

Smart Management of Electric Vehicles

Charging in Distribution Networks

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A thesis submitted to

Auckland University of Technology

In fulfilment of the requirements for the degree of

Doctor of Philosophy (PhD)

2020

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Chapter 2 to 4 of this thesis represent separate papers that have either been published or are accepted by peer-reviewed journals. All co-authors have approved the inclusion of the joint work in this doctoral thesis.

Signed:

Date: 12/06/2020

| Chapter Publication Reference | Author% |
|--|---|
| <p>Chapter 2: J. Su, T.T. Lie, R. Zamora, Modelling of Large-Scale Electric Vehicles Charging Demand: A New Zealand Case Study, Electric Power Systems Research 167 (2019) 171-182. https://doi.org/10.1016/j.epsr.2018.10.030</p> | <p>Jun: 85%</p> <p>Prof. Tek: 8%</p> <p>Dr. Ramon: 7%</p> |
| <p>Chapter 3: Su J, Lie TT, Zamora R. A rolling horizon scheduling of aggregated electric vehicles charging under the electricity exchange market. Applied Energy. 2020 Oct 1;275:115406. https://doi.org/10.1016/j.apenergy.2020.115406</p> | <p>Jun: 80%</p> <p>Prof. Tek: 10%</p> <p>Dr. Ramon: 10%</p> |
| <p>Chapter 4: J. Su, T. T. Lie and R. Zamora, "Integration of Electric Vehicles in Distribution Network Considering Dynamic Power Imbalance Issue," in IEEE Transactions on Industry Applications, vol. 56, no. 5, pp. 5913-5923, Sept.-Oct. 2020. DOI:10.1109/TIA.2020.2990106</p> | <p>Jun: 85%</p> <p>Prof. Tek: 8%</p> <p>Dr. Ramon: 7%</p> |

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Preface

This thesis was prepared at School of Engineering, Computer and Mathematical Sciences, Auckland University of Technology, New Zealand to fulfil the requirements for the degree of Doctor of Philosophy (PhD). The work has been carried out during the period from Oct 2017 to Oct 2020 under the supervision of Prof. Tek Tjing Lie, Dr. Ramon Zamora and Dr. Gilbert Foo.

The main theme of this thesis is to develop optimum scheduling and control techniques to manage extra electric vehicle (EV) charging loads in the low voltage distribution networks. The research work carried out in this thesis is divided into three parts to investigate the EV deployment. The first part of the thesis deals with the modelling of large-scale EV charging loads and applying heuristic algorithms to accommodate these extra charging loads in distribution networks. The second part develops an EV optimum scheduling technique that can be used in the energy market to produce a win-win solution for EV users and Distribution Network Operators. The last part describes a novel control technique to solve the power imbalance issue with the integration of EVs, to maximise asset utilisation.

The work carried out in these three parts is mentioned in the form of published and submitted manuscripts. The link between the work presented in each manuscript and its relevance to the main idea of the thesis is explicitly mentioned at the beginning of each chapter. Each chapter is dedicated to describing the work presented in each manuscript. The chapters of this thesis are designed following the number of manuscripts covering the topic of the entire PhD project.

Acknowledgements

With the sincerest gratitude in my heart, I would like to thank my academic supervisors, Professor Tek Tjing Lie, Dr. Ramon Zamora and Dr. Gilbert Foo. I would not have been able to complete this thesis without their generous support and encouragement. I would like to acknowledge the patience and commitment from Professor Tek Tjing Lie in guiding me to nudge my ideas towards clear and mature research throughout these three years. Also, big thanks to secondary supervisor Dr. Ramon Zamora and third supervisor Dr. Gilbert Foo for their valuable and heuristic suggestions regarding the work.

This research could never have been possible without the everlasting moral support from my parents and friends around me, who have always created a positive environment for me to complete my PhD studies. I wish to give my special thanks to AUT and the School of Engineering, Computer and Mathematical Sciences for the tuition fee scholarship. Thanks for all AUT's staff to provide their technical and moral support throughout my research. Finally, I would like to thank my wife Haowei Zhang, for her constant support and encouragement.

Abstract

For more than a decade, global transportation and power industries have played a revolutionary role in considering alternative and sustainable solutions for internal combustion engine vehicles (ICEVs) to reduce oil dependency and environmental impact. Electric Vehicles (EVs), driven by the battery, offer unique advantages regarding emission reduction, reduced petroleum use and energy efficiency. Thus, it is noteworthy to consider the positive impacts EVs may have on power systems as numbers keep increasing in future market shares. The proliferation of EVs requires the deployment of charging facilities, scheduling strategies, and advanced power control schemes in order to manage incremental charging loads better. However, the practical and efficient application of such EV-related equipment and technologies involves challenges beyond merely upgrading the existing power grid. In the distribution network, the barriers to widespread EV adoption are (1) lack of sufficient information about EV charging profiles, (2) lack of effective control and scheduling techniques to manage EV charging loads and (3) lack of market mechanisms to maximise economic benefits.

Uncontrolled EV charging can cause extra peak loading, inefficient network operation and redundant economic costs. This thesis focuses on the development of advanced modelling, scheduling, and controlling techniques that could be used within distribution networks to manage EV charging smartly. Modelling EV charging demands deals with stochastic problems related to the charging behaviours of EV users. Monte Carlo Simulation (MCS) is carried out (in manuscript 1) to demonstrate inhomogeneous charging characteristics based on a systematic investigation of the current composition of the EV fleet in New Zealand (NZ). A genetic algorithm (GA) has been applied to a smart charging strategy to mitigate the adverse impacts brought by large-scale EV integration. In a competitive market environment, EV users, utilities and charging service providers

should form a community of common interests to promote widespread usage of EVs. In manuscript 2, an online scheduling strategy is proposed to investigate the significance of economic integration under the energy trade market, where all participants' interests can be satisfied. With increasing penetrations of distributed Photovoltaic (PV) generation in addition to EVs, the intermittent and stochastic power characteristic may detrimentally affect the security of the power supply. Thus, a Dynamic Power Balance System (DPBS) with a novel control scheme is proposed (in manuscript 3) to manage dynamic power generation and consumption in the distribution network. It could be used as a supplemental measure to obtain a fast load balance response without restraining EV users and considerably curtail the risk of overloading power distribution equipment.

The findings of this study revealed that current EV adoption in NZ (and many other countries in the world) is still in its early stages while the majority of the existing distribution network is not intelligent enough to integrate large-scale EVs. It was further verified that the proposed methods in this research are theoretically flexible and capable of being applied to the power grid to smartly manage EVs' charging demand.

Chapter 1 Introduction

1. Background

During the last few decades, the reduction of fossil fuel dependency and reinforcement of environmental policies have motivated the transport sector to shift development direction from conventional internal combustion engine vehicles (ICEVs) to electric vehicles (EVs). The innovation captured by EVs is the reduction of carbon dioxide (CO₂) and the revolution in road transport, particularly in highly urbanised areas. Due to increasing concern about uplifting greenhouse gas emissions and ever-increasing fossil fuel prices, there is growing interest in EVs or their variants (e.g., Plug-in Hybrid Electric vehicles PHEVs) as a replacement for ICEVs because of various attractive features including climate change and the security of fossil energy supply.

With an increasing number of EVs in the marketplace, researchers soon realised that their environmental benefits are related to the electricity generation mixture in which the renewable energy source plays a dominant role in Green House Gas (GHG) emission reduction [1]. Major types of renewable energy sources (RES), such as wind, solar and hydro, are recommended to be placed at local sites where EV charging demand is high. The environmental benefits of EVs have received considerable attention because they are related to the cleanliness of electricity generated from the district power system. The carbon intensity of electricity is a vital index in the evaluation of GHG emission reduction from large-scale deployment of EVs. As shown in Figure 1.1, New Zealand (NZ) owns

one of the cleanest electrical power systems in the world with a carbon intensity of nearly 130g CO₂/kWh, which is less than most of the countries with a carbon intensity of more than 500g CO₂/kWh. In contrast, light passenger vehicles in NZ have a relatively high CO₂ emission value (see Figure 1.2). Compared with ICEVs, EVs have the potential to considerably reduce GHG emission within a ‘green’ grid in NZ. Therefore, the replacement of ICEVs by EVs is regarded as a substantial energy conservation measure to realise NZ’s GHG emission target, which is to reduce GHG emissions by 30% below 2005 levels by 2030 [2].

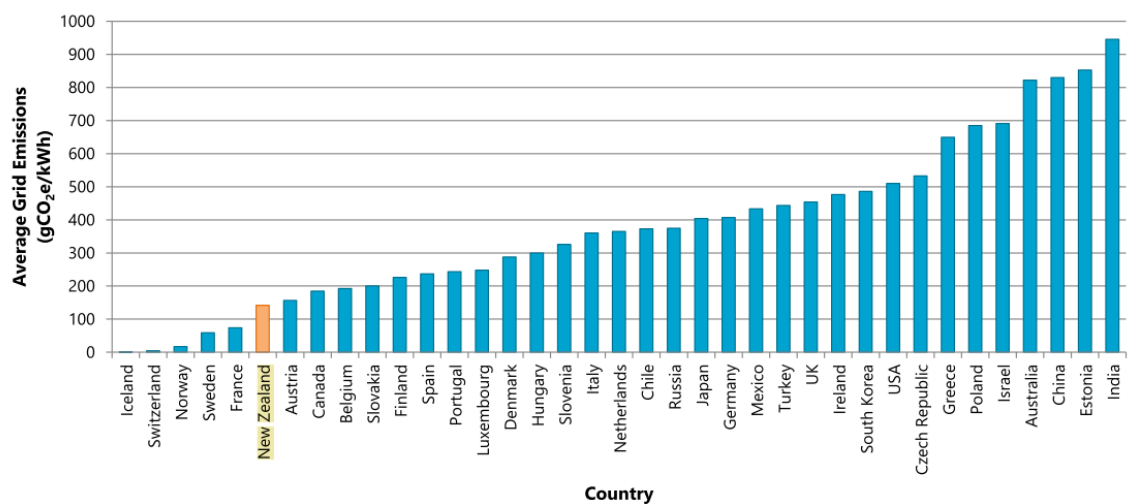


Figure 1.1 Average GHG emissions of light passenger vehicles around the world [3]

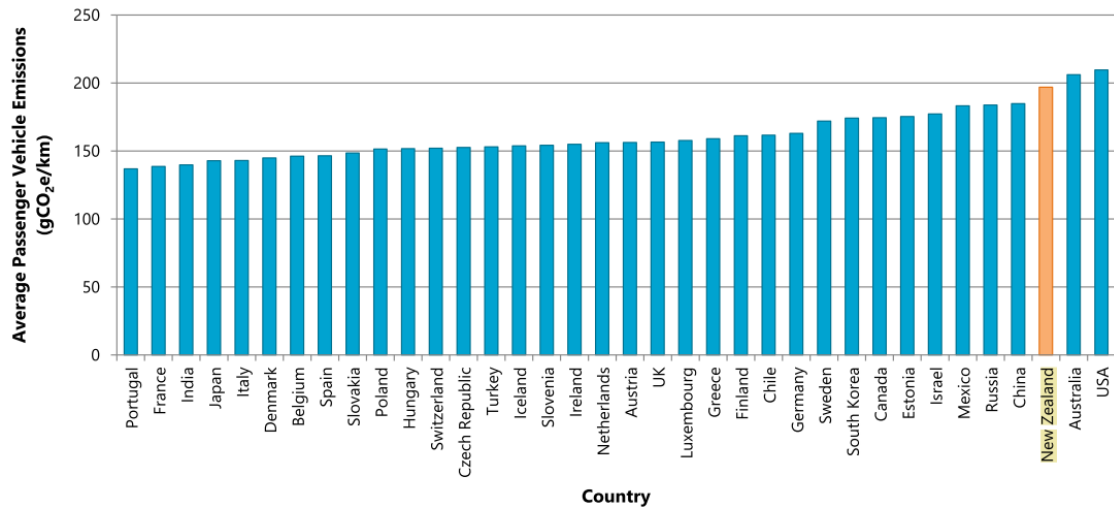


Figure 1.2 Amount of GHG emitted per unit of residential electricity consumed [3]

2. EV Fleets Composition

In 2020, annual vehicle statistics from the NZ Ministry of Transport [4] indicated there are approximately 20,000 EVs, nearly half of which are concentrated in the Auckland area, as shown in Figure 1.3. The size of the EV fleet almost doubled every year from 2015–2019 (see Table 1.1). Figure 1.3 shows a clear trend that the revolution in the use of EVs initially occurs in urbanised areas. Cities like Auckland, Wellington and Christchurch have the highest number of EVs and the distribution networks in these areas may suffer from potential problems from large-scale EV integration.

