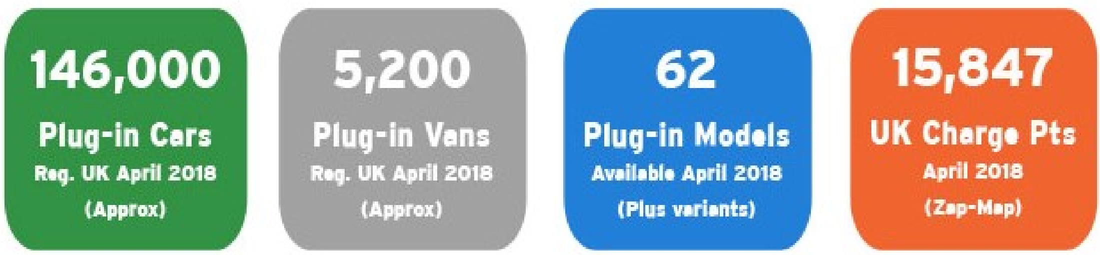

Figure 2. 1 UK electric vehicle market [13]

Despite this growth, the electric market is still at a very early and immature stage. There are some obstacles on the path to stimulate the development of the electric vehicle market which cannot be ignored. Limited battery ranges, insufficient electric vehicle charging points and stations, and charging periods which are too lengthy will lead to the range anxiety of users [14], [15], [16].

Meanwhile, compared with conventional vehicles, the sales prices of electric vehicles are still too high. Although most of the automobile manufacturers are releasing their new electric vehicle or plug-in hybrid vehicle (PHEVs) models, the available options of electric vehicles in the market are still limited. Currently, most people choose to buy an electric vehicle as the second or third car in their household, as supplementary to conventional vehicles. Furthermore, some potential concerns also have an impact on the popularisation of electric vehicles such as the lifespan of the battery package, electricity charging prices and, rapid generation switches of the electric vehicle.

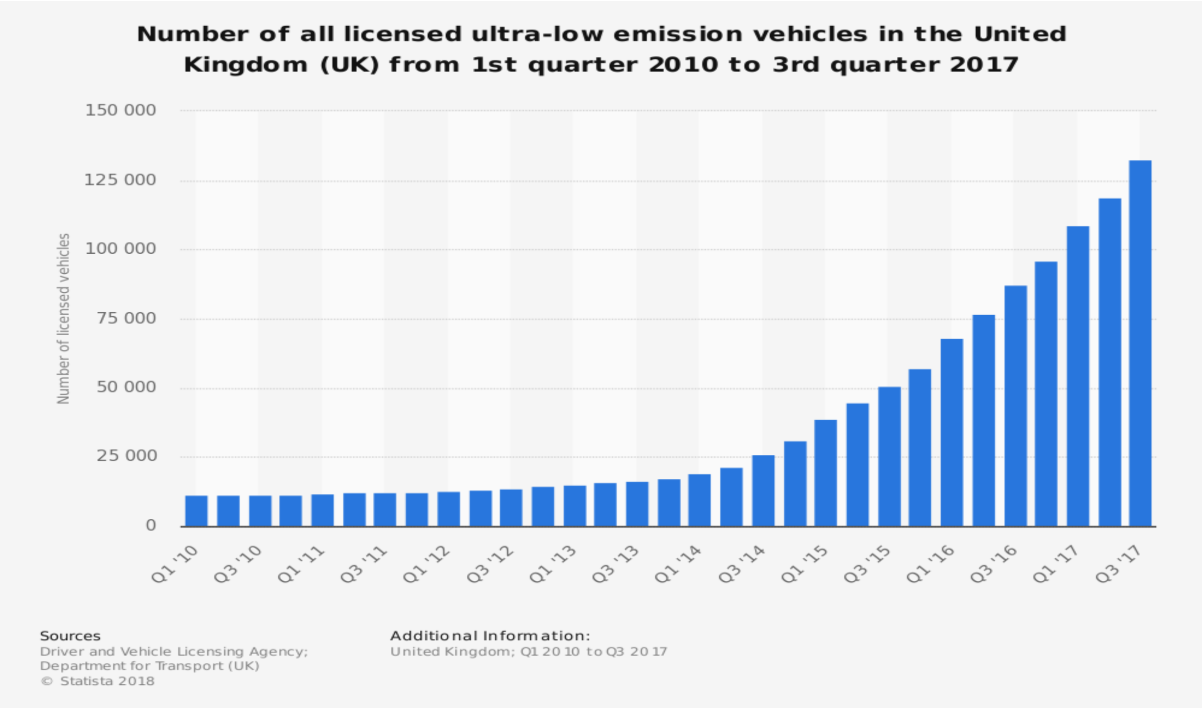

Figure 2. 2 UK electric vehicle *number* from 2010 to 2017. [17]

Therefore, it may be seen that government will play a significant role in overcoming these problems so as to promote the rapid and healthy development of electric vehicles. So far, the overall actions of the UK government can be summarised as below:

Firstly, the UK has aimed to cut greenhouse gas emissions by 80% by 2050 and is bound to this by the 2008 Climate Change Act. The King Review of low-carbon cars was commissioned by the UK government in 2007. This review concluded that electric vehicles would be necessary to achieve an 80% reduction in transport emissions [18].

The Department for Transport (DfT) and the Department for Business, Innovation and Skill (BIS) have led on EV policy in recent years, with a raft of initiatives put in place since 2007. In 2009, the Office for Low Emission Vehicles (OLEV) was created jointly within DfT, BIS and the Department of Energy and Climate Change (DECC) to oversee aspects of EV funding. They are providing over £900 million to position the UK at the global forefront of ultra-low emission vehicles development, manufacture and use. For instance, they launched a £30 million investment in revolutionary vehicle-to-grid technologies in February 2018.

The government issues a plan for an electric vehicle consumer subsidy from January 2011 which provide a subsidy of 25% of the purchase price up to a maximum of £5000 for vehicles meeting the performance, reliability and safety criteria. Moreover, £43 million worth of funding was confirmed in July 2010 to support this plan. Furthermore, there are additional financial benefits for electric vehicle owners, such as no vehicle excise duty. Some local councils also issued their incentives. All electric vehicles in London will be exempt from the central zone congestion charge. In Scotland, the government provides electric vehicle interest-free loans and funding to cover part of the cost of installing a home charging point.

In the view of the global electric vehicle market, 95% of electric vehicles are sold in 10 countries based on market shares: China, United States, Japan, Canada, Norway, United Kingdom, France, Germany, Netherlands and Sweden. These countries reached an agreement and proposed the most significant and profound electric vehicle policy in 2017 which lay a solid foundation for electric vehicles in the future.

France: Paris plans to end combustion engine vehicles, or fossil energy vehicles, by 2030. France will cease sales of petrol and diesel car by 2040, a policy announced in 2017 [19].

Britain: the UK plans to ban the sale of new petrol and diesel cars in Britain by 2040 to meet a target of having no petrol or diesel cars on the roads by 2050; this was also announced in 2017. The Scottish Government has set forth a plan for new petrol and diesel cars and vans to be phased out in Scotland by 2032, eight years ahead of the UK Government's target [20].

China: China is the world's biggest vehicle market. The government has not given a specific timetable for a ban on the productions and sale of fossil fuel cars but has announced that at some point in the future it will occur [21].

Germany: Germany's Bundesrat voted to ban all internal-combustion engines in new vehicles by 2030 completely [22].

Netherlands: The Dutch government presented its detailed plan which includes making all new cars emission-free by 2030 – virtually banning petrol and diesel-powered cars in favour of electric vehicles [23].

Norway: Norway will ban petrol-powered cars by 2025 and aim for 100% of Norwegian cars to be running on green energy by 2025 [24].

2.3 Low Voltage Network Status

The low voltage network is the final part of the electric power networks which deliver electricity from the distribution transformer to end customers. The low voltage network is designed to feed the customers with reliable and high-quality power. The low voltage networks include transformers, overhead or underground cables, various topologies and complicated load profiles. Therefore there are lots of specific requirements and regulations for network and power quality. One of the most critical indexes is the voltage level. The following table shows most of the household voltages and frequencies of alternating current (AC) electricity adopted in the world. The residential voltage level varies from 100V to 240V; most countries use the 50Hz as their AC frequency, and a few countries use 60Hz.

Country	Residential voltage level / V	Frequency / Hz
Fiji	240	50
Qatar	240	50
United Kingdom	230	50
Europe	230	50
India	230	50
Australia	230	50
Brazil	220	60
China	220	50
Mexico	127	60
United States	120	60
Canada	120	60
Cuba	110	60
Japan	100	50/60

Table 2. 1 Global voltage and frequency requirement

However, in the low-voltage distribution network, voltage level changes all the time as a result of the varying power flows between the point of connection and the bulk supply point. Sometimes, voltage fluctuations are beyond the statutory range, because most household electric appliances are designed, to operate within the proper range. Too low or high a voltage will lead to the damage of the connected equipment and will influence its performance. There are two reasons for this phenomenon.

1. The unbalance between generation and power demand is the main reason, especially when increasing renewable energy and electric appliances are

connected to the power grid. When the system is overloading, and there is a significant power surge in demand, the voltage level will become lower than the rated value. When the system is underloaded and more power is injected into the power grid such as high penetrations of renewable energy or dramatic reductions in power demand, the voltage level will become higher than the rated value.

2. Voltage loss on the transmission line: If a consumer is far away from a bulk supply point such as a substation, the voltage received in the household will be lower than normal which is because the inherent resistance and impedance of the transmission line will lead to the voltage loss. Meanwhile, the state of the wire also contributes to voltage losses such as loose connections, age and corrosion.

Therefore, national regulations determine the acceptable voltage ranges at the various voltage levels within the electricity network. A harmonised European voltage range of 230V of -6% to 10% has been proposed, i.e. it should be between 216.2V to 253V. From 1st January 2003, the European household voltage tolerance level was widened to ±10%, i.e. be between 207V to 253V. However, there is no practical change in the UK. The household voltage tolerance level is still 230V of -6% to 10%, i.e. between 216.2V to 253V, which has been stated by UK distribution code.

2.4 UK Electric Vehicle Charging Status Analysis

According to the Guide for Taxi and Private Hire Vehicle (PHV) Drivers issued by the UK Power Network (UKPN), approximately 66% electric vehicle owners will charge their cars at home, while around 20% of electric vehicles will be charged at work; only 10% of users will charge on their car route. [25]

Therefore, low-voltage distributed network operators will take the primary responsibility for supporting electric vehicle charging point (EVCP) and promoting the rapid development of electric vehicles.

Currently, DNOs define three type of charging points: slow, fast and rapid-charging; these are based on all the available electric vehicles in the market.

Slow charging: The charging rate is up to 3kW. For this charging rate, the charge point installer can assess the wiring and the equipment which connects to the network without the upgrade of the electricity supply. The DNOs should be notified.

Fast charging: The charging rate is between 7 and 22kW.

Rapid charging: The charging rate is higher than 43kW.

For fast and rapid charging, it is necessary to upgrade the electricity supply of your residential property. The application should be made from your charge point installer. Moreover, DNOs will assess your application and provide the offer if it is appropriate. The electricity supply includes changes to the household internal wiring which will be prior to installing the charging point based on the report from UK Power Networks. The Government's Office for Low Emission Vehicles (OLEV) offers grants of up to 75% (maximum £500) for the single residential charge point. For those who do not have the private parking space, charge point can be accessible in many public places such as supermarket, street parking zone and the public car park.

With the increasing penetration level of the electric vehicle, smart charging will be a top priority for the further development. The primary method of smart charging can be divided into two aspects:

1. Control or shift electricity consumptions of electric vehicle charging;

2. The utilisation of the electric vehicle battery for putting power back home or power system.

However joint effects from government and industry will be made to promote the more engagement in the smart charging in the following aspects.

1. Visibility of information

There is plenty of information need to be collected before the implementation of smart charging. The first is the information of electric vehicles such as the location of charge point, charging rates, state of charge of the vehicle, etc. These data will provide the minimum information for DNO to value and assess the further management for the network. Moreover, these data can be collected by the smart meter or from the charging point directly. However, the data privacy concerns cannot be ignored during this process. Not every customer is willing to share their household activity information such as electric vehicle charging status, electricity consumption, with the service providers and distributed network operators. DNOs believe that this problem can be solved that smart charging can make them deliver the better services to meet customers' expectations.

Apart from the information collected from electric vehicle charging process, it is also vital to make the smart charging plan simple, accessible, and beneficial to the users. At the early stage, better-informed users will be more likely joining the smart charging plan. It should ensure the smart charging plan simple and easy to choose. Above all, tariffs and benefits are the most important for users which will stimulate users' engagement in smart charging plan.

2. Standards

Standards [25] can make the sure the realisation of smart charging safe, securely. At the same time, standards are able to make the smart functionality to be scaled and applied consistently which could be beneficial to consumers. These standards are regarded equivalent to the 3G/4G/5G technology in the telecoms industry which thrive and grow the market for smartphones. Currently, the similar work is underway in the Netherlands by ElaadNL which is the knowledge and innovation centre in the field of smart charging infrastructure in the Netherlands. The outcomes developed from their lab will provide the excellent value for the UK.

The standards are designed to accommodate the different degree of electricity supply which includes:

- A simple switch on/off instruction: it is the minimum requirements for the electric vehicle charge point and should be controlled remotely via computer or cell phone.
- Instructions to change the charging rate: change rate can vary based on the requirements of consumers and DNOs;
- Change the rate and duration of charge disruption based on the electric vehicle battery state of charge;
- Bi-directional power transfer by Vehicle-to-Grid technology.

Visibility and standards make significant contributions to realising the value of smart charging. Meanwhile, electric vehicle manufacturers, aggregators, energy suppliers, network operators are supposed to work together to develop these standards.

2.5 Electric Vehicle Charging Load Modelling

Electric vehicle charging load modelling includes driving behaviour model and electric vehicle charging model. Most of the existing research conducted into electric vehicle charging management and modelling focuses on optimisation algorithms. The electric vehicle charging profiles are developed from rough probability statistics which can only describe the general trend of users' driving behaviour and charging profiles.[26]-[33]

2.5.1 Driving Behaviour Model

To model electric vehicle charging demand, the initial stage demands the generation of household users' driving behaviour profiles which are supposed to include the arriving home time, second-day departure time and, driving mileage. By reviewing related paper published recently, two principal methods are employed.

The first method is gathering data directly from electric vehicles. As the popularity of electric vehicles increases, many projects and companies are launching tracking systems on electric vehicles to collect their travelling data. [34]- [40]

For example, the CABLED project started from 2009 to June 2012. 110 ultra-low-carbon vehicles provided by some manufacturers were trialled across Birmingham and Coventry. Data collected include vehicle performance, infrastructure usage patterns, impacts and requirement within the minimum 12 months driving experience.

On the other hand, travelling data is collected from GPS fitted on gasoline or electric vehicles included trip length, duration, speed and location. The advantage of this method is to make sure all the data is derived from reality and can accurately track people's driving behaviour. However, there are some limitations. Usually, the sample size of this method is limited and the period of data collection needs to be longer.

The second method is to randomly generate a series of daily trip times based on self-defined probability distribution function which what most researchers to date have chosen. [41]- [45]

Usually, the probability can be obtained from various travel survey or report issued by transport departments. This data includes the possibility of starting travel and arriving home for 24 hours, the average daily mileage, etc. Compared with the first method, the mathematical method can easily produce a mass of electric vehicle charging profiles, but the accuracy and authenticity of the driving behaviours are not as reliable as the data directly derived from real use.

Furthermore, the final objective of driving behaviour is to obtain the household electric vehicle charging demand. [46], [47]

Then the optimisation algorithms can be implemented to achieve various targets. In most cases, electric vehicle charging demand management is conducted in the low-voltage distribution network which contains plenty of varying kinds of power demand. [48]- [52]

For the two methods mentioned above, the driving behaviour is regarded as the isolated daily activities. The relationships between electric vehicle charging demand and other household electricity consumption activities are not taken into account.

The total power demand of a household is simply the aggregation of electric vehicle charging demand and baseload demand. In actuality, electric vehicle charging demands have a strong correlation with household baseload demands. The mismatching of electric vehicle charging demand and household baseload demand will result in a negative impact on the development of optimisation algorithms for electric vehicle charging demand.

2.5.2 Electric Vehicle Charging Model

Currently, most electric vehicles are equipped with batteries which are lithium based such as Li-ion. [53], [54]

The following table shows complete charging and battery information for the most popular electric vehicles available in the market. As we can see from the table, electric vehicle charging schemes can be divided into three level. The first level is standard home charging which is usually 1-phase grid connection and below 10 kW. The second level is upgraded home charging which is usually 3-phase grid connection and around 20 kW. The third level is supercharging which is employed in the charging station. The charging rate is usually above 60 kW. The battery capacity of electric vehicles also varies from 16 to 100 kWh to meet the differing demand of customers which can provide at least 90 miles and up to 335 miles driving range in the condition of the fully charged battery. Moreover, the following information is given by the official manufacturer. However, in reality, there are plenty of external factors influencing the available range, such as ambient temperature, users' driving behaviour, the usage of the electronic devices, etc.

EV Type	Battery Capacity / kWh	Range / mile	Charging Rate / kW
Tesla S	60 - 100	335	1-phase grid connection: 7.4 3-phase grid connection: 11 Wall connector:16.5 Supercharging: above 60 up to 120
Tesla 3	50 - 70	220 - 310	
BMW i3	22 - 33	124 - 205	1-phase grid connection: 7.4 3-phase grid connection: 22 Public AC charging: 7.4
Nissan Leaf	24 - 40	120 - 168	Standard home charging: 3.3 Upgraded home charging: 6.6
Renault Zoe	22 – 41	160 - 250	Home solo charger: 3.6 / 7 / 22
Citroen C-zero	14.5	90	Home charging: 3.7 Rapid charging up to 62.5
Peugeot iOn	16	93	

Table 2. 2: Electric vehicle battery and charging information

For electric vehicle battery charging, there are three methods during the battery charging process. [55]- [61]

1. Constant Voltage (CV). The constant voltage charging method usually charges the battery at a constant voltage level which allows full current flow into the battery until it has been fully charged. This charging method is the simplest and widely implemented with various kinds of batteries. The charging current changes during the whole process. In the beginning, the charging current is quite large and then is gradually reduced to zero when the battery reaches fully charged state. This method is suitable for lead-acid types while it is not suitable for Lithium-Ion types.

2. Constant Current (CC). The constant current charging scheme is used to maintain a constant current for battery during the whole charging process. The state of charge

(SOC) will increase linearly. However, this method could lead to overheating of the battery when it is over-charged. This charging scheme is suitable for Nickel Metal Hydride (Ni-MH).

3. The combination of constant voltage and constant current. In practice, the complete charging process includes both constant voltage and constant current charging methods which will be adjusted based on the battery specifications. Here is an example for typical Li-ion battery charging profiles.

At the first pre-charge stage, the battery will be charged at a low, constant current if it is not pre-charged. Then the current will be increased to a higher value; the battery will still be charged in the constant current method. The next stage is the constant voltage when the state of charge or battery voltage reaches a certain threshold point. The current will drop slowly, and the constant voltage charging method can effectively maintain the battery voltage at the desired level. However, the main focus of this project is not modelling the electric vehicle battery charging process. Therefore, the charging voltage and current will not be taken into account in the modelling. The constant charging power will be applied in the charging process which is used for most electric vehicle charging demand simulation.

2.6 Demand Side Management (DSM)

Today, approximately 30-40% of the total energy consumption all over the world are from the residential sector. Unlike other kinds of power demand consumption, residential power demands have a strong seasonal and daily pattern. [62]- [65]

Moreover, the difference between the power demand peak and valley could be huge within a typical day. However, in order to meet these occasional power demands, the electric utilities and power network companies have to increase generation capacity to meet the demand. The philosophy of traditional power systems is to supply all power demands whenever needed and usually more power will be prepared for an emergency. However, the new philosophy of power system operation is to become more efficient and keep power demand fluctuations as low as possible.

The definition of demand side management is that end-use customers change their energy consumption patterns in response to various methods adopted such as financial incentives. Usually, there are three demand response methods customers can adopt. [66]- [70]

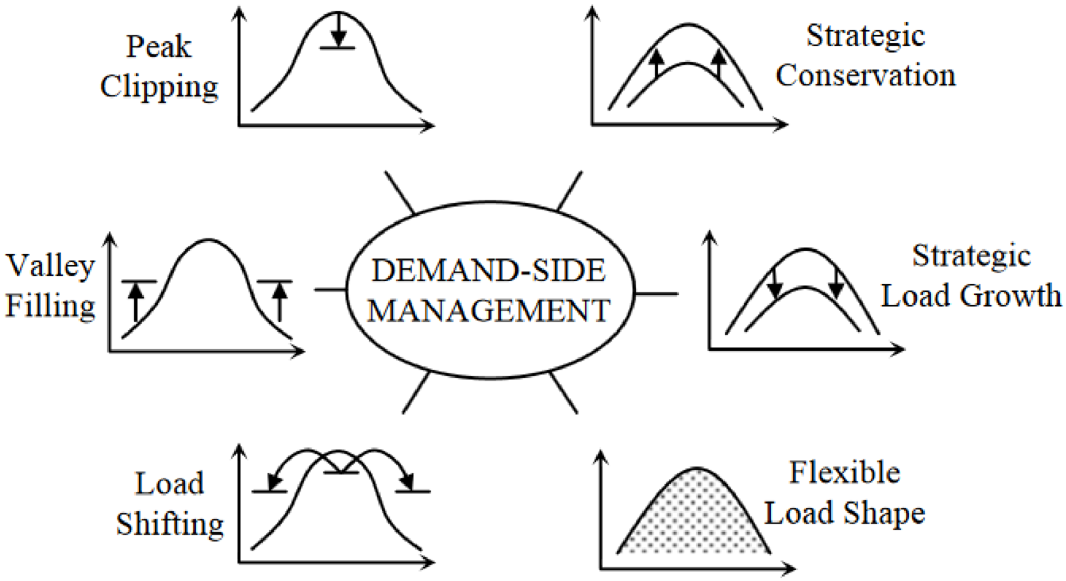

Figure 2. 3 DSM's six categories of load shaping objectives [71]

1. First is to reduce the power demand during the peak demand period without influencing users' activities or with permission from users. This method can decrease the additional power demands in the household from items such as refrigerators, air conditioners and heating systems. For instance, the refrigerator can be shut down for a few minutes during peak hours, and it will not affect the food quality.

2. Second is to shift power demand from peak periods to off-peak periods. This method is employed for some uncritical power demand such as dishwashing, tumble dryer and washing machine. For example, users could start the washing machine before they go to work in the morning. At this time, the washing machine can be postponed to a later time when electricity price is lower. It not only cuts electricity bills for customers but also reduce the peak demand pressure for power networks in the morning. Users will suffer no loss during this process.

3. The third is installing distributed generation close to or embedded within the consumer location. With the popularisation of the distributed generation system, more and more households or factories install photovoltaic panels and energy storage. Customers can use the power generated from their own distributed generation systems, which significantly reduces demands for power systems and also saves money. Compared with previous methods, this will not influence users' activity patterns, but will modify the profile of the power exchange with the grid.

Therefore, detailed demand side management method should be chosen based on various users' behaviour and different electric appliances. [72], [73]

However, electric vehicle charging demand is unlike other load demands. All three methods mentioned above can be implemented with electric vehicle charging demand. For instance, electric vehicle charging can be interrupted and also delayed during the charging process without influencing users' next travelling activities. At the same time, the electric vehicle is regarded as the flexible energy storage in the distribution network. It not only consumes electricity but also can store electricity when electricity prices are low or renewable energy is surplus in the system. It even can supply electricity back to the grid when it is necessary which will be discussed in the part of Vehicle-To-Grid (V2G) technology.

In the future, the electric vehicle will play an essential role in the demand side management in the distributed power network. Meanwhile, the development of smart grid technology will stimulate the development of demand side management.

In summary, the advantages of demand side management are obvious and can be detailed as follows:

1. Reducing the generation margin: usually the total capacity of installed generation in the power system should be larger than maximum power demand to guarantee enough power supply in case of complex power demand. It means plenty of generation capacity is built as the reserve which will not be used frequently. Demand

side management can provide an alternative form of reserve, and significantly reduce the generation margin. [75], [76]

2. Improving cost and efficiency of the distribution and transmission network: The use of demand side management can provide power system support services such as frequency response, voltage regulation, short-term operating reserve, triad management and greenhouse gas reduction. [77], [78]

3. Accommodating more intermittent renewable energy: In order to reduce the greenhouse gas emissions, the electricity generation system has to absorb more and more renewable energy such as wind and solar power. The higher uncertainty of renewable energy requires the system with the increased amount of reserve. The application of demand side management could improve the penetration level of renewable energy without increasing the extra investment to power system. [79]-[83]

The advantage of demand side management is evident. However, there still are some challenges in the application of demand side management. First is the lack of Information and Communication Technology (ICT) infrastructure such as advanced metering, control units and, communication technology beyond that contained in traditional systems. [84]

Second is the lack of appropriate incentives and solution to encourage more and more participants. It is vital to ensure that all participants and stakeholders can benefit from demand side management schemes. [85]- [88]

2.6.1 Smart Grid

The first official definition of Smart Grid was proposed by the Energy Independence and Security Act of 2007 (EISA-2007). Ten characteristics were given to describe Smart Grid, and this can be regarded as the most comprehensive and fundamental definition of the term. The smart grid should be considered the modernisation of current electricity transmission and distribution system to maintain a reliable and secure electricity infrastructure which can meet the future demand growth and also include the following characteristics. [89]- [91]

"(1) Increased use of digital information and control technology to improve reliability, security, and efficiency of the electric grid. (2) Dynamic optimization of grid operations and resources, with full cyber-security. (3) Deployment and integration of distributed resources and generation, including renewable resources. (4) Development and incorporation of demand response, demand-side resources, and energy-efficiency resources. (5) Deployment of 'smart' technologies (real-time, automated, interactive technologies that optimize the physical operation of appliances and consumer devices) for metering, communications concerning grid operations and status, and distribution automation. (6) Integration of 'smart' appliances and consumer devices. (7) Deployment and integration of advanced electricity storage and peak-shaving technologies, including plug-in electric and hybrid electric vehicles, and thermal storage air conditioning. (8) Provision to consumers of timely information and control options. (9) Development of standards for communication and interoperability of appliances and equipment connected to the electric grid, including the infrastructure serving the grid. (10) Identification and lowering of unreasonable or unnecessary barriers to the adoption of smart grid technologies, practices, and services" [92]

However, different countries propose varying Smart Grid projects which are based on differing power system situation and requirement. For example, as the world's largest consumer of electricity and demand, the State Grid Corporation of China has proposed a 5-year plan for constructing Ultra High Voltage (UHV) grids for completing a strong, smart grid by the end of 2020. According to the Strategic Development Document for Europe's Electricity Network of the Future, "Smart Grid is an electricity network that can intelligently integrate the actions of all users connected to it – generators , consumers and those that do both – to efficiently deliver sustainable, economic and secure electricity supplies."

According to the Smart Grid Vision and Routemap published in February 2014 from Department of Energy & Climate Change and Ofgem, there are three key stages in the development of a smart grid.

Figure 2. 4: Key stages in the development of a smart grid [93]

1. The first phase of smart grid development is focused on capturing the short-term benefits of deploying smart technologies and solutions, while also preparing for the accelerated deployment of distributed generation and increasing electrification of heating and transport projected to take place in the 2020s;

2. The second phase of smart grid deployment sees a much more significant role for the consumer, following the successful roll-out of a smart meter across Great Britain;

3. The third phase will see Great Britain achieve its vision objective where a smart grid enables Great Britain to develop a fully integrated smart energy system and a platform for the further development of technologies to support the increasing electrification of the heating and transport sector and smart homes and business.[94], [95], [96]

A general summary of the characteristics of the traditional power grid and smart grid are present in the following table:

Traditional Power Grid	Smart Grid
Electromechanical	Digital
One-way communication	Two-way real-time communication
Centralized power generation	Distributed power generation
Radial Network	Dispersed Network
Less date involved	A large amount of data involved
Small number of sensors	Many sensors and monitors
Manual monitoring	Automatic monitoring
Manual control and recovery	Automatic control and recovery
Less security and privacy concerns	Prone to security and privacy issues
Limited control	Extensive control system
Slow response to emergencies	Fast response to emergencies
Fewer customer choices	Many customer choices
Human attention to system disruptions	Adaptive protection

Table 2. 3: Summary of the traditional power grid and smart grid

The benefit of the smart grid can be concluded in four aspects:

1. Consumer benefits: It will effectively minimise consumer bills and encourage more consumer and community participation. The implementation of a Smart Grid will reduce plenty of infrastructure cost for the traditional power grid and finally this cost will pass through to electricity end-users. The smart meter systems will provide users with more detailed information about their electricity consumption. At the same time, some energy management can be deployed by the energy supplier. [97]

2. Economic benefits: The development of a Smart Grid will create more jobs and provide solid support for economic growth. It is estimated that approximately £13bn of Gross Value will be added from now to 2050, which could create 8000 jobs during the 2020s and rise to 9000 during the 2030s. Furthermore, the Smart Grid will increase the existing power network capacity and faster, and cheaper two-way connections will be built for suppliers and customers. Demand side management will play an increasingly vital role in the Smart Grid. [98], [99], [100]

3. Energy security benefits: It will improve power system security and reliability. The Smart Grid will offer a more intelligent network which could assist energy supplier and power grid operator to find power outages and interruptions in time. Once the power system failure occurs, it can be restored more quickly. Meanwhile, the Smart Grid will effectively widen energy system integration such as combined heat and power (CHP), heating and power (CCHP), gas fired heat pumps, energy storage system and renewable energy. The whole energy system and infrastructure will be integrated and optimised by Smart Grid. [101]- [104]

4. Low carbon transition benefits: It will enable more low-carbon technology to be deployed. The environmental-friendly energy consumption patterns will be proposed with the rapid development of new technology such as electric vehicle, renewable energy. The combination of electric vehicle and the Smart Grid will replace not only conventional petrol or diesel cars but also provide strong support to the power system reinforcement. [105]- [108]

2.6.2 Vehicle-To-Grid Technology (V2G)

Vehicle-to-Grid (V2G) technology can be defined as a system in which has the capability for controllable, bi-directional electrical energy flow between a vehicle and the power grid. The electric vehicles are regarded as the battery for storing energy from power and sending the power back when the system requires it. Currently, there are three significant benefits of V2G technology. [109]- [114]

1. Load Levelling and Peak Power Management: The V2G technology enables electric vehicles to discharge the battery when the power demand is high and charge the battery when power demand is low. It could effectively reach the target of valley filling and peak shaving and reduce the pressure of balancing the consumption and generation. [115], [116], [117]

2. Accommodate more renewable energy: In the future, the electric vehicle can achieve the goal of buffing renewable energy sources such as intermittent PV solar and wind energy. In the traditional power system, if too much energy from the

renewable source is injected into the power grid, some power plants have to be shut down. Otherwise, renewable energy will be wasted. Electric vehicles can provide the help for matching supply and demand by charging and discharging the battery. On the other hand, V2G will increase the penetration level of renewable energy in the power system and reduce the greenhouse gas emissions. [118], [119], [120]

3. Voltage and Frequency Regulation: Voltage and frequency stability is a key issue in the power system. Voltage and Frequency regulation can be achieved by changing electric vehicle charging and discharging demand. [121], [122], [123]

Furthermore, all these benefits mentioned above will accrue money the owner of an electric vehicle. The distributed network operators and utility companies will pay for V2G services such as short-term operating reserve, voltage and frequency regulation. The customers can sell the energy back to the grid from their battery and take advantage of flexible electricity prices to achieve profits. However, one issue which cannot be ignored is that batteries have a limited number of charging cycles. Moreover, the implementation of V2G technology will lead to higher frequencies of charging and discharging which is beyond normal conditions. It will severely decrease the capacity and shorten the life-span of the battery. Therefore, battery technology is one of the significant barriers to the development of V2G. [124]- [128]

2.7 Voltage Regulation

As mentioned in the previous section, voltage violation in the distributed network is a vital issue that distributed network operators (DNOs), and customers are concerned about. Severe voltage violation will lead to damage of electrical equipment and also threaten the security of distributed networks operation. In the traditional power system, concerns are mainly focused on the voltage drop issue caused by the heavy power demand. Nowadays, increased uncertainties in power demand and bi-directional power flow result in complex situations. Especially when more distributed renewable energy and storage are installed in the system, too much power injected into the power grid can cause the voltage to rise.

To maintain the voltage level in the distributed network, many different devices have been installed in the system, such as static voltage-ampere reactive (VAR) units, static synchronous compensator (STATCOM) [129], [130], [131] and, on the load tap changing transformers (OLTC). [132], [133]

There are four major categories of voltage control strategies. [134], [135], [136]

1. Centralized control: It aims at global optimisations; however, it usually requires high investment in communication equipment and electronic devices in the network. It also leads to a heavy communication burden.

2. Local control: Compared with centralized control, it can have the faster response speed while the infrastructure investment cost is lower. However, the voltage regulation capability of this system is limited.

3. Distributed control: By the coordinating between buses and nodes in the distributed networks, this voltage control strategies can reduce investment cost and improve the voltage regulation capacity to some degree. The optimisation effect will be limited and not obvious compared with the previous two strategies.

4. Decentralized control: These strategies combine the advantage of centralised and distributed control by zonal control and intercluster coordination based on the partition of the network.

Apart from control strategies, many optimised algorithms are implemented such as a genetic algorithm, [137], [138] clustering algorithm, particle swarm optimization algorithm, etc. Nowadays, with the increasing penetration of distributed renewable energy and storage system including electric vehicles, demand side management play an important role in distributed voltage regulation through active power curtailment (APC) and reactive power compensation (RPC).

2.8 Conclusion

This chapter presents a general overview of the areas related to the major research topic of this PhD thesis. It summarises the current electric vehicle policies proposed by different countries and analyses the advantage of electric vehicle development. An irrevocable trend in policy and design will lead to electric vehicles replacing the current internal combustion engine vehicles in the near future. Therefore, people's driving behaviour models and electric vehicle charging models are herein discussed to make significant contributions to further large-scale electric vehicle charging demand management. Furthermore, the existence of Smart Grid and demand side management will accelerate the development of electric vehicle and take full advantage of the electric vehicle as an energy storage system. The description of vehicle-to-grid (V2G) technology and control voltage regulation methods have been provided to support ancillary services from electric vehicle charging management.

The review and analysis of these existing policies and literature prove that the accurate driving behaviour and electric vehicle charging demand models require further optimisation and management, and advanced optimisation algorithms are required to take full advantage of electric vehicle charging demand to provide voltage regulation services. Furthermore, the implementation of electric vehicle smart charging can effectively reduce greenhouse gas emissions.

Chapter 3: Development of electric vehicles power demand model

3.1 Introduction

This chapter presents a novel electric vehicle charging power demand based on household people’s driving behaviour profiles and electric charging model. A large corpus of raw statistical data, detailing both individual’s driving activities and the characteristics of electric vehicles, has been collected and analysed to create power demand profiles using the Markov chain Monte Carlo (MCMC) method. These electric vehicles charging power demand profiles share strong correlations with individual household power demand.

The key contributions to this electric vehicle charging model are the detailed time-varying EV charging profiles of individual household in the low-voltage distribution networks. This project uses large numbers of databases on travel methods, the ownership and characteristics of electric vehicles, external influential factors, and so forth to generate one-minute resolution electric vehicle charging power demand profiles for each household. These electric vehicle charging profiles do not only make an excellent complement to the previous residential load model but also present a new idea for low-voltage distribution network demand side management. Then all these works are combined with the residential load model, which was developed by our research group, Institute of Energy Systems (IES). This model focuses on basic household electric appliances such as lighting, heating, wetload, etc. Given that electric vehicles are not taken into account in the travelling activities, travelling is regarded as a non-electricity consumption activity in the household.

In many cases, electric vehicles are regarded as energy storage to reduce the intermittency of electricity supply from renewable energy such as solar and wind [141], [142], [143]. On the other hand, research presented in [144], [145], [146] has been conducted into the demand side management strategies and related optimisation algorithms in the low-voltage network. However, the operation and performance of low-voltage networks depend on a mix of various kinds of electric loads, the users' behaviour and external factors (such as weather condition and social events). Most existing studies do not take the relationship between EVs and other household appliances into account and only focus on electric vehicles.

Currently, research presented in [147], [148], [149] has obtained the data from long-term experiments which use mobile devices installed on vehicles to record people's driving behaviours. Most of the studies use probability from a large-scale statistical survey to model people's driving behaviours [150],[151],[152].

These modelling approaches cannot provide large-scale and accurate EV charging demand profiles. Therefore the detailed time-varying model of residential load demand has been developed based on previous works executed within our research group.

This chapter demonstrates the detailed explanations step by step from collecting people's diary sampled national-scale survey data to generating final household active and reactive electric vehicle power demand profiles. It includes two developed models, driving behaviour model and electric vehicle charging model. Driving behaviour model is used to convert raw surveyed data into activity profiles. The electric vehicle charging model is built to produce power demand which takes into consideration electric vehicle characteristics and the influence of external factors. The conclusions are discussed in the final part of the chapter.

3.2 Load model development methodology

Most of the power demand in the residential load is driven by user activities. Power demand profiles can, therefore, be easily estimated as long as detailed user activity data has been provided. Markov chain Monte Carlo (MCMC) is implemented to process the real activity diaries from time user surveys.

MCMC is the stochastic algorithms which is used to sample probability distributions by Markov chains. It allows one to characterize a distribution without knowing all of the distribution's mathematical properties by randomly sampling values out of distribution. And the name MCMC contains two properties: Monte-Carlo and Markov chain. Monte-Carlo is the practice of estimating the properties of a distribution by examining random samples from the distribution. For example, a Monte-Carlo method can draw a large number of random samples from a normal distribution and calculate the sample mean rather than finding the mean of a normal distribution by calculating it from the distribution equations. And the Markov chain property of MCMC is that random samples are produced by a special sequential process. Each random sample is used as a stepping stone to generate the next random sample. Therefore, each new sample generated only depends on the previous one while it does not depend on the sample before the previous one.[153]

Monte Carlo evaluates $E[f(X)]$ by drawing samples $\{X_t, t = 1, \dots, n\}$ from distribution $p(x)$ and then approximating

$$E[f(X)] \approx \frac{1}{n}\sum_{t=1}^{n} f(X_t) \tag{3.1}$$

So the population mean of $f(X)$ is estimated by a sample mean. When the samples $\{X_t\}$ are independent, laws of large number guarantees that as the increasing sample size, the calculated approximation results can be made as accurate as possible. And sample size n is various as required. The $p(X)$ can be generated by any process which can be non-standard.

Consider the sequence of random variables$\{X_0, X_1, X_2, X_3, \dots\}$, generated from the distribution (X) , the next state X_{t+1} only depends on the current state X_t. As discussed, the next state X_{t+1} does not depend further on the history chain$\{X_0, X_1, X_2, X_3, \dots\}$. This sequence is called as Markov chain. [154]

The Monte Carlo method is implemented to add randomness in various household activities within each time step. The Markov Chain simulation is then adapted to create household daily activity profiles for a whole day. Plenty of detailed information can be gleaned from two aspects individual household and electric appliance characteristics. Household information includes the number of people in one household, the working status for each occupant and the number of children. Differing family structures lead to various user activity behaviour patterns. Household power demand is the complex mixture of various electric appliances. Each electric appliance owns its unique characteristic which means they have to be regrouped and use particular load model to generate power demand load profiles.

Unlike other household appliances such as lighting and refrigerator, electric vehicle charging load has two characteristics; flexibility and high controllability. When people drive their electric vehicles, the electric energy stored in the battery will be consumed. However, the battery will not be charged immediately until they arrive at the appropriate charging point or the battery is going to run out. Moreover, it also increases difficulties in predicting the driving behaviour of a user. On the other hand, most people charge their vehicles at night, at home, every day. Moreover, usually the allowed charging period is longer than the required charging time to make the battery fully charged, which in reality provides a good opportunity for demand side management.

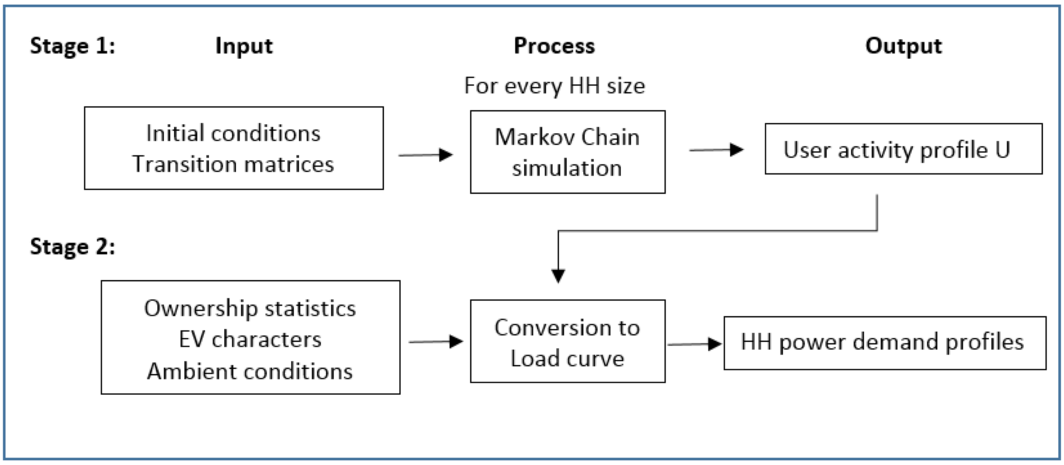

Figure 3. 1: Electric vehicle charging load model development work flow

The above figure shows flow chart of electric vehicle power demand modelling. The modelling methods can be divided into two stages:

1. User activity profile modelling

2. Conversion of user activities into power demand profiles

3.3 Driving behaviour model

Accurately forecasting and modelling people's behaviour and activities is notoriously complex. The UK Time Use Survey (TUS) was launched in 2001 and aimed to measure how household people engage in various kinds of activities during a specific period. It provides hundreds of different kinds of daily activity data from more than ten thousands of self-completion diaries, which record activity for every ten minuses, such as going out for work or entertainment, over the course of a day. In this work TUS is used as the MCMC model input for user activities, allowing the generation of realistic activity profiles based on the characteristics of the household. A similar approach was taken in [10]. For compatibility and easy integration, the same input data structure has been used and is described in the following section.

3.3.1 Time User Survey Database

The broad TUS database of activities is filtered into 13 user activity states which can be used to describe the majority of household activities. The following table contains the detailed information of 13 user activity states based on their different load model characteristics. As we can see, some activities consume electricity in the household such as ironing, watching TV and so on. On the other hand, some activities do not necessarily require electricity. Based on the previous research from our group, all mentioned activities in the table have been modelled and create the complete daily power demand profiles through a combined MCMC algorithm. However, electric vehicles are not taken into account in this model. So all travel activities are regarded as non-electricity consumption.

User activity state		Electrical use	Appliance sharing
ID	Definition		
1	Non-electrical activity in home	N	n/a
2	Sleeping	N	n/a
3	Wash/dress	Y/N	N
4	Food preparation	Y/N	N
5	Dishwashing	Y/N	N
6	Cleaning house	Y/N	N
7	Laundry	Y/N	N
8	Ironing	Y	N
9	Computing	Y	Y/N
10	Watching TV	Y	Y/N
11	Watch video/DVD	Y	Y/N
12	Listening to music/radio	Y	Y/N
13	Travel/Out of the house	Y/N	n/a
Where: Y – yes, N – no, n/a – not applicable			

Table 3. 1: User activity state definitions

In the flowchart of stage 1, initial conditions and transition matrices will be used as an input for the model and calculated from a large number of TUS data. Initial conditions are the probabilities that people start to do one activity in each 10-min slot. Thus initial conditions are 13×1 matrices for 13 activity states at the starting point of a day. Transition matrices are the probabilities that people change their current state to next state. So transition matrices contain 144 submatrices for a 10-min slot in 24 hours and each submatrix include 13×13 elements for the 13 individual activity states. For example, at 2:00 am of a working day, there is very high possibility that people are in the sleeping state. It also makes senses that people likely to continue sleeping at 2:10. However, there is still the slight chance that a person goes to the bathroom or kitchen. The appliance sharing state is defined in Table 3.1. It is because that some electric appliances are able to be shared by more than one people in the household.

$$P_{IC\_i} = \frac{N_i}{N} \tag{3.1}$$

The following equations show the detailed explanation of Stage 1 in Figure 3.1 including the initial conditions and transition matrices. Where P_{IC_i} is initial conditions for activity i, N_i is the total number of activity i at the starting point. Moreover, N is the total number of all activities during that 10-min time slot.

$$P_{TM\_ij}(t) = \frac{\sum_{j=1}^{J} n_{ij}}{n_i(t)} \tag{3.2}$$

Where: $P_{TM\_ij}(t)$ is the transition probability from activity state i to state j, including i= j, between time t and t +1, $n_{ij}(t)$ is the number of transitions from activity state i to state j between t and t +1, $n_i(t)$ is the total number of transitions from activity state i between t and t +1 and J is the total number of activity states.

Therefore, for each household, the first temporally activity is chosen based on the probabilities in the initial conditions. Once the first activity state is confirmed, the next activity state will be selected according to the probability of the transition matrices and the previous activity states at each time step. Finally, the individual detailed household people activity profiles for a whole day are produced.

3.3.2 National Travel Survey

Due to the limited data about household travelling contained in the TUS, the National Travel Survey (NTS) is also used, conducted by the Department for Transport. It is a household survey and is very similar to the TUS, providing complementary information, in that it focuses on the information of people's travelling, including why, how, when, where and other factors influencing travel. This survey aims to monitor people's long-term travel patterns and behaviour and provide useful information for making relevant policies. It covers approximately 16,000 individuals from 7000 households in the UK. According to the various travel types purposed, all travel activities are classified into seven categories including other leisure, commuting, visiting friends, personal business and other escorting, shopping, business and education. The detailed summary of each travel purpose and full definitions are presented below.

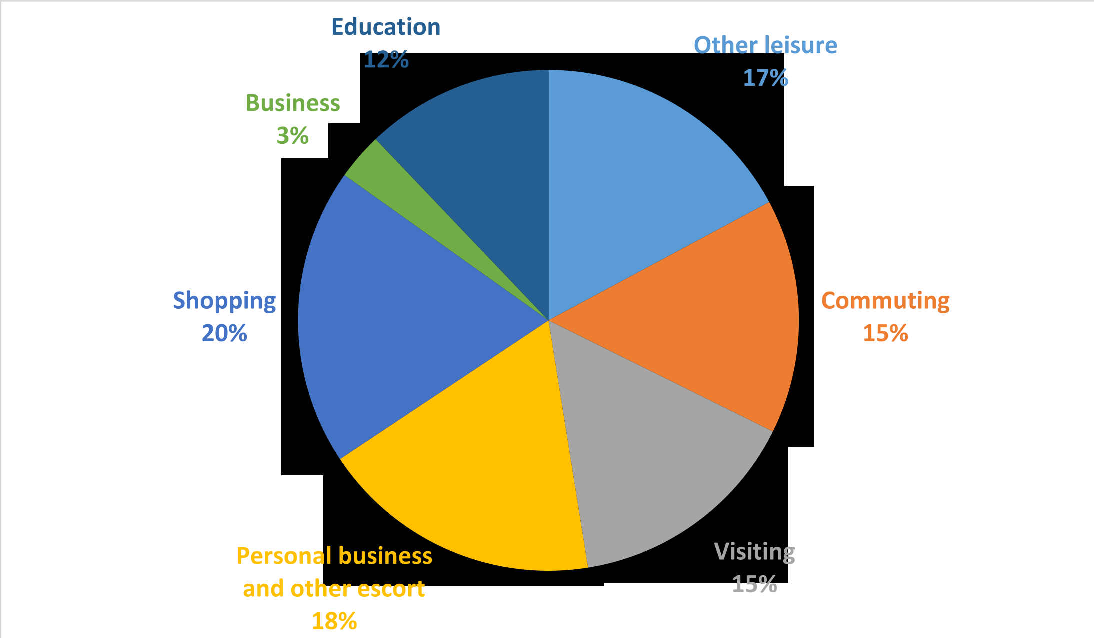

Figure 3. 2: Purpose share of average number of trips travelled from NTS

1. Commuting: trips from home to workplace or from workplace back home

2. Business: personal trips which are related to work

3. Education: trips to school or college

4. Shopping: trips to the shops or from shops back to home

5. Personal business: visit to services, medical consultations, etc.

6. Visit friends: trips to visit friends or travel to the home of someone others or elsewhere

7. Other leisure: mostly entertainment, sport, holiday and day trips.

Travel method	Walk	Bicycle	Car	Bus	Rail	Other
Probability	22%	2%	64%	7%	3%	2%

Table 3. 2: Probability of travel methods

According to the National Travel Survey (NTS), daily travel methods can be divided into six categories. Individual household travel activities will be decided based on these probabilities. For example, when the travel activity is found in the daily household diary of TUS, the possibility of travel by car is 64%. Moreover, the various electric vehicle penetrations will be used to estimate the number of EVs. The average distance per car trip is 7.1 miles according to 2013 NTS report. Therefore the random numbers generated by normal distribution will be used as the car travel distance of each trip.

3.3.4 Validation through National Travel Survey (NTS)

The following figure shows the simulated results (blue line) of car travelling activities from driving behaviour model compared with the referenced data (green line) from National Travel Survey (NTS). Although there is some difference existing between two data sheet, the general trend is the same. Two peaks are generated and at around 8 am and 18 pm. Moreover, most car travelling activities are focused in the daytime. So this can explain the match of the two datasheets and a prove the accuracy of the developed driving behaviour model.

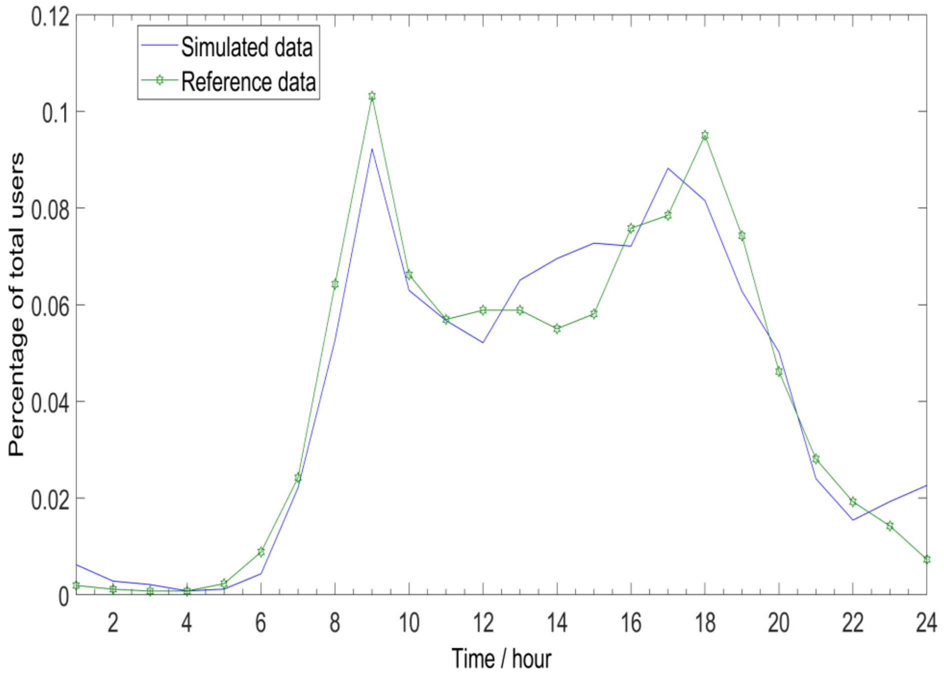

Figure 3. 3: Generate activities profiles of car travelling compared to the data from NTS

3.4 Electric vehicles charging model

This section will present a model to calculate electric vehicle consumption which is based on the day trip from the driving behaviour model. The ambient temperature will be included in this model as an essential input variable. Usually, the ambient temperature will influence the range of electric vehicles, especially in extreme seasons such as winter and summer.

On the one hand, the battery functions best at around room temperature. The cold temperature will increase the internal resistance and lower the battery capacity which could lead to starting failure. Moreover, the conductivity of electrodes and electrolyte are reduced. The following figure shows that how the DC resistance changes as the ambient temperature varies in the fixed SoC. As it shows, DC resistance increases when the temperature decrease for the same SoC. Therefore at the low temperature, the battery could reach the cut-off voltage earlier at the higher discharge rates.

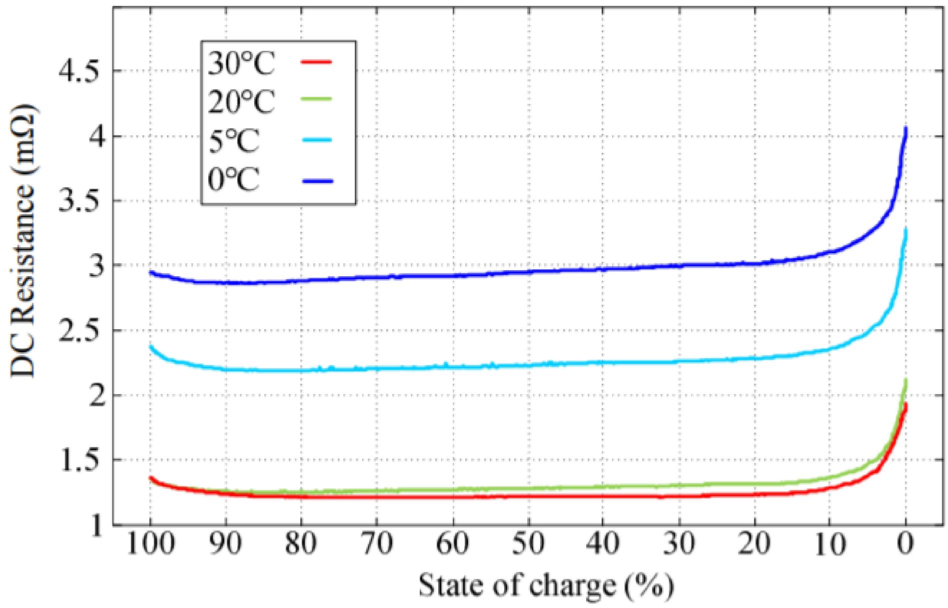

Figure 3. 4: DC resistance as a function of SoC at 0˚C, 5˚C, 20˚C, 30˚C [155]

On the other hand, cold weather presents two major challenges for electric vehicle energy consumption: lower temperature limits battery performance and running heating systems also consume energy from the battery. Therefore local temperatures are taken into account when calculating the available driving range.

3.4.1 Electric vehicle characteristics and influence of external factors

Currently, there are many kinds of electric vehicle models available in the market; these include Nissan Leaf, Toyota Prius, BMW i3 and Tesla. By the end of June 2017, more than 17,250 Nissan Leaf have been sold in the UK market making it the most popular electric vehicle today. Given the current market share of electric vehicles, the Nissan Leaf has been chosen here as the modelling sample. According to official profiles, they offer two kinds of Chargemaster home charging units. One is a standard 3.3kW, 16A onboard charger (allowing a 0% to 100% charge in 8 hours). Another is the upgraded 6.6kW, 30A home charger unit which will charge from 0% to 100% in under 4 hours. The 3.3 kW charger will be used in the simulation.

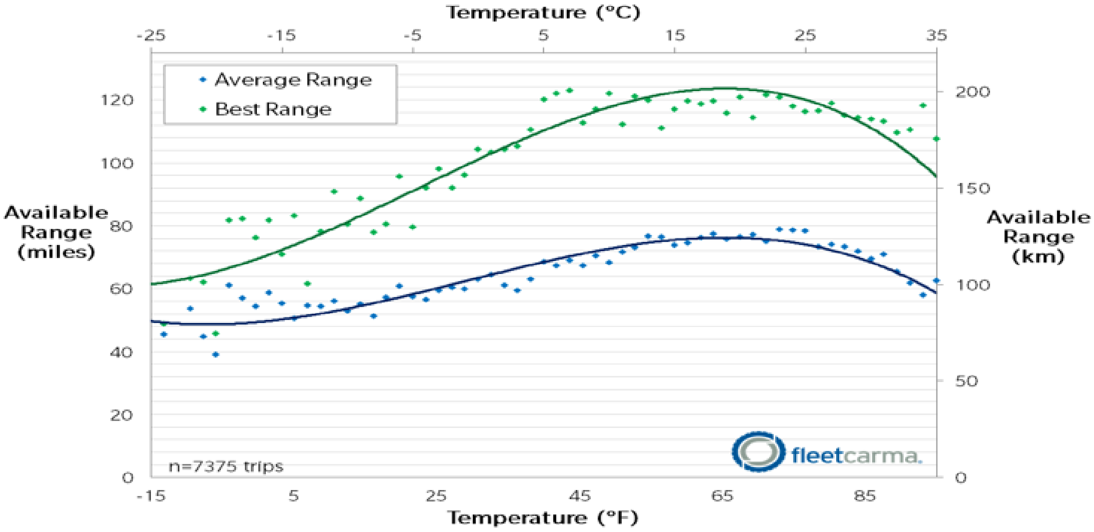

Figure 3. 5: Temperature vs available range [156]

The database of how these frigid temperatures are affecting the range of electric vehicles is based on more than 2,000 trips in the Nissan Leaf, which are provided by Fleetcarma. As can be seen in the plots in Figure 1, there is a sweet spot where drivers see the best electric ranges between 15°C and 24°C. There is a great deal of operator control, and many strategies and tactics can be taken to increase an electric vehicle's range in warm or cold conditions.

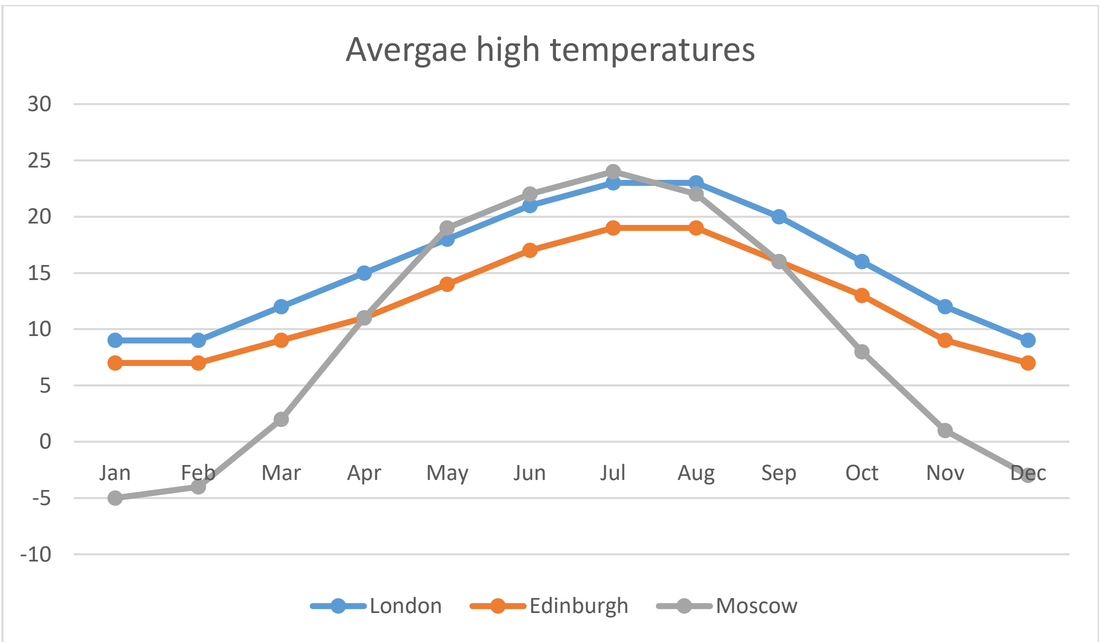

Figure 3. 6: Average high temperatures of London, Edinburgh and Moscow

The above picture is the average high temperature for a year from London, Edinburgh and Moscow. As we can see, the lowest temperatures in the year occur in January. The temperature in Moscow is -5 °C while the temperatures in London and Edinburgh are 9 °C and 7 °C which are similar. According to the database of how these frigid temperatures are affecting the range of electric vehicles, the best range of Nissan Leaf in Moscow is 90 miles while it can approximately reach 115 miles in London and 110 miles in Edinburgh. When the temperature rises in Jul, the best range of Nissan Leaf in these three cities will be similar, at around 120 miles. However, it is the average highs temperature. Usually, the temperature will be lower in January which means that the difference of available range in the various ambient temperature is more apparent. For the same location, the performance of electric vehicle will also be different. Therefore, ambient temperature is an important external factor affecting the driving range of electric vehicle and should be taken into account for electric vehicle energy consumption modelling.

Compared with previous EV models, more accurate battery capacity can be obtained according to ambient temperature. The hourly temperature of 1st January in Edinburgh was chosen here as input data to demonstrate the available range of the Nissan Leaf. For this reason, the state of charge (SOC) after each trip i can be calculated based on battery capacity (BC), travel distance (D) and average energy consumption per/km at temperature T°C (AEC_t).

$$SOC_{i+1} = SOC_i - \frac{AEC_t \times distance}{BC} \tag{3.3}$$

Usually, most of the people's charging behaviour follows an uncontrolled charging plan. It is assumed that all electric vehicles are in a fully-charged state in the morning before they are going to start their first trip of the day and the vehicles will be charged again as soon as they finish their last trip and arrive home in the evening without taking other electricity demands on the distribution network into consideration. The charging process will stop until the state of charging (SOC) reaches 100%, or the next trip starts. Moreover, electric vehicles are connected to the grid during this period.

3.4.2 Electric vehicle charging power demand

The following three graphs detail respectively the base load, electric vehicle charging load and total load of one household randomly chosen from 10000 household load profiles. People’s activities can be easily observed from the based load demand. From 0:00 to 6:00, baseload demands keep repeated cycles caused by the constant use of items like fridge, while the household remains asleep. There is then an increase in power demand around 6:00 which people start to get up in the morning. From 9:00 to 18:00, baseload demand returns to repeated cycles again which mean people are most likely going out. It is also evident that people come back home around 18:00 because the baseload starts to increase. Therefore, the electric vehicle starts charging at the same time point and end charging around 21:00. Each EV profile has a high correlation with individual household daily activities.

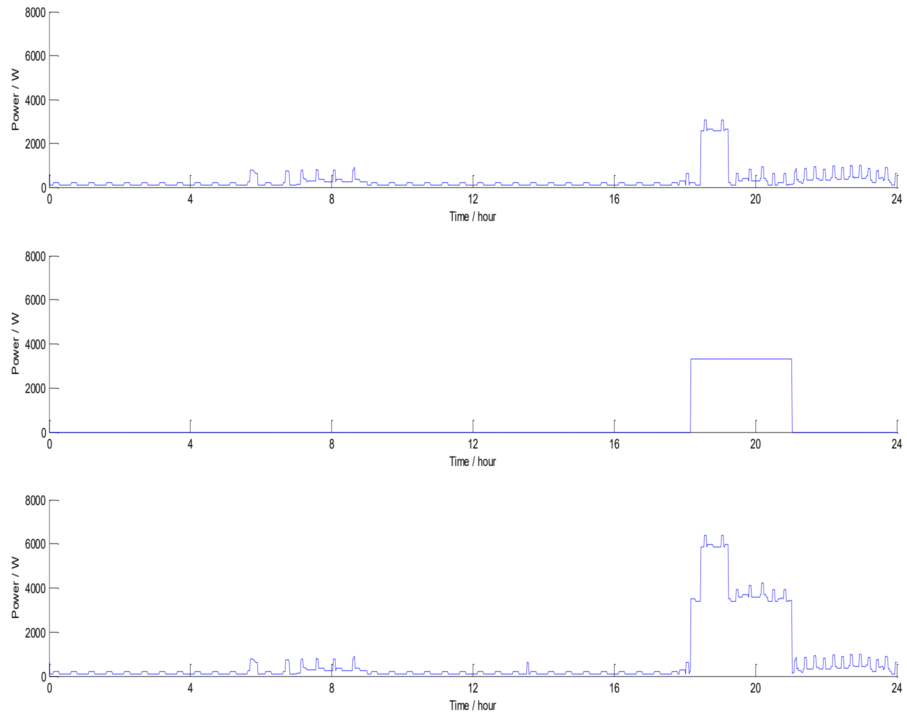

Figure 3. 7: Single household power demand

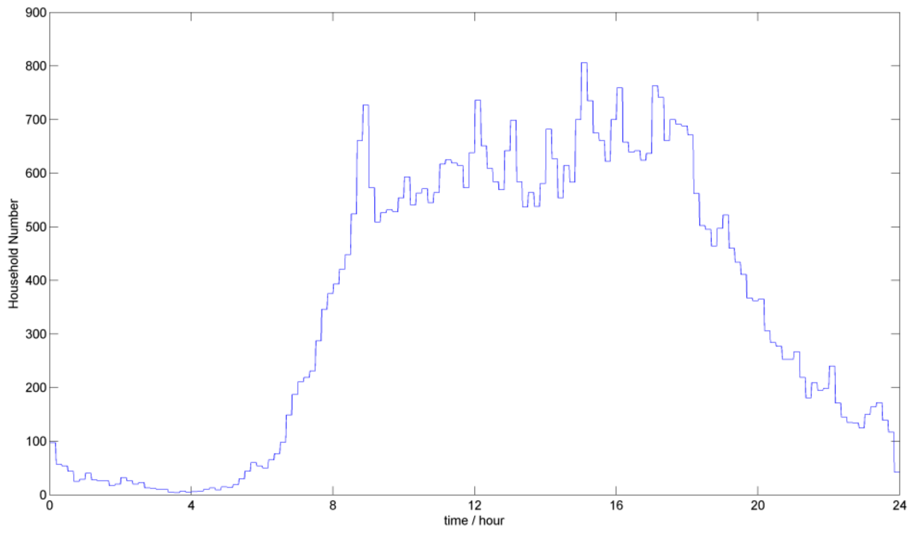

Figure 3. 8 Total number of household in car travelling for 10000 household

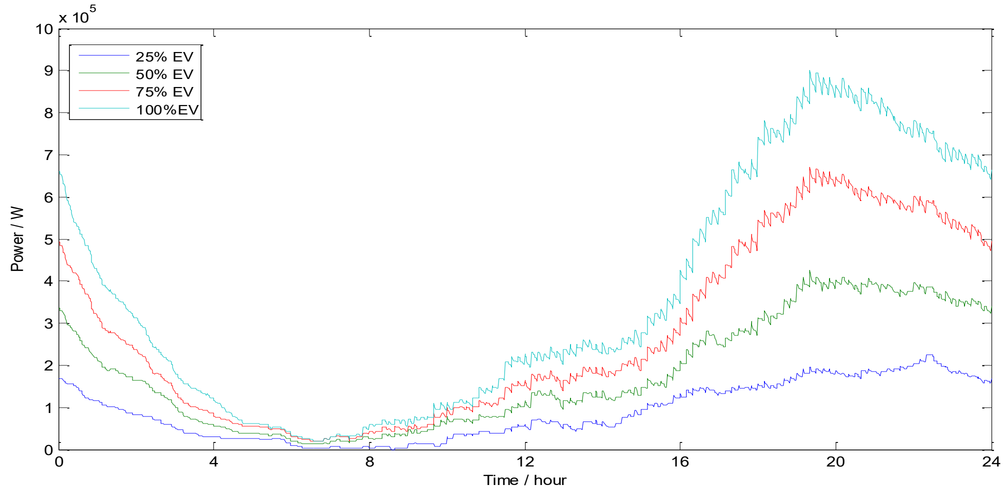

Figure 3. 9: EV load demand for 1000 household with various penetration levels

The above graph shows electric vehicle charging demand for 1000 household generated by the developed electric vehicle charging power demand model. While electric vehicle charging demand is a different pattern, it can be observed that EV demand begins to increase from 12:00 step-by-step and reaches its peak at around 20:00. Although four various penetration levels, 25%, 50%, 75% and 100%, are implemented, they share the similar power demand patterns.

3.5 Validation through UK Electric Vehicle Data

The developed electric vehicle charging model is to generate the large-scale uncontrolled electric vehicle charging profiles which will make significant contributions to distributed network systems.

The results of this model are verified against the available data from the report, Impact & Opportunities for wide-scale EV deployment, published by Low Carbon London Learning Lab in the Imperial College London. The electric vehicle data presented in this report are collected from three areas:

1. Metered electric vehicle charging data for 72 residential and 54 commercial charging point;

2. Data on the charging events collected at 491 public charging points;

3. Vehicle logger data capturing driving and charging behaviour for 30 EVs;

The critical information of EV data includes active power for charging, the start charging time and duration of charging events and the energy consumption in the EV charging process. For residential EV charging demand, data of 54 EVs are collected in the report. Moreover, most vehicles charged at 3.7 kW, although both higher (up to 7.4 kW) and lower (1.7 kW) maximum charging powers are also observed. 3.3kW charging rate is employed in developed EV charging model which is similar with them. According to the definition in the report, the maximum profile is obtained by finding the highest value of average charging power per EV across all instances of the 10-minute interval. The average profiles are acquired by finding the average value of charging power per EV across all instances of the 10-minute interval.

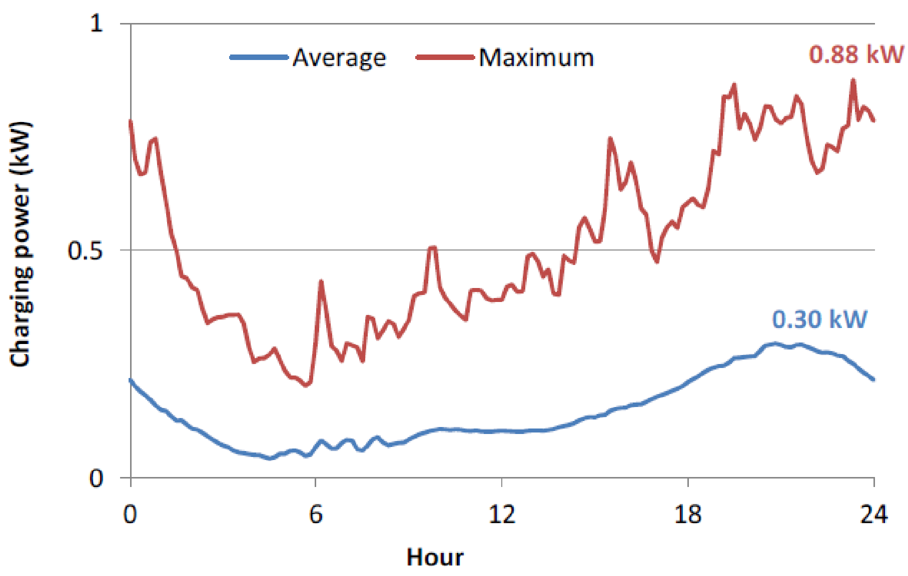

Figure 3. 10 Maximum and average charging profiles per EV for residential users

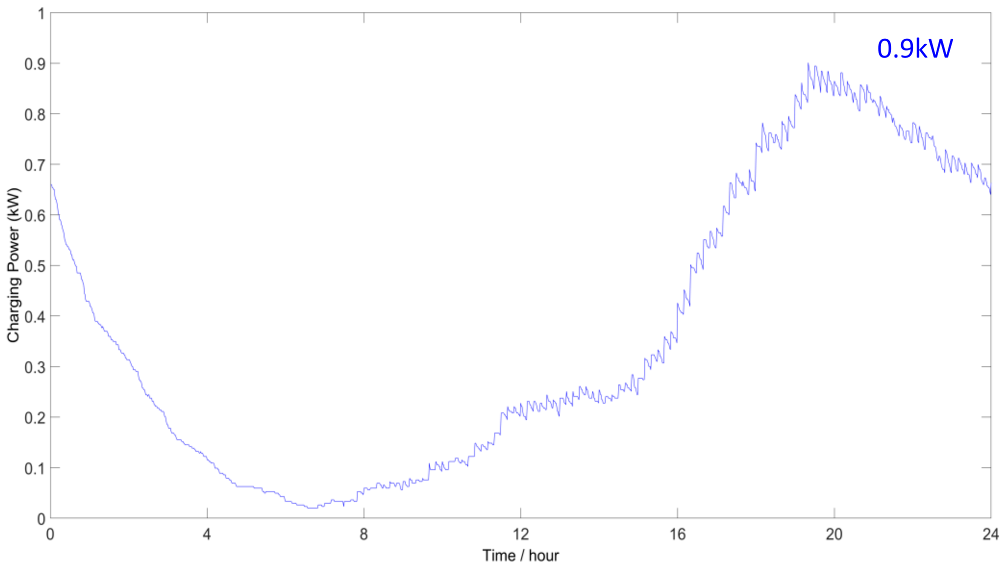

Figure 3. 11 Average charging profiles per EV

As we can see from the above two figures, figure 3.10 is the maximum and average charging profile per EV for residential users which are collected from 54 EVs. While figure 3.11 is the average charging profiles per EV which is obtained from the developed model. The peak demand from the model output (0.9kW) is similar with reference data (0.88kW). For the tendency of two figures, the charging power begins to increase from morning around 8am and reach the peak in the evening around 20pm. Then the charging demand starts to decrease from the midnight and reach the lower point in the morning around 6am. However, the curve from the model output is smoother than reference data. It is because that model output is the average data from 10000 EV charging profiles with 1-min time interval while reference data is derived from 54 EV profiles.