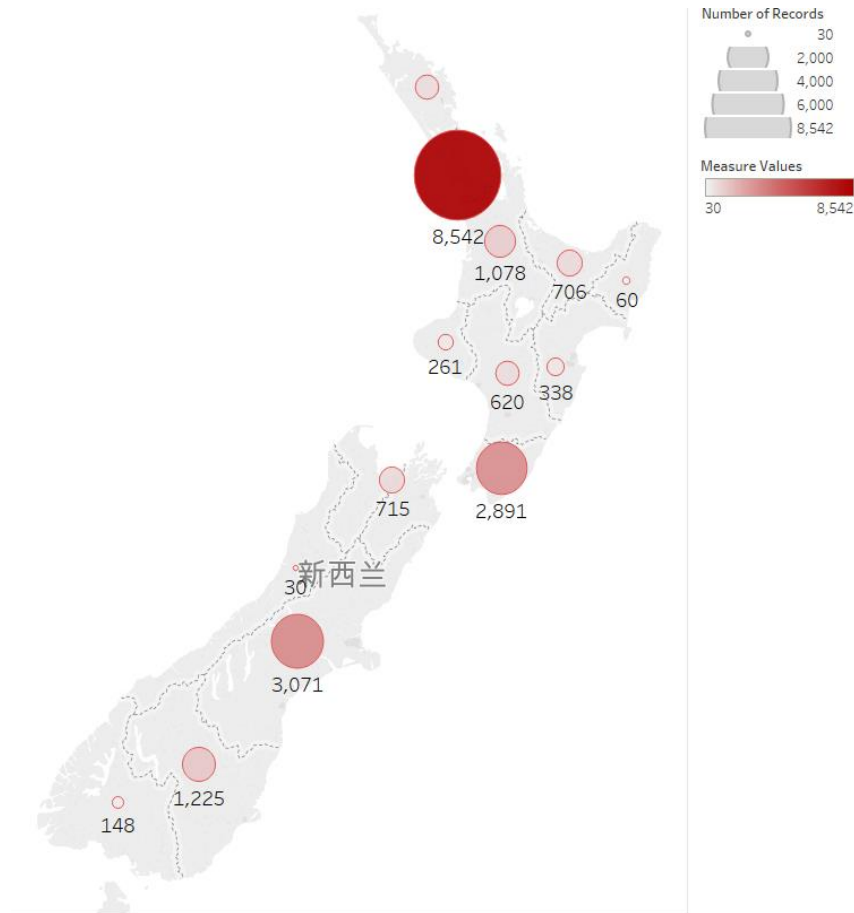


Figure 1.3 EVs distribution map in New Zealand in 2020

The EVs fleet composition displayed in Figure 1.4 provides a trail on consumers' preferred EV models. As of December 2019, Japanese EV manufacturers such as Nissan and Toyota have the most significant market share, with more than 60% of all EV registrations in NZ. The average growth rates of EVs have kept above 200% over the past five years, as illustrated in Table 1.1. Although a growing interest in EVs has been witnessed in recent years, market penetration is only 0.44% of the overall vehicles in stock in 2019. It means that EVs still have not gained mainstream acceptance because of limited driving ranges, high costs and inadequate charging infrastructure. However, it

could be foreseen that the EV sales market has the potential to grow rapidly due to concerns over CO₂ emissions and oil dependency in the future.

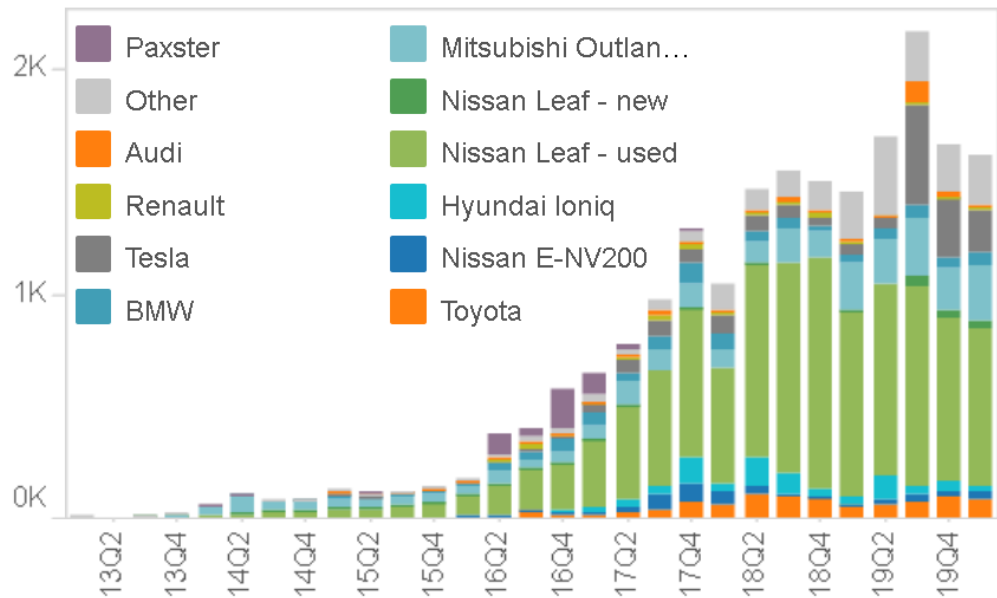


Figure 1.4 Quarterly light EV registrations in NZ - main makes and models [4]

Table 1.1 EV penetrations in New Zealand from 2014~2019

| Year | EVs Fleet | All Vehicles | Annual EVs Fleet Growth | EV Penetration |
|---|-----------|--------------|-------------------------|----------------|
| 2014 | 232 | 3545050 | | 0.01% |
| 2015 | 592 | 3674100 | 255.17% | 0.02% |
| 2016 | 1114 | 3813688 | 188.18% | 0.03% |
| 2017 | 2752 | 3972783 | 247.04% | 0.07% |
| 2018 | 6613 | 4144771 | 240.30% | 0.16% |
| 2019 | 18696 | 4289903 | 282.72% | 0.44% |
| EV Penetration (%): the percentage of EVs out of all vehicles | | | | |

3. Charging Characteristics of EVs

Technically, EVs require a battery to support electric engine operation. The charging characteristics of the EV's battery is a crucial factor in the power load. The coincident charging behaviours may result in severe operational problems in the power grid, such as

an increase of power demand, equipment overloading, phase unbalance, system losses, harmonics and stability issues [5]. To evaluate the adverse impact of EV charging in the power grid, it is necessary to investigate the charging parameters of the main EV manufacturers, as displayed in Figure 1.4.

In general, EVs can be classified into two categories: i) plug-in electric vehicles (PEV) and ii) plug-in hybrid electric vehicles (PHEV). The charging parameters of various types of EVs are presented in Table 1.2. It summarises the classifications and technologies of available EVs models in the current NZ market [3, 4].

The EV charger is the device that connects PHEV and PEV to the power supply; the battery packs can be recharged externally from the power grid. It is designed to convert AC power from the grid to a suitable DC power level for EV battery charging. A typical EV charger usually consists of an AC/DC or DC/DC converter. The charging power is well below 10 kW in slow charging mode but goes up to 50 kW in fast mode. To perform a fast-charging task, an additional DC/DC converter is required in the design of the fast EV charger, such as the Tesla DC supercharging station with a 75 kW power level [6, 7].

In the current market, there are two main types of charging methods, namely off-board and on-board [8]. The Tesla charging solution is an off-board EV charger, which is built at dedicated locations to provide a fast-charging service. For the on-board charging method, energy conversion takes place within the vehicle where the EVs has its own built-in charger [7, 9].

Table 1.2 Charging specifications for 2019 generation EVs on the market

| Vehicle Models | Charging level | Charging Mode | Charging Rating (KW) | Charging Level (SAE charging level) | Battery Capacity(kWh) |
|-----------------------------|----------------|---------------|----------------------|-------------------------------------|-----------------------|
| Nissan Leaf | PEV | slow | 6.6 | AC level 2 | 24/40 |
| Tesla | PEV | slow | 8 | AC level 2 | 60-100 |
| | | fast | 11 | | |
| | | fast DC | 75 | DC level 2 | |
| BMW i3 series | PEV | slow | 3.7 | AC level 2 | 33 |
| | | fast | 11 | | |
| | | fast DC | 50 | DC level 2 | |
| Nissan E-NV200 | PEV | slow | 3.3 | AC level 2 | 24 |
| | | fast | 6.6 | | |
| | | fast DC | 50 | DC level 2 | |
| Renault | PEV | slow | 3 | AC level 2 | 41 |
| | | slow | 7 | | |
| | | fast | 43 | AC level 3 | |
| Paxster | PEV | slow | 1 | AC level 1 | 5.1-9.2 |
| Mitsubishi Outlander | PHEV | slow | 3.3 | AC level 2 | 12 |
| | | fast | 50 | AC level 3 | |
| Hyundai Ioniq | PEV/EV | slow | 6.6 | AC level 2 | 28 |
| Toyota Prius (plug-in type) | PHEV | slow | 2 | AC level 2 | 8.8 |
| | | fast | 3 | | |
| Audi A3 e-Tron | PHEV | slow | 1.3 | AC level 1 | 8.8 |
| | | fast | 3.8 | AC level 2 | |

4. State-of-the-Art Techniques on EV charging management

This section presents overall vision of state-of-art EV modelling methods and grid-based charging management studies. The studies [10-13] have concentrated the impacts of uncontrolled EV charging interconnection on the power grid. The positive and negative aspects of EV integration were thoroughly discussed in [14]. The key factor is how to make collective decisions to achieve proper EV coordination for charging and discharging. A comprehensive review in [15] presented cutting-edge charging-discharging methods, optimisation strategies and optimisation objectives with respect to EVs and possible interaction with renewable generation or residential loads.

The EV charging demands in the power system planning have been studied and quantified mainly by means of mathematical, deterministic and probabilistic models, as shown in Table 1.3. The reviews of various studies on the modelling of EV charging demand regarding the weakness and strength of each approach have been carried out in [16]. The study conducted in [17, 18] proposed a mathematical analysis of EV charging demand by using the fluid dynamic traffic model and queueing theory. The Markov chain models on EV charging demand were assessed in [19, 20], uncertainties related to when and where EVs will be recharged were pre-defined by a global transition matrix in which charging events for the next time interval were only influenced by pre-determined transition probabilities.

In deterministic studies, distribution network constraints were utilised to estimate the threshold level of EV penetrations that would exceed thermal ratings [21, 22]. In

probabilistic studies, stochastic procedures were used to complete the quantitative analysis [23, 24]. The national transport survey was adopted in support of the extraction of probability density functions. The method of Monte-Carlo Simulation (MCS) was presented in [20], where loading profiles with the integration of EVs were acquired by probabilistic density functions (PDFs). The study [13] also employed MCS to evaluate EV deployment impacts on a distribution network with increasing penetration levels.

The big data technology was firstly conducted by the authors of [25], where the EV charging demand was predicted by using historical real-world traffic data and weather data. Then, the data-driven methods were widely adopted to identify the driving patterns of the EVs, so as to carry out quantitative analysis of EV flexibility for integrated transport and power system analyses [26-28].

Table 1.3 Summary of EV demand Forecasting literature

| Applications | Methods | Implementation Pathways | References |
|-------------------------------------|----------------------|--|-----------------|
| EV demand modelling and forecasting | Deterministic Method | | [21, 22] |
| | Markov Chain Method | | [20] [13] |
| | Probabilistic Method | Monte-Carlo Simulation | [23, 24] [19] |
| | Mathematical Method | Queueing Theory | [17, 18] |
| | Data-driven Method | Cluster Analysis Optimal Cluster Charging | [25-27] [28] |

Numerous studies have been carried out to deal with uncertainties in EV charging load profiles. The study in [29, 30] introduced a passive control strategy to reduce the peak load demand with the aid of the forced time-delay charging and orderly charging approach. It assumed that all EV users negotiate with the charging station about their

charging schemes one day ahead; thus, the charging start time was rescheduled at night when loading level is relatively low to avoid creating a peak power demand. However, this method may result in an almost simultaneous EV charging scenario during off-peak hours, leading to a sudden power demand increment.

A massive amount of research has been done on the development of metaheuristic algorithm for scheduling of EV charging process. Most of smart charging strategies made use of the data aggregator to obtain EV charging information [31, 32], as shown in Figure-1.5. The data communication between the EV charger controller and the aggregator is realised by either wire or wireless method. The information hub executes an internal optimisation algorithm to generate charging scheduling with the consideration of network constraints. Then, the charging scheduling is sent back to EV chargers.

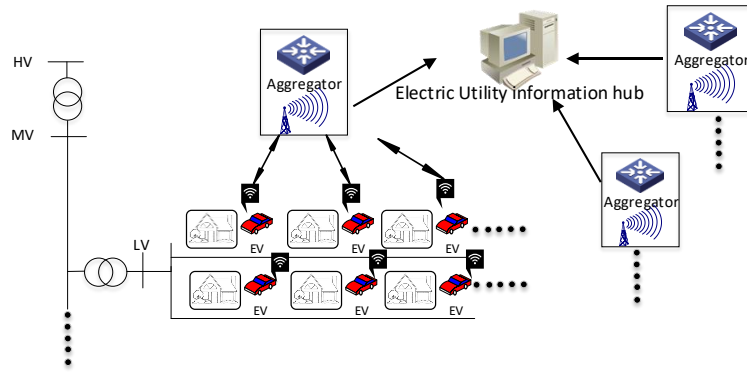


Figure 1.5 Communication system architecture in the distribution network with EVs

A multi-objective optimisation method was proposed in Ref. [33], in which an optimal allocation of renewable energy resources (RES) and sizing of EV charging station were assessed in the IEEE 33-bus system. The hybrid genetic algorithms were introduced to maximise renewable energy use in EV charging. The proposed method gives a solution

in the stage of system planning to accommodate large-scale penetration of RES and EV without stressing the network.

The primary purpose of the study in [34] focused on distributed demand-side management (DSM) for balancing supply from wind energy and demand stemming from charging EVs. The assumption was based on a distribution network that consists of a balance responsible party (BRP), multiple subscribers and a coordinator. The BRP aims to maintain the balance by changing EV demand and wind generation by agreement. Thus, the imbalance cost needs to be minimised in the optimisation solution requirement. In this study [36], more than 60% EV demands could be supplied by wind energy, which is 20 % higher compared to the uncoordinated scenario. The similar approach presented in [31, 35] provides a maximum benchmark for the utilisation of RES through the EV charging strategy. The results demonstrated that wind energy complies better than solar energy in the integration of EVs as it possesses a more consistent generation pattern. The main benefit of balancing EV charging loads and distributed renewable generation is the substantial reduction in carbon intensity of the power system.

The integration of electric vehicle and RES in the micro-grid (MG) was proposed in [32, 36]. An intelligent EV parking lot model which participates in providing reserve capacity was developed in the study [32]. The reserve capacity provided by aggregated energy storage of EVs could be used for compensating the renewable power forecasting error. The paper [36] examined the viability of the reconfigurable MG in facilitating the integration of EV from operation cost and reliability perspectives. A scenario-based

framework is devised to test the optimal scheduling problem consisting of switches status (on/off), EV charging management, electricity price, wind/solar generation and active loads.