	Model output	Reference dataset
Average daily energy / kWh	5.09	3.57
Average charging time	2h27min	1h57min

Table 3. 3 Average energy consumption and charging time

For the energy consumption, the model output is 5.09 kWh which is higher than reference dataset 3.57kWh. Therefore for the average charging time, the model output results require more charging time than reference dataset. The reason caused that is electric vehicles in the model are charged on the weekday and the winter of Edinburgh. According to the electric trial data in table 3.4, energy consumption of electric vehicle in the workday is higher than weekend.

Meanwhile, the low temperature will lead to more energy consumption than a normal temperature which has been explained in the previous section. Compared with model output, electric vehicles in the reference dataset are located in London which is warmer than Edinburgh, and the average energy consumption includes weekday and weekend. Furthermore, the total number of samples is 54 which is limited.

Day type	The energy requirement for charging (kWh)
All days	3.52
Workdays	3.68
Weekend	3.09

Table 3. 4 Average daily energy requirements per EV for residential EV sample

In a word, electric vehicle charging profiles generated from model share the very similar tendency with reference dataset. For the key index of electric vehicle charging such as energy consumption, charging time, peak charging demand, there is some difference between them. It is because the various parameters setting and external factor assumption of the model are unlike the reference dataset.

3.6 Residential Load Model

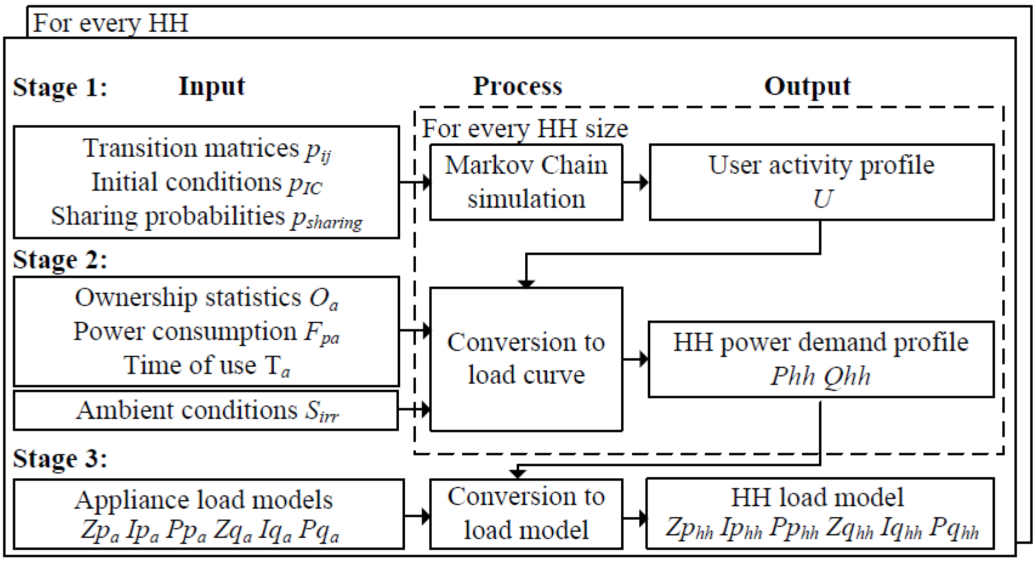

Figure 3. 12: Load model development work flow [10]

A similar load model for residential power demand has been previously proposed [10]. The developed EV charging demand model was specifically designed in a way that can be seamlessly integrated with the domestic demand model. For completeness, this domestic demand model is briefly presented here. This model adopts a Markov chain Monte Carlo to create household activities and power demand profiles. Three stages are presented below:

1. Modelling users' activities: Input is the probability matrices for various activities and the relationship with others. For households with more than one person, sharing probabilities will be used. All these probability matrices are derived from the Time User Survey (TUS). MCMC algorithms are used in this stage to obtain household activity profiles.

2. Converting users' activities into household electrical appliance use: In this stage, the load model of each household electrical appliances will be created based on the characteristics of electrical appliances. Furthermore a massive of information is necessarily required detailing ownership statistics, power consumption, time of the

user and ambient conditions. The specific categories of household electrical appliances are presented below:

Categories	Electrical appliances
Cold loads	Refrigerator
Wetload	Washing machine, tumble dryer, washing dryer, dishwasher
Electric shower	Electric shower
Consumer electronics (CE)	TVs, game consoles, audio Hi-Fi
Information and communications technology (ICT) loads	Desktops, monitors, laptops, office equipment, mobile phone, fax
Cooking loads	Electric hob, electric oven, microwave oven, toaster, food processor, extraction hood
Housework loads	Vacuum cleaner, iron
Light	Lighting bulbs
Heating	Electric heaters

Table 3. 5: The categories of household electric appliances

3. Aggregation of household electrical appliances to obtain time-series power demand profiles and household load models: According to the varying natures of electrical appliances, each electrical appliance is modelled in a different way and thus, the ZIP load model is introduced.

The following picture is the aggregation of 1000 household baseload demand. There are two peak period for daily baseload in the graph. One period is from 7:00 to 9:00 in the morning when people get up and prepare for work. Another peak load period starts from 16:00 until 22:00 in the evening when the household returns home.

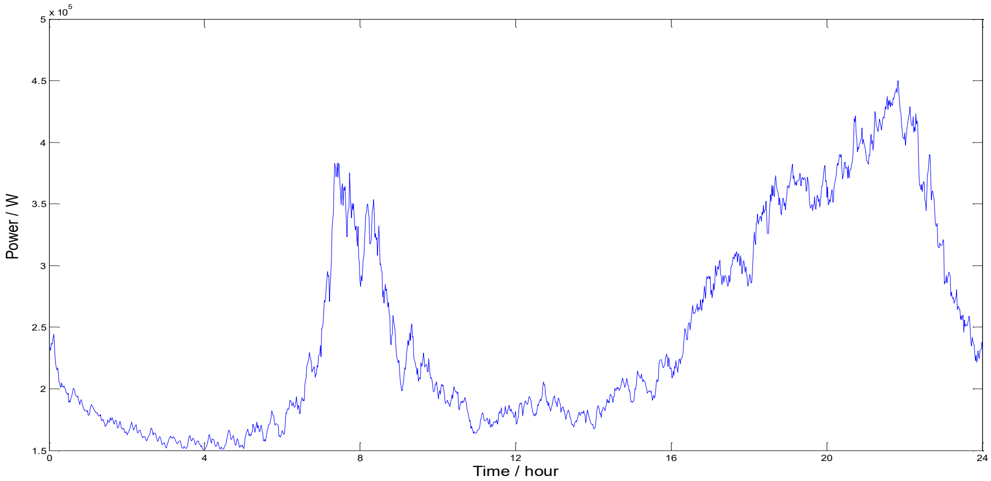

Figure 3. 13: Baseload demand

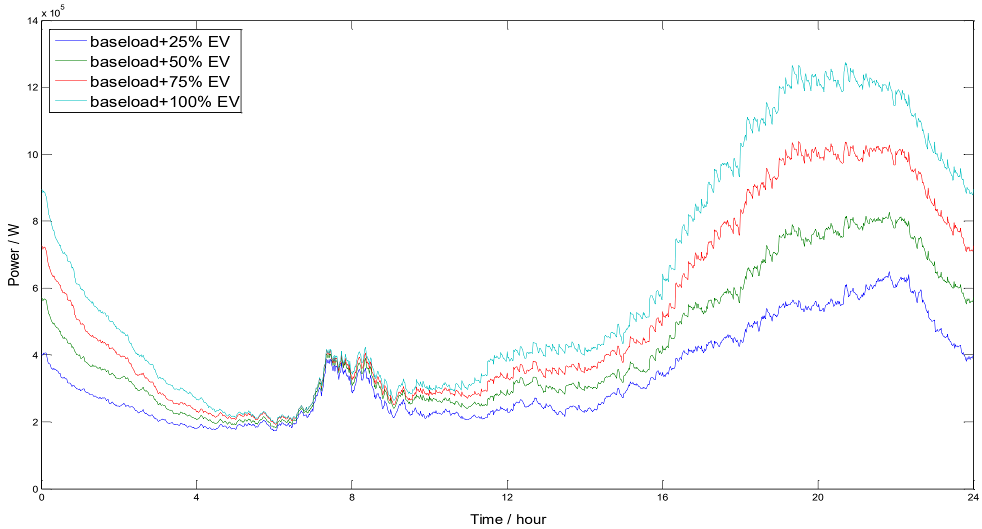

Figure 3. 14: Total demand

The above graph is the aggregation of the baseload and EV charging demand. When the electric vehicle charging demand is added to the household, the demand peak in the evening becomes more apparent and this period then also extends to midnight. However, the previous demand peak in the morning becomes more moderate because it is the electric vehicle charging demand valley.

3.6 Conclusion

This chapter describes the detailed processes behind developing driving behaviour and electric vehicle charging models. The driving behaviour model based on Markov Chain Monte Carlo can generate a one-minute resolution of people's daily activity profiles, which provide the solid foundation for further power demand simulations. In this model, people's driving activities are not isolated from other household tasks. Driving activities are derived from and correlate with other household activities. Therefore simulated household activities profiles can avoid inaccuracy caused by the disadvantage of face-to-face surveyed results such as randomness and incompleteness.

Electric vehicle charging model takes lots of external factors into account in order to estimate the state of charge of each electric vehicles. In the meantime, the energy consumption of each vehicle is calculated based on every single trip during a day. Furthermore, this model can also provide an accurate departure and arrival time for each vehicle, which is a significant contribution to electric vehicle charging demand management. Moreover, it also plays an important role in assessing the influence of various electric vehicle penetrations on the power system.

Ultimately, these two developed models successfully simulate activity profiles based on the interconnection among different daily household activities; they also convert these activity profiles into electric energy consumptions, especially in regarding of electric vehicles. Further demand side management would require accurate prediction of the EV charging demand and household electric appliances, in which 'flexible' domestic loads such as washing machines and dishwashers are used by the optimisation algorithm for demand side management.

Chapter 4 Voltage control with demand side management

4.1 Introduction

In order to decrease the fluctuation of distributed network bus voltage, and keep it within the accepted range, electric vehicle charging demand is regarded as the shiftable load in the household for controlling the bus voltage in the low voltage distributed network, especial for the radial network. In the first part of this chapter, the generic UK low voltage highly urban distributed network is introduced and simulated in OpenDSS. An uncontrolled electric vehicle charging plan is adopted to assess the influence on the bus voltage of the distributed network.

In the low-voltage distributed network, the household load can be divided into two categories according to their various characters, shiftable load and non-shiftable load. For the shiftable load, those load demand can be rescheduled without affecting people's activities, which can provoke in users discomfort and a disinclination to participate in a demand side management plan, such as wetload and electric vehicle charging load. However, there are still some differences between them. Wetload cannot be interrupted during the working cycle, and this includes dishwashers, washing machine, tumble dryers and washing dryers. The only method adopted is delaying their starting time without disturbing the user's activities. Compared with the wetload, electric vehicle charging load shares more flexible charging plan which can be interrupted during the charging process, postpone charging to a later time and even changing the desired charging target without affecting user's driving activities the next day.

On the other hand, the wetload usually consume around 5% of the total daily household power demand in the UK. With increasing penetrations from electric vehicles, electric vehicle charging load will escalate to take a more significant percentage of total daily household power demand. Based on the previous research results, the electric vehicle charging demand can account for more than 30% of the total daily household power demand in the 50% EV penetration scenario which potentially has a significant impact on reshaping the total power demand.

The key contribution of this chapter is to propose two smart large-scale electric vehicle charging demand optimisation algorithms to achieve peak load shaving, spinning reserves and energy regulation services. One is based on the various bus voltages in the distributed network to make the most efficient optimisation plan. The second is using voltage sensitivity to establish the interactive effect among all connected buses in the low voltage network.

The previous developed household load demand model is implemented to generate power demand profiles for each household. The detailed method and effects are presented herein.

There are some very similar works have been done in this paper [157].

This paper also uses Nissan Leaf as electric vehicle model whose battery capacity is 24 kWh and charging rate is 3.3 kW. The low voltage networks contain five feeders and 428 customers. Moreover, various electric vehicle penetrations are implemented. The results show that two feeders will face the significant voltage drop for 20% penetration level. The number of affected customers will increase significantly for penetration level more than 80%. The Gain K of the P controllers will be implemented. The state of charging is the dominated factors for selection of electric vehicles. Moreover, three control cycles are used, 1 min, 5min and 10 min separately. The results show that the longer the control cycle, the higher the number of unaffected customers.

4.2 Voltage sensitivity

Generally speaking, voltage sensitivity are defined to describe how the load power changes, with active and reactive power, and influences the variation of voltage in the power system. In terms of the radial distribution network with N buses, the power flow equations are displayed below:

$$P_k = \sum_{j=1}^{N} |V_k||V_j|\left(G_{kj}\cos\left(\theta_k - \theta_j\right) + B_{kj}\sin(\theta_k - \theta_j)\right) \tag{4.1}$$

$$Q_k = \sum_{j=1}^{N} |V_k||V_j|\left(G_{kj}\cos\left(\theta_k - \theta_j\right) + B_{kj}\sin(\theta_k - \theta_j)\right) \tag{4.2}$$

Where P_k is the net active power injected into bus k, G_{kj} and B_{kj} are the real part and imaginary part of the bus admittance matrix Y_{bus} , with respect to the k_{th} row and j_{th} column, and θ_k, θ_j are the voltage angle for the k_{th} and j_{th} bus. Usually, the slack bus voltage is kept constant. Therefore any variation of load in the distribution network will lead to changes in bus voltage. The power flow equations play an important role in gaining the complete voltage magnitude and angle of each bus in the power system for the given information of generator, loads and transmission line. However, due to the non-linear character of this problem, there are several numerical methods which are widely adopted to solve the power flow equations. Moreover, the Newton-Raphson load flow algorithm is the most popular and convenient method. The voltage sensitivity of the distribution network can be derived from computing the Jacobian matrix which is shown below.

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix} = J \cdot \begin{bmatrix}\Delta\theta\\ \Delta V\end{bmatrix} \tag{4.3}$$

Moreover, *J* is the Jacobian matrix

$$J = \begin{bmatrix}\frac{\partial P}{\partial\theta} & \frac{\partial P}{\partial V}\\ \frac{\partial Q}{\partial\theta} & \frac{\partial Q}{\partial V}\end{bmatrix} \tag{4.4}$$

Voltage sensitivity can be obtained from the Jacobian matrix

$$\frac{\partial V}{\partial P} = {J_{12}}^{-1}, \frac{\partial V}{\partial Q} = {J_{22}}^{-1} \tag{4.5}$$

It seems that voltage sensitivity can be easily calculated from the aspect of the theory. However, power flow equations are usually solved by specific power system software such as Matpower in Matlab, OpenDSS, Sincal .etc. Moreover, these software packages do not allow users to gain access to the Jacobian matrix. On the other hand, voltage sensitivity are changing all the time, with as any tiny variations in the power system. In the proposed voltage regulation algorithm [158], voltage sensitivity are the critical factor in determining the sequences of electric vehicle charging optimisations and are supposed to be updated after each iteration. Therefore, this chapter proposes a new approach to calculating voltage sensitivity, replacing the traditional Jacobian matrix method.

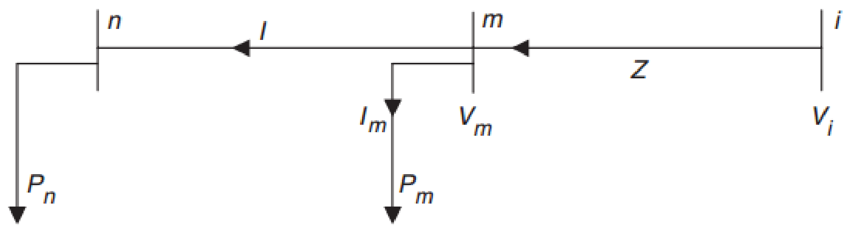

Figure 4. 1: 3 buses distribution system

$$\frac{\partial V_m}{\partial P_m} = \frac{\partial V_m}{\partial I_n} \times \frac{\partial I_n}{\partial P_n} \tag{4.6}$$

When the load at bus n is P_n, the current goes through bus m is I_m, the current goes through bus n is I, the voltage at bus m is given by

$$V_m = V_i - (I + I_m) \cdot Z \tag{4.7}$$

$$\text{Where } I_m = \frac{P_m}{V_m} \tag{4.8}$$

When the load at bus n is increased from P_n to $P+\Delta P_n$, which also lead to the change of current from I to $I+\Delta I$ and from I_m to $I_m + \Delta I_m$. So the voltage at bus m is shown below

$$(V_m + \Delta V_m) = V_i - (I + \Delta I + I_m + \Delta I_m) \cdot Z \tag{4.9}$$

If the power at bus m is constant, then

$$I_m + \Delta I_m = \frac{P_m}{V_m + \Delta V_m} \tag{4.10}$$

From (4.8) and (4.10), we can get

$$\Delta I_m = \frac{P_m}{V_m} \cdot \left(\frac{-\Delta V_m}{V_m + \Delta V_m}\right) \tag{4.11}$$

From (4.9) and (4.11), we can derive

$$(V_m + \Delta V_m)\left[1 - \frac{P_m \Delta V_m}{V_m \times (V_m + \Delta V_m)^2}\right] = V_i - (I + \Delta I + I_m) \cdot Z \tag{4.12}$$

In the network, ΔV_m is too small compared with V_m and impedance Z is also very small, hence

$$\left[1 - \frac{P_m \Delta V_m}{V_m \times (V_m + \Delta V_m)^2}\right] \approx 1 \tag{4.13}$$

Therefore,

$$(V_m + \Delta V_m) = V_i - (I + \Delta I + I_m) \cdot Z \tag{4.14}$$

From (4.7) and (4.14)

$$\Delta V_m = -(\Delta I) \cdot Z \tag{4.15}$$

$$\left|\frac{\Delta V_m}{\Delta I}\right| = -|Z| \tag{4.16}$$

$$\frac{\Delta |V_m|}{\Delta |I|} = -|Z| \tag{4.17}$$

Given the variation is very small, (4.16) can be written as

$$\frac{\partial |V_m|}{\partial |I_n|} = -|Z_{mn}| \tag{4.18}$$

Due to load variation at bus n, equation (4.18) can be written as

$$\frac{\partial |V_m|}{\partial |P_n|} = -|Z_{mn}| \times \frac{\partial |I_n|}{\partial |P_n|} \tag{4.19}$$

Where

$$\frac{\partial |I_n|}{\partial |P_n|} = \frac{\partial (|P_n|/|V_n|)}{\partial |P_n|} \tag{4.20}$$

or

$$\frac{\partial|I_n|}{\partial|P_n|} = \frac{1}{|V_n|} - \frac{|P_n|}{|V_n|^2}\frac{\partial|V_n|}{\partial|P_n|} \tag{4.21}$$

From (4.19) and (4.21), we can obtain

$$\frac{\partial|V_m|}{\partial|P_n|} = -|Z_{mn}|\left[\frac{1}{|V_n|} - \frac{|P_n|}{|V_n|^2}\frac{\partial|V_n|}{\partial|P_n|}\right] \tag{4.22}$$

Therefore the voltage sensitivity of a bus with respect to its own load variation when m=n, from (4.22)

$$\frac{\partial|V_n|}{\partial|P_n|} = \frac{-|Z_{mn}||V_n|}{|V_n|^2 - |Z_{mn}||P_n|} \tag{4.23}$$

For a general system,

$$\frac{\partial|V_m|}{\partial|P_n|} = -|Z_{mn}|\left[\frac{1}{|V_n|} + \frac{|P_n|}{|V_n|}\frac{|Z_{mn}|}{(|V_n|^2 - |Z_{mn}||P_n|)}\right] \tag{4.24}$$

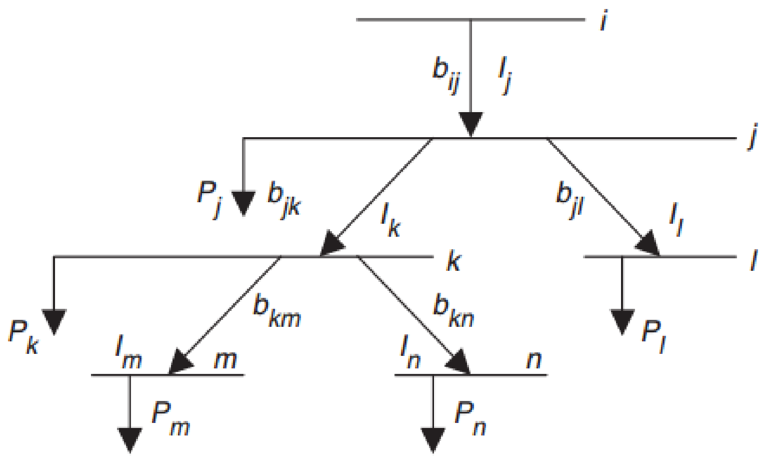

Figure 4. 2: 6 buses radial distribution system

This is a distribution network which includes six buses, namely i , j, k, l, m, n. $Z_{mn}=Z_j+Z_k$ (impedance of branch b_{ij}+ impedance of branch b_{jk}). In general, Zxy is the sum of all the shared impedance from root bus to load bus x and y.

4.3 Network analysis

Low-voltage distribution networks usually operate at 415 V or similar and the distribution transformers are used to step down the voltage from 11kV to 0.4kV. The typical layout of the low-voltage network is radial which can provide higher reliability and stability for customers. The underground cables or overhead lines are then used to deliver the electricity. According to the various locations and load densities being supplied, the low-voltage distribution networks can be divided into following four categories:

Highly-urban generic low-voltage distribution network: Usually located in big cities, the low-voltage network is an underground system in the radial layout and connected with plenty of 1-phase customers from several branches. The detailed information of this network will be presented in the next section.

4.3.1 UK low-voltage highly urban network

Given the current situation, most electric vehicles are distributed within the centre of the big city. At the same time, highly urban networks suffer the most severe load pressure which includes a large number of customers and complex electricity consumption patterns. Therefore, the low-voltage highly urban network has been chosen for modelling

The following graph demonstrates the Highly-Urban Generic LV Distribution Network which corresponds to an existing network operated by E.ON UK Central Networks. This network has four three-phase trunk feeders. The LV busbars infeed 1 MVA 11/0.4kV substation and supplies a total of 380 single-phase customers who are randomly distributed from HU1 to HU19. The line characteristics of the network can be found in the following table. Compared with the urban and rural networks, the highly urban network usually has a high load density, strict power system constraints and more complicate load profiles which lead to increased instability and disturbance problems. Based on the information provided above, the highly urban network will be built in the OpenDSS to check the power system stability problems caused by load variations such as voltage violations and demand fluctuations.

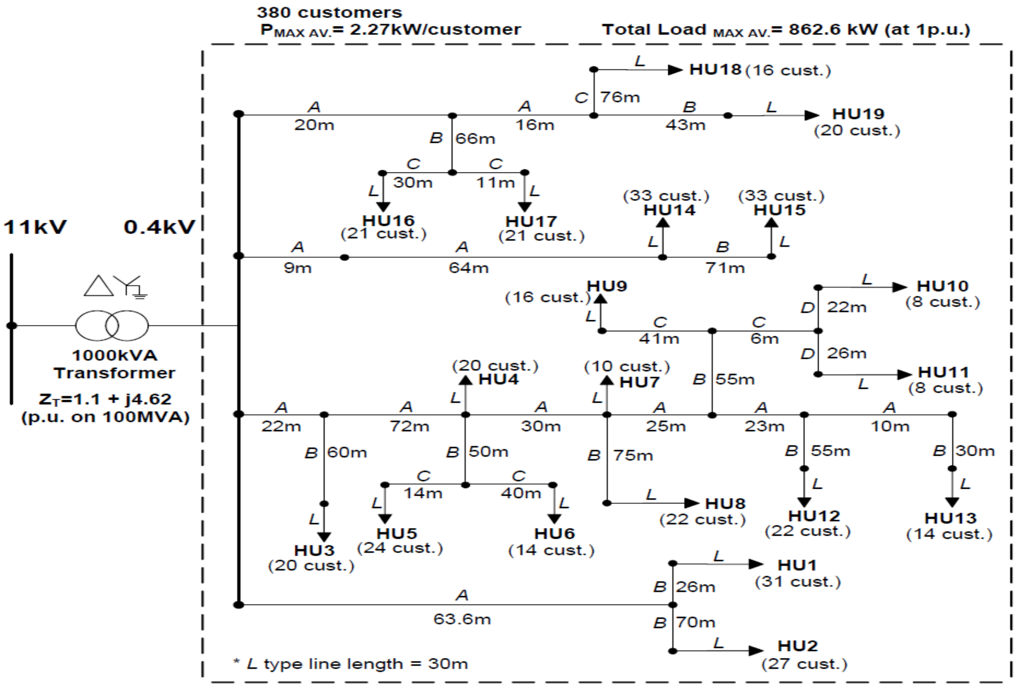

Figure 4. 3: Highly--urban generic LV distribution network [159]

Line Id.	Cross sectional Area (CSA) (mm^2)	Positive sequence R_{ph} (Ω/km)	X_{ph}
Underground Line (Cable)			
A	300	0.1	0.073
B	185	0.164	0.074
C	120	0.253	0.071
D	95	0.320	0.075
E	70	0.443	0.076
Overhead Line			
H	95	0.32	0.085
Service Connection			
L	35	0.851	0.041

Table 4. 1: The line characteristics of the network

4.3.2 Extended network

However, with the rapid development of urbanisation, more and more commercial and residential loads will be connected to a pre-existing network. These loads usually have a higher load density and more complex load profiles, compared with the previously existing load.

The extended highly-urban network is one typical example. Ten more buses will be newly-built, including 646 single-phase customers, which are almost double the previous 19 buses. The extended highly-urban network will share the same line characteristics of the existing network and transformer. The following figure is the extended highly-urban generic LV distribution network. The network in the red dash line box is the original highly--urban generic LV distribution network, from bus 1 to bus 19. The other parts, from bus 20 to bus 29, is the extended network.

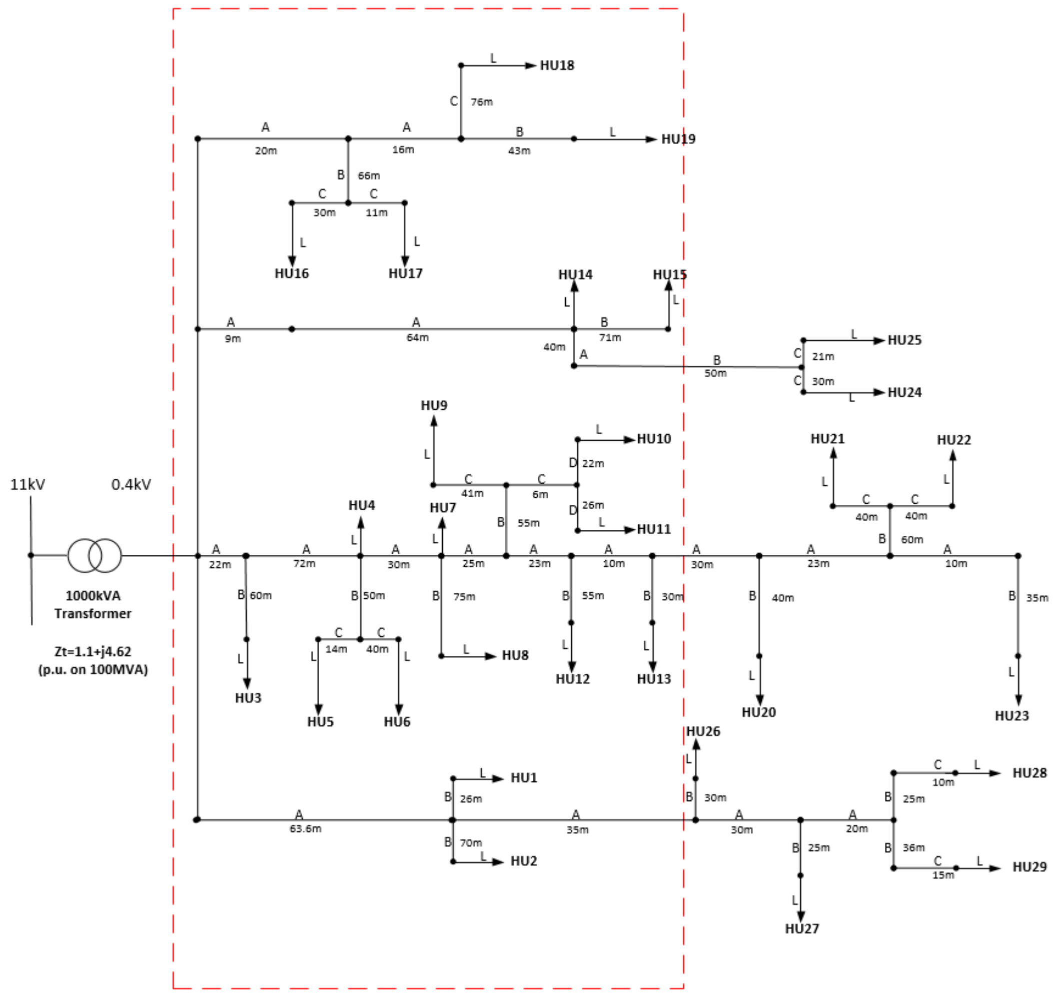

Figure 4. 4: Extended highly-urban generic LV distribution network

4.3.3 Influence of uncontrolled charging on the voltage profiles

In this section, the voltage profiles of uncontrolled charging with four electric vehicle penetration levels, 0%, 25%, 50% and 75% are presented and analysed in the context of the extended highly-urban generic low voltage distribution network. The statutory limits of the voltage in the UK are from +10% to -6% of the nominal voltage 230V for the distributed power system network. Moreover, in this case, electric vehicles only are regarded as the consumer of electricity and cannot output the electricity back to the grid. Therefore a lower limit of voltage is considered and set as 0.94 p.u. In general, these four voltage profiles all have two periods where the voltage is reduced dramatically. The first is in the morning around 8:00 while the voltage reduction is acceptable. The second is in the evening from 18:00 to 22:00. However, the voltage reduction of the second period is much more severe than the first. Moreover, the voltage profiles share the inversed pattern with the power demand profiles.

The first following figure is the voltage profile detailing only the baseload power demand. As we can see, the safe margin for the bus voltage is still large even in the extended distributed network. The lowest voltage reaches 0.96 p.u. However, when electric vehicles are connected to the network, only the voltage of two buses with 25% EV penetration level falls to 0.94 p.u. In the case of 50% EV penetration, the voltage of 4 buses drop below the lower limit 0.94 p.u, and the lowest voltage is 0.924 p.u.

Furthermore, for 75% EV penetration, there is 9 buses' voltage reduction beyond the accepted range.

Moreover, the lowest voltage magnitude is 0.906 p.u. Therefore, uncontrolled electric vehicles charging in the distributed network results in severe voltage variation problems, especially as the popularity of electric vehicles increases. For electric power system, maintaining the bus voltage level within the required range is an essential issue for a power supplier. Once the voltage fluctuations exceed the accepted range, it would increase the operation cost of the system and even damage household electric appliances. It should be noted here that the distribution network used is deliberately weak to clearly highlight the effect of increased EV penetration in the grid.