The intelligent charging strategy with vehicle-to-grid (V2G) technique is a new concept related to bi-directional power flow between grid and EVs. The considerable numbers of aggregated battery vehicles act as controllable loads or storages to facilitate power system stable operation. Adding V2G technology to EVs can help to maintain a balance between power demand and supply, so as to increase the fraction of electricity from abundant RES. A national energy system example demonstrated in [37] made use of V2G to consume a higher share of wind electricity without excess Combine Heat Power (CHP) electric production, which achieves substantial GHG emissions reduction at a national level. Binary particle swarm optimisation (BPSO) is applied to a smart V2G charging strategy in EV parking lot to figure out a potential solution that maximises the EV owner's power-selling profit while satisfying power system constraints [38]. The multiple system services derived from the participation of EVs at the national level were mentioned in [39]. It presented that the 10% penetration of EVs controlled by the proposed charging strategy could decrease overall system cost and wind curtailment. Furthermore, the importance of EVs with V2G technology was recognised through their active participation in the provision of energy and reserve service. The study [40] proposed a control strategy to utilise aggregated EV batteries as a fast release energy storage to improve MG islanding operating condition. The storage capability of EV was integrated

into MG by the adoption of local control and centralised control strategies, contributing to frequency control and voltage balancing. Currently, the primary technology limitations related to the realisation of the V2G concept is the battery degradation and the degree of aggregation. When solving the battery lifetime barriers, V2G could be of great worth to maximise customer satisfaction and power grid stability [29].

The summary of the literature on EV charging strategies and their related applications are presented in Table 1.4. The multi-objective optimisation approach is widely used in the current research to control EV charging process and intermittent RES generation. The genetic algorithm (GA) is recommended to be used in the EV charging scheduling because of the confident convergence performance. Also, the optimised results from GA are independent of the initial condition.

With the increase mixture of EV charging loads and distributed Photovoltaic (PV) generation, the phenomenon of the power imbalance loading condition is becoming serious issue in the distribution network. It is well known that EVs as mobile loads may be randomly plugged in or out as unplanned events among feeders. These events may lead to the unbalanced loading scenarios, in which one feeder is heavily loaded whereas adjacent one is lightly loaded. Similarly, unbalanced loading scenarios among three phases of a feeder also result in several negative impacts on distribution network, such as voltage deviation and voltage unbalance [41]. The possible solution for imbalance issues either in three phases or among feeders might be provided by AC-DC or DC-DC converter having a bidirectional power flow topology [14]. The study [42] utilised EV

inverters to regulate voltage by the reactive discharging capability of those inverters, so as to achieve ancillary voltage support among three phased of the feeder. The inverters in PV plant are reconfigured in [43] to interconnect multiple distribution feeders. The reconfiguration expanded the use of PV generation for management of bidirectional power flow between interconnected feeders. In [44], considering the feeder loading capability, a feeder equalization control strategy was proposed to reduce the power fluctuation and peak demand of the feeders in order to maximise utilisation of the loading capacity of feeders. P-Q and DC voltage control schemes were applied into PI controllers to drive flexible multi-state switch (FMSS) to adjust bidirectional power flow based on assigned power values. Another similar flexible interconnection scheme for distribution network feeders was studied in [45] to achieve power flow reversal in FMSS. The increasing penetrations of EVs and PV in distribution network are quite likely to lead to imbalance loading scenarios due to randomly charging behaviours of EVs and intermittent PV generation. Therefore, it is essential to explore a possible control technique that could be used among adjacent feeders to mitigate the imbalance condition caused by EVs and PV.

Table 1.4 Literature on EVs charging strategies

| Strategies | Algorithms | Decision Variables | Objects | Applications | References |
|--------------------|--|---|--|--|--------------|
| Non-Smart Charging | Scenarios Modelling | Off-peak charging | Flatten load | Mitigate Load Variance (Centralized Control) | [30] [29] |
| | Non-cooperative games | Adapting the charging rates | Min cost | Mitigate Load Variance (Decentralized Control) | [46] |
| | Binary particle swarm | Adapting the charging/discharging rates and time | Max profit | Parking lot scheduling, V2G | [38] |
| | Probabilistic Optimization | Off-peak charging | Min fluctuation | Mitigate Load Variance (Centralized Control) | [13] |
| | Hybrid Genetic algorithm mixed integer programming | Adapting the charging/discharging rates and time[33] Optimal allocation of EV charging resources[31, 35] | Multi-objective: Max renewable energy utilisation[31, 33] Min cost and emission [35] | Integrate wind and solar energy (Centralized Control) | [31, 33, 35] |
| Smart Charging | Mixed integer linear programming | Optimal allocation of EV charging and discharging resources | Min cost | Reserve Capacity Service (Centralized Control) | [39] |
| | Multi-Master Operation | Adapting the charging/discharging rates and time | Multi-objective: voltage, frequency, generations, loads | Frequency and Voltage Regulation (Centralized and Decentralized control) | [40] |
| | Distributed algorithm | Adapting the charging rates and time | Multi-objective: Energy loss, Voltage, EV charging demand and costs | Integrate wind energy (Decentralized Control) | [34] |
| | Mixed integer linear programming | Adapting the charging/discharging rates and time | Multi-objective: Min MG Power exchange and operation cost, Reserve Capacity | Micro-grid Control | [32] |
| | Depth-First Search (DFS) algorithm SAMCSA algorithm | Adapting the charging/discharging rates and time | Reconfiguration to improve MG viability | Micro-grid Control | [36] |

5. Research Problem Statement

Given the background information above, it should be noticed that the power generation, transmission, and distribution infrastructure should be upgraded to meet additional EV charging demand. The importance of a robust power system is indisputable to accommodate extra charging loads. The balance scenario between energy generation and energy consumption may be broken by the growing number of EVs in the coming years. EVs will be randomly plugged in or out at any node within distribution networks in the form of mobile loads, which has long been a question of peak demand, overloading and power quality fields.

In most countries, current grids with existing infrastructure cannot ensure a stable and safe operation with the high penetration of EVs. The possible solution derived from smart grids have attracted much attention and have been thoroughly discussed in recent years. The shifting of power systems from the past to the future adopts more ICT infrastructure and components like EVs, renewable energy sources and battery storage, which are expected to increase in capacity and number. To accurately analyse EV charging loads, it is essential to investigate the pattern of EV charging behaviours. The stochastic approach could be applied to take into account uncertainty factors, such as vehicle travel demands, personal charging behaviours, battery charging characteristics, charging infrastructures and the numbers of EVs. An appropriate combination and analysis of various techniques are necessary for modelling these uncertain factors.

In manuscript 1 of the thesis, a comprehensive probabilistic model is built in the stochastic approach to describe EVs' charging loads. It is necessary to estimate an expected power level that may be used by utilities to upgrade their infrastructure for supporting extensive penetration of EVs. Additionally, the increment charging loads exerted on the power grid may threaten the stability of network operations, especially at the distribution level. An elaborate scheduling strategy needs to be developed to obtain peak-shaving and valley-filling effects, in part, on the power curve to maximise utilisation of existing network facilities. This necessitates the thorough and careful design of an EV charging scheduling strategy to mitigate potential impacts like thermal loading, harmonic distortion, system imbalance and loss, as displayed in Figure 1.6.

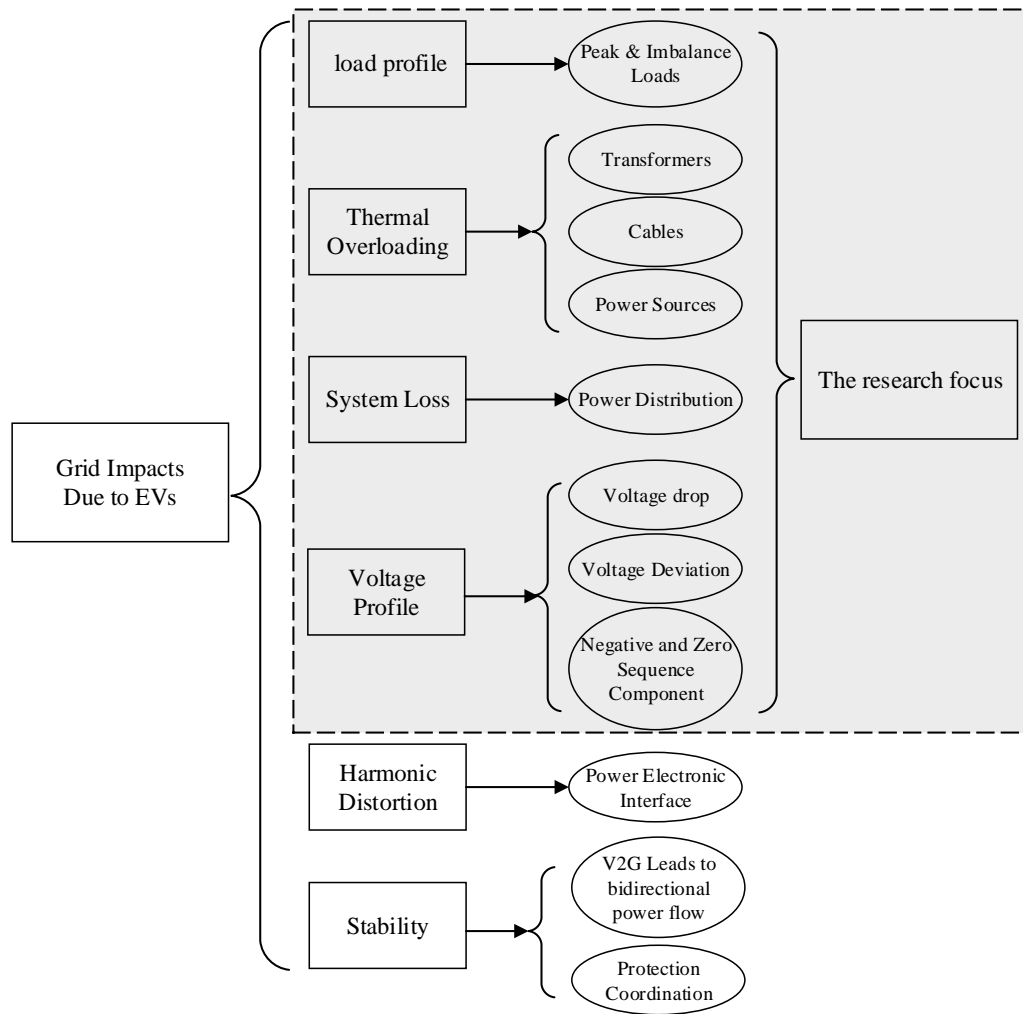


Figure 1.6 EVs impacts on the power grid

As a part of EV deployment considerations, it is necessary to investigate the economics underlying the scheduling strategy, which may furnish a vision for operating charging services. In an electricity market, the retailers purchase electricity from the grid and sell it to EV users. The retailers could be utilities or EV aggregators as long as they can make profits from the charging service. Figure 1.7 depicts a typical relationship between participants regarding charging services in the distribution network; these participants include EV users, Distribution Network Operators (DNOs) or charging operators and high-voltage grid utilities. The hierarchical framework describes the decision-making

mechanism based on signal information between each group. Note that each group adapts to changes in the market environment by reacting to fulfil collective or individual economic goals. In the energy market environment, a reasonable EV scheduling strategy is to make sure that all participants can benefit from the charging service by economic incentives, rather than by strict rules and policies. The cost-effective investment in charging infrastructure needs to be considered before the wide deployment of EVs as it provides affordable service to both EV users, DNOs or charging operators. Therefore, manuscript 2 in the thesis is to discuss the pricing mechanism of the EV scheduling strategy in the energy market. The optimisation focuses on both technical and economic indexes to produce a win-win solution for stakeholders in distribution networks.

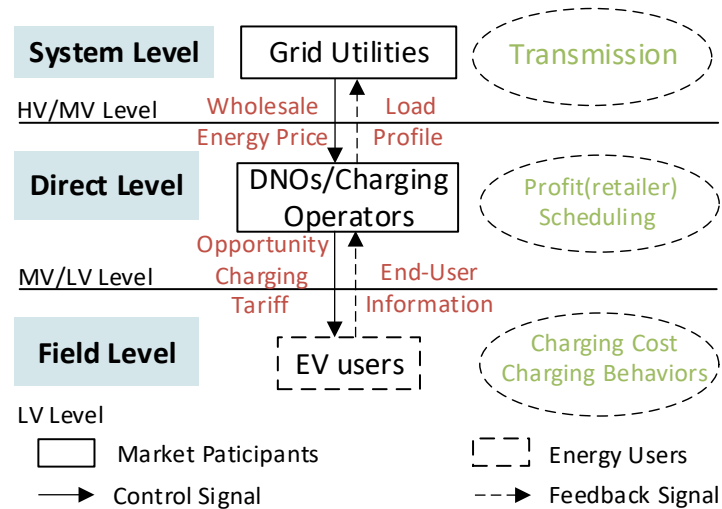


Figure 1.7 The relationship between participants in EV charging service in the energy market

Manuscript 1 and 2 deals with optimisation problems in the scheduling strategy that is derived from EV charging loads in distribution networks. These problems have static forms in which the decision variables do not vary in response to detailed variations in the

system state. The variations could happen to either the power consumption or power generation profile. For instance, the load profile of feeders within the distribution network could vary because EV users might dispersedly plugin or plugin at any available spot instead of ensuring identical distribution across feeders. This might result in one feeder getting heavy EV charging loads, whereas the adjacent feeder might only be lightly loaded. Also, the wide diffusion of distributed PV generation has been witnessed in the Low-Voltage (LV) distribution network in recent years. The intermittent PV generation, in addition to random EV charging loads, could potentially alter the load profile and make it highly dynamic. Both of them interact with the distribution network through a single-phase connection. This may result in a typical power imbalance issue among LV feeders. In this circumstance, the scheduling strategy cannot force all EV users to jointly accept direct control without compromising their expected target. The third part of the thesis proposes a novel control scheme to manage the imbalanced power derived from EV charging and PV generation among feeders through a control system composed of tie-line voltage source converters (VSCs). It could be used as a supplemental measure to effectively address the power imbalance without restraining the EV charging process while curtailing the risk of overloading the power distribution equipment.