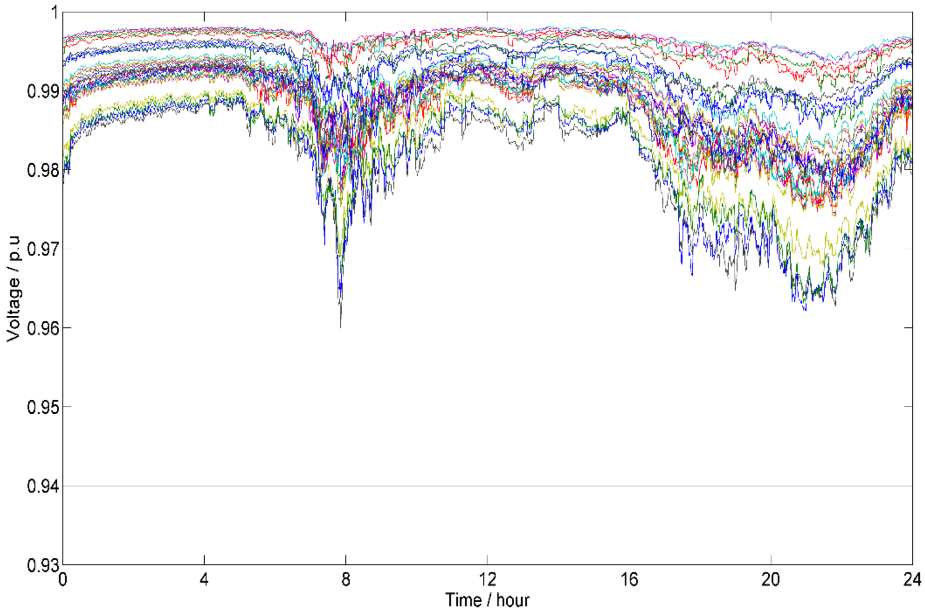

Figure 4. 5: The voltage profile for 29 buses without EV load

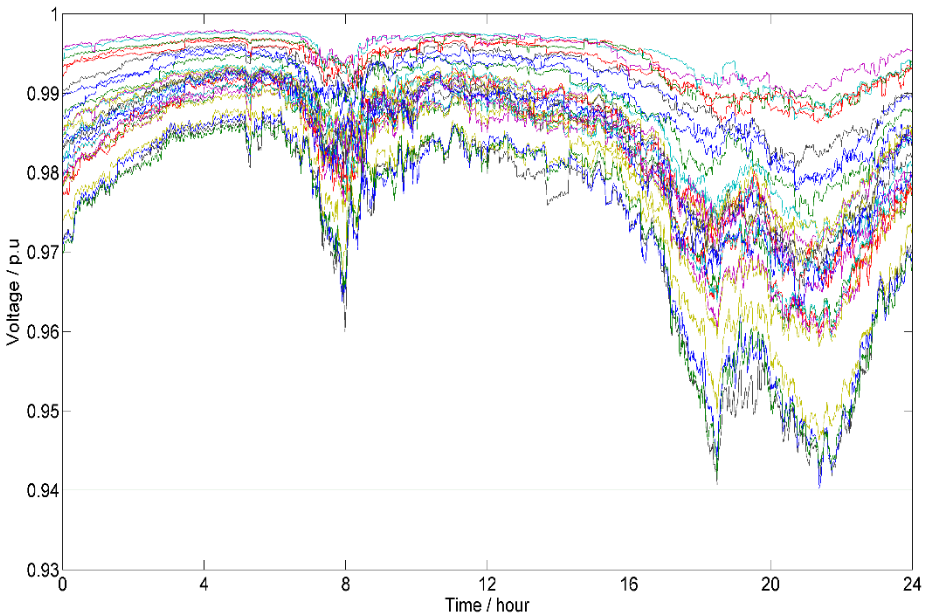

Figure 4. 6: The voltage profile for 29 buses with 25% EV penetrations Voltage at the most remote nodes falls just inside the statutory limit of 94%

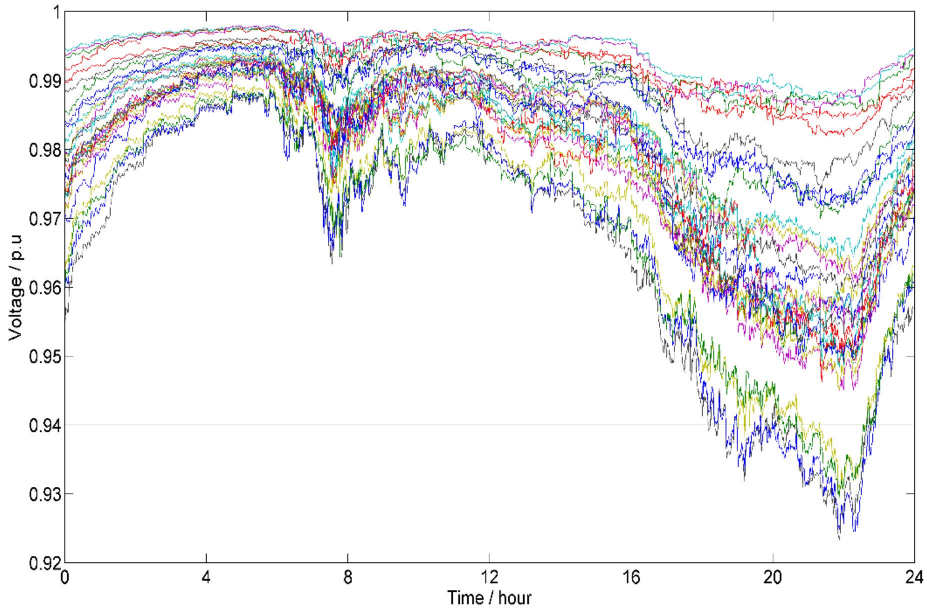

Figure 4. 7: The voltage profile for 29 buses with 50% EV penetrations Voltage at the most remote nodes violates the statutory limit of 94% for about 4 hours.

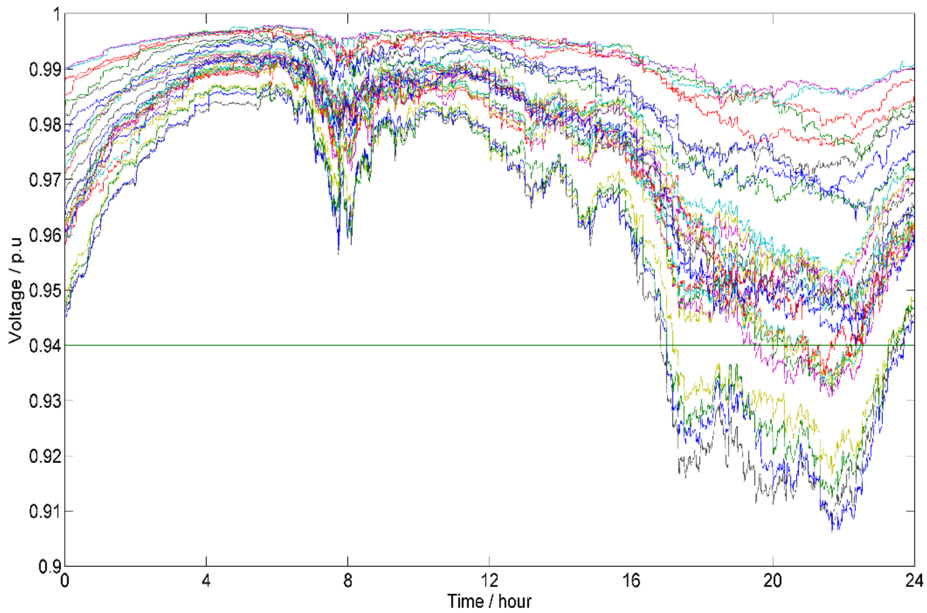

Figure 4. 8: The voltage profile for 29 buses with 75% EV penetrations. Voltage at the most remote nodes violates the statutory limit of 94% for more than 6 hours.

4.4 Methodology

In this chapter, two proposed voltage control optimisation algorithms are illuminated. The target of these two algorithms is to maintain the voltage within the accepted range with minimum influence on electric vehicle charging. Usually, the lowest voltage bus is located at the end of the simple single line network, and its voltage has the highest sensitivity on the load itself. For example, assuming that voltage at bus 12 is the lowest in the network, the operator usually shuts down the power demand at bus 12 itself to raise the voltage back to normal. However, there may be the situation where all the available power demand has been shut down, and yet, the voltage at bus 12 is still below the accepted range. At this point, decisions should be made to choose the next load demand which has the most influence on the voltage of bus 12. It would be easier for single line network. However, for a radial distributed network with complex load profiles, voltage sensitivity are a necessary and useful method for solving this problem. Especially when demand side management is implemented in the optimisation, voltage sensitivity keep changing all the time with tiny variations in each load profile. Another optimisation algorithm is based on bus voltage. The influence of loads on the specific bus voltage is determined by the magnitude of all bus voltages. The lower the magnitude of bus voltage has, the more influence the demand side management has upon this bus. Therefore these two optimisation algorithms are facilitated in the same power system and simulated. Optimisation results are compared and analysed.

4.4.1 Voltage control based on bus voltage optimisation algorithm

Step 1: The aggregator gets the baseload demand and uncontrolled EV charging demand with a 1-min resolution from all households at each time step. In the uncontrolled EV charging plan, it assumed that all electric vehicles begin their charging at home when they finish their last trip and arrive home. Moreover, charging is stopped when the state of charge reaches the expected level or users start their next journey. Furthermore, the charging rate is fixed (3.3kW).

Step 2: The power demand profiles are input into Opendss to run the power flow at each time step T. The bus voltage list will be generated. All buses in the network are sorted in the ascending order based on their bus voltage magnitude in p.u.

Step 3: Find the lowest voltage bus N on the bus voltage list at the time T and compared V_N with pre-set bus voltage lower limit V_{LL}. If $V_N \leq V_{LL}$, it means that the voltage at bus N drops too far beyond the acceptable range and voltage regulation methods will be implemented. This leads to Step 5. If $V_N \geq V_{LL}$, it means that the voltages of all buses are in the accepted range. This results in a return to Step 2 and running the power flow for the next time step T+1.

Step 4: Collect input data of each electric vehicle arriving time $t_{arriving}$, the state of charge (SOC), t_{begin} the time when people are going to use EV. Based on the above information, the priority list will be created to decide optimisation order for each vehicle.

$$Priority = x \cdot order_{t_{arriving}} + y \cdot order_{soc} + \ z \cdot order_{t\_begin} \tag{4.25}$$

Where x, y, z are the weighting factors for three parameters, respectively. $Order_{t\_arriving}$ is the value of each vehicle in the ascending sequence of arriving time. $Order_{SOC}$ is the value of each vehicle in the descending sequence of the state of charging. $Order_{t\_begin}$ is the value of each vehicle in the descending sequence of beginning the next trip. The smaller value the car get from that equation, the higher priority given to that car. The higher priority means this electric vehicle needs to be charged urgently.

Step 5: Based on the calculated the bus voltage list and charging priority, the lowest charging priority electric vehicle at the lowest voltage magnitude bus will be delayed charging for 5 minutes.

Step 6: Run the power flow again and check the voltage of bus N. If $V_N \leq V_{LL}$, delay the next lower charging priority car until $V_N \leq V_{LL}$. If all electric vehicles at the lowest voltage magnitude bus have been discharging at this time point and the voltage of bus N is still below the voltage limit, electric vehicles at the next lowest voltage magnitude bus will be controlled following step 4 and 5. If $V_N \geq V_{LL}$, go to step 2 and check the voltage of other buses.

Step 7. All bus voltage is in the accepted range, T=T+1. Go to step 2.

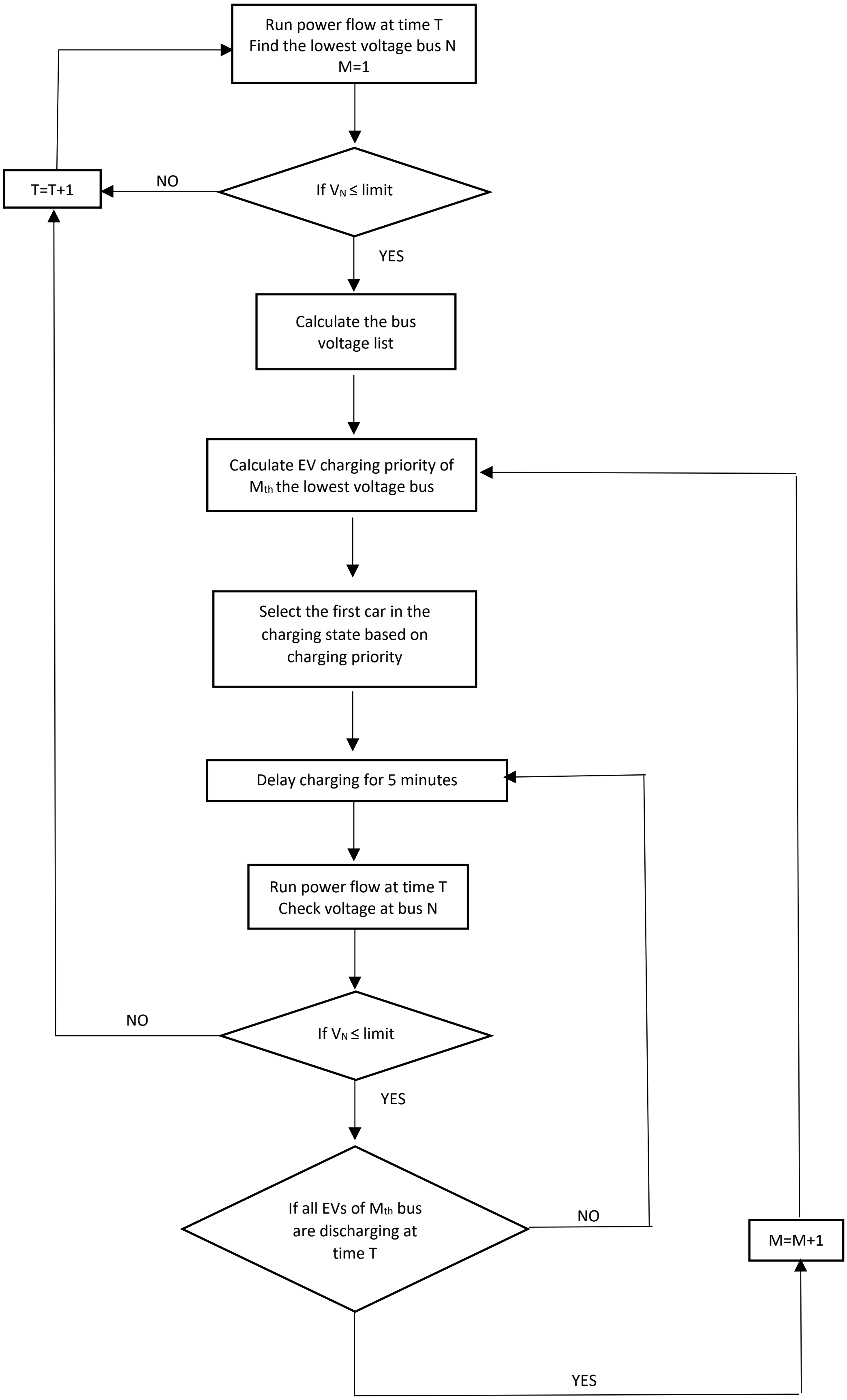

Figure 4. 9: Voltage control based on bus voltage optimisation algorithm flow chart

4.4.2 Voltage control based on voltage sensitivity Optimization algorithm

Step 1: The aggregator gets the base load demand and uncontrolled EV charging demand with a 1-min resolution from all households at each time step. In the uncontrolled EV charging plan, it assumed that all electric vehicles begin their charging at home when they finish their last trip and the charging rate is fixed (3.3kW).

Step 2: The power demand profiles are input into Opendss to run the power flow at time T. The bus voltage list will be generated. All buses in the network are sorted in the ascending order based on their bus voltage magnitude in p.u.

Step 3: Find the lowest voltage bus N and compared V_N with pre-set bus voltage lower limit V_{LL}. If $V_N \leq V_{LL}$, it means that the voltage at bus N drops too much and voltage regulation methods will be implemented. Then go to Step 4. If $V_N \geq V_{LL}$, it means that the voltages of all buses are in the accepted range. Then move back to Step 2 and run the power flow for next time step.

Step 4: Calculate the voltage sensitivity of the lowest voltage bus N. The voltage sensitivity of bus N describe how the active power changing of all buses in the network influences the voltage of bus N.

Step 5: Collect input data for each electric vehicle arriving time $t_{arriving}$, the state of charge (SOC) and, t_{begin} the time when people are going to use EV. Based on the above information, the priority list will be created to decide the optimisation order for each vehicle.

$$Priority = x \cdot order_{t_{arriving}} + y \cdot order_{soc} + z \cdot order_{t\_begin} \tag{4.26}$$

Where x, y, z are the weighting factors for three parameters, respectively. $Order_{t\_arriving}$ is the value of each vehicle in the ascending sequence of arriving time. $Order_{SOC}$ is the value of each vehicle in the descending sequence of the state of charging. $Order_{t\_begin}$ is the value of each vehicle in the descending sequence of beginning the next trip. The smaller value the car get from that equation, the higher the priority given to that car. The higher priority means that this electric vehicle need to be charged urgently. Moreover, people are less likely to participate in demand side management.

Step 6: Based on the calculated voltage sensitivity and charging priority, the lowest charging priority electric vehicle at the highest voltage sensitivity will experience delayed charging for 5 minutes.

Step 7: Run the power flow again and check the voltage of bus N. If $V_N \leq V_{LL}$, delay the next lower charging priority car until $V_N \leq V_{LL}$. If all electric vehicles at the highest voltage sensitivity bus have been discharging at this time point and the voltage of bus N is still below the voltage limit, electric vehicles at next higher voltage sensitivity will be controlled following steps 5 and 6. If $V_N \geq V_{LL}$, go to step 3 and check the voltage of other buses.

Step 8: All bus voltage is in the accepted range, T=T+1. Go to step 2.

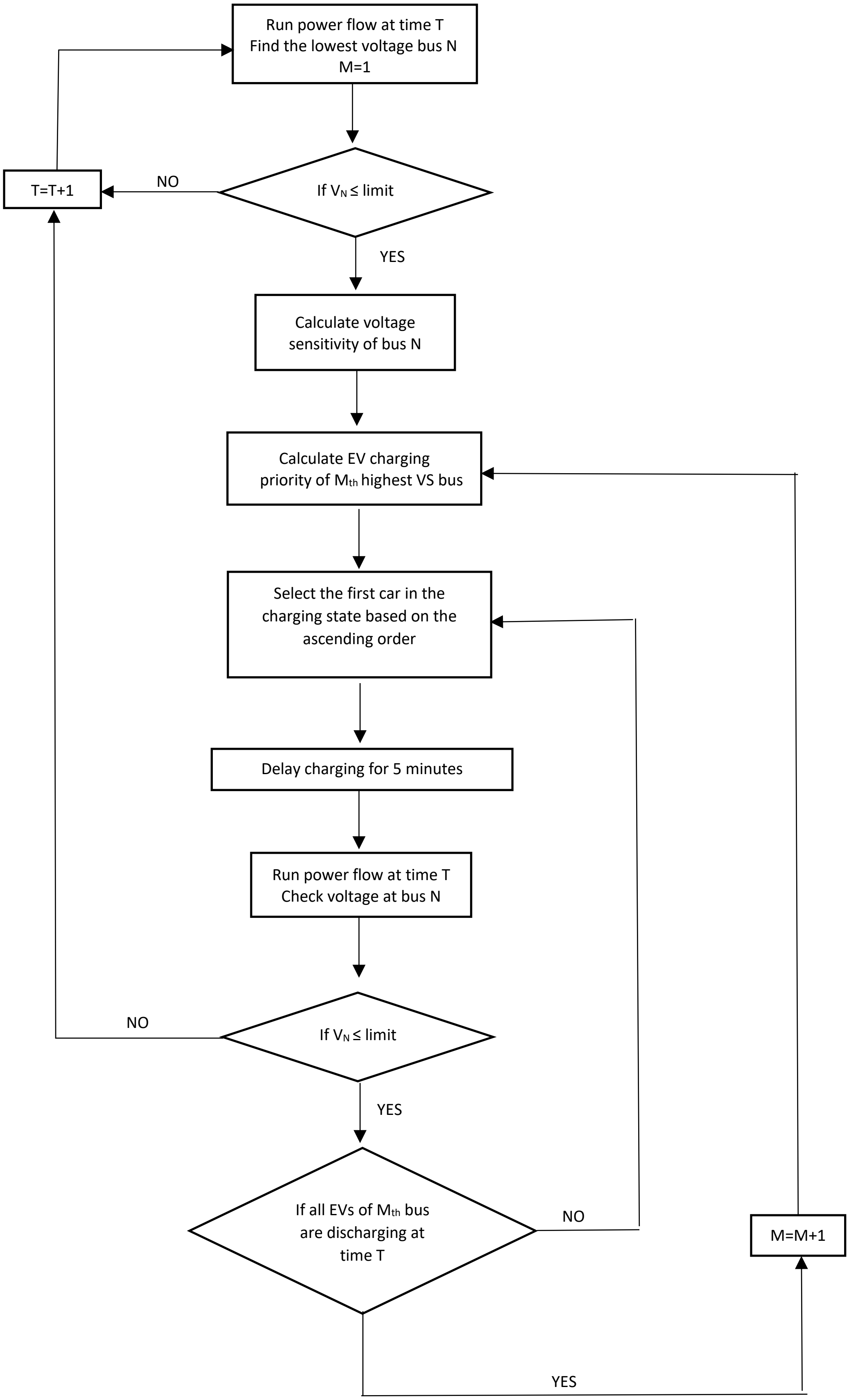

Figure 4. 10: Voltage control based on voltage sensitivity optimisation algorithm flow chart

4.5 Results

The 100 power load scenarios have been generated from 10,000 household power demand profiles. Moreover, each power load scenario contains 1,026 household load profiles. Three electric vehicle penetration levels (25%, 50% and 75%) are applied in the simulations. The results are presented based on two optimisation methods. The first part is the voltage profiles for uncontrolled charging plan and optimised charging plan with voltage sensitivity. The second part is the comparison between two optimisation algorithms from the 100 power load scenarios.

4.5.1 Results based on voltage sensitivity

Figure 4.14 is the voltage profiles for 29 buses in scenario 28 with 50% electric vehicle penetrations. There are four buses' voltages below the lower voltage limit 0.94 p.u. In general, all of the buses' voltage profiles have two periods where the voltage is reduced hugely. The first one is in the morning at around 8:00, but the voltage reduction is acceptable. The second is in the evening from 18:00 to 22:00. The voltage reduction of the second one is much more severe than the first one, four buses' lowest voltage magnitude is below 0.94 p.u. Moreover, the voltage profiles share the inversed patterns with the power demand profiles. Figure 11 is the optimised voltage profiles for 29 buses in scenario 28.

It is evident that the previous four buses whose voltage is below 0.94 p.u have risen their voltage above the lower limit. These four buses are bus 20, 21, 22 and 23. Figure 4.16 and Figure 4.17 are the original power demand and voltage profiles of the four individual buses. Figure 4.18 and Figure 4.19 are power demand and voltage profiles of the four individual bus implemented with voltage sensitivity method. In the power demand profiles, based load demand, electric vehicle charging demand and the aggregation of these demands, are presented with different colours. The results with the bus voltage optimisation method are not shown because it cannot achieve the expected target of rising all of the buses' voltages above 0.94 p.u.

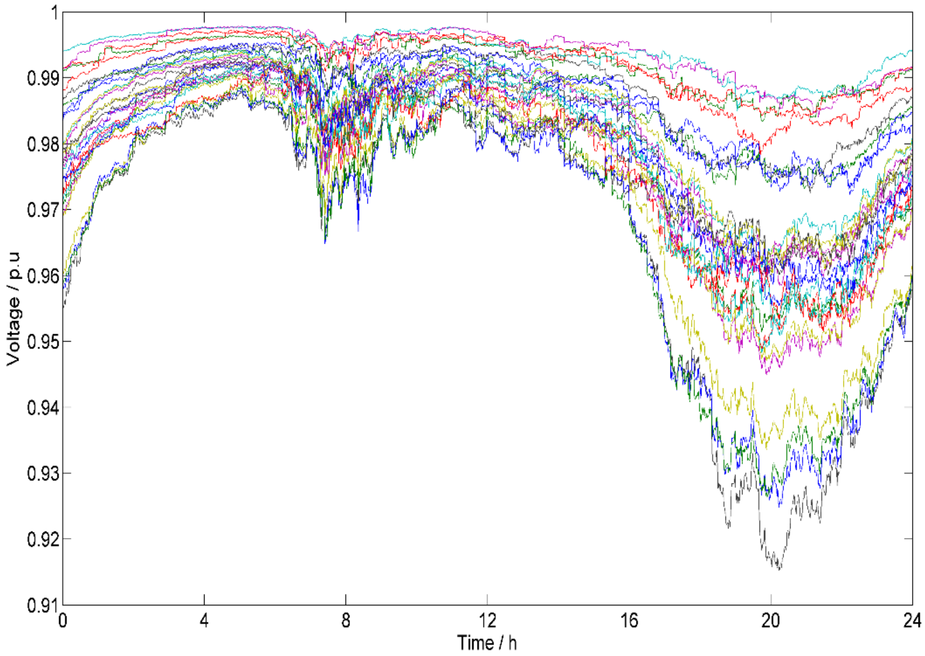

Figure 4. 11: The voltage profile for 29 buses in scenario 28

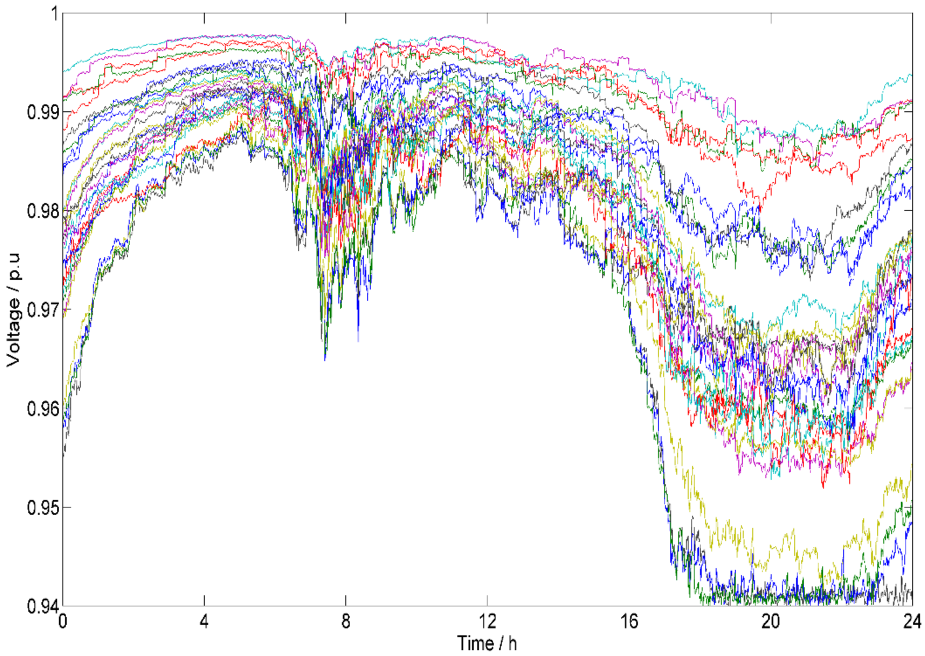

Figure 4. 12: The optimised voltage profiles for 29 buses in scenario 28 based on voltage sensitivity

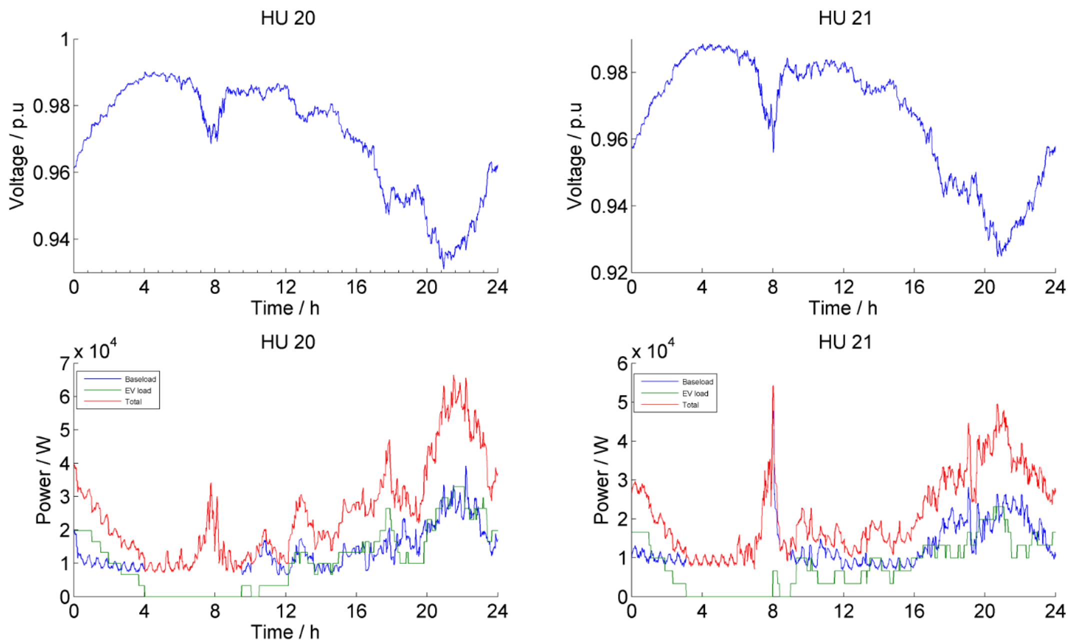

Figure 4. 13: The voltage and power demand profile for bus 20 and 21 in scenario 28

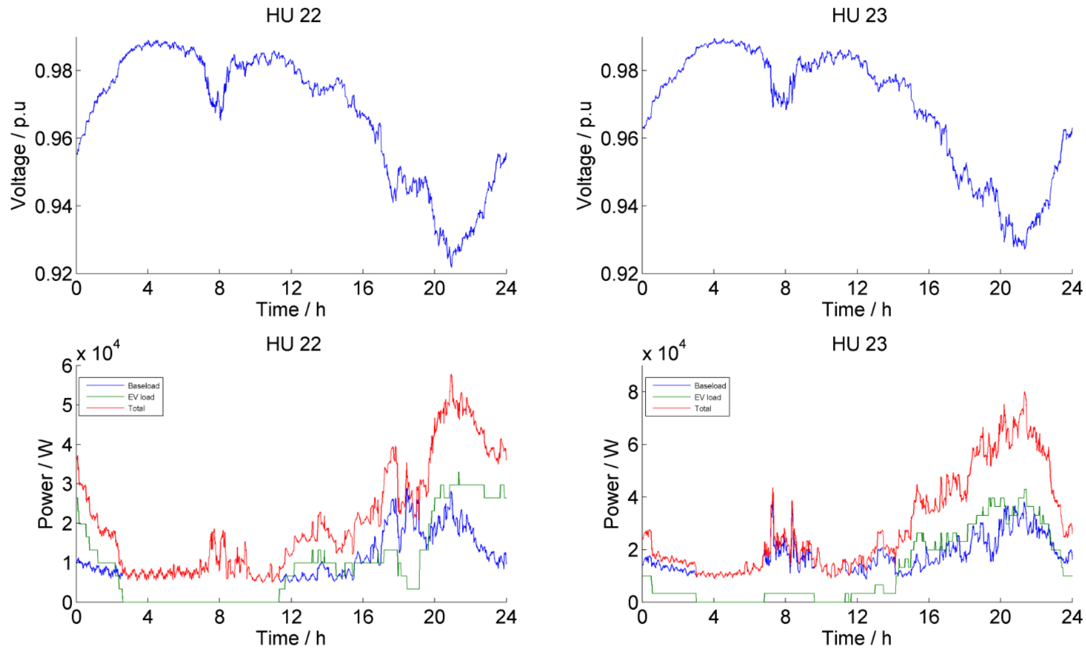

Figure 4. 14: The voltage and power demand profile for bus 22 and 23 in scenario 28

These four buses, 20, 21, 22 and 23 are the most distant buses in the extended LV highly-urban network. Furthermore, the feeder 3 these four buses belong to is the most complex and heavily loaded of the four feeders, which owns 14 out of the 29 buses and 508 of 1032 household in total. Therefore the feeder 3 are responsible for almost half of the power demand in the network. The voltage issues all occur during the evening throughout power demand peak hours. Although only 50% of households own electric vehicles, the uncontrolled charging power demand is almost the same as the baseload demand. Household power demand is determined by users' activities. Therefore, charging demand and baseload demand are generated during a similar period which leads to more volatility and a higher power demand peak in the evening.

Looking into the optimised power demand of the four buses, most of the electric vehicle charging demand is postponed to a later time in the evening or an earlier time the next day. To a large extent, an optimised charging plan shaves the power demand peak in the evening and fill the power demand valley with electric vehicle charging demand. It effectively maintains the bus voltage above the lower statutory limits of 0.94 p.u. Furthermore, not all electric vehicles charging are delayed when the voltage issues occur. This is the advantage of the proposed optimisation algorithm. Based on voltage sensitivity and charging priorities, it is aimed to minimise the number of electric vehicles which are delayed to achieve the expected voltage level. On the other hand, it also indicates that there is still the potential for voltage rising.

Although the power demand of bus 20 remains the same before and after the optimisations, the voltage magnitudes rise above 0.94 after the optimisations. This is because the buses' voltage is correlative and interactional. For each cycle of optimisation, only the lowest voltage magnitude bus is regarded as the target, and one single electric vehicle is supposed to be shifted. However, all the buses' voltage in the network is affected to various degrees. Therefore, the voltage of bus 20 is improved as the optimisation of the other buses is conducted.

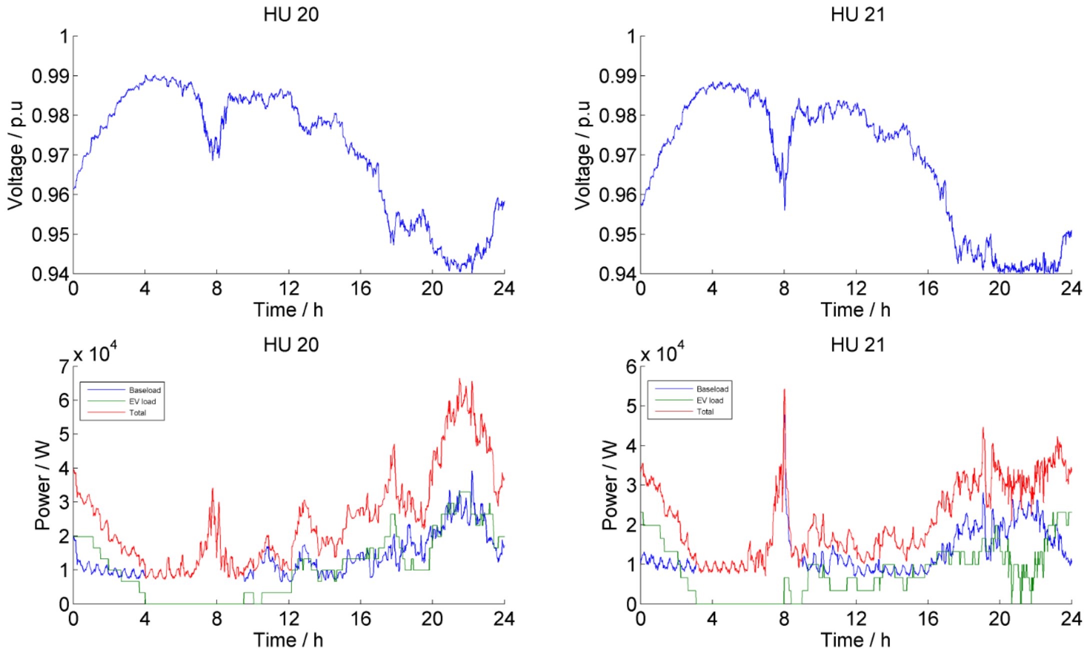

Figure 4. 15: The optimised voltage and power demand profile for bus 22 and 23 in scenario 28

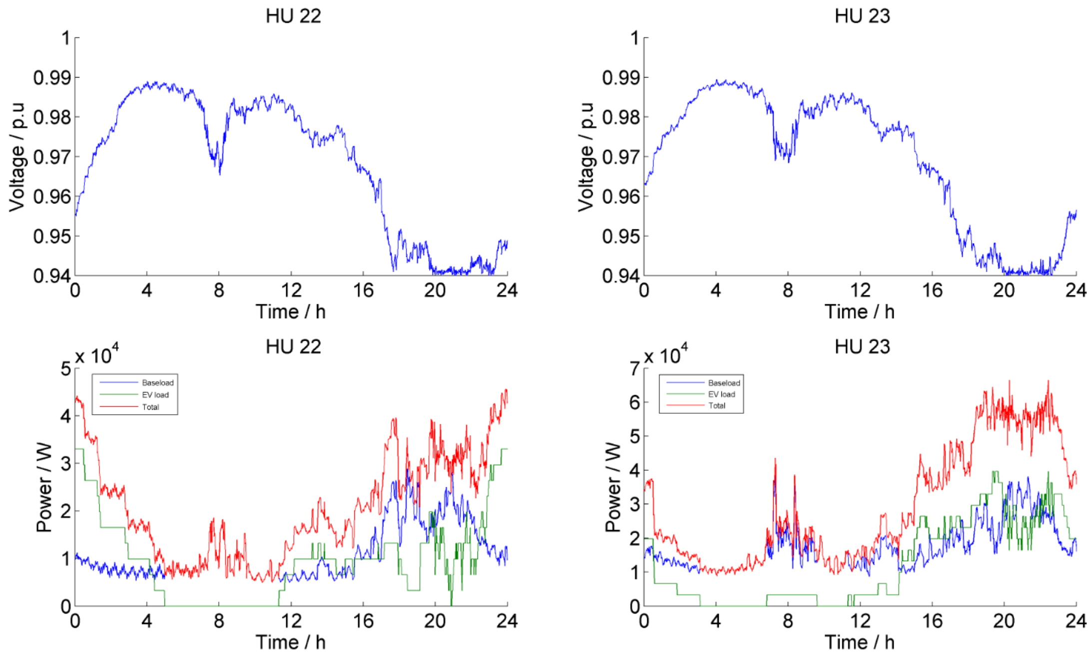

Figure 4. 16: The optimised voltage and power demand profile for bus 20 and 21 in scenario 28

4.5.2 Comparison between two optimisation algorithms

In this section, two proposed optimisation algorithms are implemented with 100 scenarios in the Opendss. Three electric vehicle penetration level, 25%, 50% and 75%, and two lower voltage limits, 0.94 p.u and 0.945 p.u are adopted in the simulations. The simulation results are concluded and analysed from the following three defined indices.