Based on the description of the problem above, the following research questions need to be answered:

- How to develop a model of EV charging demand that can be used in estimating the charging load level and planning of distribution network upgrades?

- How to design a scheduling strategy to manage EV charging loads considering the uncertainty factors mentioned above?
- How to enable economic operation into the EV scheduling strategy to generate a win-win solution for all participants in the energy market framework?
- What control technique needs to be developed for solving the power imbalance issue with the integration of EVs and intermittent PV generation?

6. Research Aim and Objectives

The previous subchapter discusses the main issues that are negatively affecting the EV charging in the distribution network. To address these problems, the primary research aim of this study is to develop effective optimisation and control techniques to manage EVs charging loads in the distribution network. To this end, the following objectives were recorded in Table 1.5 below.

Table 1.5 Research aim and objectives

| Research Aim |
|--|
| To develop effective optimisation and control techniques to better manage EV charging loads in the distribution network. |
| Research Objectives |
| (1) Develop a modelling technique for large-scale EV charging demand |
| (2) Determine key indexes for expected loading levels, allowing DNOs to plan network reinforcements |

- (3) Apply appropriate heuristic algorithms into an EV scheduling strategy to optimise charging loads by flattening the load and voltage profile within distribution networks
 - (4) Design a pricing mechanism into the proposed EV scheduling strategy, satisfying all participants in the energy market environment
 - (5) Develop a control scheme that could solve the power imbalance caused by random EV charging loads or intermittent PV generation in adjacent LV feeders
-

7. List of Publications

This thesis is based on work presented in the form of manuscripts. As listed in Table 1.3, the entire aim of this thesis is divided into multiple tasks, where each manuscript is dedicated to addressing one or two tasks. Manuscripts address individual problems lying under the main theme of the PhD project. When combined, the individual work addressed in each manuscript is considered to represent the entire PhD project.

The research work described in this thesis has been accepted for publication or published/under reviewed in the following peer-review journals:

Journal Papers

- i. J. Su, T.T. Lie, R. Zamora, Modelling of Large-Scale Electric Vehicles Charging Demand: A New Zealand Case Study, *Electric Power Systems Research* 167 (2019) 171-182. <https://doi.org/10.1016/j.epsr.2018.10.030>

- ii. Su J, Lie TT, Zamora R. A rolling horizon scheduling of aggregated electric vehicles charging under the electricity exchange market. *Applied Energy*. 2020 Oct 1;275:115406. <https://doi.org/10.1016/j.apenergy.2020.115406>
- iii. J. Su, T. T. Lie and R. Zamora, "Integration of Electric Vehicles in Distribution Network Considering Dynamic Power Imbalance Issue," in *IEEE Transactions on Industry Applications*, vol. 56, no. 5, pp. 5913-5923, Sept.-Oct. 2020. [DOI:10.1109/TIA.2020.2990106](https://doi.org/10.1109/TIA.2020.2990106)

8. Thesis Contribution

The work presented in this thesis contributes to developing optimisation and control techniques that could be used for the smart management of EV charging in distribution networks. The following research tasks are proposed to meet thesis objectives:

- A temporal EV charging demand is generated based on the multivariate probabilistic model.
- The EV charging process is scheduled using GA strategies for load profile flattening.
- A rolling horizon scheduling approach based on GA is proposed to provide a win-win strategy for both DNOs and EV users. It deals with the online optimal scheduling problem of aggregated EVs in the energy exchange market.
- A dynamic power balance system (DPBS) is developed to manage the power imbalance derived from EV charging and distributed PV generation, by which the

unbalanced power can be transferred from the heavily loaded feeder to the neighbouring feeder that is lightly loaded through the power electronic interface.

9. Thesis Outline

This entire piece of work is divided into manuscripts, where the work presented in each manuscript has a unique contribution mentioned in each manuscript Chapter. In Chapter 2, manuscript one contributes to the aspects of the scheduling strategy that optimise the EV charging process to obtain peak-shaving and valley-filling effects on load profile. The techniques are developed such that the resulting load profile avoids creating extra peak demand. In Chapter 3, manuscript two further develops the algorithm to enable the scheduling strategy to be applied to the online system. In this way, the economic interests of EV users, DNOS or charging operators can be satisfied. A dynamic power balance system (DPBS) is proposed in manuscript three in Chapter 4. The DPBS could be installed as an additional component to the existing distribution network. It has fast response capability to smooth and balance out bidirectional power flowing among feeders. Chapter 5 concludes the thesis by integrating the key research findings into the research objectives. This chapter highlights the research contributions and provides suggestions and opportunities for future research arising from the current study.

Chapter 2 Manuscript 1

This manuscript deals with modelling technique to estimate EV charging demands in NZ. The majority of studies on EV charging load impacts made assumptions for the EV charging demand profiles as real EV charging information is not publicly available due to privacy concerns. A modelling framework based on Monte-Carlo Simulation (MCS) was developed to extract the useful information hidden in vehicle travelling statistics, which can be utilised to estimate EV charging loads. A case study with projected EVs numbers in the future is presented to demonstrate the modelling performance. The resulting loading levels can be used to estimate the potential risk level of EV charging demand among different geographical areas. After that, a smart charging strategy is developed to obtain load shifting effects on power curves while guaranteeing charge completion for each EV before the next trip.

The manuscript was published in the journal of ‘Electric Power Systems Research’ under the title: “Modelling of large-scale electric vehicle charging demand: A New Zealand case study”.

Modelling of Large-Scale Electric Vehicles Charging Demand: A New Zealand Case Study

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Abstract

Due to increasing electric vehicles (EVs) uptakes, power system distribution network will have to accommodate the increased load level for charging EVs. Thus, the importance of a robust power system especially in the distribution network level is indisputable. During the planning or reinforcement stage of distribution networks, it is paramount to have some estimations and analyses done on system-wide EV charging loads that will be placed in the network. Thus, this paper systematically investigates the EV fleet composition, market shares, and charging patterns within New Zealand (NZ) area. A multivariate probabilistic modelling of dependent random variables and cumulative distribution functions is adopted for the accurate estimation of aggregated EV charging demands. Several vehicle travel survey data sets are utilised to quantitatively determine charging behaviours and driving patterns of EVs. The developed methodology based on Monte-Carlo simulation (MCS) is utilised to generate results close to the real use-cases daily power demand, which can be further utilised in the analysis of EV charging strategies. In addition, non-smart and smart EV charging strategies are introduced to mitigate impacts of the large-scale EV deployment and to guarantee the charging completion for each EV.

Keywords: Genetic algorithm, EV charging demand, Probabilistic modelling, Smart charging strategies

1. Introduction

During the last decade, the reduction of fossil fuel dependency and the reinforcement of environmental policies had motivated the automotive industry to shift development directions from conventional internal combustion engine vehicles (ICEVs) to electric vehicles (EVs). Both opportunities and challenges of EV deployments need to be identified in the electricity industry to achieve better integration at the planning and operational levels [47]. Along with expected environmental benefits, the increasing penetration of EVs may potentially reshape electricity load profiles due to the grid-to-vehicle and vehicle-to-grid power flow [48].

EV deployment impacts on transportation, manufacturing, economy or long-term power system plan have been identified, studied and quantified mainly by means of mathematical, deterministic and probabilistic models. Such models are necessary primarily for two reasons. Firstly, real world data about EV use is not publicly available due to the privacy concern and the low EV uptake to date. Secondly, although data is available, there will still be a concern on how to make use of the data to access and mitigate impacts for the conditions with different EV charging and driving patterns [16]. Moreover, the EV charging demand is considered as an essential input for EV charging strategies to carry out scheduling subject to a set of constraints. In order to demonstrate

the convincing effectiveness of EV charging strategies, it is necessary to consider the randomness and heterogeneity of EV charging demands.

Reviews of the studies on the modelling of EV charging demand to identify the weakness and strength of each approach have been carried out in Ref. [16]. The studies conducted in Refs. [17, 18] proposed mathematical analyses of EV charging demands, in which the fluid dynamic traffic model and the queueing theory were utilised to evaluate the charging demands regarding spatial and temporal dynamics. The Markov chain models were built in Refs. [19, 20], uncertainties related to when and where EVs will be recharged were pre-defined by a global transition matrix in which charging events for the next time interval were only influenced by pre-determined transition probabilities. In deterministic studies, distribution network constraints were utilised to estimate the threshold level of EV penetrations that would exceed thermal ratings [21, 22, 49]. In probabilistic studies, stochastic procedures are used to complete the quantitative analysis [50]. The national transport survey was adopted in support of the extraction of probability density functions. The method of Monte-Carlo Simulation (MCS) was presented in Refs. [20, 51], where loading profiles with the integration of EVs were acquired by probabilistic density functions (PDFs). Ref. [13] also employed MCS to evaluate EV deployment impacts on a distribution network with increasing penetration levels.

The diverse stochastic techniques become a popular choice to generate EV charging data, which is considered as essential input parameters of controlled or optimised charging strategies to evaluate EV deployment impacts. Different charging algorithms, methods

and strategies in the field of smart EV charging systems were reviewed in Ref. [52]. A number of metaheuristic approaches can be found in centralised and decentralised charging strategies that manage EV charging behaviours to achieve optimisation targets, such as the minimum cost, the minimum power variance and the minimum emission [13, 53, 54]. The scheduling of EV charging loads in each domain is carried out by measuring local parameters or associated criteria, such as tariff signals or local electrical signals [55-59].

A rigorous estimation of EV deployment impacts at the system level is considered important for distribution network operators (DNOs) in the planning phase of network reinforcements. Most of the existing research works evaluate EV deployment impacts mainly based on reasonable assumptions about the randomness characteristic while ignoring the heterogeneity characteristic. For instance, in Ref. [20], the authors merely made use of a BMW i3 model to represent all EVs within the distribution network. The fixed EV plug-in time and plug-out time were assigned in Ref. [21] to simulate the worst-case scenario in which the EV charging demand overlap the peak residential loads. Ref. [60] introduced an example of the stochastic charging scenario with the application of the conditional Gaussian distribution to simulate arrival times, charging times and departure times for an EV fleet. A probabilistic model of EV driving patterns was developed in Ref. [19] based on different PDFs extracted from transportation survey data, but only one charging mode was considered in the model.

The research gap among these studies is the lack of consideration for heterogeneity in the modelling of EV charging demands so that the effectiveness level of charging strategies is not convincing. Such heterogeneity in EV charging loads is composed of factors that will change the profiles of EV charging loads, such as different daily driving mileages, recharging times and different compositions of EV fleets. For example, equivalent numbers of commercial EVs and private EVs may result in entirely different charging demands, which has been investigated in Ref. [61]. More importantly, despite the importance of EV charging behaviours in fore-mentioned works summarised, current smart charging strategies primarily rely on the simplistic representation of EV charging and travel behaviours. The promotion of EV usages will potentially alter the transport and electricity network. Hence, it is necessary to develop an empirically estimated model amenable for these integrated cross-sector analyses based on existing statistics data available. By this modelling technique, the proposed EV charging strategies can be carried out to validate the performance and effectiveness closer to a real case.

From the practical operation view, the EV scheduling problem is formulated as an optimization model in this paper in order to identify the grid benefits solution that satisfies the charging requests. Therefore, the main contributions of the paper are:

1. A large-scale EV charging model that bridges the gap between the representations of charging behaviour used in integrated transport and power system analyses for the appraisal of smart charging strategies.

2. A multivariate probabilistic model to estimate aggregated EVs charging loads with the consideration of randomness and heterogeneity based on transportation statistic data.
3. A case study to test effectiveness of non-smart and smart charging strategies regarding peak-shaving and valley-filling impacts on the aggregated EVs charging loads.

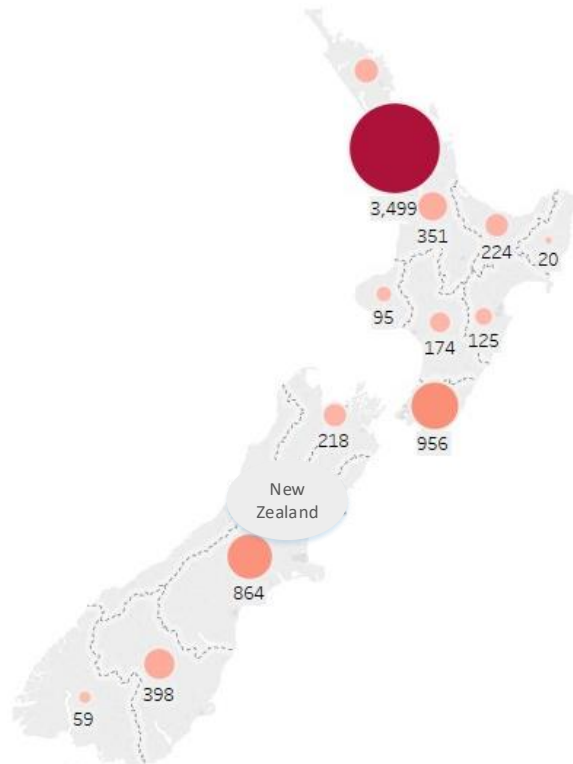
The rest of the paper is organised as follows. The EV charging and driving patterns considering all relevant factors are explained in Sections 2 and 3. Section 4 provides the modelling approach based on MCS. Then, the charging strategies and a case study are described in Section 5. The results and discussion are presented in Section 6, and the paper is concluded in Section 7.