The possibility of occurrence of voltage issues: This is the possibility that divides the total number of power load scenarios in the test by the total number of power load scenarios where the voltage drops below the limit over the course of 1440 minutes (24 hours). This index is defined to describe how the optimisation algorithms solve the voltage drop problems. The lower the possibility of the occurrence of voltage issues, the higher the success rate of the optimisation algorithms.

The average time before the occurrence of voltage issues: This is average time before each power load scenario meets the voltage drop problem. This index is used to describe how long the power system works smoothly without meeting any voltage could drop problems. Under the same circumstances, the longer average time before occurrence of voltage issues means the better performance of optimisation algorithms.

The average shifted cycles for 1440 minutes: Due to the application of demand side management shifting electric vehicle charging, some power load scenarios can keep the voltage of all buses above the limit during the 24 hours period. The average shifted cycles are the average number of shifted cycles for these scenarios. This index is used to check a total number of the shifted electric vehicle during the whole optimisation process. The original intention of the optimisation algorithms is to minimise the influenced electric vehicles numbers as little as possible and raise the voltage level at the same time. More average shifted cycles of electric vehicles could lead to users' to become less involved in demand side management, and also some potential problems include the ageing of the battery, the unnecessary waste of energy and so forth.

	Without DSM	DSM base on bus voltage	DSM base on VS
Possibility of occurrence of voltage issues(below 0.94 p.u)	46%	2%	2%
The average time before occurrence of voltage issues	1234	1436	1436
The average shifted cycles for 1440 minutes		3.9	3.7

Table 4. 2: Voltage limit=0.94 p.u 25% EV penetrations

	Without DSM	DSM base on bus voltage	DSM base on VS
Possibility of occurrence of voltage issues(below 0.94 p.u)	100%	32%	25%
The average time before occurrence of voltage issues	1078	1229	1275
The average shifted cycles for 1440 minutes		261	216

Table 4. 3: Voltage limit=0.94 p.u 50% EV penetrations

	Without DSM	DSM base on bus voltage	DSM base on VS
Possibility of occurrence of voltage issues(below 0.94 p.u)	100%	90%	88%
The average time before occurrence of voltage issues	796	1125	1154
The average shifted cycles for 1440 minutes		608	580

Table 4. 4: Voltage limit=0.94 p.u 75% EV penetrations

	Without DSM	DSM base on bus voltage	DSM base on VS
Possibility of occurrence of voltage issues(below 0.94 p.u)	92%	6%	4%
The average time before occurrence of voltage issues	1201	1269	1331
The average shifted cycles for 1440 minutes		31.2	30.4

Table 4. 5: Voltage limit=0.945 p.u 25% EV penetrations

	Without DSM	DSM base on bus voltage	DSM base on VS
Possibility of occurrence of voltage issues(below 0.94 p.u)	100%	78%	74%
The average time before occurrence of voltage issues	1053	1270	1296
The average shifted cycles for 1440 minutes		304	198

Table 4. 6: Voltage limit=0.945 p.u 50% EV penetrations

	Without DSM	DSM base on bus voltage	DSM base on VS
Possibility of occurrence of voltage issues(below 0.94 p.u)	100%	100%	100%
The average time before occurrence of voltage issues	992	1163	1176
The average shifted cycles for 1440 minutes		389	394

Table 4. 7: Voltage limit=0.945 p.u 75% EV penetrations

Based on the results presented in the above table, some conclusions can be drawn. For 25% of the electric vehicle penetration in the extended highly-urban distributed network, 54% of power demand scenarios meet with serious voltage drop issues when lower voltage limit is 0.94p.u. With the increase of electric vehicle penetration level and lower voltage limit, almost 100% of power demand scenarios suffer from the voltage problems. Therefore, uncontrolled electric vehicle charging has seriously affected the bus voltage stability of the distributed power system network.

Furthermore, the average time before the occurrence of voltage issues become longer when more and more electric vehicles are connected to the power system. For the 25% penetration level, voltage issues occur after around 1200 minutes at 20:00, which is evening peak hour. At the 50% penetration level, it moves 2 hours earlier, at around 18:00, which is the beginning of the evening peak hour. For the 75% penetration level, it has been shifted to 475 minutes at 8:00, which is the morning peak hour. For the most severe case where the lower voltage level raises to 0.045 p.u, the average time before the occurrence of voltage issues is 129 minutes at 2:00 in the morning.

Comparing the two optimisation algorithms, for lower electric vehicle penetration levels, the advantage of demand side management with voltage sensitivity is not markedly obvious. It only can have 2% leading than demand side management with bus voltage. When the penetration level increases, demand side management with voltage sensitivity can achieve a 5% to 7% more successful rate. However, for the 75% penetration level and lower voltage limits 0.945 p.u, there is no chance for the voltage to rise above the expected level, even using demand side management with voltage sensitivity. It is because the household power demand has exceeded the affordable levels of the current power system.

Although the proposed optimisation algorithms can solve the voltage drop problems in all scenarios, demand side management with voltage sensitivity significantly improve the average time before the occurrence of voltage issues. It can extend the normal working period to 200 minutes longer compared with uncontrolled power demand, and around 30 minutes longer compared with demand side management for bus voltage. In the case of a voltage limit of 0.94 p.u and the 75% penetration level, the average time before the occurrence of voltage issues has been delayed by 679 minutes.

Concerning the average shifted cycles of 1440 minutes, demand side management with voltage sensitivity can achieve a better performance than demand side management based on bus voltage in the optimisation process. For the case of a voltage limit of 0.94 p.u and 50% penetration, it can decrease around 50 shifted cycles and achieve a higher success rate in solving the voltage problems. In general, the results of the average shifted cycles for 1440 minutes demonstrate another advantage of demand side management with voltage sensitivity, in that it can effectively reduce the influence of demand side management on original electric vehicle charging behaviour.

4.7 Conclusion

In this chapter, the implementation of two voltage control optimisation algorithms was studied to maintain the bus voltage levels within the reasonable range through electric vehicle charging demand management. Although the concept of voltage sensitivity has been discussed for a long time, it is the first time that voltage sensitivity have been used to evaluate the influence of active power demand on the bus voltage in the distributed power system network. Therefore some conclusions can be drawn as follow.

Uncontrolled electric vehicle charging has a negative impact on the stability and reliability of the distributed power system network. This is particularly true when electric vehicle penetration levels increase, as the voltage drop issues become much more apparent. The detailed influence on each bus has been analysed and presented. The proposed voltage control optimisation algorithm is employed in the simulation. The results suggest that this algorithm makes excellent contributions to bus voltage control in the radial distributed power system network in the following aspects.

1. The proposed algorithms can significantly solve the voltage drop issues during 24 hours in the low and medium electric vehicle penetration level. Moreover, it has the better success rate in solving voltage drop problems than demand side management algorithms based on bus voltage.

2. From the aspect of users, the proposed algorithms can decrease the number of affected electric vehicles in the network to achieve the same or even better optimisation results than other algorithms. To a certain degree, it could reduce people's reluctance to participate in demand side management. In other words, it means that proposed algorithms are capable of meeting the higher requirement of lower voltage limits

3. For high electric vehicle penetration level, the proposed algorithms cannot maintain the bus voltage above the lower limit across the 24 hours. However, it can efficiently extend the period before the occurrence of voltage issues, which provides room for the implementation of other optimisation methods.

Ultimately, the proposed algorithms can achieve the expected target to a great extent and offer the better performance than other algorithms. However, for some particular circumstance, further demand side management methods are required for issues such as wetload demand management.

Chapter 5 Combined Household loads and EV DSM

5.1 Introduction

In Chapter 3, all household activities were divided into 13 categories based on their various load characteristics. However, from the aspect of demand side management, household power demand can be reclassified into baseload, wetload and electric vehicle charging load demand. Baseload demand is defined as the power demand which cannot be shifted and controlled such as lighting, electrical entertainment appliances, cooking, cold loads and so forth. Electric vehicle charging demand is regarded as the storage system in which there is the capability for controllable, bi-directional electrical energy flow between a vehicle and the power grid. Wetload demand also can be used as a moveable load in the household; this includes dishwashers, washing machine, tumble dryers and washing dryers. The ultimate objective of this work is to develop a combined domestic load/EV charging management strategy. In the previous chapter, an EV charging algorithm was proposed. Here, a DSM algorithm is presented that deals with the wet load management in the household, and combined with the EV charging algorithm to create a single management structure.

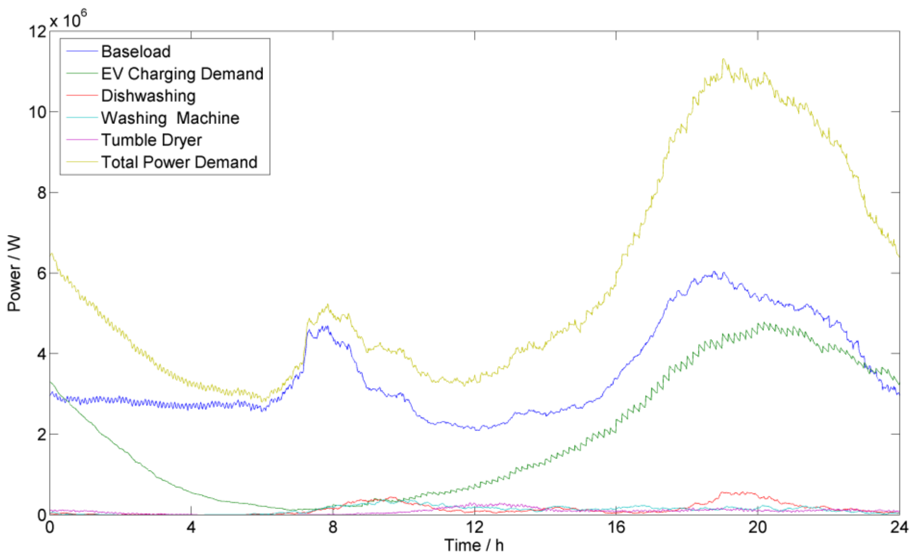

Figure 5. 1: 10000 Household detailed power demand

This graph demonstrates the baseload, electric vehicle charging demand, dishwashing, washing machine, tumble dryer and total power demand consumption of 10000 households within the 50% electric vehicle penetration level, as a result of the demand model presented in the previous chapter. It is clear that the baseload and electric vehicle charging are still the major power consumers in the household, during the peak demand period from 18:00 to 22:00, when the peak demand is almost the four times that of the valley demand. There is no doubts that electric vehicle charging demand makes excellent contribution to this. Wetload demand only accounts for a small proportion, compared with the other two significant demands in the household. Wetload demand shares similar shapes with the baseload. A detailed description of this will be presented in the next section. The following table shows the proportion of the total household power demand consumptions based on 10000 household load profiles.

EV penetration level	Baseload	EV charging demand	Wetload
0	91%	0	9%
25%	73%	20%	7%
50%	61%	33%	6%
75%	52%	43%	5%
100%	46%	50%	4%

Table 5. 1: The proportion of various household load demand

With the increase of the EV penetration level from 0 to 100%, EV charging demand occupies more and more proportion even up to 50%, which is more than the baseload. The proportion of wetload drops from 9% to 4%. In this chapter, wetload is regarded as a flexible load demand in the household. A combined household demand side management is proposed which includes EV charging and wetload demand, which will provide the large power demand space for management. The wetload demand plays the same role as EV charging demand in maintaining a stable voltage level in the distribution network.

5.2 Household wetload analysis

The mainly household wetload electric appliances are dishwashers, washing machine and tumble dryers. Differing from electric vehicle charging demand, wetload power demand shares the following three characteristics.

1. Continuity: it cannot be interrupted during the working cycles based on the household users' behaviours and their load. It will be not finished until the end of the programme.
2. Necessity: Not all household are fitted with wetload electric appliances, and the frequency of operation for wetload is also low. It is not a daily running electrical appliance, such as lighting.
3. Variability: Because of special working characteristics, the power consumption of the wetload are not constant, and they change during the working cycles.

The electric vehicle charging process can be interrupted and divided into several separate periods based on requirements. However, for the wetload power demand, in light of the above three characteristics, the only method feasible without disturbing the user's activities is delaying their starting time.

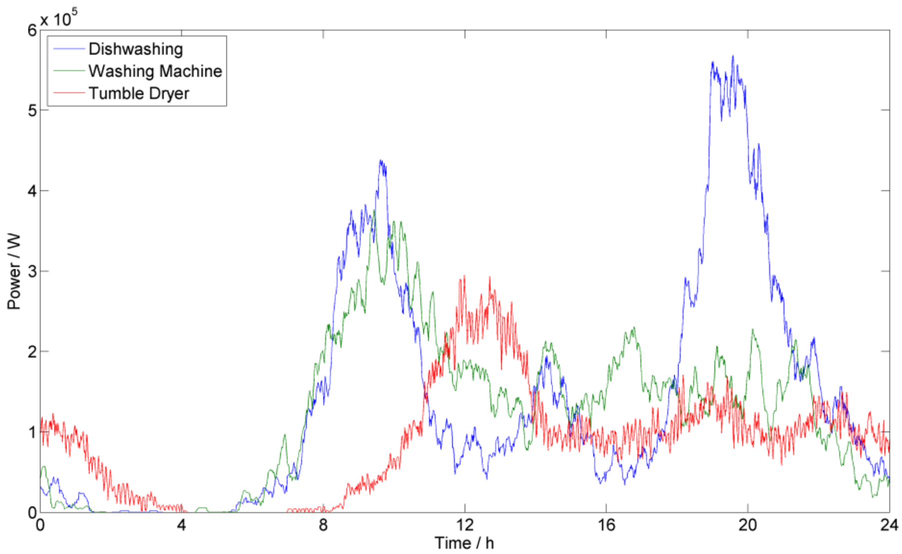

Figure 5. 2: 10000 household wetload demand

The above figure is the aggregate of three major wetload electric appliances power demand from 10000 households. The blue line is the dishwashing power demand. The demand peaks occur at a similar time as the baseload, in the morning and evening when people finish their breakfast and dinner. The green line is the washing machine, and the red line is tumble dryer. These two electric appliances are complementary goods from the view of microeconomics. The washing machine power demand is focused in the morning after the baseload rush hour. The tumble dryer work usually two hours after the washing machine which is decided by their complementary relationship and washing machine working cycle. Because not all household is equipped with tumble dryer, the total power demand of tumble dryers is less than for washing machines. Therefore in this chapter, the combined household load and electric vehicle demand side management are proposed. Based on the previous developed household power demand profiles, baseload, electric vehicle charging and wetload account for 60 %, 35% and 5% respectively of the daily total power demand for 50% electric vehicle penetration level. Therefore almost 40% of household power demand can be optimised and the wetload demand is implemented as the supplement of demand side management based on electric vehicle charging.

5.3 Voltage control based on wetload optimisation algorithm

Voltage control based on wetload optimisation algorithm is derived from the voltage control based on voltage sensitivity optimisation algorithm discussed in the previous chapter. They share the same processing step with electric vehicle charging demand side management until step 7. The detailed processing procedures are explained below.

Step 1: The aggregator gets the base load demand and uncontrolled EV charging demand with a 1-min resolution from all households at each time step. In the uncontrolled EV charging plan, it is assumed that all electric vehicles begin their charging at home when they finish their last trip, and the charging rate is fixed (3.3kW).

Step 2: The power demand profiles are input into OpenDSS to run the power flow at time T. The bus voltage list will be generated. All of the buses in the network are sorted in ascending order based on their bus voltage magnitude in p.u.

Step 3: Find the lowest voltage bus N and compared V_N with the pre-set bus voltage lower limit V_{LL}. If $V_N \leq V_{LL}$, it means that the voltage at bus N has dropped too much and voltage regulation methods will be implemented. Then go to Step 4. If $V_N \geq V_{LL,}$ it means that the voltages of all the buses are in the accepted range. Move back to Step 2 and run the power flow for the next time step.

Step 4: Calculate the voltage sensitivity of the lowest voltage bus N. The voltage sensitivity of bus N describe how the active power changing of all buses in the network influence the voltage of bus N.

Step 5: Collect input data of each electric vehicle arriving time $t_{arriving}$, the state of charge (SOC) and t_{begin} the time when people are going to use EV. Based on the above information, the priority list will be created to decide the optimisation order for each vehicle.

$$Priority = x \cdot order_{t_{arriving}} + y \cdot order_{soc} + z \cdot order_{t\_begin} \quad (5.1)$$

Where x, y, z are the weighting factors for three parameters, respectively. $Order_{t\_arriving}$ is the value of each vehicle in the ascending sequence of arriving time. $Order_{SOC}$ is the value of each vehicle in the descending sequence of the state of charging. $Order_{t\_begin}$ is the value of each vehicle in the descending sequence of beginning next trip. The smaller value the car gets from that equation, the higher the priority given to that car. The higher priority means these electric vehicles need to be charged urgently. Moreover, people are less likely to participate in demand side management.

Step 6: Based on the calculated voltage sensitivity and charging priority, the lowest charging priority electric vehicle at the highest voltage sensitivity will have its charging delayed for 5 minutes.

Step 7: Run the power flow again and check the voltage of bus N. If $V_N \leq V_{LL}$, delay the next lowest charging priority car until $V_N \leq V_{LL}$. If all electric vehicles at the highest voltage sensitivity have been discharging at this time point and the voltage of bus N is still below the voltage limit, wetload working states are checked for bus N.

Step 8: For bus N, if wetload electric appliances are about to start work at this time constant, the start time will be postponed for 5 minutes. If the wetload electric appliances are in the working state, no further action will be implemented.

Step 9: After all the wetload electric appliances have been checked, If $V_N \leq V_{LL}$, electric vehicles at next higher voltage sensitivity will be controlled following step 5 and step 6. If $V_N \geq V_{LL}$, go to step 3 and check the voltage of other buses.

Step 8: All bus voltage are in the accepted range, T=T+1. Go to step 2.

The detailed flowchart of the combined EV charging demand and household load demand side management is presented below. Furthermore, some rules are set in the wetload demand side management to make the optimisation to be more realistic. For example, the start time of the washing machine cannot be later than the tumble dryer for one household.

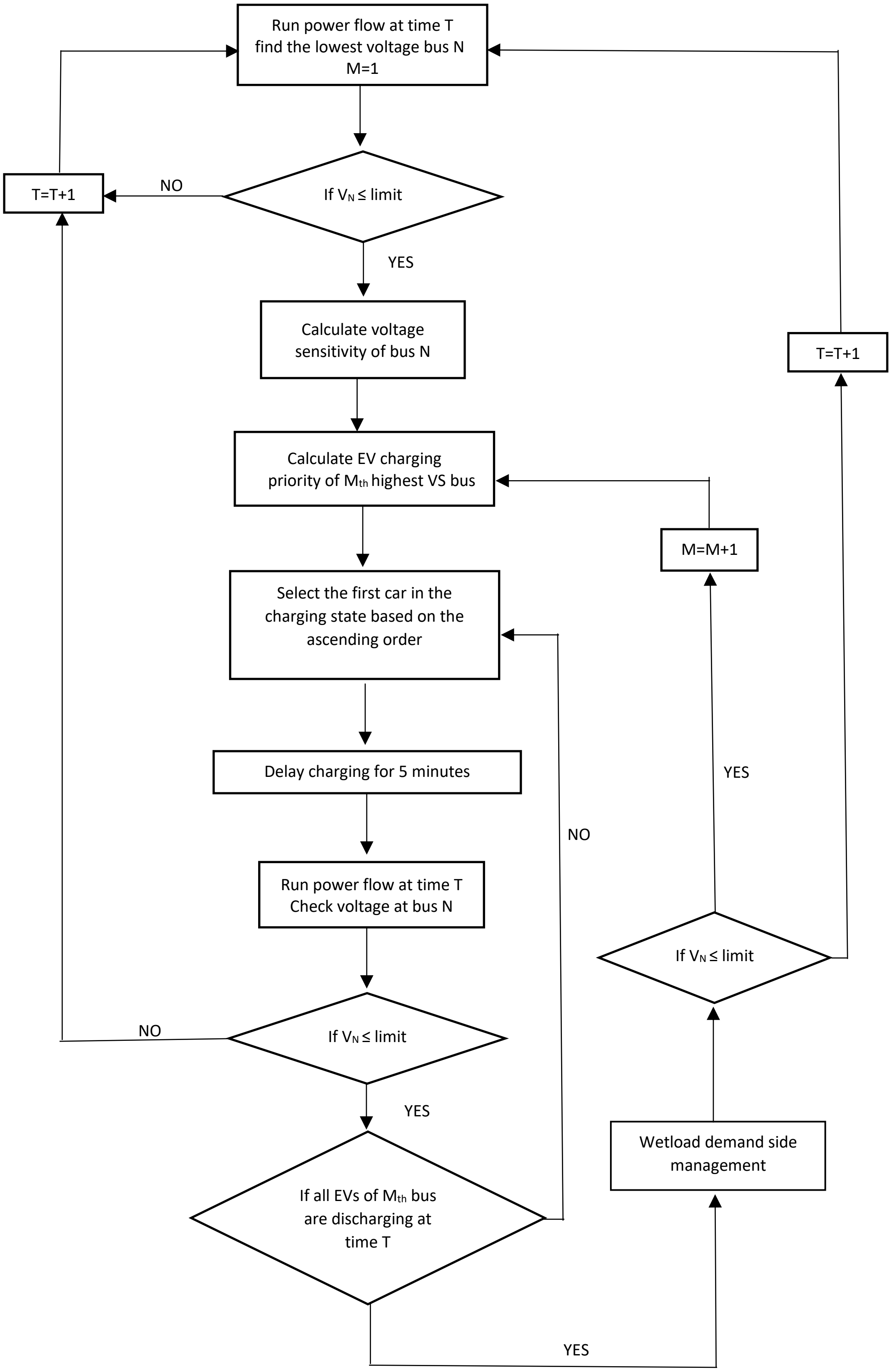

Figure 5. 3: Voltage control based on voltage sensitivity optimisation algorithms flow chart

5.4 Results

The same processing procedures are adopted in this chapter as the electric vehicle charging demand side management. The 100 power load scenarios will be generated from 10,000 household power demand profiles with a separate wetload power demand. Each power load scenario contains 1026 household load profiles. Also, three different electric vehicle penetration (25%, 50% and 75%) levels were implemented in the simulations. In the previous chapter, two optimisation algorithms were compared. Demand side management with the voltage sensitivity showed the better performance in maintaining the bus voltage level than the demand side management with the bus voltage. So demand side management with voltage sensitivity will be applied in this chapter. The optimisation results in the wetload will be compared with demand side management for electric vehicles. The identical extended highly urban generic low voltage distribution network will also be chosen in the simulation. Three same defined parameters the possibility of the occurrence of voltage issues, the average time before occurrence of voltage issues and the average shifted cycles for 1440 minutes are introduced to measure the performance of optimisation results.

5.4.1 Results based on wetload demand side management

Figure 7.3 and Figure 7.5 show the voltage and power demand profiles for buses 20, 21, 22 and 23 in Scenario 10 with 50% electric vehicle penetrations. Different power demand is demonstrated in various colours. The blue line is the baseload demand. The green line is the electric vehicle charging demand. Light green, purple and red lines are the washing machine, tumble dryer and dishwasher demand respectively. The yellow line is the aggregation of all these household power demands. The voltage of these four buses is below the lower voltage limit of 0.94 p.u among all 29 buses in the distribution network. For bus 23, the lowest voltage magnitude is even below 0.93 p.u at around 0.926 p.u which happens at 18:50. As we can see, all the voltage issues occur between 18:00 and 20:00. This is due to baseload and electric vehicle charging demand both reaching the demand peak during this period. The wetload demand is distributed evenly from 8:00 to 22:00 in the view of each bus.

The optimisation results with the electric vehicle charging demand are not presented because they do not achieve the expected target of rising all of the buses' voltages above the lower limit of 0.94 p.u during the 24-hour simulations. It means that even though all available electric vehicles experience delayed charging at the certain time point, some buses' voltage is still below 0.945 p.u. The optimised bus voltages and demand profiles shown are based on the combined household demand side management algorithm. Unlike the simulation in the previous chapter, the pre-set voltage optimised target is lifted to 0.945 p.u.

For bus 20, the voltage drop is not as severe as for the other three buses. When comparing the wetload demand before and after optimisation, the wetload demand is kept the same. It is partly because the electric vehicle charging demand is enough to raise the voltage above the lower voltage limit of 0.945 p.u. Even with the electric vehicle charging demand, only a few cars are delayed. Another reason leading to this phenomenon is that the voltage level of one bus is not only influenced by its power demand but also affected by the load condition of other buses. For example, bus 23 is the most distant from the slack bus and burdened with the most massive load. The demand side management of bus 23 results in raising its voltage level; meanwhile, it also has a positive impact on the other buses' voltage level.

For the other three buses, bus 21, 22 and 23, they all experience the severe voltage drop issues. The optimised voltage profiles share a similar shape, and they are all closed to the lower voltage limit of 0.945 p.u from 18:00 to 23:00. Furthermore, most of the electric vehicle charging demand during the peak time is shifted to the morning of the next day which is the power demand valley period. It also can be observed that some washing machine demand (light green) and the tumble dryer (purple) are postponed to the next daytime to avoid the evening peak demand hour. Because plenty of power demand in the evening moves to the early morning of next day, it causes a slight voltage drop from 0:00 to 5:00, but it is still within the accepted range. From the aspect of the energy side, the primary target of demand side management of the combined household load is to improve the bus voltage profiles. At the same time, it also effectively reduce the power demand fluctuation to a certain extent. Given the small proportion of wetload demand in the household compared with the baseload and electric vehicle charging demand, the demand change after the optimisation is not so evident as electric vehicle charging demand. In the case of the electric vehicle charging demand side management, the bus voltage will drop below 0.945 p.u at 18:52.

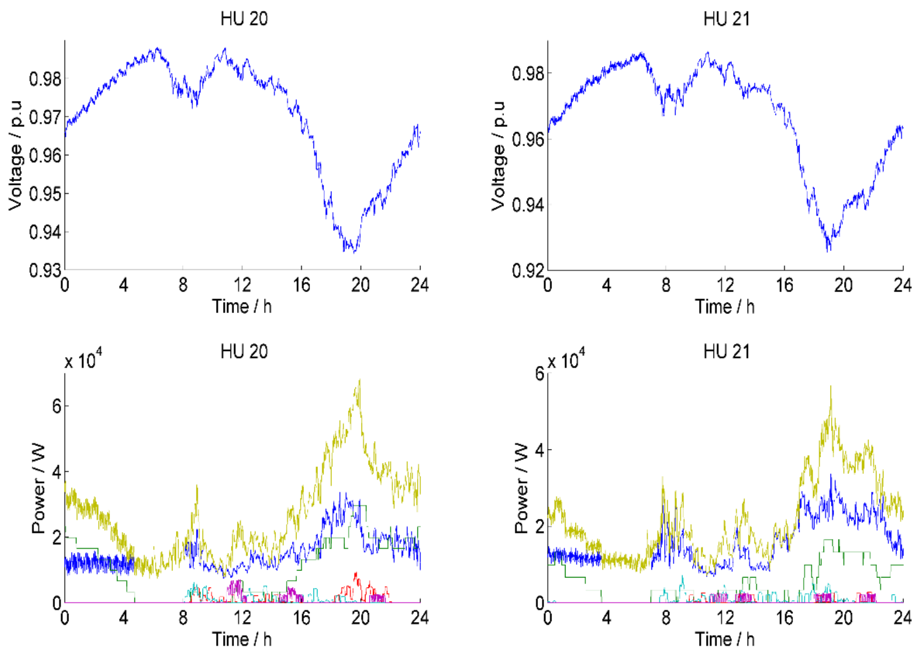

Figure 5. 4: The voltage and power demand profile for bus 20 and 21 in scenario 10

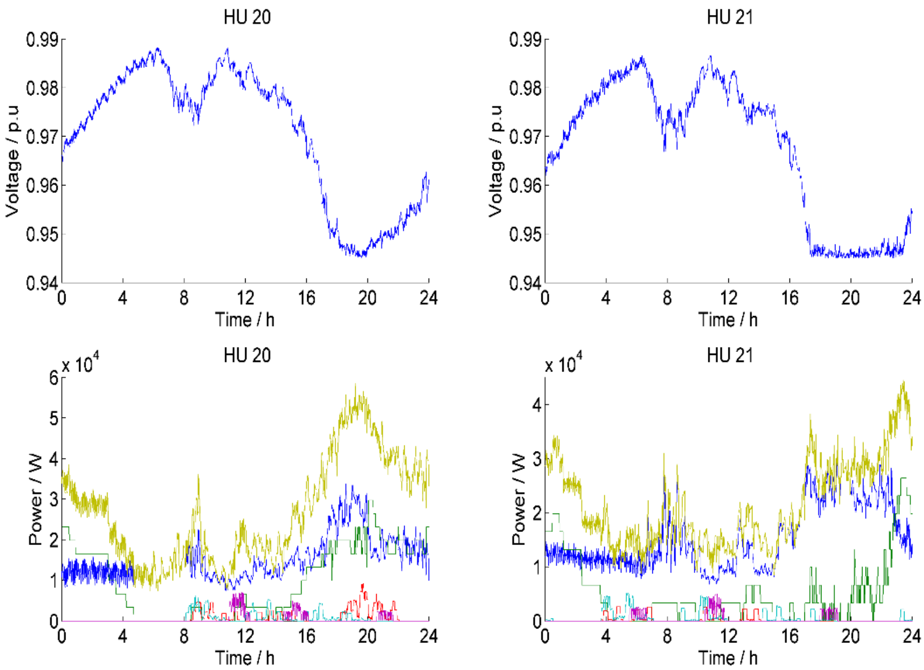

Figure 5. 5: The optimised voltage and power demand profile for bus 20 and 21 in scenario 10

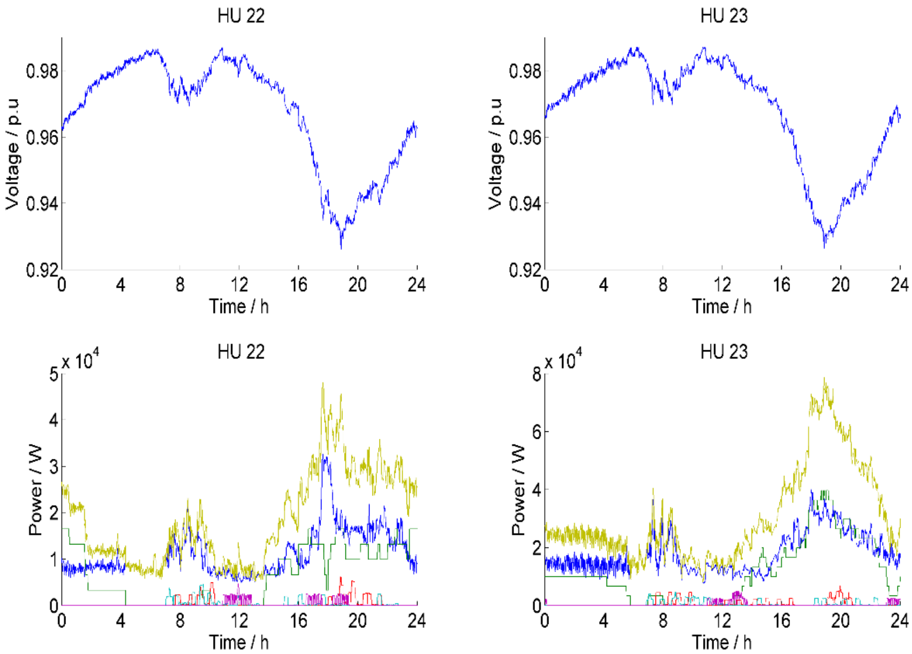

Figure 5. 6: The voltage and power demand profile for bus 22 and 23 in scenario 10

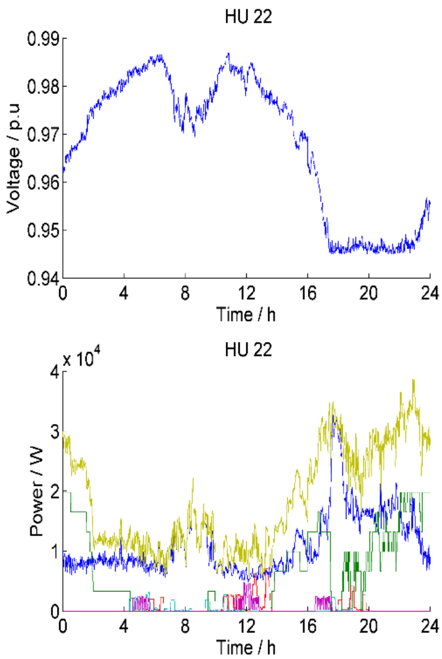

Figure 5. 7: The optimised voltage and power demand profile for bus 22 and 23 in scenario 10

5.4.2 Comparison between two optimisation algorithms

This section will demonstrate the performance of two proposed optimisation algorithms based on 100 scenarios simulated in the OpenDSS. Three electric vehicle penetration levels 25%, 50% and 75% and two lower voltage limits, 0.94 p.u and 0.945 p.u are introduced in the simulation. Three parameters are used to measure the performance including the possibility of the occurrence of voltage issues, the average time before the occurrence of voltage issues and the average shifted cycles for 1440 minutes. The detailed definitions of these three parameters have been explained in the Chapter 6.5.2.

When comparing two optimisation algorithms, for lower electric vehicle penetration level and voltage limits, such as 25% and 0.94 p.u, the advantage of combined household demand side management is not necessarily apparent. When the lower voltage limit is set as 0.945 p.u, the slight advantage of combined household demand side management is shown which could have 4% less possibility of occurrence of voltage issues and provide around 40 minutes extra time for the power system. For the 50% electric vehicle penetration, the advantage of a combined household demand side management is proved, in that it is able to reduce the possibility of the occurrence of voltage issues from 78% to 60% and extend the average time before the occurrence of voltage issues from 1275 to 1322 under the circumstance of a lower voltage limit of 0.945 p.u. It also decreases the average shifted cycles from 204 to 165 which means that fewer households are influenced in the demand side management. Even in the case of the lower voltage limit 0.94 p.u, the combined household demand side management can also offer a significant advantage over the demand side management based on an electric vehicle. When the electric vehicle penetration level increases to 75%, the combined household demand side management shares a similar performance to the electric vehicle charging demand side management. Especially when the lower voltage limit is lifted to 0.945 p.u, the combined household demand side management can only reduce the average shifted cycles.