2. EV Fleets Composition in NZ

The 2018 annual vehicles statistic from NZ Ministry of Transport [4] indicated that over 7000 Electric Vehicles (EVs) are running on the road, 49% of which are concentrated in Auckland as presented in Fig. 1. As shown in Table 1, although the EV penetration in NZ has experienced a rapid growth in recent years, it merely occupied nearly 0.1% in 2017 [4]. The EV penetration represents the percentage of the total EVs number over the total vehicles number.

Table 1 EV penetrations in New Zealand from 2014 to 2018

| Year | EVs Number | Annual EVs Fleet Growth | EV Penetration |
|------|------------|-------------------------|----------------|
| 2014 | 232 | | 0.01% |
| 2015 | 592 | 255.17% | 0.02% |
| 2016 | 1114 | 188.18% | 0.03% |
| 2017 | 2752 | 247.04% | 0.07% |
| 2018 | 7000 | 240.30% | |

**Fig. 1.** EVs Distribution Map in New Zealand in 2018

2.1 Projected Ownership of Electric Vehicles

The EV population is a critical determinant of EV charging demands. The New Zealand Center of Advanced Engineering (CAENZ) proposed four scenarios about future EV uptakes in Ref. [62] based on NZ government and consulting company works as shown in Table 2.

Table 2 Predicted EV populations in NZ

| Years | EV uptake scenarios (unit: millions) | |
|---------|--------------------------------------|------------|
| | Lower Case | Upper case |
| 2040 | 0.9 | 2 |
| 2030 | 0.3 | 1.2 |
| Current | 0.007 | |

2.2 Projected EV Fleets Composition

EV populations can be categorized into five main fleets according to EV ownership statistics in NZ, which are private EVs, utility EVs, commercial EVs, electric goods trucks, and electric buses [4]. The fleet categories include a variety of EV manufacturers, in which each brand has its own endurance mileage, battery capacity and charging power. Table 3 introduces five mains EV models to represent each EV fleet in the modelling of charging demands. Their technical parameters will be used in MCS. Fig. 2 depicts the composition ratio of ICEV fleets in NZ [4]. The present and projected amount of various EV fleets in Table 4 are derived from predicted EV populations in Table 2 with the assumption that the composition ratio of the five EV fleets is equivalent to that of the ICEV fleets in Fig. 2.

Table 3 Charging parameters of five types of EV models

| EV types | Manufacturers Model | Battery Capacity (kWh) | Charging Power (kW, P_C) | | Full endurance mileage (km, D) |
|---------------------|---------------------|------------------------|-----------------------------|----------------|-----------------------------------|
| | | | Slow Charging | Quick Charging | |
| Private Vehicle | Nissan-Leaf | 24/40 | 6.6 | 11 | 150/250 |
| Utility Vehicle | Nissan-Leaf | 40 | 6.6 | 11 | 250 |
| Commercial Vehicles | Nissan-Leaf | 40 | -- | 11 | 250 |
| Goods Truck | EMS 18 series | 240 | -- | 80 | 250 |
| Bus | AUT-BUS | 202 | -- | 50 | 200 |

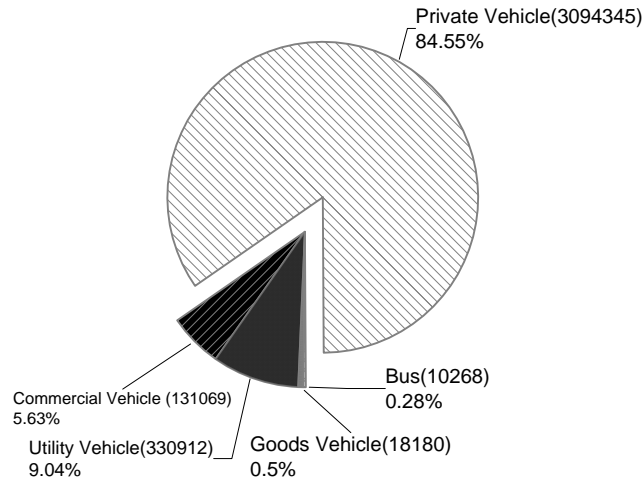


Fig. 2 2018 composition ratio of ICEV fleet in NZ

Table 4 The present and projected EV fleets in NZ

| EV uptake scenarios | Private Electric Vehicle | Electric Utility Vehicles | Electric Commercial Vehicle | Electric Goods Truck | Electric Bus |
|------------------------|--------------------------|---------------------------|-----------------------------|----------------------|--------------|
| 2018 Uptake | 5919 | 633 | 394 | 35 | 20 |
| 2030 Lower Case Uptake | 253660 | 27127 | 16881 | 1490 | 842 |
| 2030 Upper Case Uptake | 1014641 | 108507 | 67524 | 5961 | 3367 |
| 2040 Lower Case Uptake | 760981 | 81380 | 50643 | 4471 | 2525 |
| 2040 Upper Case Uptake | 1691068 | 180844 | 112540 | 9935 | 5611 |

3. Analysis of EV Charging Behaviour

Some existing studies [19, 20, 60, 63] in the appraisal of charging strategies relied on simplistic representation of EV fleets conforming to a certain probability model, which merely considered randomness of charging behaviours while ignoring heterogeneity. A multivariate probabilistic model is introduced to characterise both randomness and heterogeneity in the modelling of EV charging demand based on the summary statistics in NZ. Such model can be used to represent of consistent charging behaviours used in

integrated transport and power system analyses. It is assumed that advent of EVs will not affect daily travel patterns and lifestyles in general so that EVs have similar driving patterns with ICEVs. The following uncertainty factors are considered when modelling the 24-hour EV charging demand: (i) EV charging duration, (ii) EV charging power, (iii) EV daily travel distance/EV initial battery SoC, (iv) EV recharge probability, (v) EV plug-in time. These uncertainties were treated separately for each EV, which are random variables generated by predefined PDFs in Table 5.

The PDFs of EV daily driving distances are either of normal or logarithmic distribution type with a positive value of the travel distance [64-66]. It can be expressed by Eqs. (1) and (2), respectively.

$$f_{D1}(x_{i,j}) = \frac{1}{\sigma_{D1,j}\sqrt{2\pi}} \exp\left[-\frac{(x_{i,j}-\mu_{D1,j})^2}{2\sigma_{D1,j}^2}\right], x > 0 \quad (1)$$

$$f_{D2}(x_{i,j}) = \frac{1}{x\sigma_{D2,j}\sqrt{2\pi}} \exp\left[-\frac{(\ln x_{i,j}-\mu_{D2,j})^2}{2\sigma_{D2,j}^2}\right], x > 0 \quad (2)$$

where $i = \{1, 2, 3 \dots N_j\}$ represents i^{th} EV in the specific EV fleet, $j = \{1, 2, 3, 4, 5\}$ is the total vehicle amount in the specific EV fleet, specifically 1: private EVs, 2: utility EVs, 3: commercial EVs (taxies), 4: electric goods trucks, 5: electric buses. $x_{i,j}$ is the daily travel distance of an EV, $\mu_{D1,j}, \mu_{D2,j}$ are mean values, and $\sigma_{D1,j}, \sigma_{D2,j}$ are standard deviation values. For different EV fleets, the corresponding mean values and standard deviations are defined in Table 5.

The endurance mileages of different EV models are related to their corresponding battery capacities. Given the full endurance mileage D_j , the initial state of charge $SOC_{i,j}$ can be estimated by Eq. (3).

$$SOC_{i,j} = 1 - \frac{d_{i,j}}{D_j * \eta_1}, \quad 0.05 \leq \frac{d_{i,j}}{D_j * \eta_1} \leq 0.95 \quad (3)$$

where $d_{i,j}$ represents the daily travel distance of i^{th} EV, which is a random variable derived from Eqs. (1) and (2). All vehicles need to be fully charged before the next journey starts.

Various studies about the efficiency of EV powertrain have been carried out to include the loss of battery power in driving cycles and the battery life cycle [67, 68]. This study considered $\eta_1 = 0.95$ to represent the loss of battery power during EV running.

The plug-in time $tp_{i,j}$ is given in Eq. (4).

$$f_t(tp_{i,j}) = \frac{1}{\sigma_{t,j}\sqrt{2\pi}} \exp\left[-\frac{(tp_{i,j}-\mu_{t,j})^2}{2\sigma_{t,j}^2}\right] \quad (4)$$

where $tp_{i,j}$ is the plug-in time of an EV, $\mu_{t,j}$ is the mean value, and $\sigma_{t,j}$ is the standard deviation. For different EV fleets, the corresponding values of $\mu_{t,j}$, $\sigma_{t,j}$ are defined in Table 5.

In Eqs. (5)-(8) $tc_{i,j}$ is the charging duration of i^{th} EV in j^{th} fleet type, $Cap_{i,j}$ is the full battery capacity, charging efficiency η_2 is 0.95 in all cases, N_j is the total number of the specific EV fleet. $td_{i,j}$ is the charging duration to reach $SOC_{i,j} = 0.95$ with rated charging power $P_{C_{i,j}}$ defined in Table 3. $P_{EV_{i,j}}(t)$ is the charging power of each EV at time t, $P_{EV}(t)$ the total EV charging power at time t.

$$tc_{i,j} = \sum_{i=1}^{N_j} (0.95 - SOC_{i,j}) \times \frac{Cap_{i,j}}{P_{C_{i,j}} \times \eta_2} \quad (5)$$

$$td_{i,j} = tp_{i,j} + tc_{i,j} \quad (6)$$

$$\begin{cases} P_{EV_{i,j}}(t) = P_{C_{i,j}}, & tp_{i,j} \leq t \leq td_{i,j} \\ P_{EV_{i,j}}(t) = 0, & \text{other time} \end{cases} \quad (7)$$

$$P_{EV}(t) = \sum_{j=1}^5 \sum_{t=i}^{N_j} P_{EV_{i,j}}(t) \quad (8)$$

Over 80% of light vehicles were parked overnight at private residences or private off-street locations [62]. The assumptions in this model are to consider that 80% of the private EVs plug in the charging infrastructure during the off-work period 18:00 p.m.- next 07:00 a.m. and the remaining 20% will be recharged during working hours 9:00 a.m.-17:00 p.m. The values of μ_{D2} and σ_{D2} for private EVs are considered to be 3.2 and 0.92 respectively based on the average daily travel distance of 23.2 km specified in [62]. Due to the absence of travel data on utility EVs, it is assumed that it has the same driving pattern with private EVs. Typically, there are three working shifts for commercial EVs (Taxies) per day, 0:00-9:00, 9:00-16:00, 16:00-24:00. In Ref. [69], authors pointed out driving distances of taxi drivers in every driving shift are ranging from 33 km to 350 km (an average of 195.49 km, μ_{D1} , std. dev. of 49.99, σ_{D1}), thus charging twice a day is necessary to support the driving requirement. It is reasonable to assume that commercial EVs are quite likely to be charged with the fast charging mode because the shorter charging time implies longer service hours to make profit. A survey of 95 truck drivers carried out in Ref. [69] also revealed that daily driving distances are ranging from 38 km to 500 km (an average of 201.80 km, μ_{D1} , std. dev. of 94.42, σ_{D1}). Two charging times and the high charging mode are essential to electric goods trucks as well. The electric buses are usually recharged with the high charging mode during off-service periods. As electric buses have relatively fixed daily routes so that their daily travel distances are relatively stable. The probability

distribution parameters are $\mu_{D1} = 155, \sigma_{D1} = 10$ according to electric bus operation data from Auckland University of Technology [70].

According to the summary of travel survey discussed above, Fig. 3 presents the probability distributions of five EV fleets' daily travel distances. The corresponding PDFs parameters are summarised in Table 5.

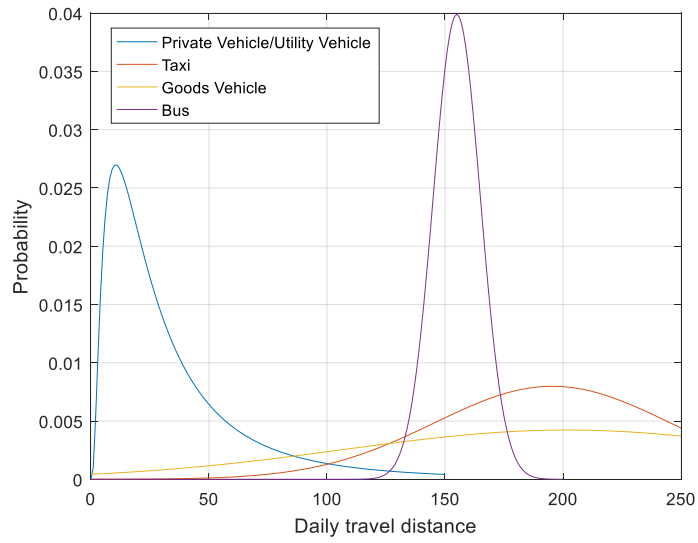


Fig. 3 Probability distributions of daily travel distances by vehicle types

4. Modelling Method of EVs Charging Load

4.1 Monte Carlo Simulation

The multivariate probabilistic model in MCS aims to estimate EV charging demands according to the transportation statistics data in New Zealand. The following are assumptions made for the simulation conducted in this paper:

- a. Charging facilities are enough so that the EV owners start charging immediately once parked.
- b. The generation capacity is enough to supply EV loads.
- c. The charging power is rounded to the nearest integers toward infinity in the hourly charging power calculation

4.2 Calculation Process of EV Charging Load based on MCS

In the MCS, $tp_{i,j}$, M_c and $SOC_{i,j}$ are independent stochastic variables for each EV, which are generated based on the modelling parameters in Table 5. The MCS schematic process is presented in Fig. 4, specifying the following steps:

1. Initiate EV modelling parameters listed in Table 3 and Table 4.
2. Based on the probability density functions of stochastic variables, EV charging demand data is generated by Eqs. (1)-(4).
3. Get the charging load of each EV based on Eqs. (5)-(6).
4. Accumulate the charging load of each EV. Loop counts until total EV calculation complete by Eqs. (7)-(8).