	Without DSM	DSM base on EV	DSM based on EV&WL
Possibility of occurrence of voltage issues(below 0.94 p.u)	48%	0%	0%
The average time before occurrence of voltage issues	1200	1440	1440
The average shifted cycles for 1440 minutes		7	7

Table 5. 2: Voltage limit=0.94 p.u 25% EV penetrations

	Without DSM	DSM base on EV	DSM based on EV&WL
Possibility of occurrence of voltage issues(below 0.94 p.u)	100%	28%	20%
The average time before occurrence of voltage issues	1076	1245	1309
The average shifted cycles for 1440 minutes		202	150

Table 5. 3: Voltage limit=0.94 p.u 50% EV penetrations

	Without DSM	DSM base on EV	DSM based on EV&WL
Possibility of occurrence of voltage issues(below 0.94 p.u)	100%	84%	80%
The average time before occurrence of voltage issues	848	1094	1133
The average shifted cycles for 1440 minutes		555	512

Table 5. 4: Voltage limit=0.94 p.u 75% EV penetrations

	Without DSM	DSM base on EV	DSM base on EV&WL
Possibility of occurrence of voltage issues(below 0.94 p.u)	88%	6%	2%
The average time before occurrence of voltage issues	1161	1322	1364
The average shifted cycles for 1440 minutes		30	24

Table 5. 5: Voltage limit=0.945 p.u 25% EV penetrations

	Without DSM	DSM base on EV	DSM base on EV&WL
Possibility of occurrence of voltage issues(below 0.94 p.u)	100%	78%	60%
The average time before occurrence of voltage issues	1029	1275	1322
The average shifted cycles for 1440 minutes		204	165

Table 5. 6: Voltage limit=0.945 p.u 50% EV penetrations

	Without DSM	DSM base on EV	DSM base on EV&WL
Possibility of occurrence of voltage issues(below 0.94 p.u)	100%	98%	98%
The average time before occurrence of voltage issues	950	1034	1038
The average shifted cycles for 1440 minutes		354	273

Table 5. 7: Voltage limit=0.945 p.u 75% EV penetrations

5.5 Conclusion

In this chapter, the characteristics of three household wetload including washing machine, tumble dryer and dishwashing are analysed, and detailed wetload demand profiles are generated. Based on their three characteristics, continuity, necessity, and variability, a combined household demand side management is proposed. This optimisation algorithm effectively reduces the variation of the bus voltage level in the distribution network. As a supplement to electric vehicle charging demand side management, it has been proven that better performance can be obtained, especially in the medium electric vehicle penetration level. However, with the increase of electric vehicle penetration level, the proportion of wetload is decreasing, and the effect of combined household demand side management is not significant compared with electric vehicle charging demand side management.

Chapter 6. Multi-Objectives Demand Side Management (MoDSM)

6.1 Introduction

This chapter investigates the potential impact incurred by a fleet of electric vehicles charging on the cost of electricity generation, greenhouse gas emissions (GHG) and power system demand through low voltage residential demand-side management (DSM). The optimisation algorithm is used to shift electric vehicles charging loads to minimise the combined impact of three critical parameters: financial, environmental, and demand variability. The results show that it is possible to reshape the power demand and reduce electricity cost and GHG emissions without affecting people's driving patterns.

Demand side management strategies are focusing on shifting flexible loads outside the peak demand periods, typically in the morning and evening hours for the UK. Current research focuses on responsive measures that shift loads to a later time (typically during the night). However, in a system with large numbers of EVs, this may cause new problems, as EVs are, usually charged overnight. This, therefore, may not be the optimal solution, as it may be cheaper and more environmentally friendly to shift loads earlier, e.g. during the mid-day valley when local penetration from domestic PV is also high. However, this requires an accurate prediction of the EV charging demand. Therefore, a stochastic model of people's driving behaviours using the Markov Chain Monte Carlo (MCMC) method has been developed to calculate the EV charging load for household customers and has been added to previous work, in which 'flexible' domestic loads such as washing machines and dishwashers are used by the optimisation algorithm for demand side management. Each EV profile has a strong correlation with individual household daily activities.

6.2 Methodology

6.2.1 Optimisation problem definition

This study focuses on the three areas of power system operation, the total daily cost of electricity generation, the greenhouse gas emissions that derive from consumption of energy and the fluctuation of power demand caused by various domestic lifestyle habits. The combined impact is introduced to measure the contributions of these three costs to the whole power system. In order to minimise the combined impact on the entire power system, EV charging is shifted to reshape the power demand profiles. However, electric vehicle charging cannot be shifted without any limitation. In reality, the owners of EVs will prefer finishing charging as soon as possible so as to have the car available for their next journey. A penalty factor is therefore used in the optimisation to constrain the delay time.

The objective function can be described mathematically by the following equation:

$$min \sum_{i=1}^{t} c_{comb} = min \sum_{i=1}^{t} (x \cdot c_{wi} + y \cdot em_{wi} + z \cdot sy_{wi}) \cdot (1 + pen_i) \qquad (6.1)$$

Where c_{comb} is the combined impact which is calculated by c_{wi}, em_{wi} and sy_{wi}. These are the normalised values of electricity price, greenhouse gas (GHG) emissions, and system cost respectively, where system cost sy_{wi} is defined as the normalised difference between the instantaneous active power and the mean daily power. The weighting factors x, y and z are used to set the ratio of the influence of three criteria in the calculation; pen_i is the penalty factor which is used to reduce the delay time; t defines the 1440 time steps (24 hours at 1-min resolution).

The profiles of three criteria: electricity price, greenhouse gas (GHG) emissions and system active power demand are weighted according to the following equations:

$$f = \frac{(h \cdot p) - \min(h \cdot p)}{\max(h \cdot p) - \min(h \cdot p)} \qquad (6.2)$$

$$sy_{wi} = \frac{\Delta P_i - \min(\Delta P)}{\max(\Delta P) - \min(\Delta P)} \qquad (6.3)$$

Where f represents the normalised values for c_{wi} and em_{wi}, by replacing h with c and em respectively. Electricity price is in £/MWh, GHG emissions in tons of CO_2 eq./MWh and sy in MW. P is the active power demand and ΔP_i is the absolute difference between the instantaneous active power and the daily mean power at each time step i.

The penalty factor used to limit the delay time is given by:

$$pen = \begin{cases} x \cdot \frac{1}{2880}, 1 \leq x \leq 1440 \\ 0.5, \ x \geq 1440 \end{cases} \tag{6.4}$$

When the delay time x is less than 1440 minutes, it increases linearly. When the delay time is more than 1440 minutes, the penalty factors will be 1. The constraints are defined in following equations (6.5)-(6.7)

$$E_{new} = E_{old} \tag{6.5}$$

$$t_{end\_new} - t_{start\_new} = t_{end\_old} - t_{start\_old} \tag{6.6}$$

$$t_{end_{new}} \leq t_{begin} \tag{6.7}$$

Where E_{new_old} is the daily energy demand before and after EV load shifting, t_{end_new}, t_{start_new} ,t_{end_old} ,t_{start_old} are the start and end charging times before and after shifting. t_{begin} is the time when people are going to use EV. The algorithm ensures that before and after shifting, the charging time and energy consumption will be the same and that electric vehicles will be fully charged or stop charging before the next trip.

6.2.2 Optimisation algorithm

Step 1: The aggregator gets the base load demand and uncontrolled EV charging demand with a 1-min resolution from 100 households. In the uncontrolled EV charging plan, it assumed that all electric vehicles begin their charging at home when they finish their last trip.

Step 2: Collect input data of each electric vehicle arriving time $t_{arriving}$, the state of charge (SOC), t_{begin} the time when people are going to use EV. Based on the above information, the priority list will be created to decide upon an optimisation order for each vehicle.

$$Priority = x \cdot order_{t_{arriving}} + y \cdot order_{soc} + \ z \cdot order_{t\_begin} \qquad (6.8)$$

Where x, y, z are the weighting factors for three parameters, respectively. $Order_{t\_arriving}$ is the value of each vehicle in the ascending sequence of arriving time. $Order_{SOC}$ is the value of each vehicle in the ascending sequence of the state of charging. $Order_{t\_begin}$ is the value of each vehicle in the ascending sequence of beginning next trip. The smaller value the car gets from that equation, the higher priority given to that car.

Step 3: Assume charging process cannot be interrupted, and all electric vehicles will be fully charged or stop charging when people are going to use the vehicle.

$$t_{shift} = t_{begin} - \left(t_{arriving} + \frac{1-SOC}{cr} \cdot BC\right) \qquad (6.9)$$

Where t_{shift} is available shifting cycles for each vehicle. CR is charging rate 3.3kW. BC is battery capacity 24kWh. The initial SOC is determined by ambient temperature and people's driving behaviour.

Step 4: for k=1: t_{shift}, shifting start charging time t_{start} to ($t_{arriving}$+k), then generate new charging profiles of EV_i and calculate the combined impact of the whole system using equation (1) and (2) at each available shifting cycle of EV_i. Electricity price is derived from market information published online by the balancing mechanism reporting agent. GHG emissions' data are the short term marginal emissions derived from operational and market data for generation plants on the British grid. System cost is defined as follows:

$$\Delta P_i = P_{tot\_i} - P_{ave} \qquad (6.10)$$

$$P_{tot\_i} = P_{base\_i} + P_{ev\_i} \qquad (6.11)$$

$$P_{ave} = \frac{\sum_{i=1}^{t} P_{tot\_i}}{\sum_{i=1}^{t} i} \qquad (6.12)$$

Where P_{tot} is total real power demand including base load and EV of the system. P_{base} is total baseload demand of the system. P_{ave} is the total daily power divided by the total time step 1440. ΔP_i is the difference between average power demand and real power demand.

Step 5: find the shifting cycle of EV_i when the whole system reaches the minimum combined impact. Then use this shifting cycle to reschedule the electric vehicle charging and generate the new charging profiles.

Step 6: Update charging profiles of EV_i and power demand of the whole system. Given the update of electric vehicle charging profiles, ΔP will also be recalculated. Increase value of i by 1 and start from step 3. The closed-loop optimisation is selected to avoid creating another new peak demand. Otherwise, each electric vehicle will choose minimum combined impact timing as their starting charging point without the consideration of other electric vehicles. As I increases, ΔP is approaching zero which means that optimized power demand of the whole system gets close to the average power demand. Go to Step 7 when i is equal to electric vehicle number.

Step 7: Optimisation end. Generate the new power demand of the whole system.

6.3 Case study

6.3.1 UK residential load

The methodology mentioned in chapter 3 is applied to a test system to generate 100 household baseload demand and electric vehicle charging demand. The following picture is the aggregation of 100 household baseload demand. It can be clearly observed that there is two power demand peak during a typical working day. The first one occurs in the morning around 8:00 when people get up and prepare for work. The second one starts from 18:00 until 22:00 when people come back home from work.

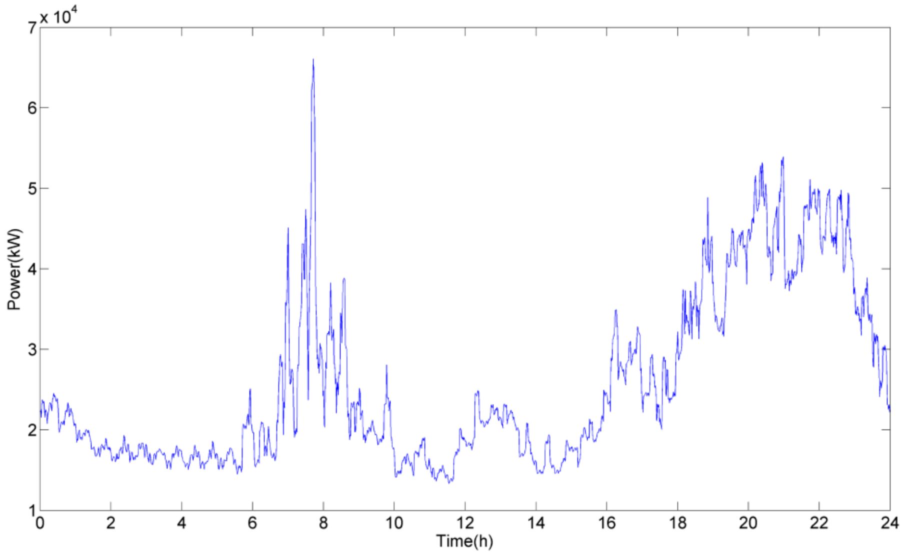

Figure 6. 1: Power demand of the total household demand

Test case	Financial criterion	Environmental criterion	Demand variation criterion
Case 1	0	0	1
Case 2	0	1	0
Case 3	1	0	0
Case 4	0.4	0.3	0.3

Table 6. 1: The weighting factors of four cases

Four cases are used to study the sensitivity of the effect of the three drivers on the impact on the aggregate power demand. In case 1, case 2 and case 3, only one criterion is taken into account, while the other two criteria are ignored in each case. In case 4, all three criteria contribute to the optimisation. Meanwhile, three penetrations of electric vehicles (30%, 60% and 100% of the total number of cars, assuming there is one car per household) are also applied to each case.

6.3.2 Uncontrolled charging plan

The 100 individual household daily power demand profiles are selected. According to various electric vehicles penetrations, 30, 60 and 100 electric vehicles, uncontrolled charging profiles are implemented.

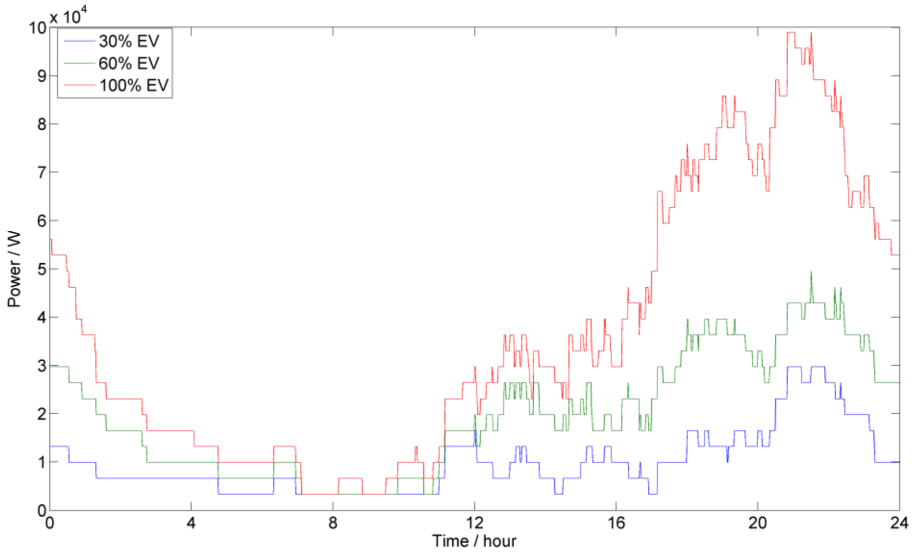

Figure 6. 2: Power demand for EV loads

There are two peaks for base household power demand in one day. One is in the morning between 6:00 and 10:00 when people get up and prepare for work. Another is in the evening between 20:00 and 24:00 when people have returned home. In figure 2, most of the electric vehicle charging starts from 12:00; peak period occurs between 18:00 and 22:00. The charging profiles after 24:00 are shifted to the morning of the same day in figure 2 to keep the continuity of charging.

6.3.3 Case 1: Demand variation criterion

For case 1 which only considers demand variability as an objective for three electric vehicles penetrations, the power demand shape becomes much flatter and is closed to the desired power demand. Moreover, the difference between unshifted power demand and shifted power demand is reduced. Comparing the uncontrolled charging power demand with shifted charging power demand, it can be easily seen that most electric vehicle charging in the night is shifted to the morning of the next day. The optimisation algorithm almost achieves the target that fills the power demand valley and reduces the power demand peak. There are some conditions presumed in the optimisation, namely that electric vehicle charging processes can be interrupted and the state of charge has to reach the desired level before the next journal. Electric vehicle charging is unlike other non-critical electric appliances; they share more limitations during the optimisation process such as allowable shifting period and unstoppable charging which are the reasons behind the difference between optimised power demand and desired power demand.

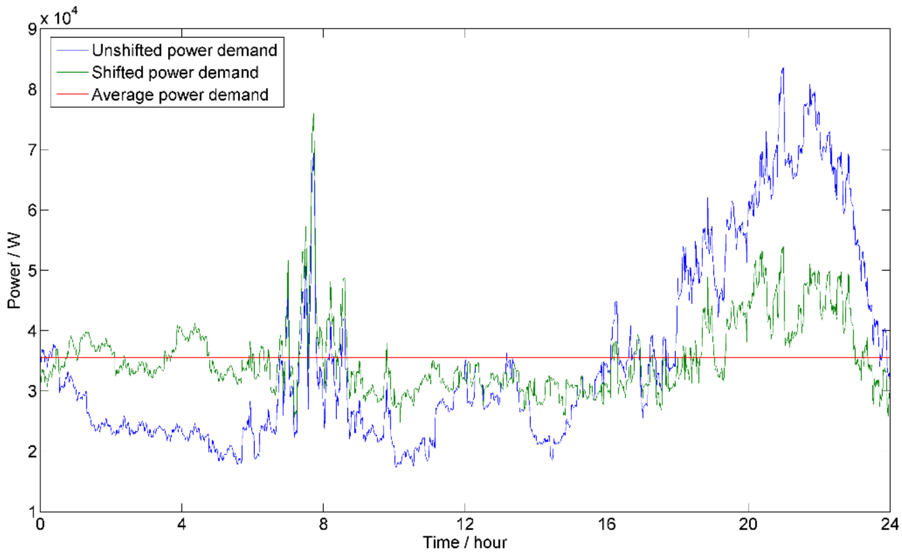

Figure 6. 3: Case 1: Power demand with 30% EV penetrations based on unrealistic optimisations

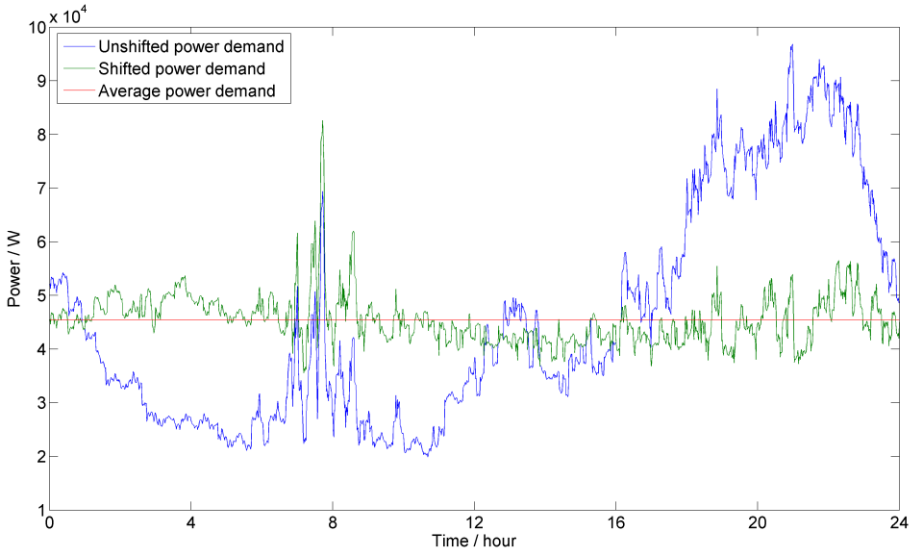

Figure 6. 4: Case 1: Power demand with 60% EV penetrations based on unrealistic optimisations

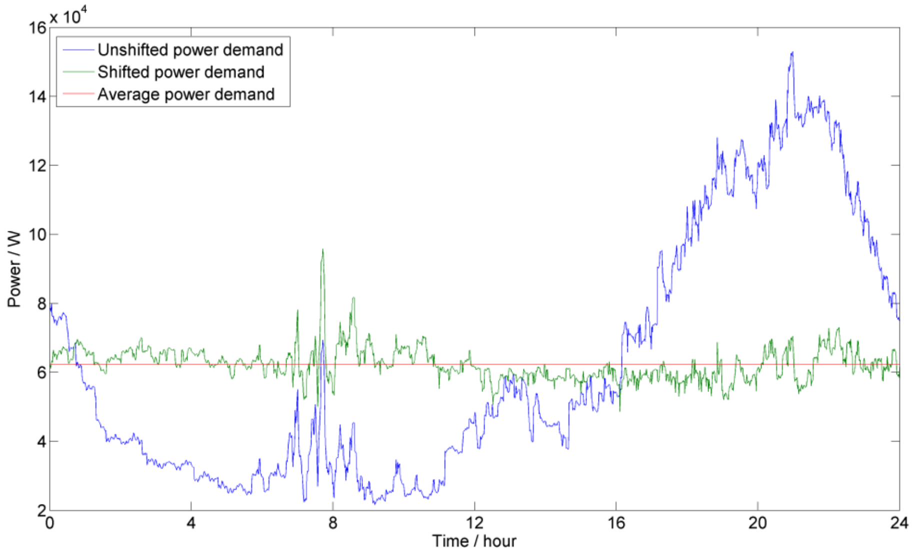

Figure 6. 5: Case 1: Power demand with 100% EV penetrations based on unrealistic optimisations

Case 1 :Demand variation criterion		
	Cost for uncontrolled charging	Cost for shifted charging
30% EV	126.6669	2.8846
60% EV	130.3834	3.5342
100% EV	186.7622	4.6833

Table 6. 2: Results for case 1

The table above presents the results from the aspect of numerical value. The cost of the demand variation criterion is the concept proposed in order to measure the difference between shifted power demand and unshifted power demand which are normalised results. At the same electric vehicle penetration level, the effect of shifted charging is visible which can be concluded from the decrease in charging cost. For the first column, the costs for uncontrolled charging increase as more electric vehicles are connected to the network. This is because most of the users charge their vehicles during peak hours for uncontrolled charging plan which leads to a surge in power demand in the evening. However, the costs for shifted charging are reduced considerably with the increase in electric vehicle penetration level. The reason for this is that higher penetration electric vehicles bring a more flexible power demand capacity. That capacity can be quickly shifted to fill in the power demand valley and meet the requirement for desired power demand.

However, there are still some spikes in the morning between 6:00 and 8:00; this is because most households use unshiftable electrical appliances during that period, which exceed the desired power demand. As with the increase of electric vehicle penetration, the desired power demand also raises a significant amount. As a result, the power demand spikes in the morning are reduced. Therefore more electric vehicles are involved in the optimisation algorithm, and better optimisation results can be achieved.

6.3.4 Case 2: Environmental criterion& Case 3: Financial criterion

When considering electricity price and GHG emissions in Case 2 and Case 3, the significant peak is created in figures 4, 5 and 6. As mentioned above, generation cost and GHG emissions cost are fixed data in our study, which are derived from the power supplier and determined by various factors. It will not be updated as a single distributed network power demand change; for each electric vehicle, they all choose the lowest cost point in their allowable period to start charging without regard to other vehicles' charging plan and the change of total power demand. Thus the large peaks are created in the following power demand graphs.

In Case 2 (environmental criterion=1), the green line is the power demand results of optimisations. Compared with unshifted power demand (blue line), two power demand peaks are created in the graph for three varying electric vehicle penetration level. The greenhouse gas price reaches its peak at around 21:00 and falls to its minimum value around 22:00, then fluctuates at the lower level. The power demand, therefore, has been shifted to 15:00-16:00 and 21:00-22:00 separately. The daytime charging demand focuses on the first peak area. Moreover, the evening charging demand moves to the second peak demand area.

In Case 3 (financial criterion=1), the red line is the power demand results of optimisations. Differing from power demand in Case 2, one colossal power demand peak is generated during the early morning. It can be easily observed that the electricity price varies throughout the course of a 24 hours day and is lower from 0:00 to 6:00 when most people sleep and thus the base load demand is obviously reduced.

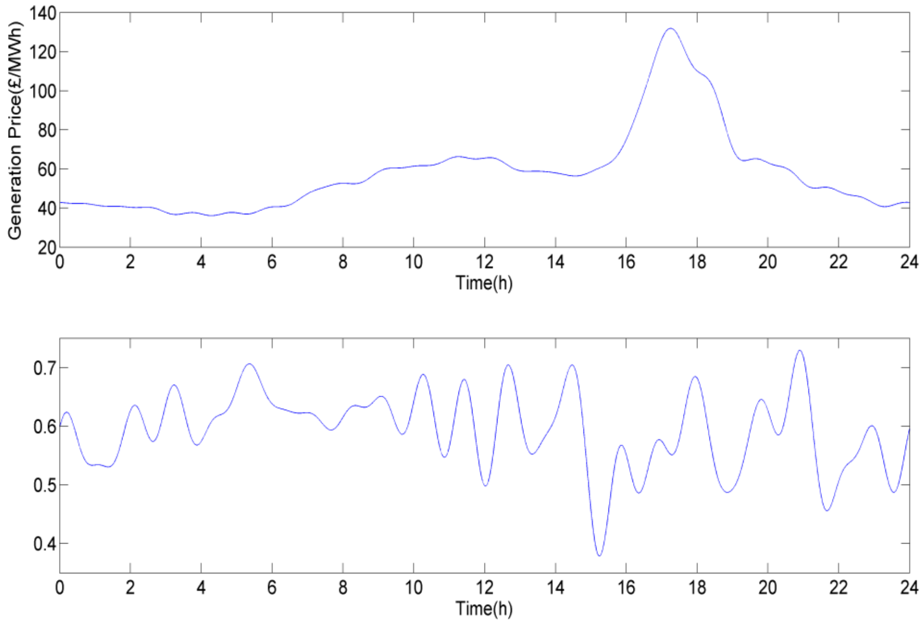

Figure 6. 6: Daily profiles of price and GHG emissions per MWh

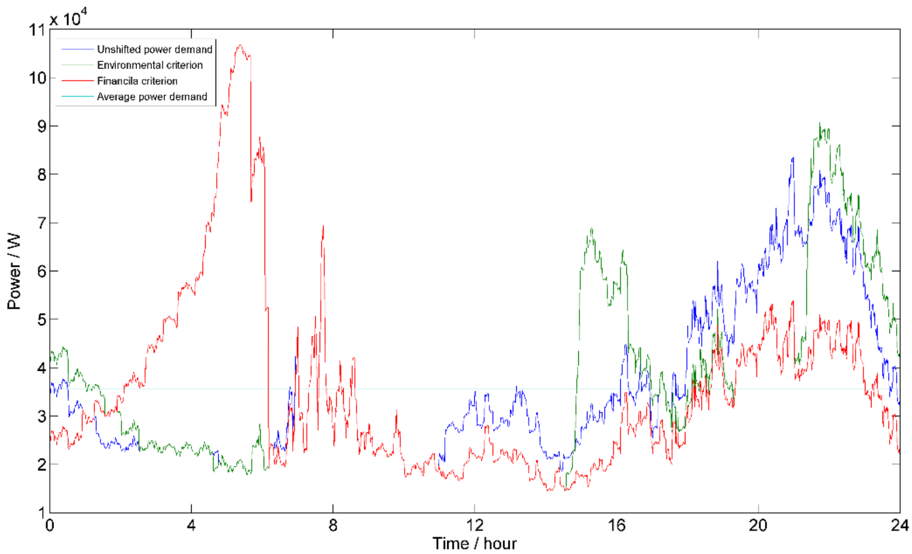

Figure 6. 7: Case 2 & 3: Power demand with 30% EV penetrations based on unrealistic optimisations

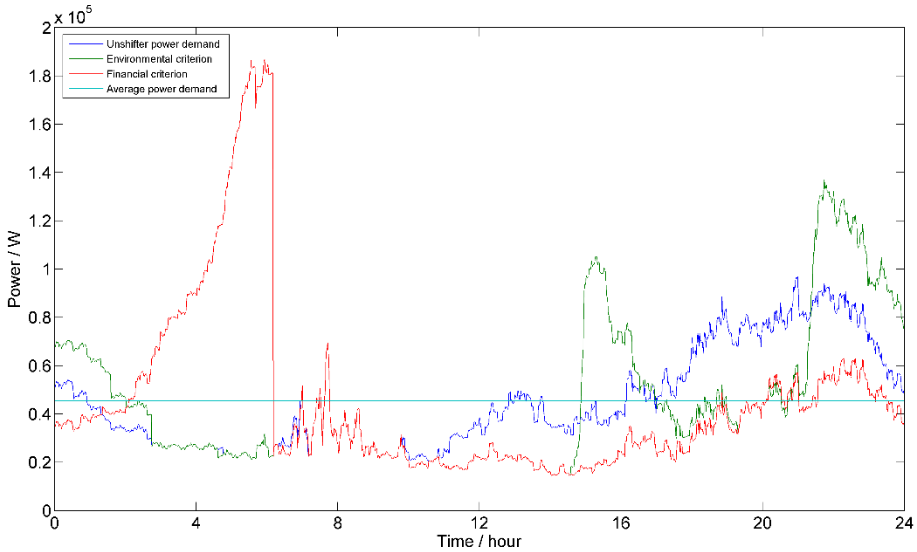

Figure 6. 8: Case 2 & 3: Power demand with 60% EV penetrations based on unrealistic optimisations

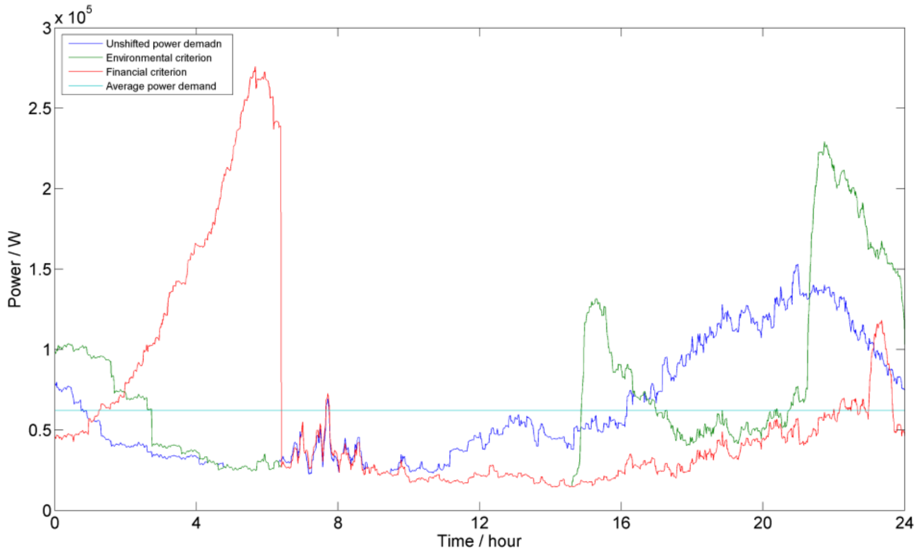

Figure 6. 9: Case 2 & 3: Power demand with 100% EV penetrations based on unrealistic optimisations

Case 2: Environmental criterion		
	Cost for uncontrolled charging	Cost for shifted charging
30% EV	304.3570	103.4131
60% EV	368.3850	182.5585
100% EV	437.0358	319.3889

Table 6. 3: Results for case 2

Case 3: Financial criterion		
	Cost for uncontrolled charging	Cost for shifted charging
30% EV	359.6725	122.4364
60% EV	391.3639	171.1022
100% EV	459.6727	253.0161

Table 6. 4: Results for case 3

There is a growing tendency for the cost in Case 2 and Case 3 to increase as more electric vehicles are connected to the network in the uncontrolled and shifted charging plan. However, as expected, the cost for shifted charging is lower than uncontrolled charging at the same electric vehicle penetration level. It proves that the proposed shifted charging plan effectively reduces the financial and greenhouse gas cost of the distributed network.

However, the huge power demand peaks are produced in Case 2 and Case 3, which causes the more severe power system problems mentioned in Case 1. It is not accepted by the power supplier and even leads to power system crashes. Therefore, single objective optimisation is only considered theoretically and used to validate the relationships between these three criteria and power system demands in the distributed network.

6.3.5 Case 4: Combined impact

In Case 4, three criteria, financial, environmental, and system, make various contributions to the optimisation. To give an example of the functionality of the MoDSM algorithm, based on the multi-objective functions defined previous, the weighing factors x, y, and z are set as 0.4, 0.3 and 0.3 separately as the ratio of the influence of three criteria.

Similar conclusions can be obtained from observing of the table below. The higher electric vehicle penetrations level results in a higher combined cost for the optimisation. Moreover, the cost of shifted charging is always lower than the cost of uncontrolled charging. Furthermore, from the view of the power demand shape, Case 4 presents more comprehensive and practical results which are tied to reality and more likely to be accepted by the power supplier. It effectively eliminates the huge peaks generated in Cases 2 and 3. In the meantime, the power demand shape is closer to the average power demand which means less power demand variability. However, there are still some gaps between Case 1 and 4 from 2:00 to 6:00, and the power demand shape in Case 4 is above the power demand shape in Case 1. It is because that economic factor makes contributions to the final results in Case 4. The electricity price is low during this period. Shifting more power demand into this period is helpful for reducing the total financial cost for power suppliers. A similar process occurs when greenhouse gas prices are low in the evening. Generally speaking, power demand shape in Case 4 is dominated by three criteria, and the ratio of influence can be adjusted easily according to different requirements.

Case 4: Combined impact		
	Cost for uncontrolled charging	Cost for shifted charging
30% EV	129.0333	88.9318
60% EV	186.7338	141.8740
100% EV	301.0085	235.1781

Table 6. 5: Results for case 4

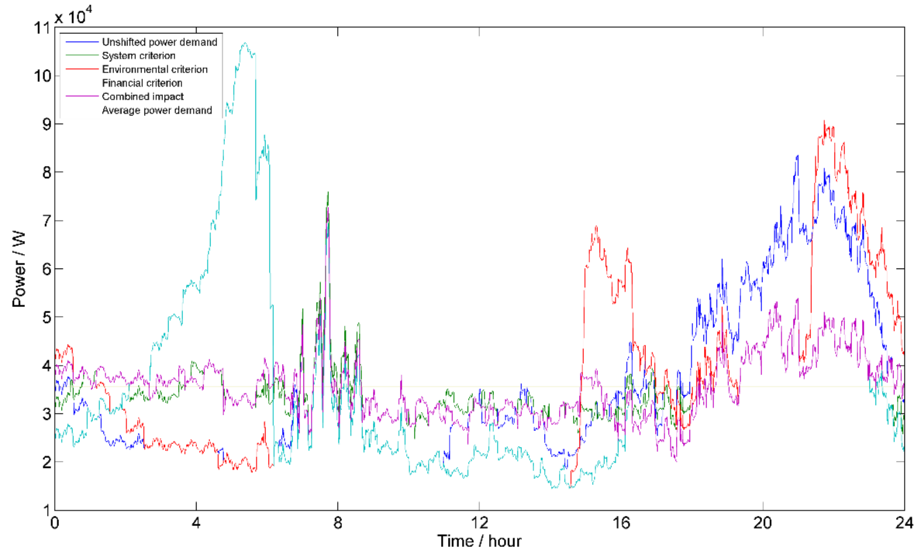

Figure 6. 10: Case 4: Power demand with 30% EV penetrations based on unrealistic optimisations

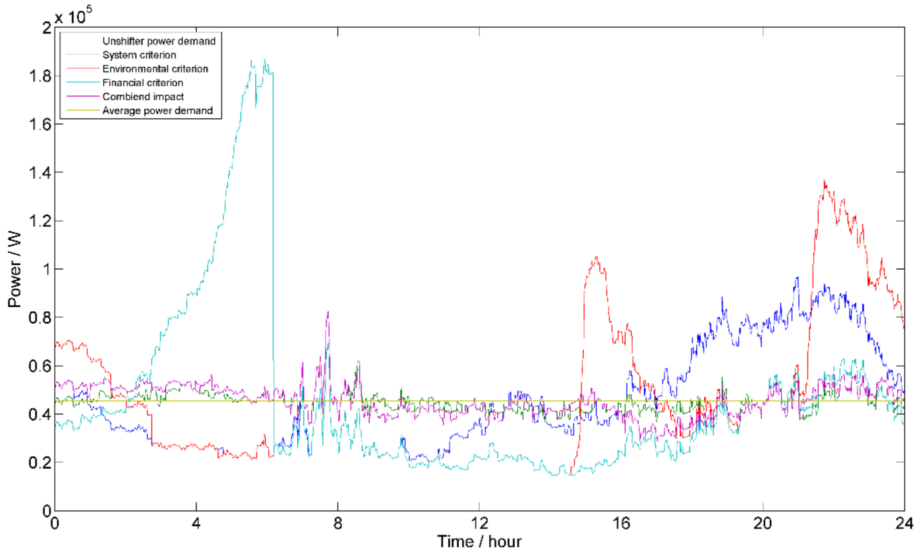

Figure 6. 11: Case 4: Power demand with 60% EV penetrations based on unrealistic optimisations

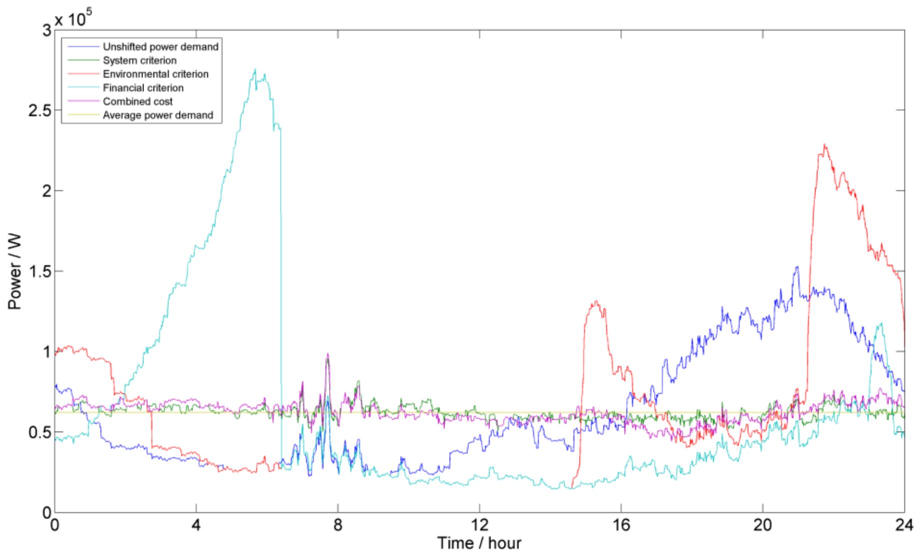

Figure 6. 12: Case 4: Power demand with 100% EV penetrations based on unrealistic optimisations

6.3.6 Influence of penalty factors

In reality, all owners of electric vehicles prefer finishing charging as soon as possible, and the delay of charging will give rise to people's driving-range anxiety and unwillingness to participate in demand side management. Given the reason mentioned above, penalty factors are defined to minimise the delay time in this paper. Comparing the combined impact displayed in the table for uncontrolled charging, shifted charging and charging with penalty factor, it is evident that shifted charging plan can provide the lowest combined impact.