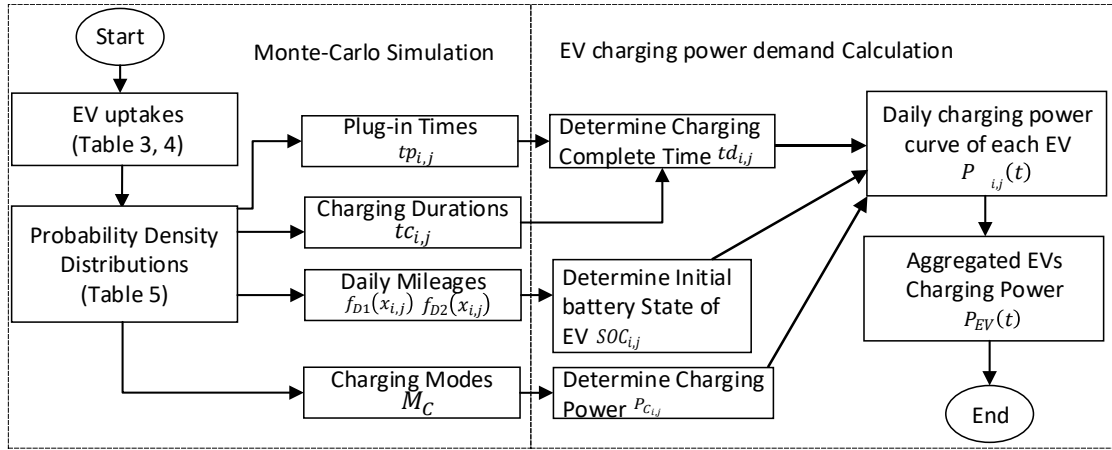


Fig. 4 The schematic process of EV charging demands simulation

5. EV Charging Strategies

According to empirical estimations, private EVs, utility EVs and electric buses have more charging flexibility during the night. In contrast, commercial EVs and electric goods trucks are essential to be fully charged within the shortest time for the next driving work so that they are not participated in charging strategies.

The flowchart of the proposed EV charging strategies is displayed in Fig. 5. The input parameters for each charging strategies are obtained from the MCS. The targeted EV fleets selected by the proposed charging strategies are private EVs, utility EVs and electric buses when they plug in networks after $Tp=18:00$ p.m. and plug out before $Td=\text{next } 7:00 \text{ a.m.}$ (next day usage constraint). Optimization algorithms aims to achieve peak-shaving and valley-filling effect on the typical daily power curve, and at the same time, to guarantee selected EV fleets to be fully charged before expected usage time 7:00 a.m.

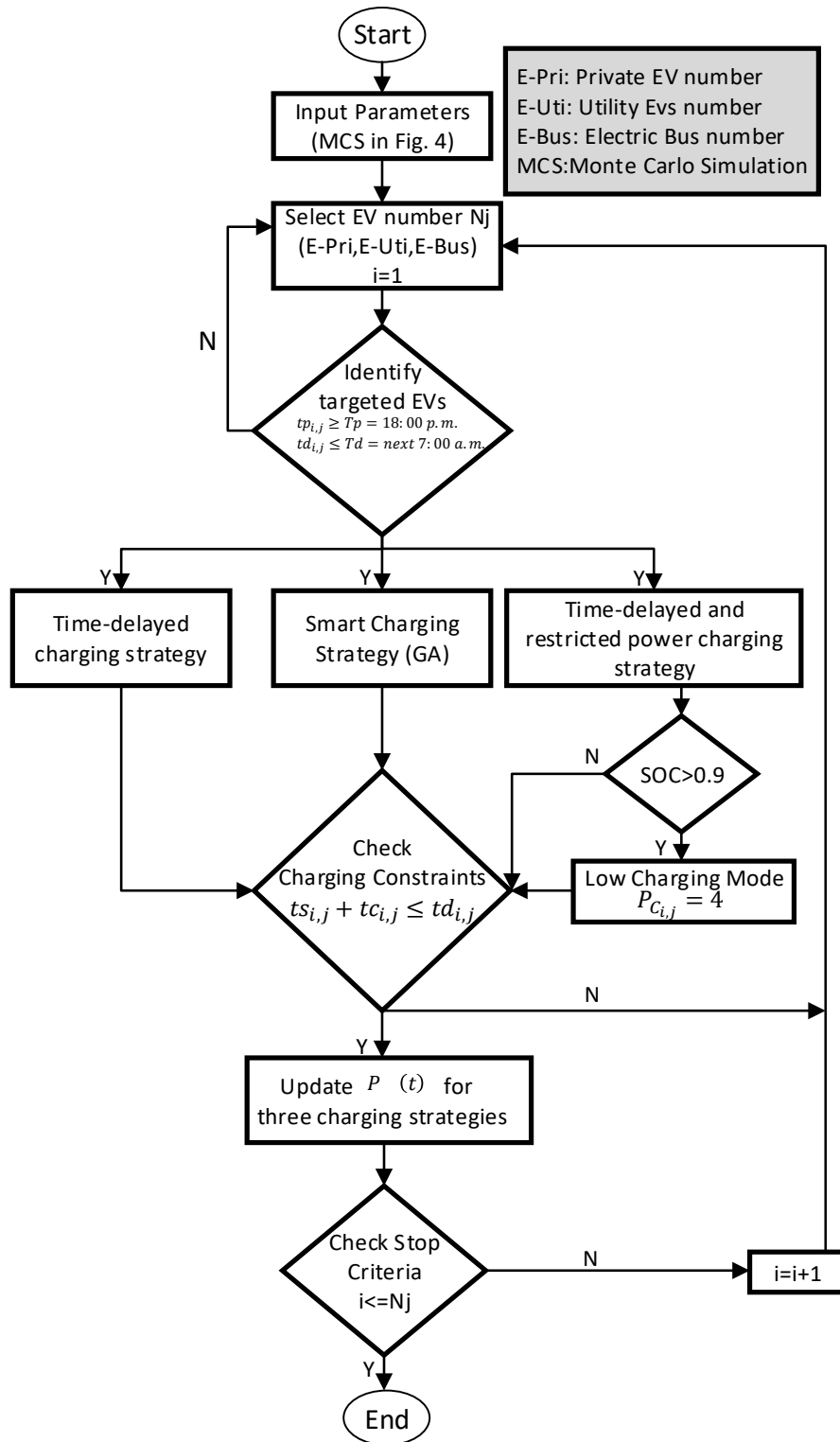


Fig. 5 Flowchart of EV charging Strategies

5.1 Non-smart EV Charging Strategies

5.1.1 Time-Delayed EV Charging Strategy

EV charging data is obtained from MCS described in Fig. 4. The selection process of specific EV fleets for the charging strategy is presented in Eq. (9): Only private EVs, utility EVs and electric buses are considered in the charging strategy. The scheduling duration is between 18:00 p.m. and next 7:00 a.m.

$$\begin{cases} tp_{i,j} \geq 18:00 \text{ p.m.} & j = \{1,2,5\} \\ td_{i,j} \leq \text{next } 7:00 \text{ a.m.} & j = \{1,2,5\} \end{cases} \quad (9)$$

Eq. (10) delays start charging time $ts_{i,j}$ by 3 hours after EV plug-in time $tp_{i,j}$ and verifies charging period constraints to make sure that each EV completes the charging before $td_{i,j}$ (the next day expected usage time 7:00 a.m.)

$$\begin{cases} ts_{i,j} = tp_{i,j} + 3 & j = \{1,2,5\} \\ ts_{i,j} + tc_{i,j} \leq td_{i,j} & j = \{1,2,5\} \end{cases} \quad (10)$$

5.1.2 Time-Delayed and Restricted Power EV Charging Strategy

This charging strategy combines the time delayed process and the restricted charging power process. The time-delayed process is the same as described above. The additional restricted power process is to assign a new charging power $P_{C_{i,j}} = 4 \text{ kW}$ instead of 6.6 kW, to private EV and utility EVs if the initial battery SoC is over 0.9, as described in Eq. (11)

$$\begin{cases} P_{C_{i,j}} = 4, \text{ for } 0.9 < SOC_{i,j} \leq 1 \\ P_{C_{i,j}} = 6.6, \text{ for } 0.05 < SOC_{i,j} \leq 0.9 \end{cases} \quad (11)$$

5.2 Smart Charging Strategy based on Genetic Algorithm

The same EV fleets and scheduling duration as previously described are considered in the smart charging strategy. The objective function in Eq. (12) is to minimize the peak-valley difference on power curves by applying Genetic Algorithm (GA). The decision variable in Eq. (13) is the start charging time $ts_{i,j}$ of each EV.

- Objective Function

$$\text{Min } \sum_{t=1}^T P_{T.var}(t) = P_{T.max}(t) - P_{T.min}(t) \quad (12)$$

- Decision Variable

$$tp_{i,j} < ts_{i,j} \leq td_{i,j} - tc_{i,j} \quad (13)$$

- Charging Conditions

In the smart charging strategy, the charging power of each EV is set up based on Eq. (11) as well, except for electric buses with the high charging mode. The total charging power are calculated according to Eqs. (14) and (15).

$$\begin{cases} P_{EV_{i,j}}(t) = P_{C_{i,j}}, & ts_{i,j} \leq t \leq ts_{i,j} + tc_{i,j} \\ P_{EV_{i,j}}(t) = 0, & \text{other time} \end{cases} \quad (14)$$

$$P_T(t) = P_{base}(t) + P_{EV}(t) \quad (15)$$

where $P_{base}(t)$ is the original demand-side base load at time t , $ts_{i,j}$ is the start charging time; in the smart charging strategy, the EVs do not have to be recharged once parked.

The start charging times is subject to the optimization process. $P_{T,\max/\min}(t)$ is the total electrical load at time t . The subscripts mean maximum and minimum values.

5.3 Genetic Algorithm Implementation

An appropriate scheduling of the charging times may lead to energy savings, but at the same time, it also increases the complexity as it needs to satisfy constraints from a set of EV users and the electrical network. The choice of scheduling optimisation algorithms depends on several aspects, such as the computation time, the required quality of solutions, and the selection of the problem's constraints or objective functions.

The use of GA has been discussed in Refs. [53, 71-73] as a well-established heuristic approach to compute EV scheduling. In particular, the natural evolution character of GA is able to make the process more likely to converge to a global optimum. Therefore, it has been proven to be robust optimisation techniques dealing with non-linear and non-convex problems in the EV scheduling [71]. Also, GA has the ability to work with search spaces by using multiple points of the population and iterative characteristics and to exploit any kind of heuristic knowledge from the problem domain, and by doing so, it is competitive with the most efficient methods in the scheduling [73]. Given that decision variables used in this study are a type of floating numbers, according to the satisfactory performance of GA for discrete spaces [53], GA was selected to solve EV scheduling problems in this study.

In this article, three adjustable parameters P , Cr , Mr need to be defined to solve the scheduling problem. P is the population size in each generation (alternatively iteration),

which directly affects the computation time and convergence rate. In genetic operators, Cr and Mr are crossover rate and mutation rate, respectively, to enable GA to enhance search capability. The adjustment of P , Cr and Mr tries to remove the undesirable response and to obtain more optimal solutions at the given computation time step. A sensitivity analysis based on the empirical method is conducted to determine values of P , Cr and Mr , aiming to achieve lowest mean fitness of the obtained results in each generation, in other words, to achieve the lowest power variation on the load curve, as displayed in Fig. 9b. With a population size of 10, cases 1-3 in Fig. 6 demonstrate that $Cr=0.8$ and $Mr=0.1$ obtain the highest computing efficiency. The purpose of cases 4-6 in Fig. 6 is to find an appropriate value of population size ($P=300$) to obtain the best solution set at the given computation time step, which is considered as 3 minutes for 2018 EV uptake.

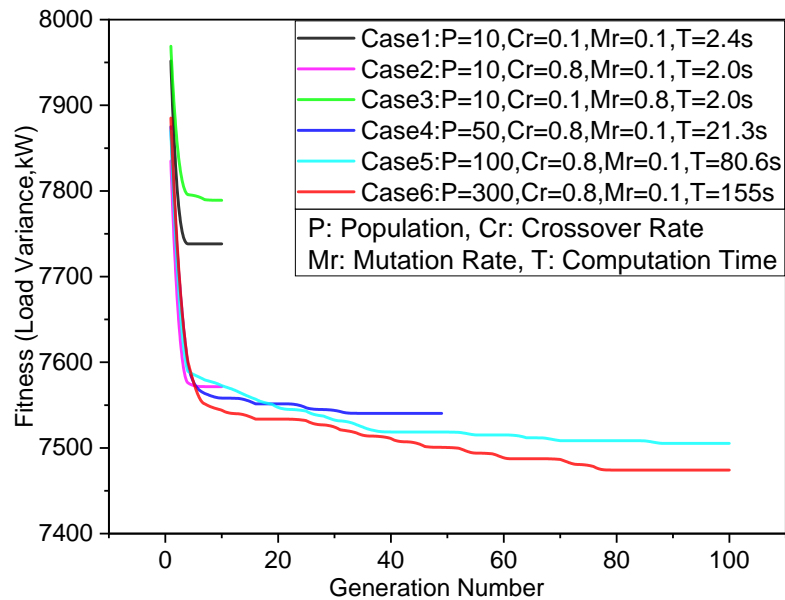


Fig. 6 The average fitness of the population in the parameter tuning

The GA implementation begins with the encoding, in which EV charging data specified in Table 5 is used as constraints ($tp_{i,j}, td_{i,j}$) to determine the feasible solution space of the population. The decision variable $ts_{i,j}$ for a set of EVs are encoded into a chromosome of parent generation. The population size ($P=300$) in each generation is composed of 300 chromosomes. The chromosome of offspring generation inherits part of genes from the parent generation while also receives some modified part of gene from crossover and mutation operator, which can be described as the global searching capability for the decision variable in Eq. (13). A proper fitness function described in Eq. (12) is designed to search a potential set of $ts_{i,j}$ to give a lowest grid load variance, at the same time, to guarantee selected EV fleets to be fully charged before expected usage time 7:00 a.m. The loop iteration will repeat again to produce new generations until iteration converges to stopping criteria.

5.4 Case Study

A case study is utilized to evaluate the effectiveness of the proposed charging strategies. The Auckland real-time base load and demand-side wholesale electricity price from [74] are used in the simulation. The NZ 2030 lower case EV uptake is considered in the Auckland city case study. There will be 0.3 million EVs running on the road, 49.9% of which are in Auckland District. The composition ratio of five EV fleets is based on the current statistical data introduced in Fig. 2. The total charging cost of EV could be estimated based on Eq. (16).

$$Tcost = WEprice(t) \times P_{EV}(t) \quad (16)$$

where $WEprice(t)$ is demand side wholesale electricity price.

5.5 Applicability

The modelling of EV charging demand could be either on-line or off-line. In the off-line system, the EV travel and charging patterns were extracted from summary statistics, as the real world data about EV use is not publicly available. The variability of EV travel and charging patterns could be redefined in Table 5 to access short-term EV charging demand if on-line charging events data can be obtained. The modelling process may appear suitable for long-term planning, such as planning of power generation capacity, planning of network reinforcement.

The proposed strategies can be potentially applied for on-line smart charging systems. Fig. 7 displays a schematic structure of the on-line smart EV charging system. Start charging times $ts_{i,j}$ of EVs are considered as decision variables in the optimisation process. The data communication between EV chargers and local servers could be realized by either wire or wireless technology, such as internet of things and the power line communication. Overall, the operation of the system is based on the event-driven architecture. The main event in this system is the occurrence of EVs plug-in and plug-out. In this methodology, EV users, EV chargers, local servers and main server should perform a set of tasks, as shown in the following process:

- Every EV charger transmits battery parameters and requests a start charging time for the specific parking duration and the expected battery SoC set by the user.
- The local server acts as a data aggregator to collect all EV charging requests within its domain at each computation time step (3 minutes).

- The main server executes the optimal charging algorithm taking into account all EV chargers' data and predicted base loads at the current time step. The scheduled start charging times $ts_{i,j}$ are sent back to all chargers through local servers.
- The requested EV chargers update the charging schedule and execute it.
- Any charging process is interrupted before the estimated plug-out time. EV chargers will send a disconnection request to the local server.
- The main server will receive interrupted charging signals and update new EV charging loads for scheduling in the next time slot.

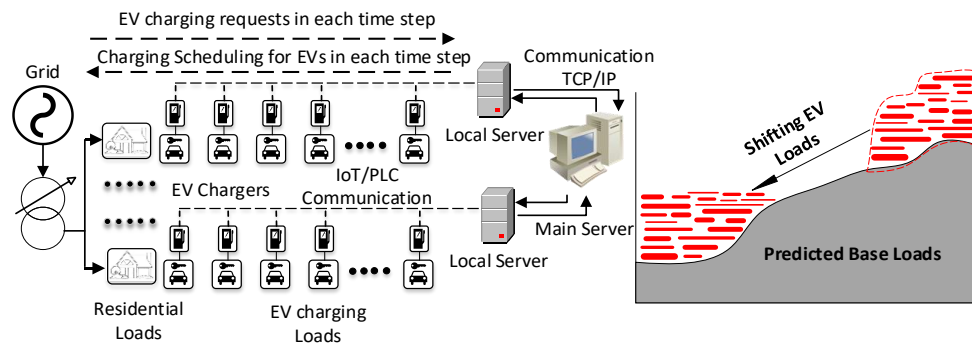


Fig. 7 Schematic structure of an on-line smart EV charging system

6. Results and Discussion

6.1 Free EV Charging Power Demand

The 2018 EV uptake defined in Table 4 have been applied in MCS to generate a charging demand that is closer to the real-case in NZ. The temporal distribution of the uncontrolled EV's charging demand is conducted in the probabilistic model as depicted in Fig. 8a. The simulation results display private EVs and utility EVs are mainly recharged in early hours during on-work and off-work periods. Due to longer daily travel distances, the electric goods trucks, commercial EVs and electric buses have lower initial battery SoC, represented by blue, green and pink dots.

After the EV charging data is obtained, the total daily EV charging power $P_{EV}(t)$ could be calculated based on the flowchart described in Fig. 4. By far the greatest charging demand in Fig. 9a is from private EVs, contributing roughly 14MW rapid growth on the black power curve between 18:00 a.m. and 24:00 p.m. The uncontrolled EV charging scenario gives rise to the overall charging demand at early night with a peak power of 19 MW, which is almost the same time as when households turn their heating, cooking and other appliances on.

The charging period of private EVs, utility EVs and electric buses could be further delayed to avoid peak hours as their charging process almost ends up before 2:00 a.m. when it is still too early for the next day's usage.

6.2 Coordinated EV Charging Power Demand

The free EV charging load profiles in Fig. 8a and Fig. 9a reveals that private EVs and utility EVs are the primary sources contributing to the rapid power raise due to higher penetrations. As introduced in Section 5, three charging strategies are designed to coordinate selected EV fleets when plugged-in during 18:00 p.m.-next 7:00 a.m. without affecting EV use in the next day. Fig. 10 presents a comparison between coordinated EV charging load curves and original EV charging load curves, where the peak power point was decreased from 19 MW to 12.5 MW and finally levelled out at 10.9 MW in the smart charging strategy. Therefore, it is apparent from Fig. 8b and Fig. 9b that the concentrated charging loads in peak hours were delayed to span on off-peak periods to reduce load variance.

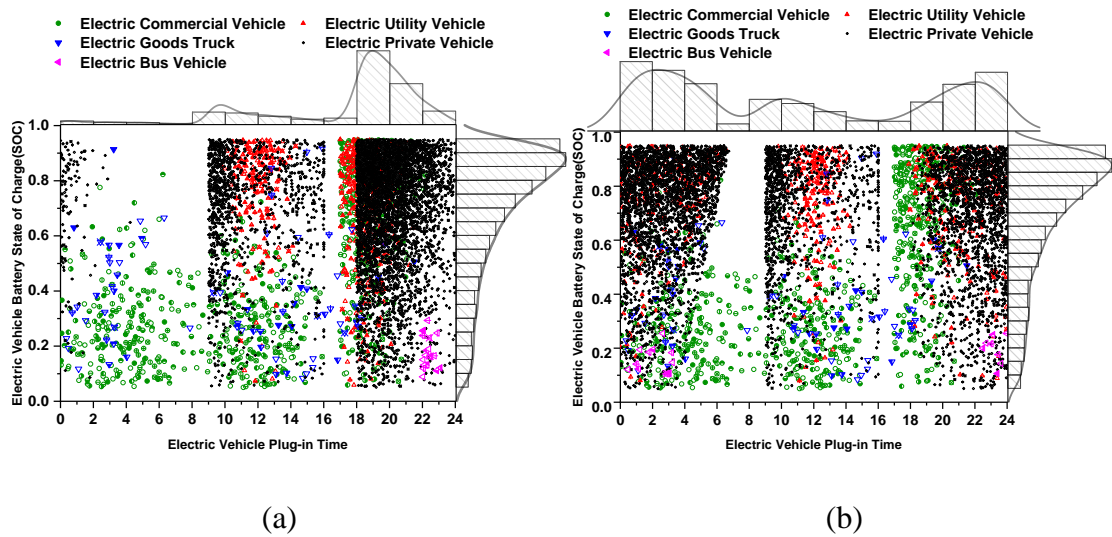


Fig. 8 (a) Scatter plot between plug-in time and initial SoC in 2018 NZ free charging scenario (b) Scatter plot between plug-in time and initial SoC in 2018 NZ smart charging scenario

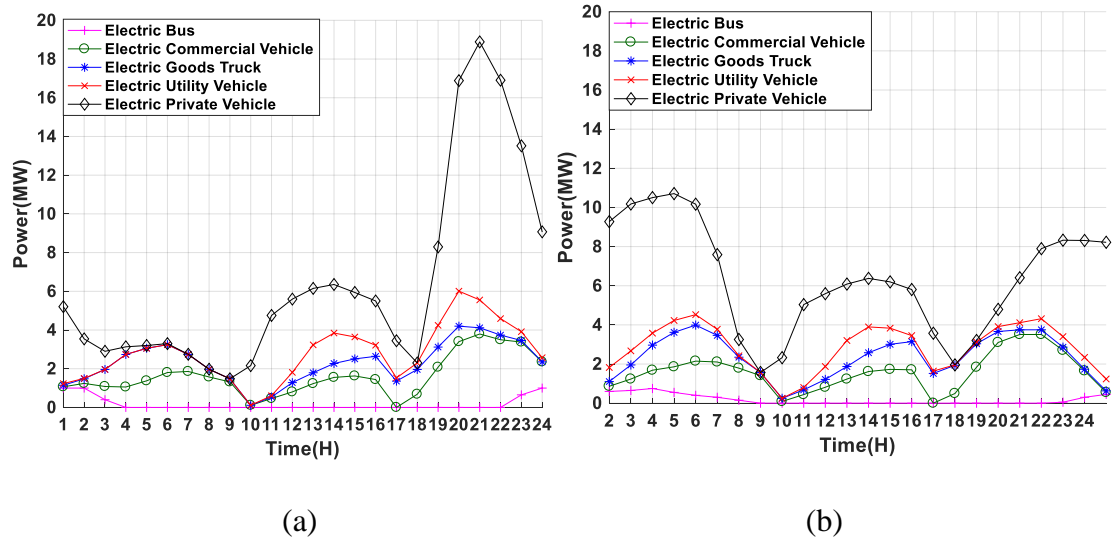


Fig. 9 (a) Indicated NZ EV charging profile in 2018 free charging scenario
(b) Indicated NZ EV charging profile in 2018 smart charging scenario

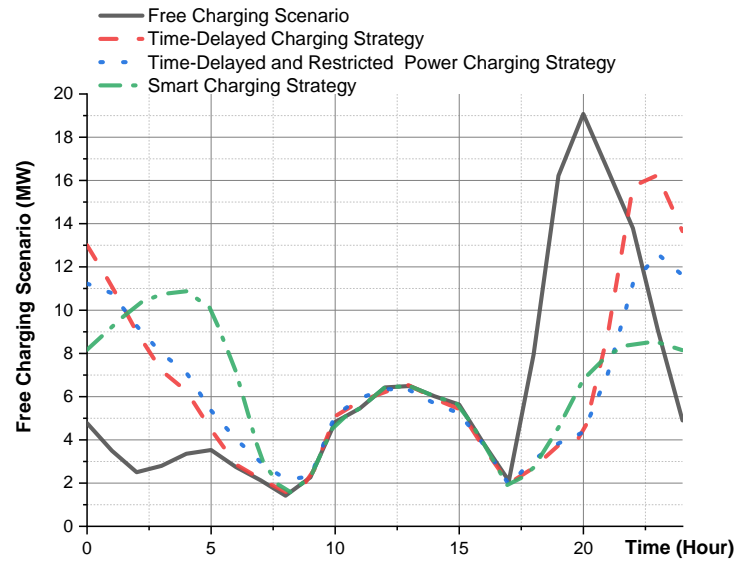


Fig. 10 Indicated NZ EV charging load profile in 2018 with three charging strategies

6.3 Management of EV Charging Demand: Case Study

Currently, there are just 3499 EVs in Auckland and may not lead to a distinct increase in the daily power load profile. Therefore, the 2030 lower case EV uptake is adopted in the case study as detailed in Section 5.4.

Fig. 11 displays EV deployment impacts on the Auckland electrical load curve (22/05/2018). From the free charging load curve (red dotted), we can see that the peak charging demand coincides with peak hours of the day, leading to a peak power of nearly 1400 MW. Comparing charging load curves in three charging strategies, it is found that there is no noticeable load spike as the peak charging demand is delayed to off-peak periods. Consequently, proposed non-smart and smart charging strategies demonstrate a positive correction on the electricity load profile regarding peak-shaving and valley-filling influences.

The further statistical analysis shown in Fig. 12 demonstrates effectiveness levels of three charging strategies. The smart charging strategy achieves the best performance to flatten the power curve with a power variance range between 788.55 MW and 1173.83 MW. With the extra EV burden, various power curves have similar mean values nearly 990 MW, which could be explained by the electrical energy consumptions from the same EV uptake. The analysis results are summarised in Table 6. In 2030 EV lower case, the growth rate of Auckland peak loads will reach 31% without proper management of the EV charging demands. Whereas, by applying the proposed charging strategies, the growth rate can be restricted to merely 6%~9%. The standard deviation of the electrical loads with integration of EVs decreases from 234 MW to 128 MW. The charging cost savings due to the lower electricity price after midnight gives an economic incentive to EV owner to give up direct control of the charging process.