As mentioned above, the penalty factors are defined by the following equations. X is the delayed cycles.

$$pen = \begin{cases} x \cdot \frac{1}{2880}, 1 \leq x \leq 1440 \\ 0.5,\ x \geq 1440 \end{cases} \tag{6.13}$$

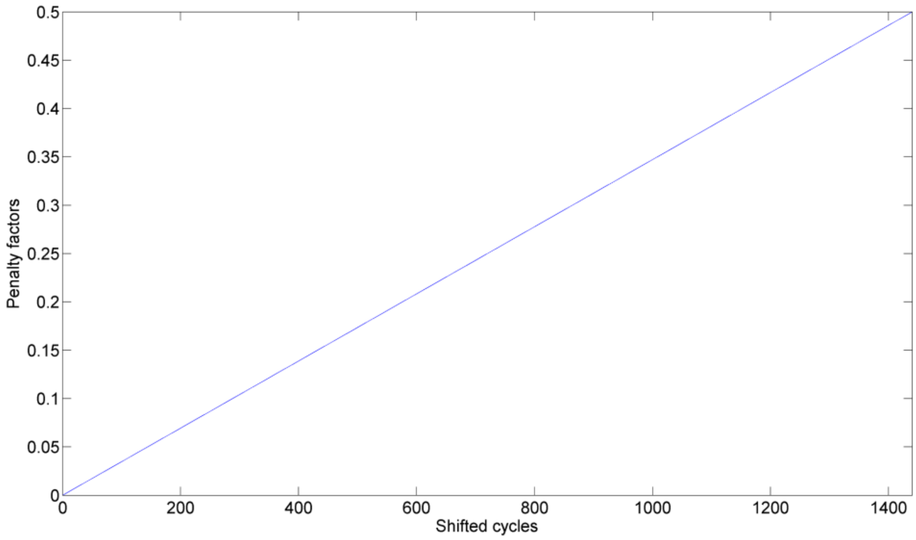

Figure 6. 13: Penalty factors

In this chapter, four cases are implemented with penalty factors. The final cost for each case is displayed below.

Moreover, the power demand curve of four cases with 60% electric vehicles penetration also is presented. The cost of shifted charging with penalty factors is higher than the shifted charging plan while it is still lower than the uncontrolled charging plan. In the shifted charging plan, each electric vehicle can find the lowest cost point from its allowable period without any limitation. In the shifted charging with penalty factors plan, the penalty factor will become more prominent as the shifted cycles increase, which also leads to a rise in final cost for each case. As a result, the peaks in Cases 2 and 3 are dramatically reduced. In Case 1, the power demand curve with penalty factors is much flatter than the unshifted power demand. For Case 4, the impact of three drivers is evident in the different time zones compared with unshifted power demand. From 2:00 to 6:00, some demand shifted to this period because electricity is cheap. The lower greenhouse gas price leads to the two peaks produced between 16:00 and 24:00.

Moreover, the overall trend of power demand curve flattens. When penalty factors are implemented, the previous minimum cost point could result in more considerable cost because its delayed cycles result in a more significant penalty factor. It can be clearly observed from the power demand curve that less power demand is shifted.

Furthermore, it is necessary to be very cautious when choosing the suitable penalty factors in the simulations. The selection of penalty factors depends on a number of variables. If the penalty factors grow too fast, it will restrict the effect of the three drivers on the final results. Most of the consumers are not willing to shift their load to a later time which could lead to a higher extra cost. An optimisation algorithm can only find the optimum local value rather than achieve the global minimum. On the contrary, if the penalty factors grow too slowly, it means the consumers pay less attention to the charging delay and electric vehicle charging loads are more flexible to be managed.

Case 1: Demand variation criterion			
	Cost for uncontrolled charging	Cost for shifted charging	Cost for shifted charging with a penalty factor
30% EV	126.6669	2.8846	6.4880
60% EV	150.3834	3.5342	10.8284
100% EV	186.7622	4.6833	16.7622

Table 6. 6: Results for case 1

Case 2: Environmental criterion			
	Cost for uncontrolled charging	Cost for shifted charging	Cost for shifted charging with a penalty factor
30% EV	304.3570	103.4131	262.2053
60% EV	368.3850	182.5585	293.3332
100% EV	437.0358	319.3889	357.2005

Table 6. 7: Results for case 2

Case 3: Financial criterion			
	Cost for uncontrolled charging	Cost for shifted charging	Cost for shifted charging with penalty factor
30% EV	359.6725	122.4364	256.8846
60% EV	391.3639	171.1022	298.4239
100% EV	459.6727	253.0161	362.4066

Table 6. 8: Results for case 3

Case 4: Combined impact			
	Cost for uncontrolled charging	Cost for shifted charging	Cost for shifted charging with penalty factor
30% EV	129.0333	88.9318	95.7557
60% EV	186.7338	141.8740	163.5607
100% EV	301.0085	235.1781	274.7444

Table 6. 9: Results for case 4

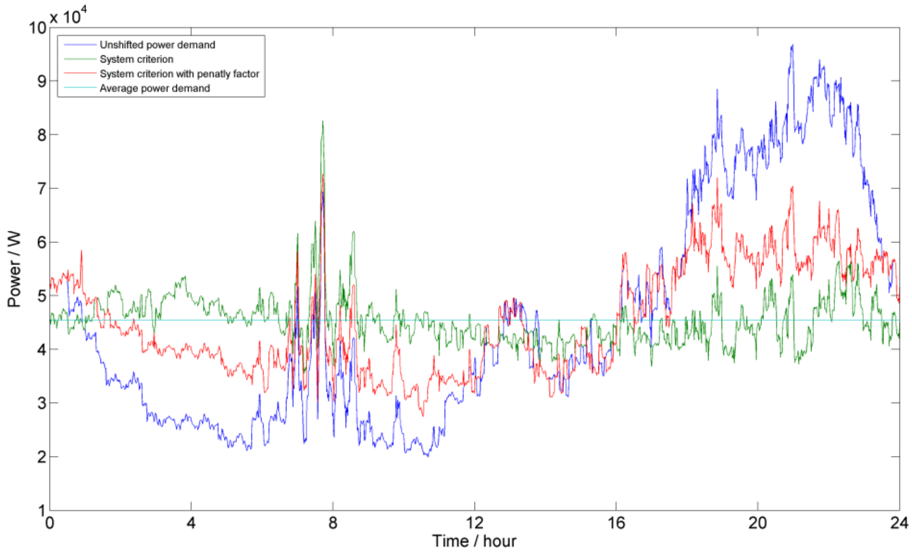

Figure 6. 14: Case 1: Power demand with 60% EV penetrations and penalty factor based on unrealistic optimisations

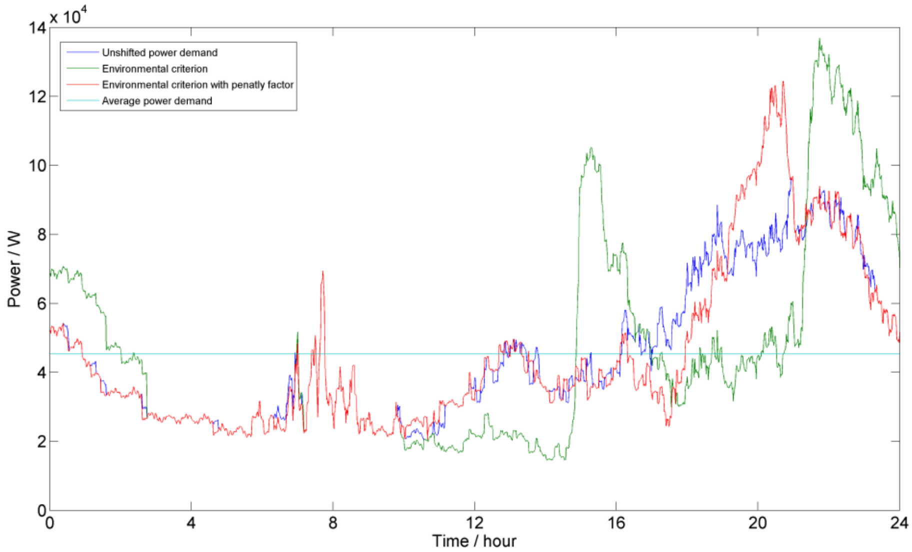

Figure 6. 15: Case 2: Power demand with 60% EV penetrations and penalty factor based on unrealistic optimisations

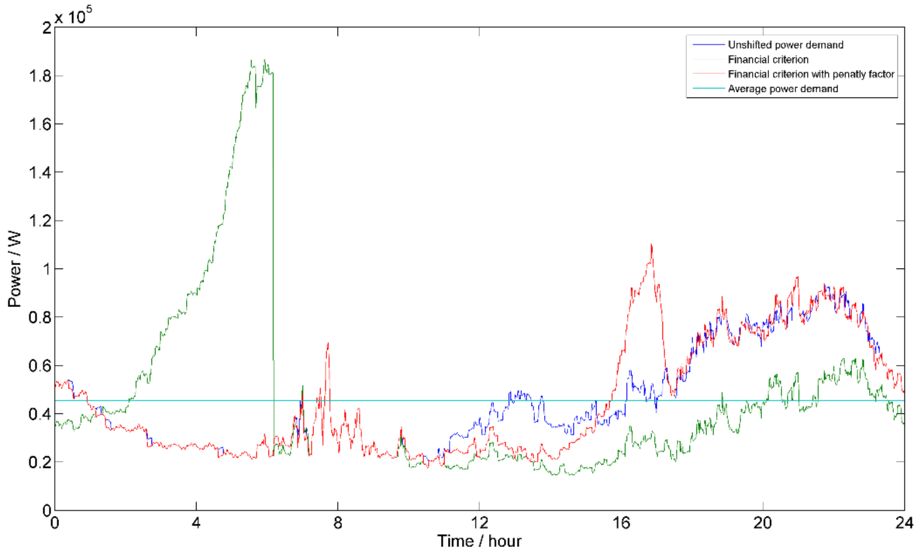

Figure 6. 16: Case 3: Power demand with 60% EV penetrations and penalty factor based on unrealistic optimisations

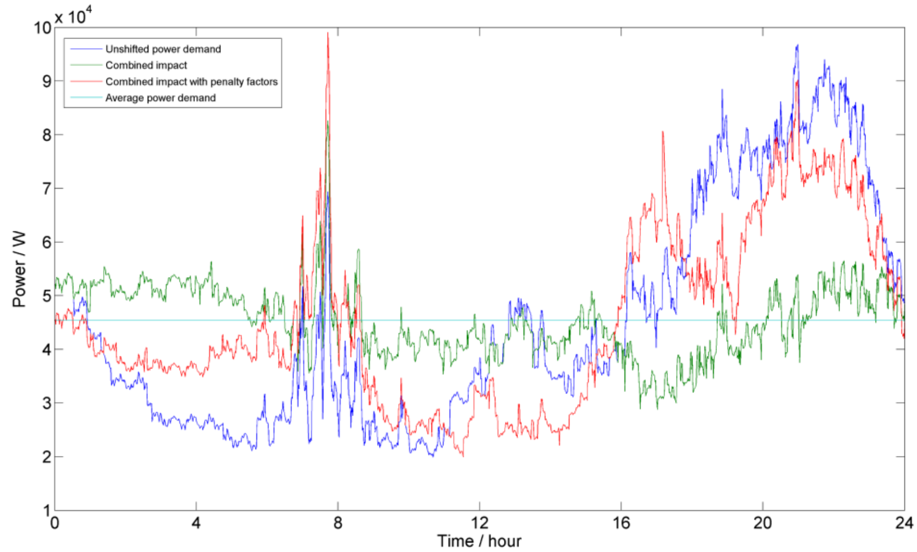

Figure 6. 17: Case 4: Power demand with 60% EV penetrations and penalty factor based on unrealistic optimisations

6.4 Case study 5： Minimise cost and greenhouse gases emissions in the future distribution network

The future of electricity distribution network will incorporate large capacities of photovoltaics and electric vehicles, while residential electricity demand will also increase. The soon-to-be ubiquitous smart metering will also enable more flexible ways to manage both demand and generation within the distribution system. The research presented in this case study employs both decentralised PV management as well as centralised demand scheduling, with the primary objectives being minimising generation cost and losses through demand side management while considering residential users' habits and voltage statuary limits of the distribution power network. The extent to which network load elements can be changed by demand side management is quantified by considering realistic parameters and constraints for a generation, distribution network and demand. The final results show that the proposed electric vehicle charging demand side management can effectively maximise the PV penetration level and minimise the combined cost within the acceptable voltage range.

Accurate PV power forecasting and detailed household power demand profiles are essential for simulations. Additionally, large volumes of work have been done from the economic and energy perspectives; it is also important to study the combined influence of PV and electric vehicle charging on the distribution network. The higher penetration level of PV will lead to voltage rise within the power system. Conversely, large-scale electric vehicle charging demand will cause voltage drops, in ways currently difficult for distribution network operators to predict.

The highly-urban network was chosen and the original 19-node system was extended by 10 more nodes to serve a total of 776 single-phase customers. The extended highly-urban network will share the same line characteristics of existing network and transformers. The following figure is the extended highly-urban generic LV distribution network. The network in the red dash line box is the original highly-urban generic LV distribution network, from node 1 to node 19. The remaining nodes (20 to 29) form the extended network.

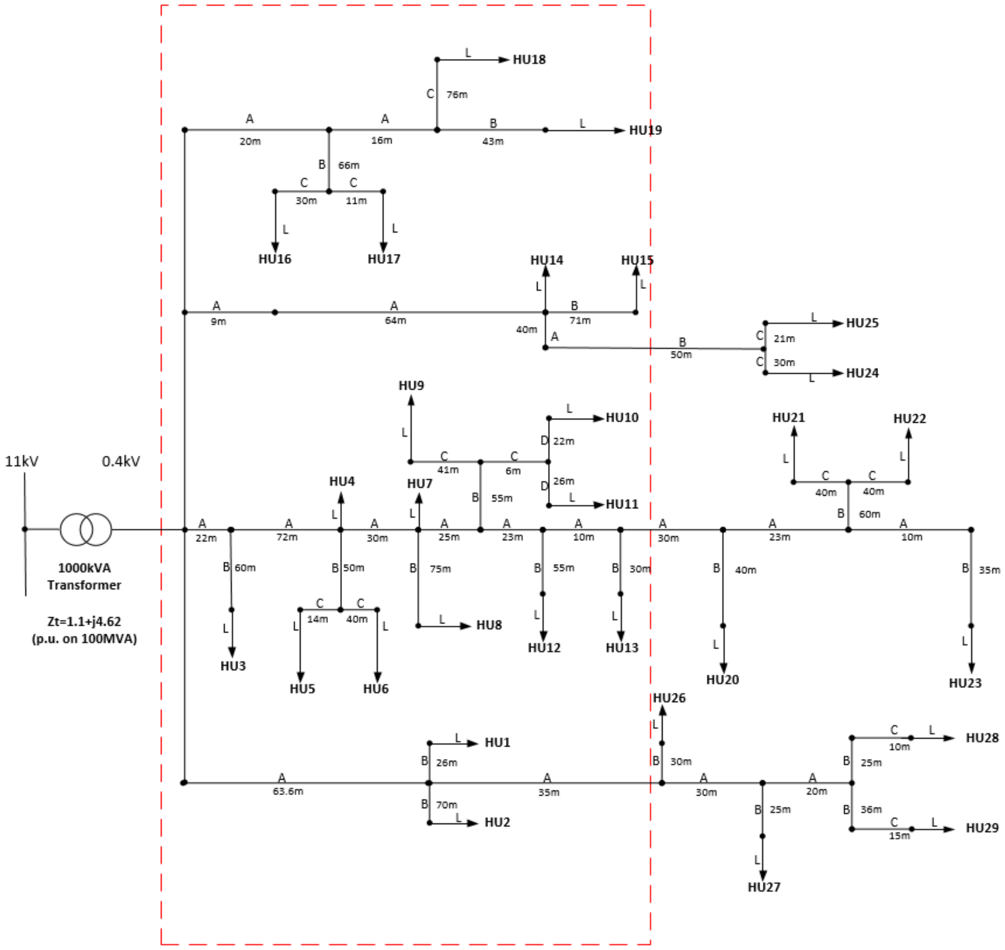

Figure 6. 18: Extended 29 bus network

6.4.1 Methodology

The first step is to use a generic algorithm to find the optimal deployment of photovoltaic arrays in the distribution power network. This algorithm will show the maximum PV array capacity that the power system can accommodate and the location of each PV array to prevent the node voltage from exceeding the limited upper range. Based on UK regulations, the acceptable household voltage levels are -6% to 10% of nominal, i.e. be between 216.2V to 253V.

The second step is to implement the multi-objective functions to minimise the combined cost through electric vehicle charging demand management. This optimisation is based on one-day ahead demand side management. The fundamental principle is to shift electric vehicle charging demand into the period that contains the maximum PV power output, or the lowest electricity and greenhouse gas emission costs. A penalty factor is also applied to reduce the delay of the charging time.

The third step is to distribute the optimised household demand into the power network and maintain the node voltage level through the proposed demand side management based on node voltage sensitivity.

This process is described in detail in the following section.

6.4.2 Optimization problem definition

The multi-objective function used can be described mathematically by the following equation:

$$\min \sum_{i=1}^{t} c_{comb} = \min \sum_{i=1}^{t} (x \cdot c_{wi} + y \cdot em_{wi}) \cdot (1 + pen_i) \qquad (6.14)$$

Where c_{comb} is the combined impact which is calculated by c_{wi}, and em_{wi}. These are the normalised values of electricity price and greenhouse gas (GHG) emissions. The weighting factors x and y are used to set the ratio of the influence of two criteria in the calculation; pen_i is the penalty factor which is used to optimise the delay time; t defines the 1440 time steps for a whole day (24 hours at 1-min resolution).

The profiles of two criteria: electricity price and greenhouse gas (GHG) emissions are weighted according to the following equations:

$$f = \frac{(h \cdot p) - \min(h \cdot p)}{\max(h \cdot p) - \min(h \cdot p)} \qquad (6.15)$$

Where f represents the normalised values for c_{wi} and em_{wi}, by replacing h with c and em respectively. Because the electricity and greenhouse gas emissions share different units, they have to be normalised between 0 and 1 in the equation.

Electricity price is in the unit of £/MWh and GHG emissions in tons of CO_2 eq./MWh.

The penalty factor used to limit the delay time is given by:

$$pen = \begin{cases} x \cdot \frac{1}{2880}, 1 \leq x \leq 1440 \\ 0.5,\ x \geq 1440 \end{cases} \tag{6.16}$$

When the delay time x is less than 240 minutes, it increases linearly. When the delay time is more than 240 minutes, the penalty factors will keep constant as 0.5. This is used to emulate electric vehicle owners' willingness of anticipating demand side management. The constraints are defined in the following equations (5.29)-(5.31)

$$E_{new} = E_{old} \tag{6.17}$$

$$t_{end\_new} - t_{start\_new} = t_{end\_old} - t_{start\_old} \tag{6.18}$$

$$t_{end_{new}} \leq t_{begin} \tag{6.19}$$

Where $E_{new,old}$ are the daily energy demand before and after EV demand shifting, t_{end_new} , t_{start_new} , t_{end_old} , t_{start_old} are the start and end charging times before and after charging demand shifting. t_{begin} is the time when people are going to start their next travel by EV. The algorithm ensures that before and after shifting, the charging time and energy consumption will not be changed and that electric vehicles will be fully charged or stop charging until the next trip starts.

6.4.3 Optimization algorithms

In this paper, two optimisation algorithms are employed; one is the multi-objective optimisation algorithms which was introduced in Chapter 6. The second is the voltage control regulation based on voltage sensitivity which was discussed in Chapter 4. Because the PV energy is deployed in the network, the energy consumed during the solar power output will lead to free electricity and greenhouse gas emissions costs. Once the household load demand is supplied from solar power, the combined numerical cost will be zero.

6.4.4 Results and Discussions

50% of electric vehicle penetration levels are implemented in this case, including 388 electric vehicles. According to the genetic algorithm for PV deployment, eight nodes have been are chosen to be populated with PV arrays, and the detailed capacity of each PV array is displayed below.

Bus Number	1	3	4	7	14	17	19	26
Max. Capacity / kW	68.6	69.3	60.4	53.4	86.2	67.8	74.9	61.1

Table 6. 10: PV location and capacity

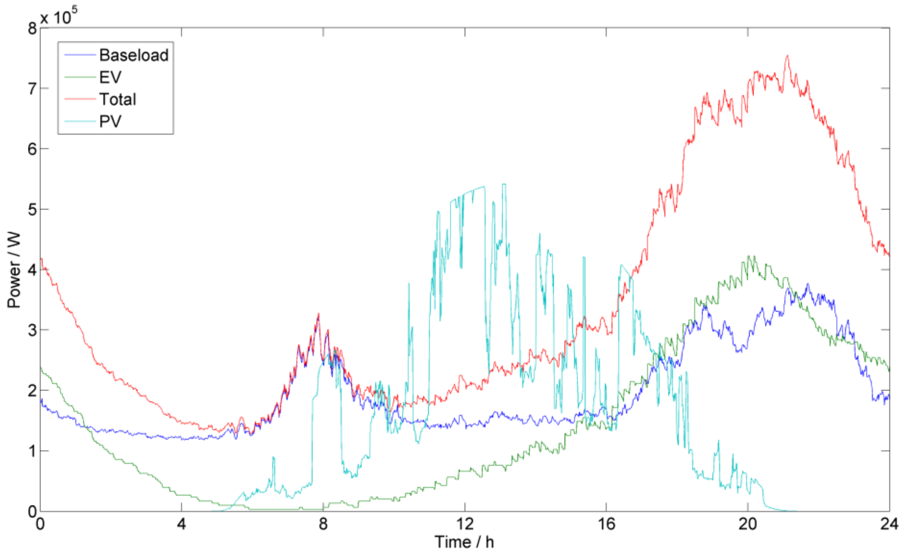

Figure 6. 19: Household power demand and PV profiles

As Figure 6.19 shows, the blue line is the baseload demand. The green line is the electric vehicle charging demand. The red line is the sum of the baseload and electric vehicle charging demand and the light green is total power demand of eight PV arrays' output. It is clear that there are two peak periods for household power demand, while PV output occurs during daytime and most of the electric vehicles start their charging in the evening.

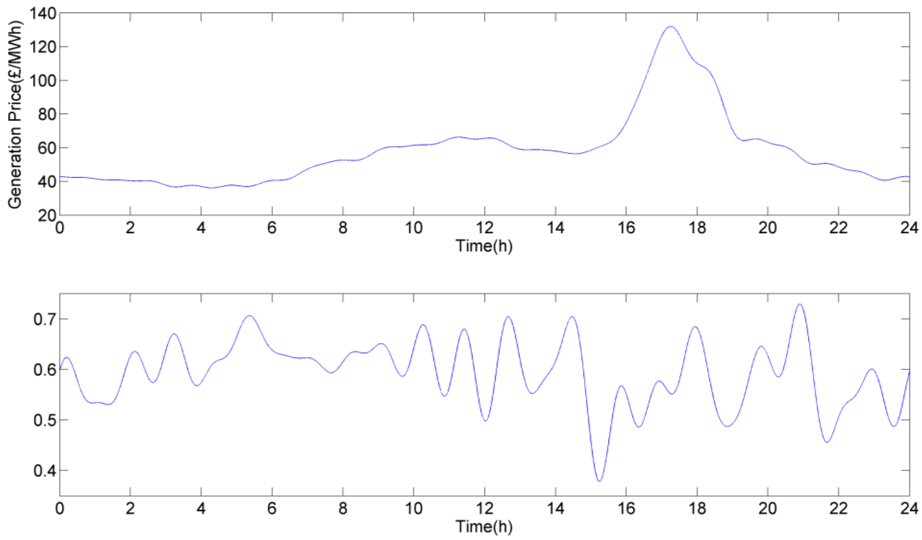

Figure 6. 20: Daily profiles of generation cost (top) and GHG emissions (bottom) per MWh

In figure 6.20, the average electricity and greenhouse gas emissions price between winter 2008-2009 are shown. The average values of electricity price will largely remain stable due to long-term contracts. It is obvious that electricity price increases in the daytime and becomes cheaper at night. The GHG emissions are the marginal emissions derived from power plants operational data on the British grid. It can be seen that marginal GHG emissions fluctuate significantly through the day.

This paper examines the three test cases as Table 6.11 shows below. In Case 1 and 2, only one criterion is taken into account (weighting factor = 1), while the other criterion is ignored (weighting factor = 0). In Case 3, both of the two criteria contribute equally to the optimisation (x=y=0.5).

Test case	Financial criterion (x)	Environmental criterion (y)
Case 1	1	0
Case 2	0	1
Case 3	0.5	0.5

Table 6. 11: Case information with corresponding weighting factors x and y

	Cost for uncontrolled charging	Cost for shifted charging	Cost for shifted charging with penalty factor
Case 1	372.06	133.12	240.52
Case 2	381.53	149.25	280.51
Case 3	379.63	149.22	274.69

Table 6. 12: the Combined cost of various cases

Table 6.12 above summarises the results of the three studied cases. At the same electric vehicle penetration level, the effect of shifted charging is apparent which can be concluded from the decrease in charging cost. The cost of uncontrolled charging is the largest. When penalty factors are implemented, the combined cost increases a great deal but is still lower than the cost of uncontrolled charging.

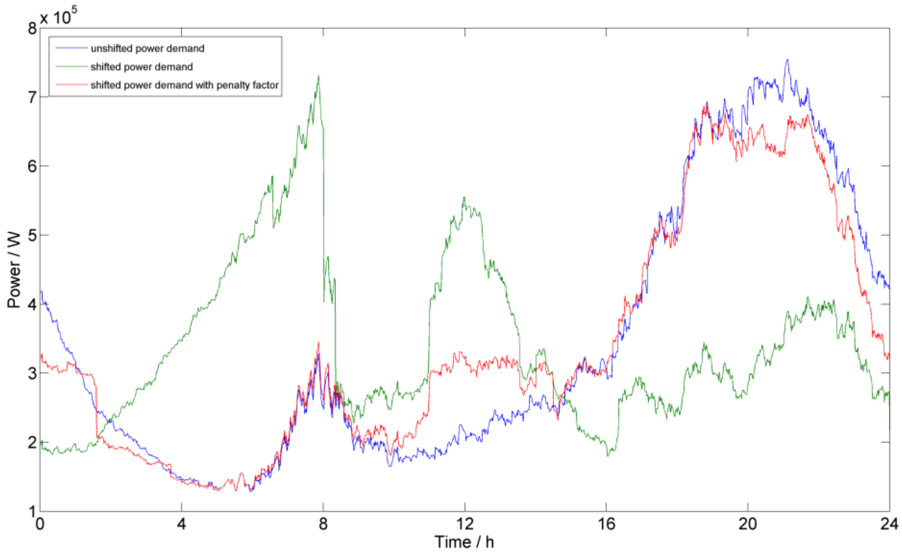

Figure 6. 21: Power demand for Case 1 based on unrealistic optimisations

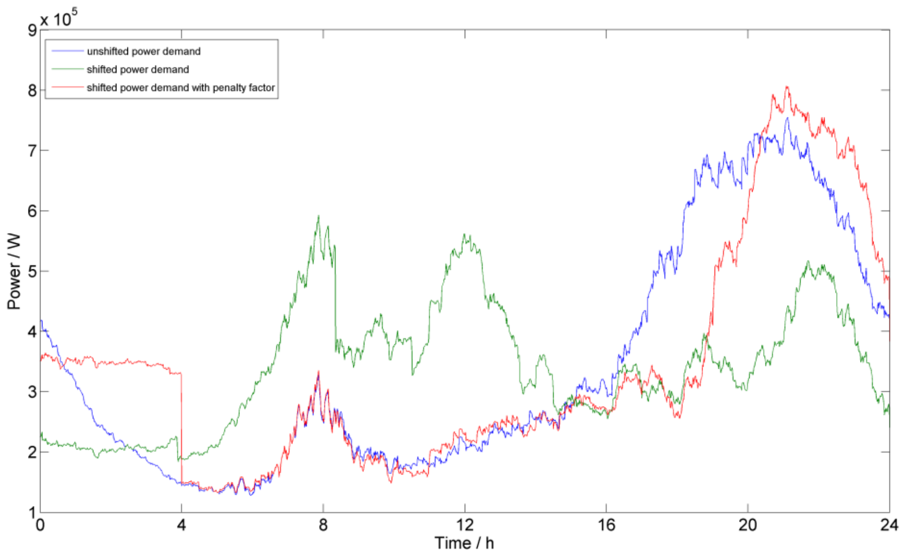

Figure 6. 22: Power demand for Case 2 based on unrealistic optimisations

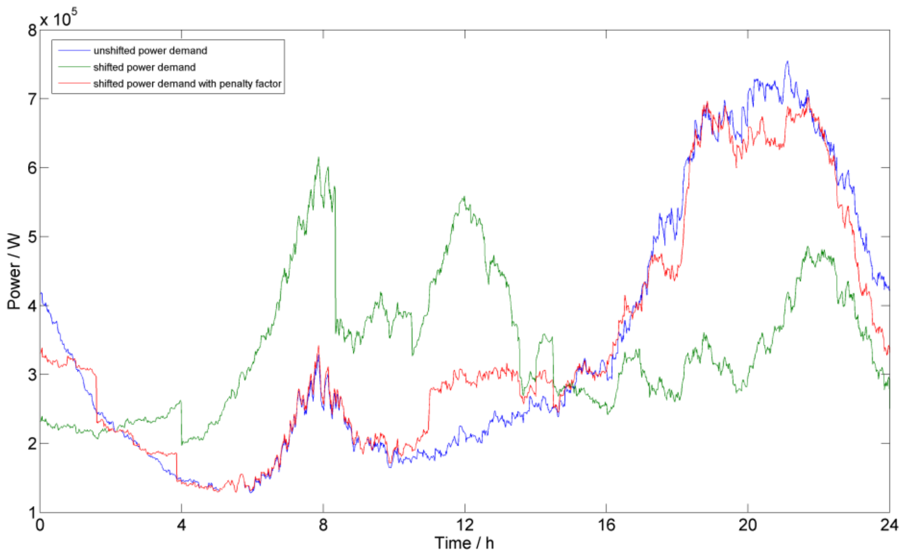

Figure 6. 23: Power demand for Case 3 based on unrealistic optimisations

For Case 1 and 2, as regards the consideration of electricity price and GHG emissions, a large peak is created as can be seen in Figures 6.21 and 6.22. As mentioned above, the generation cost and GHG emissions cost are fixed data in this study (derived from the energy supplier) and are not dynamically updated as a result of the demand management. Therefore, for each electric vehicle, the lowest cost point in their allowable period to start charging is chosen without regard to other vehicles' charging plan and the change of total power demand. Before considering the charging delay penalty factor, for both cases, this generates a power spike in the daytime from 8:00 to 16:00 (green traces). This is because solar power energy is supplied in the network and available electric vehicle charging demand is shifted during this period as cost and GHG emissions are minimal. When the penalty factor is taken into account, it can be seen that these peaks are reduced. This is because the penalty factor will become more prominent as the number of shifted cycles increases, which also leads to a rise in total cost for each case. As a result, the peaks in Case 1 and 2 are dramatically reduced in Figures 6.21 and 6.22 (red traces). For Case 3, the same weighting are given for financial and environmental criteria. However, the shape of the shifted power demand (green traces) is similar to the power demand in Case 2. Some differences occur around 14 pm, which is because the electricity price increases. For power demand with penalty factor (red traces), it becomes smoother, and some demands are shifted to the daytime to minimise the cost. It can conclude that the environmental criteria play a dominant role in Case 3, even though the financial and environmental criteria shares the same weight value. This may be due to the fact that GHG emissions fluctuate considerably throughout the day while the electricity price is much more stable.

When the optimised one-day ahead power demand profiles are distributed to each node, the real-time power flow is run by OpenDSS to check the node voltage level. Three cases include six different profile scenarios. The voltage issues only occur in Case 2 when electric vehicles are shifted with penalty factors. As shown in figure 8, the voltage of nodes 21 and 23 drops below the lower limit 0.94 p.u. Once the system detects voltage issues, demand side management based on voltage sensitivity will be implemented. It is clear that some electric vehicles are forced to stop charging for 5 minutes until the node voltage is back above the lower limit of 0.94 p.u. Furthermore, not all electric vehicles charging is delayed when such voltage issues occur. That is the advantage of the proposed optimisation algorithm. Based on voltage sensitivity and charging priorities, it is aimed to minimise the number of electric vehicles which are delayed to achieve the expected voltage level. On the other hand, it also indicates that there is still more potential room for voltage rising. Although the electric vehicle charging demand of bus 23 does not have too much fluctuation after the optimisations, the voltage magnitudes still rise above 0.94 after the optimisations. It is because the buses' voltage is correlative and interactional. For each cycle of optimisation, only the lowest voltage magnitude bus is regarded as the target, and one single electric vehicle is supposed to be shifted. However, all the buses' voltage in the network is affected to various degrees. Therefore, the voltage of bus 23 is improved as the optimisation of other buses is conducted.

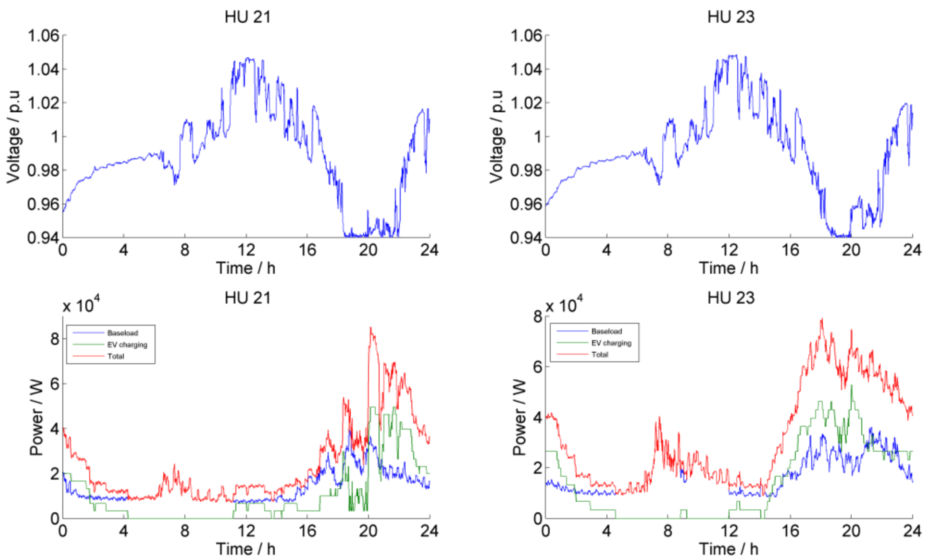

Figure 6. 24: DSM based on node voltage sensitivity.

6.5 Conclusion

This chapter presents the impact of uncontrolled electric vehicle charging on the power demand shape of a distributed power system network according to various electric vehicle penetration level. The results show that uncontrolled electric charging behaviour aggravates the previous power demand peak during the evening and even extend the peak hour to the end of the day. Such consequences incurred by electric vehicle will intensively destroy the balance between power demand generation and consumption and will also produce increased financial and environmental costs. Therefore, it is necessary to implement demand side management of electric vehicle charging.

The optimisation results show that the proposed algorithm can effectively reduce the combined impact and meet various system requirements, such as financial cost and greenhouse gas emissions, especially in the optimisation of the power demand curve. Four case studies explain the influence of three drivers on the distributed power system network in detail. Although the new expected power demand peaks are produced in Case 2 according to an environmental criterion, and in Case 3 according to a financial criterion, optimisation algorithms still achieve the presumed single objective to minimise the cost. It is the first time that the influence of electric vehicle charging on the environment from the aspect of greenhouse gas emissions has been addressed. Furthermore, the applications of penalty factors take into account customers' willingness to participate in demand side management. Electric vehicles charging demand are derived from the improved residential load model, which also plays a significant role in getting more accurate and realistic optimisation results.

However, it must be noted that the optimisation algorithms developed in this chapter only focus on the energy side and have not considered the effect on the power system, such as voltage variations. Therefore, a further experiment into power system simulation Case 5 is conducted. By combining centralised and decentralised control and management methods, it is possible to maximise the benefits from the new technologies added to the system while meeting the often conflicting operational, economic and environmental targets. The optimisation results show that the proposed algorithm can effectively reduce the combined impact and meet various system requirements, such as financial cost and greenhouse gas emissions. For the control voltage regulation, it is the first time to use voltage sensitivity to evaluate the influence of active power demand on the bus voltage in the distributed power system network. Moreover, it can significantly solve the voltage drop issues for 24 hours in the low and medium electric vehicle penetration level.

Chapter 7 Conclusions and further work

7.1 Thesis summary

This thesis first presents detailed household driving behaviour and electric vehicle charging load models which have strong correlations with other household load profiles. From this, the comprehensive household load model is generated. Based on this model, the impact of uncontrolled large-scale electric vehicle charging on the distributed networks is investigated from three aspects: power systems, financial cost and greenhouse gas emissions. The multi-objectives functions are employed to optimise the combined cost of these three areas. Following this, the further research is focused on the voltage regulation service that electric vehicle charging demand management can provide. At last, the comprehensive household demand optimisation algorithms are proposed and tested in the generic highly-urban low-voltage distributed networks including wetload and electric vehicle charging demand. The general conclusions and discussions of each chapter are presented below.

Chapter 2 reviews the available literature published on the three main subjects pertinent to this thesis electric vehicle charging model, demand side management and voltage control regulation. In the section on electric charging modes, various electric vehicle charging demand methods and models were analysed and compared. The first question was how to model people's travelling activities and the second is how to simulate the electric vehicle charging model. The accuracy of the results of these two parts serve as the input data of the whole model and are critical to the further assessment of the influence of uncontrolled charging and implementation the optimisation algorithm. As the foundation of this research, electric vehicle policy will play an essential role in the future development of vehicle-to-grid technology. Therefore, the global electric vehicle policy was summarised and analysed, with particular attention paid to the UK. The demand side management part included the introduction of smart grid and vehicle-to-grid technologies, which provided the solid technical support for the implementation of ancillary services of electric vehicle charging demand management. Knowledge of the low-voltage distribution networks is also introduced to show the reasons why demand side management is necessary and essential to the current distribution network operator. The review and analysis of these existing policies and literature prove that accurate driving behaviour and electric vehicle charging demand models are necessary for further optimisation and management. Advanced optimisation algorithms are required to take full advantage of electric vehicle charging demand to provide voltage regulation services. Furthermore, the implementation of electric vehicle smart charging can effectively reduce greenhouse gas emissions.

Chapter 3 demonstrates the methodology used to develop the household users' travelling activity profiles and the electric vehicle charging demand model. For household users' travel activity profiles, the detailed processing steps were presented and explained using a large body of raw data from the UK Time User Survey to the final mathematical model which could generate the complete highly-correlated household activity profiles. For the electric vehicle charging demand model, it generated the uncontrolled charging demand based on various specifications of the electric vehicle. Ambient temperatures, as an important, influential factor of battery performance, will also be taken into account. The results show that these two developed models successfully simulate activity profiles based on the interconnection among different daily household activities and also convert these activities profiles into electric energy consumptions, especially regarding the aspect of electric vehicles.

Further demand side management would require accurate predictions of the EV charging demand and household electric appliances, in which 'flexible' domestic loads such as washing machines and dishwashers are used by the optimisation algorithm for demand side management

Chapter 4 presents a demand side management optimisation algorithm based on voltage sensitivity to solve voltage variation issues in the low-voltage distribution network. At first, the effect of uncontrolled charging demand with various penetration levels was analysed. The methodology of calculating voltage sensitivity was also demonstrated step-by-step. Another optimisation algorithm based on bus voltage was then compared with the proposed algorithm. Four defined parameters were employed to measure the performance of optimisation algorithms. The results suggest that this algorithm makes great contributions to bus voltage control in the radial distributed power system network. It can also, significantly, solve the voltage drop issues experience over the 24 hour day in the low and medium electric vehicle penetration level. From the users' perspective, the proposed algorithms can decrease the number of affected electric vehicles in the network to achieve the same, or even better, optimisation results than other algorithms. It is capable of meeting the higher requirement of lower voltage limits. To a certain degree, it could reduce people's disinclination to participate in demand side management. For high electric vehicle penetration level, the proposed algorithms cannot maintain the bus voltage above the lower limit over 24 hours. However, it effectively extends the period before the occurrence of voltage issues, which provides the room for the implementation of other optimisation methods.

Chapter 5 shows demand side management of wetload demand in the household. The detailed household wetload demand profiles are demonstrated and analysed. The combined household demand side management is then implemented based on voltage sensitivity including electric vehicle charging and wetload demand. At last, comparisons are conducted between the combined household demand side management and electric vehicle charging demand management. This optimisation algorithm effectively reduces the variation of bus voltage level in the distribution network. As a supplement to electric vehicle charging demand side management, it has been proven that better performance can be obtained, especially within the medium electric vehicle penetration level.

Chapter 6 investigates the potential impact of a fleet of electric vehicles uncontrolled charging on the cost of electricity generation, greenhouse gas emissions (GHG) and power system demand. In order to decrease the negative impact of uncontrolled charging, multi-objective optimisation algorithms are proposed through low voltage residential demand-side management (DSM). These two developed models successfully simulate activities profiles based on the interconnection among different daily household activities and also convert these activities profiles into electric energy consumption, especially from the perspective of electric vehicles. Further demand side management would require accurate prediction of the EV charging demand and household electric appliances, in which 'flexible' domestic loads such as washing machines and dishwashers are used by the optimisation algorithm for demand side management. It is the first time that the influence of electric vehicle charging on the environment from the aspect of greenhouse gas emissions has been considered.

Furthermore, the applications of penalty factors take customers' willingness into account when considering demand side management. However, the optimisation algorithms proposed in this chapter are based on the energy aspect, which doesn't include power system issues such as voltage variation. The next chapter thus discussed and solved these problems from the power system aspect.

7.2 Thesis statement

The first part of the original Thesis Statement claimed that a bottom-up, user-inclusive electric vehicle charging model could provide accurate aggregated demand profiles. As summarised in the previous section, work presented in chapter 3 proved that a stochastic (MCMC-based) model of EV usage and charging can generate accurate demand profile time series, compared to measured data found in current literature.

For the second part of the Thesis statement, it was hypothesised that stochastic EV charging models can be used to develop charging management strategies that can improve voltage regulation, generation costs and environmental impacts within the future electricity system. It was shown that the multi-objective optimisation strategies presented in chapters 4-6 can yield individual and overall reduction of the negative impacts of EV charging from all of these aspects.

7.3 Implications of the research

This thesis presents a complete, step-by-step modelling and management framework for EV charging, to help investigate the influence of electric vehicle charging and the advantages of charging demand management, from raw data processing to the final optimisation algorithms. Each chapter presents a different part of the model and/or algorithm developed, although they are all linked together into a single model that can be easily modified and used for further research.

First is the residential load model. The residential load model is developed to generate detailed individual household load profiles including electric vehicle charging, which is to be implemented for the first time in the UK. The load profiles generated from this model will provide accurate input data for demand side management in the distribution network. In this project, the primary focus is placed upon the electric vehicle charging demand and wetload power demand. The data contained in the model about other household activities can also be used for related research. However, the implications of this model extend much further than that. More simulations and research into demand side management in the distributed network can be conducted.

Furthermore, distributed network companies can use this model to forecast the future power demand and make flexible electricity tariffs. Also, all the raw data is available to the public. This model presents a novel method to model the time series data, which are mutually influenced. It can be used for various other kinds of research aspects, such as an economic approach.

The second implication is the proposal of the concept of using electric vehicles to optimise the overall cost of electricity supply. It provides new insights into electric vehicle charging management from the power demand, electricity price and greenhouse gas emission perspectives. Due mainly to decreased greenhouse gas emissions, electric vehicles are regarded as an environmental-friendly transport method, as compared with others, but this is only true when the utilised primary sources of energy are low- or zero-carbon at the time of charging. The implementation of demand side management can thus take full advantage of electric vehicles to achieve further reductions in greenhouse gas emissions. Although three factors have been investigated in this optimisation, they play various roles in reshaping the power demand.

The third implication is voltage control regulation based on voltage sensitivity. Although the concepts of voltage sensitivity and voltage regulation have been discussed for a long time, this is the first project to use voltage sensitivity to evaluate the influence of active power demands on bus voltage in the distributed power system network. From a financial perspective, it will adequately maintain the voltage stability of distributed networks without installing additional, expensive equipment. Additionally, electric vehicle owners can also make money from the ancillary service and reduce their financial burden. On the other hand, the proposed algorithm is capable of achieving the expected target with a minimum impact upon users' driving behaviour. Furthermore, the implementation of a priority list and penalty factors take into consideration more realistic conditions in the optimisations, which will encourage more consumers to participate in the electric vehicle charging demand side management scheme.

7.4 Limitations of the research

Although the proposed residential load model can provide various accurate household load data, there are still a few electronic appliances which are not included in this model. Especially given the rapid development of portable electronic devices and high-speed upgrades of these electronic appliances, it is difficult to model the detailed power consumption characteristics and total power demand of the household unless accurate input data is available. Residential load demand is most complex and contains plenty of uncertainties and variables. It also varies with many external factors such as geography, economic status, and the composition of individual household, weather conditions and some unexpected factors. The mathematical model cannot take all of these variables into considerations. However, it can present the overall trend of the household load power demand and meet the requirements of research and industry.

Regarding the multi-objectives of demand side management (DSM), it is assumed that all the electric vehicle owners will make immediate responses with combined costs. However, in reality, it will be very difficult to predict the subjective decisions made by people. It can also take some time for people to make a decision. Therefore, there is always a gap between the real-time power demand and simulation results. As we can see from the results, even when the same weighting factors are given for three criteria power system, finance and environment, their impact on the final power demand shape is different. The power demand is the most dominant factor among them because it is most directly with the final power demand shape. While the environmental criterion makes the least impact on the power demand, it means that people are less likely to make a change based on the current greenhouse gas emission cost system.

As regard voltage control regulation, the primary limitation is the capacity of the voltage regulation provided by electric vehicle charging demand side management. As mentioned in the literature review, this is the disadvantage of decentralised control. In the meantime, compared with reactive power, the influence of active power in regulating voltage is limited based on the transmission characteristics of power systems. Furthermore, all the load is assumed and simulated in the constant power model which is the simplification of the real load model. In reality, most household electronic appliances are represented by the exponential and polynomial / ZIP load model. On the other hand, all the simulations are real-time based which means the necessary communication and data transmission infrastructure can support the demand side management without delay.

7.5 Further Works

The developed model was used to generate results illustrating the impact of the connection of large proportions of electric vehicles in a distribution grid and propose control strategies to minimise those impacts. Additionally, it provides an extensive and solid base for further research, which can be broken down to the following indicative areas.

Residential load model: This model can be enhanced in many aspects. Some new loads could be simulated and added into this model. More social and demographic factors could be taken into account and presented in the model. Moreover, with the popularisation of the smart meter, more accurate and real-time data could be collected to make contributions to the residential load model.

Electric vehicle charging model: In the current electric vehicle charging model, one electric vehicle type (Nissan Leaf) and a fixed charging rate (3.3kW) are used. Only household home charging is considered. Therefore, in the future, a comprehensive electric vehicle charging model will be employed which contains various kinds of electric vehicles and different charging rates. The charging environmental will also be diversified such as charging station, office and shop parking charging and so forth.

The introduction of renewable energy: More distributed renewable energy will be introduced into the distributed power network in the future, such as roof-top solar panels and wind generators. Electric vehicles regarded as the storage buffer of renewable energy can increase their capacity for renewable energy and reduce greenhouse gas emissions to achieve the zero emissions target. Given the limited difference in the electricity prices in a day and the cost of a battery, it is challenging to implement vehicle-to-grid (V2G) technology. The combination of electric vehicles and renewable energy can solve this issue.

Auxiliary services: In this project, voltage regulations are regarded as the top priority of the auxiliary services. Electric vehicle can provide other services for the power system such as frequency responses, triad management, short-term operating reserve (STOR), etc. The implementation of these services will simulate the potential market for electric vehicles and will help distributed network operators to save money for their customers by avoiding massive infrastructure investment. Customers even can make money from these service provided by their electric vehicles.

Comprehensive household demand side management: Unlike traditional power systems, the distributed network in the future will include energy storage, local renewable energy generators, electric vehicles and plenty of the latest home electronic appliances. The development of Smart Grid and communication technologies can make demand side management more effective and efficient and also extend the current services. A comprehensive household demand side management and algorithms should, therefore, be proposed to include all these new capacities.

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Published Work

The publication that was produced by the presented work are list below:

1. Rentao Wu, G. Tsagarakis, A. J. Collin, and A.E. Kiprakis, "EV charging scheduling for cost and greenhouse gases emissions minimization", published in: 2017 Twelfth International Conference on Ecological Vehicles and Renewable Energies (EVER)

Rentao Wu, G. Tsagarakis, A. J. Collin, and A.E. Kiprakis, “EV charging scheduling for cost and greenhouse gases emissions minimization”, published in: 2017 Twelfth International Conference on Ecological Vehicles and Renewable Energies (EVER)

EV charging scheduling for cost and greenhouse gases emissions minimization

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Abstract—**This paper investigates the potential impact of a fleet of electric vehicles charging on the cost of electricity generation, greenhouse gas emissions (GHG) and power system demand through low voltage residential demand-side management (DSM). The optimisation algorithm is used to shift electric vehicles charging loads to minimize the combined impact of three key parameters: financial, environmental, and demand variability. The results show that it is effective to reshape the power demand and reduce electricity cost and GHG emissions without affecting people’s driving patterns.**

*Keywords—**demand side management, optimisation algorithm, electric vehicles, residential load, low voltage.***

I. INTRODUCTION

With the increasing penetration of varying renewable energy and the introduction of new types of electrical loads, current power systems are facing more challenges in the balancing of generation and demand. Electric vehicles (EVs), as a booming entity, become much more important in the system.

In many cases, electric vehicles are regarded as energy storage to reduce the intermittency of electricity supply from renewable energy such as solar, wind [1], [2], [3]. On the other hand, there are some researches on the demand side management strategies and related optimisation algorithms in the low-voltage network [4], [5], [6]. However, the operation and performance of low-voltage networks depend on a mix of various kinds of electric loads, the users' behaviour and external factors (such as weather condition and social events). Most existing studies do not take the relationship between EVs and other household appliances into account and only focus on electric vehicles. Meanwhile, few studies describe how the impact of electric vehicles charging on the GHG emissions. Although electric vehicles are regarded as green and environment-friendly compared to standard petroleum-based cars, nowadays most of the electricity is still generated by coal and gas fired power plant. It is, therefore, inevitable that electric vehicles are still responsible for GHG emissions.

The relationship between traffic and weather condition has been investigated for many years. Usually, unseasonable or extreme weather such as hail and storm will lead to the reduction of traffic activity and lower traffic speed and flow [7], [8]. Currently, some researches obtain the data from long-term experiments which use mobile devices installed on the vehicles to record people′s driving behaviours [9], [10]. Most of the studies use random probability from large-scale statistical survey to model people′s driving behaviours. These modelling approaches cannot provide large-scale and accurate EV charging demand profiles.

Demand side management strategies are focusing on shifting flexible loads outside the peak demand periods, typically in the morning and evening hours for the UK. Current research focuses on responsive measures that shift loads to a later time (typically during the night). However, in a system with large numbers of EVs, this may cause new problems, as EVs, usually are charged overnight. Therefore this may not be the optimal solution as it may be cheaper and environmentally friendlier to shift loads earlier, e.g. during the mid-day valley when local penetration from domestic PV is also high. However, this would require accurate prediction of the EV charging demand. Therefore, a stochastic model of people's driving behaviours using the Markov Chain Monte Carlo (MCMC) method has been developed to calculate the EV charging load for household customers and has been added to previous work [11], in which 'flexible' domestic loads such as washing machines and dishwashers are used by the optimisation algorithm for demand side management. Each EV profile has strong correlation with individual household daily activities.

II. METHODOLOGY

This study focuses on the three areas of power system operation, the total daily cost of electricity generation, the greenhouse gas emissions that derive from consumption of energy and the fluctuation of power demand caused by various domestic lifestyle habits. The combined impact is introduced to measure contributions to this three cost to the whole power system. In order to minimize the combined impact on the entire power system, EV charging is shifted to reshape the power demand profiles. However, electric vehicle charging cannot be shifted without any limitation. In reality, the owners of EVs will prefer finishing charging as soon as possible so as to have the car available for their next travel. A penalty factor, is therefore used in the optimisation to constrain the delay time.

1. Optimization problem definition

The objective function can be described mathematically by the following equation:

$$min \sum_{i=1}^{t} c_{comb} = min \sum_{i=1}^{t} (x \cdot c_{wi} + y \cdot em_{wi} + z \cdot sy_{wi}) \cdot (1 + pen_i) \qquad (1)$$

Where c_{comb} is the combined impact which is calculated by c_{wi}, em_{wi} and sy_{wi}. These are the normalised values of electricity price, greenhouse gas (GHG) emissions, and system cost respectively, where system cost sy_{wi} is defined as the normalised difference between the instantaneous active power and the daily mean power. The weighting factors x, y and z are used to set the ratio of the influence of three criteria in the calculation; pen_i is the penalty factor which is used to reduce the delay time; t defines the 1440 time steps (24 hours at 1-min resolution).

The profiles of three criteria: electricity price, greenhouse gas (GHG) emissions and system active power demand are weighted according to the following equations:

$$f = \frac{(h \cdot p) - \min(h \cdot p)}{\max(h \cdot p) - \min(h \cdot p)} \qquad (2a)$$

$$sy_{wi} = \frac{\Delta P_i - \min(\Delta P)}{\max(\Delta P) - \min(\Delta P)} \qquad (2b)$$

Where f represents the normalised values for c_{wi} and em_{wi}, by replacing h with c and em respectively. Electricity price is in £/MWh, GHG emissions in tons of CO_2 eq./MWh and sy in MW. P is the active power demand and ΔP_i is the absolute difference between the instantaneous active power and the daily mean power at each time step i.

The penalty factor used to limit the delay time is given by:

$$pen = \begin{cases} x \cdot \frac{1}{240}, 1 \le x \le 240 \\ 1,\ x \ge 240 \end{cases} \quad (3)$$

When the delay time x is less than 240 minutes, it increases linearly. When the delay time is more than 240 minutes, the penalty factors will be 1. The constraints are defined in following equations (4)-(6)

$$E_{new} = E_{old} \quad (4)$$

$$t_{end\_new} - t_{start\_new} = t_{end\_old} - t_{start\_old} \quad (5)$$

$$t_{end_{new}} \le t_{begin} \quad (6)$$

Where $E_{new,old}$ are the daily energy demand before and after EV load shifting, t_{end_new}, t_{start_new}, t_{end_old}, t_{start_old} are the start and end charging times before and after shifting. t_{begin} is the time when people are going to use EV. The algorithm ensures that before and after shifting, the charging time and energy consumption will be same, and that electric vehicles will be full charged or stop charging before the next trip.

2. Optimization algorithm

Step 1: The aggregator gets the base load demand and uncontrolled EV charging demand with 1-min resolution from 100 households. In the uncontrolled EV charging plan, it assumed that all electric vehicles begin their charging at home when they finish their last trip.

Step 2: Collect input data of each electric vehicle arriving time $t_{arriving}$, the state of charge (SOC), t_{begin} the time when people are going to use EV. Based on the above information, the priority list will be created to decide optimization order for each vehicle.

$$Priority = x \cdot order_{t_{arriving}} + y \cdot order_{soc} + z \cdot order_{t\_begin} \quad (7)$$

Where x, y, z are the weighting factors for three parameters, respectively. $Order_{t\_arriving}$ is the value of each vehicle in the ascending sequence of arriving time. $Order_{SOC}$ is the value of each vehicle in the ascending sequence of the state of charging. $Order_{t\_begin}$ is the value of each vehicle in the ascending sequence of begin next trip. The smaller value the car get from that equation, the higher priority given for that car.

Step 3: Assume charging process cannot be interrupted and all electric vehicles will be fully charged or stop charging when people are going to use the vehicle.

$$t_{shift} = t_{begin} - (t_{arriving} + \frac{1-SOC}{cr} BC) \quad (8)$$

Where t_{shift} is available shifting cycles for each vehicle. CR is charging rate 3.3kW. BC is battery capacity 24kWh. The initial SOC is determined by ambient temperature and people's driving behavior.

Step 4: for k=1: t_{shift}, shifting start charging time t_{start} to ($t_{arriving}$+k), then generate new charging profiles of EV_i and calculate combined impact of the whole system using equation (1) and (2) at each available shifting cycle of EV_i. Electricity price is derived from market information published online by the balancing mechanism reporting agent. GHG emissions’ data are the short term marginal emissions derived from operational and market data for generation plants on the British grid. System cost is defined as follows:

$$\Delta P_i = P_{tot\_i} - P_{ave} \quad (9)$$

$$P_{tot\_i} = P_{base\_i} + P_{ev\_i} \quad (10)$$

$$P_{ave} = \frac{\sum_{i=1}^{t} P_{tot\_i}}{\sum_{i=1}^{t} i} \quad (11)$$

Where P_{tot} is total real power demand including base load and EV of the system. P_{base} is total base load demand of the system. P_{ave} is the total daily power divided by the total time step 1440. ΔP_i is the difference between average power demand and real power demand.

Step 5: find the shifting cycle of EV_i when the whole system reaches the minimum combined impact. Then use this shifting cycle to reschedule the electric vehicle charging and generate the new charging profiles.

Step 6: Update charging profiles of EV_i and power demand of the whole system. Given the update of electric vehicle charging profiles, ΔP will also be recalculated. Increase value of i by 1 and start from step 3. The closed-loop optimization is selected to avoid creating another new peak demand. Otherwise, each electric vehicle will choose minimum combined impact timing as their starting charging point without the consideration of other electric vehicles. As I increases, ΔP is approaching zero which means that optimized power demand of the whole system gets close to the average power demand. Go to Step 7 when i is equal to electric vehicle number.

Step 7: Optimization end. Generate the new power demand of the whole system.

III. CASE STUDY

The methodology above is applied on a test system including 100 households. Four cases are considered to study the sensitivity of the effect of the three drivers on the impact on the aggregate power demand.

Test case	Financial criterion	Environmental criterion	System criterion
Case 1	0	0	1
Case 2	0	1	0
Case 3	1	0	0
Case 4	0.4	0.3	0.3

In case 1, case 2 and case 3, only one criterion is taken into account, while other two criterions are ignored in each case. In case 4, all three criteria contribute to the optimisation. Meanwhile, three penetrations of electric vehicles (20%, 60% and 100% of the total number of cars, assuming there is one car per household) are also applied to each case.

1. Residential load and electric vehicle profiles

The 100 individual household daily power demand profiles are selected. According to various electric vehicles penetrations, 20, 60 and 100 electric vehicles uncontrolled charging profiles are implemented. In figure 1,

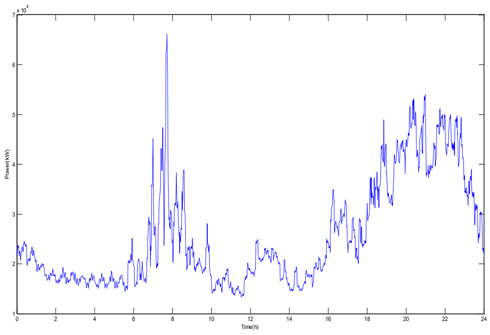

Fig 1. Power demand of the total household demand

There are two peaks for base household power demand in one day. One is in the morning between 6:00 and 10:00 when people get up and prepare for work. Another is in the evening between 20:00 and 24:00 when people are back home. In figure 2, most of the electric vehicle charging starts from 12:00 and peak period occurs between 18:00 and 22:00. The charging profiles after 24:00 are shifted to the morning of the same day in figure 2 to keep the continuity of charging.

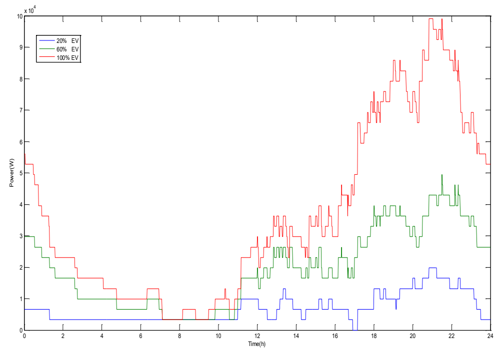

Fig 2. Power demand of EV loads

2. Generation price and GHG emissions

In figure 3, the first picture is the daily profiles of generation price. The average electricity price of 2008-2009 winter is used in this paper. Although the shifting of electric vehicle charging will create changes of generation, the average values of price will largely remain stable due to long term contracts. It is obvious that electricity price is increasing in the daytime and become cheaper during the night. The GHG emissions are the marginal emissions derived from power plants operational data on the British grid [13]. The data of 2008-2009 winter is chosen in this paper. In figure 3, it can be seen that marginal GHG emissions fluctuate through the day.

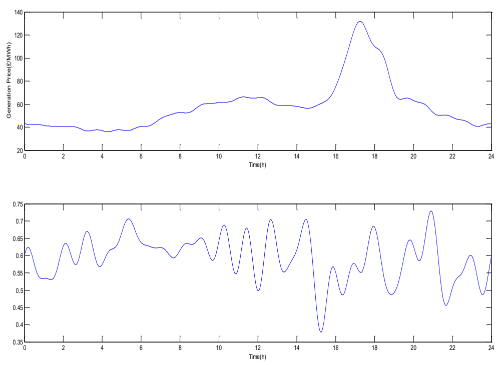

Fig 3. Daily profiles of price and GHG emissions per MWh

Emissions become lower at the time of high demand. This is because coal-fired power plants are the marginal generators at this times of low demand while gas-fired power plants work at the periods of high demand and they have lower GHG emissions.

IV. Results

The results of optimisation algorithm on the four cases and three electric vehicle penetrations are presented in fig 4, 5 and 6 respectively, and the results of combined impact for each case are also presented in the table below. For case 1 which only considers demand variability as an objective for three electric vehicles penetrations, the power demand shape becomes much flatter and is closed to desired power demand. Comparing the uncontrolled charging power demand with shifted charging power demand, it can be easily seen that most of electric vehicle charging in the night are shifted to the morning in the next day. The optimisation algorithm almost achieves the target that fills the power demand valley and reduces the power demand peak. But electric vehicle charging is different from other non-critical electric appliances; they share more limitations during the optimisation process such as allowable shifting period and unstoppable charging which are the reasons behind the difference between optimized power demand and desired power demand.

HH number=100 EV number=20			
	Cost for uncontrolled charging	Cost for shifted charging	Cost for shifted charging with penalty factor
Case1	127.4145	46.4971	77.2385
Case2	315.5678	205.3412	287.4353
Case3	381.0614	201.6715	326.9328
Case4	285.3192	267.2134	277.4657

HH number=100 EV number=60			
	Cost for uncontrolled charging	Cost for shifted charging	Cost for shifted charging with penalty factor
Case1	220.3044	10.8190	57.5922
Case2	368.3850	162.0970	306.4991
Case3	391.3639	140.2716	275.4362
Case4	333.1524	223.6511	318.9856

HH number=100 EV number=100			
	Cost for uncontrolled charging	Cost for shifted charging	Cost for shifted charging with penalty factor
Case1	186.7622	4.8616	147.9929
Case2	337.0358	153.2148	325.0251
Case3	359.6727	177.5751	308.2374
Case4	301.0085	200.2029	256.4286

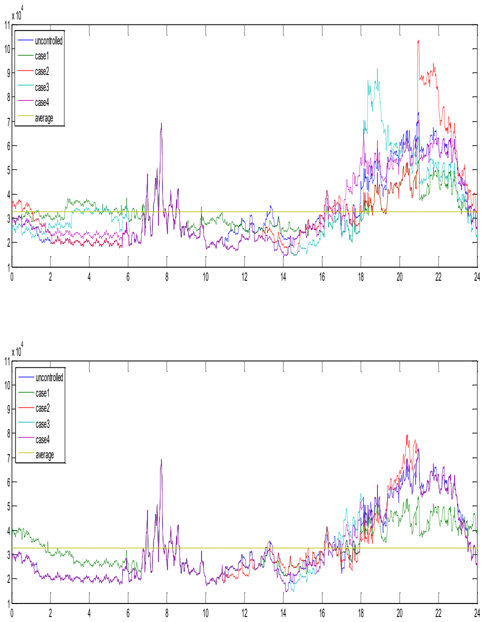

Fig 4. The normalised combined impact profile for 20% EV without and with penalty factor

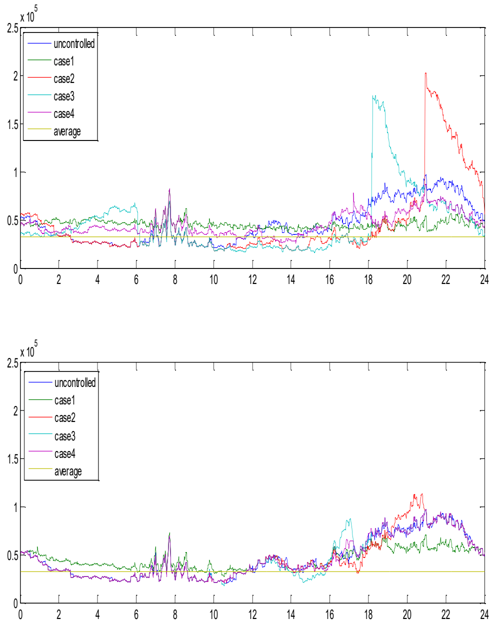

Fig 5. The normalised combined impact profiles for 60% EV without and with penalty factor

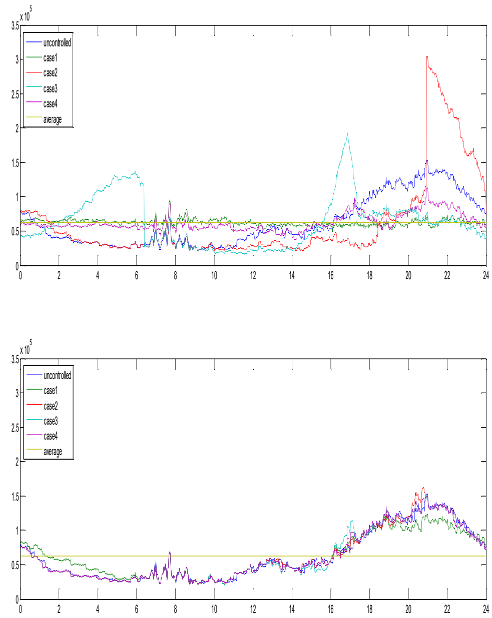

Fig 6. The normalised combined impact profiles for 100 EV without and with penalty factor

However there are still some spikes in the morning between 6:00 and 8:00; this is because most households use unshiftable electrical appliances during that period, which exceed the desired power demand. As the increase of electric vehicle penetration, the desired power demand also increase a lot. As a result, the power demand spikes in the morning are reduced. Therefore more electric vehicles are involved in the optimization algorithm, and better optimization results can be achieved.

For case 2 and case 3 only with the consideration of electricity price and GHG emissions, the huge peak is created in figure 4, 5 and 6. As mentioned above, generation cost and GHG emissions cost are fixed data in our study. It will not be updated as the power demand change. So for each electric vehicle, they all choose the lowest cost point in their allowable period to start charging without regard to other vehicles' charging plan and the change of total power demand.

In reality, all owners of electric vehicles prefer finishing charging as soon as possible, and the delay of charging will give rise to people's driving-range anxiety and unwillingness participating in demand side management. Given the reason mentioned above, penalty factors are defined to minimize the delay time in this paper. Comparing the combined impact displayed in the table for uncontrolled charging, shifted charging and charging with penalty factor, it is obvious that shifted charging plan can provide the lowest combined impact.

The combined impact of shifted charging with penalty factors is higher than shifted charging plan while it is still lower than uncontrolled charging plan. In shifted charging plan, each electric vehicle can find the lowest combined impact point from its allowable period without any limitation. In shifted charging with penalty factors plan, the penalty factor will become bigger as the shifted cycles increase which also leads to rising of combined impact. In figure 4, 5 and 6, the peaks in case 2 and 3 are dramatically reduced. When penalty factors are implemented, the previous minimum combined impact point could result in larger combined impact because its delayed cycles result in bigger penalty factor. Furthermore, the selection of penalty factor depends on the type of loads. If the penalty factors grow too fast, it will restrict the effect of three drivers on final results.

V. CONCLUSION

This paper shows that the proposed optimisation algorithm can effectively reduce the combined impact and meet various system requirements, especially in the optimisation of the power demand curve. Electric vehicles charging demand derived from the improved residential load model play a major role in getting more accurate and realistic optimisation results.

Future work will focus on the assessment of electric vehicle charging impact on a multitude of network variables such as reactive power, voltage variance and thermal limits.

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