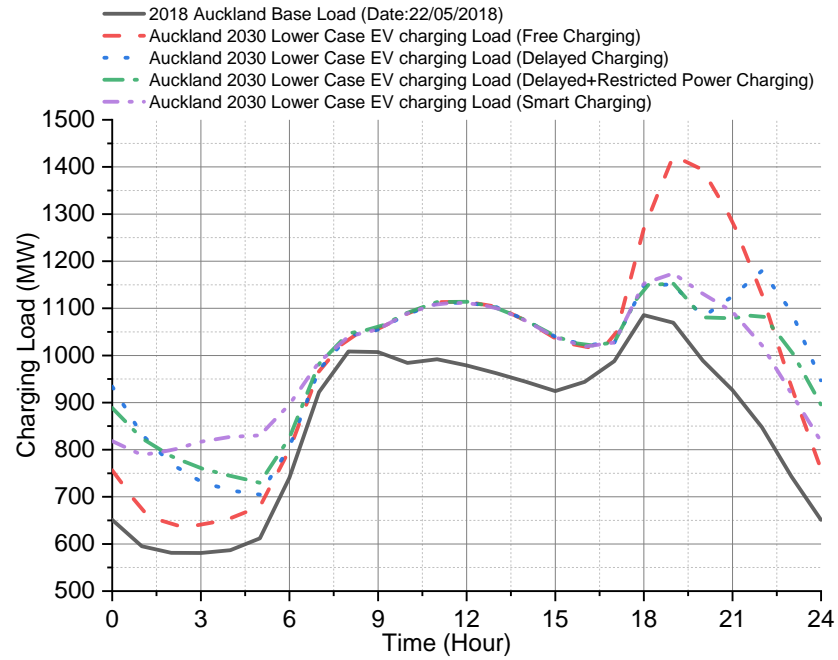


Fig. 11 Indicated EV charging load profile with three charging strategies

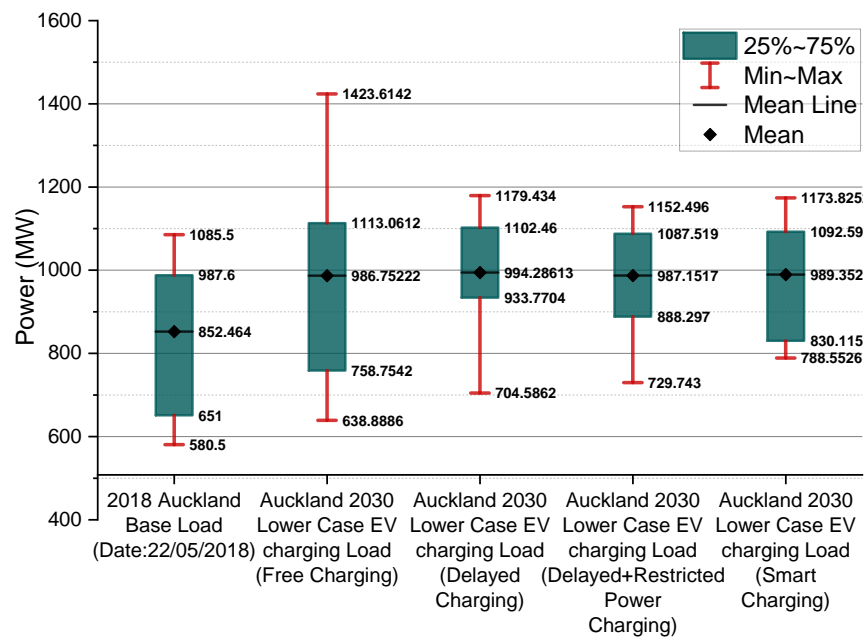


Fig. 12 Box plot of indicated EV charging load profile in 2030 with three charging strategies

Table 6 Charging indexes of large-scale EVs deployment in Auckland power system

| | Auckland Electricity Load in 2018 | Auckland 2030 Lower Case EV charging Load | | | |
|-------------------------------------|-----------------------------------|---|---------------------------|--|-------------------------|
| | | Free charging | Delayed charging strategy | Delayed and restricted power charging strategy | Smart charging strategy |
| Peak Load(kW) | 1086 | 1423 | 1179 | 1152 | 1173 |
| Peak Load-Growth Rate | | 31% | 9% | 6% | 8% |
| Load Standard Deviation(kW) | 175 | 234 | 149 | 136 | 128 |
| Load Standard Deviation Change Rate | | 34% | -15% | -22% | -27% |
| <i>Tcost</i> (Thousands NSD\$) | | 118 | 109 | 107 | 113 |

6.4 Future EV Deployment Impacts

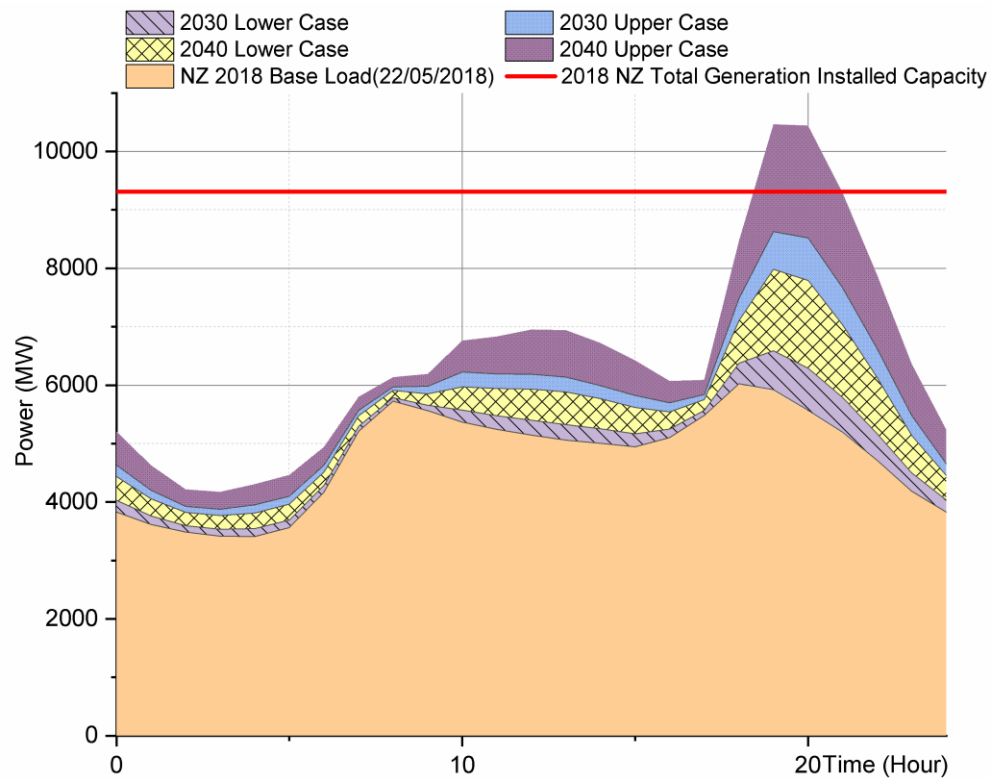
**Fig. 13** Indicated Charging load profile of future EV uptakes

Fig. 13 exhibits the indicated 24-hour base load profile with future EV uptakes specified in Table 4. Without consideration of the base load growth, the lack of demand-side

management on EVs may challenge NZ national power system regarding power generation, transmission and distribution equipment, leading to peak loads from 6024MW to 10464MW. It may exceed New Zealand's total installed generation capacity of 9281MW [75].

7. Conclusions and future research

In this paper, the uncertainty problems in planning of distribution networks with integration of EVs have been addressed. The estimation of aggregated EV charging loads based on the elaborated multivariate probabilistic model is implemented in MCS, taking into account several factors that may affect the loading profiles. EV charging and driving patterns are considered in the modelling in order to present the EV charging demand closer to a realistic scenario, in which the randomness and heterogeneous characteristics have been detailed by the proposed methodology. Moreover, the evaluation of EV charging demand at the national level reveals the potential shortage of generation installed capacity in NZ based on future EV uptakes. The case study demonstrates the peak charging demands as a result from the coincidence of EV charging loads and residential loads has been mitigated by the proposed coordinated charging strategies, in which targeted EV fleets were rescheduled to flatten the load curve, so as to postpone the investment of network reinforcement.

This study has shown the EV modelling technique used for the cross-sector analysis (transport and energy sectors) regarding the temporal distribution of charging behaviours, and charging strategies. However, more research and analysis are required to justify the

adoption of EVs on the spatial distribution in electrical networks, and on economic incentives in demand-side response. Future works will explore price and non-price incentives for behavioural change in the design of EV charging strategies under a smart distribution network environment. Extending the smart charging strategy into temporal, spatial and economic considerations in the distribution networks could be a focal spot for the analyses of integrated transport and power systems at the tactical and operational level.

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This manuscript further develops the scheduling strategy that runs on an online management system. The online system is developed in the rolling horizon scheduling framework with considerations of EV availability, power flow constraints and profitability of charging service. All the information in the rolling horizon scheduling strategy will be updated, calculated and partially forecasted at each time interval until the end of the day. From the economic operation view, the profitable charging problem is formulated as an online optimisation model to identify the economic solution that satisfies both EV users and DNOs. In the competitive energy market, this active management scheme is proposed to solve the economic integration of the aggregated EVs in distribution networks.

The manuscript was published in the journal of 'Applied Energy' with the title: "A rolling horizon scheduling of aggregated electric vehicles charging under the electricity exchange market".

A rolling horizon scheduling of aggregated electric vehicles charging under the electricity exchange market

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Abstract

The uncertainty of plug-in electric vehicle (EV) charging behaviour is a crucial factor that not only influences the peak power demand in distribution networks, but also the tariff plans of EV charging service. The uncertain upstream electricity price considerably complicates the issue regarding how to achieve specific economic goals for distribution network operators (DNOs) while guaranteeing EV users' interest. A rolling horizon scheduling approach based on Genetic Algorithm (GA) is proposed in this paper to provide a win-win strategy for both DNOs and EV users. It deals with the online optimal scheduling problem of aggregated EVs in the energy exchange market. The objective of the scheduling strategy is to maximise DNOs' profit margin by charging EVs in the low price time intervals as well as shifting peak charging loads. The operational constraints of EVs' availability and electricity bidding are all considered in the time rolling horizon framework, meaning all this information will be updated, calculated and partially forecasted at each time interval until the end of the day. A case study is carried out with a 33-node distribution network to verify the effectiveness of the proposed scheduling strategy. In detail, specific tariff plans can be determined toward possible values of uncertain market price to satisfy utilities' economic targets. In this way, both individuals

and energy providers that participate in the energy market can benefit from the proposed rolling horizon strategy and keep the uncertainty under control.

Keywords:

Electric vehicle, online scheduling algorithm, win-win strategy, rolling horizon, genetic algorithm

1. Introduction

In response to incentives on carbon emission reductions, the general goal of governments around the world is to encourage the deployment of electric vehicles (EVs) in the densely populated area. The trending of electrification in the vehicle manufacturer is considered a sustainable and environmentally friendly alternative to conventional vehicles [76]. For instance, the New Zealand (NZ) emission reduction target under the Paris Agreement aimed to reduce Green House Gas (GHG) emissions by 30 per cent below 2005 levels by 2030. Under this background, the NZ government announced an EV program with a short-term goal of reaching 64,000 EVs on the road by the end of 2020 [77]. In most countries, the current grids with existing infrastructure cannot ensure an economic and stable operation with the increasing penetrations of EVs. It has been noticed that uncoordinated EV charging behaviours are quite likely to result in inefficient operations in the power system, such as elevated peak loads, the power quality degradation and increased energy losses [24, 78]. Various scheduling strategies have attracted many attentions and have been thoroughly discussed in recent years, aiming to adopt more intermittent and random electricity prosumers like EVs and renewable energy [79].

Implementing a cost-effective upgrade on power utility infrastructure normally comes with an economic solution that benefits stakeholders participated in the EV integration, such as charging operators, EV customers and distribution network operators (DNOs). It involves extra investments in charging facilities and power distribution equipment. In this situation, it is necessary to investigate economic scheduling strategies before reaching a wide deployment of EVs [80]. The economic EV integration may refer to an optimal scheduling problem in the energy trade market. Under the competitive market environment, the EV charging tariff is the key factor to affect the charging demand as high demand periods normally accompany with high costs. The pricing mechanism of the charging tariffs potentially shifts the extra EV charging demands into the load-valley period to minimise the network's loading level. However, the challenge is to make a trade-off situation in which proposed charging tariff can achieve appropriate load-shifting effectiveness for DNOs while satisfying economic interests for EV owners. The tariff plan means that EV users pay different rates for power. The tariff price is normally higher than the wholesale electricity price to gain appropriate profits for DNOs. [81, 82]. In order to achieve the economic EV integration, DNOs may need to determine the optimal tariff plan by resorting to appropriate strategies, which implies the necessity of online optimal scheduling for EVs [83].

As discussed in [84], the online charging scheduling problem was naturally formulated as finite-horizon dynamic programming with continuous state space and action space. It was referred to the general model predictive control (MPC) to generate a near-optimal solution for exogenous random variables in each time stages. Ideally, the charging

demand can be flattened as much as possible if the future information about the plug-in event is known in advance. In practice, the charging station can only know the plug-in time of EVs that have been arrived. Fortunately, statistical information on plug-in events can be estimated from daily driving mileage and charging behaviour analysis [85]. However, the problem is to decide the proper charging tariff to manage the EV charging demand. With the uncertain upstream electricity pricing, the risk-involved participation urges charging operators or DNOs to predict future energy price to carry out profitable scheduling [86]. To overcome this issue, there is a persistent need to adopt partially forecasted price information in the design of online EV scheduling algorithms [87]. In this paper, the proposed online scheduling strategy, on one hand, deals with EV charging scheduling within certain time interval by deciding EV's start charging time for the sake of lower charging cost; on the other hand, helps DNOs to develop a profitable charging tariff by partially forecasting wholesale electricity prices. It would considerably reduce risks of electricity auctions for market players, yet, offering relatively lower charging costs to EV users.

Numerous algorithms were found in centralised, decentralised or agent-based charging strategies that manage EV charging processes to achieve optimised targets [88]. Comparing to the centralised strategy, the agent-based or decentralised strategies offer great flexibility in the multi-targets control, and good computation and convergence capabilities [89, 90]. Several optimisation algorithms such as genetic algorithm (GA) [91], particle swarm optimisation [92], water filling algorithm [93] were considered robust techniques in the EV scheduling strategies to cater for complex power system

constraints [94]. An overview of the research pathway among these latest research works is briefly described in Fig. 1, regarding the integration of EVs into distribution networks. The dynamic problem has been discussed in many studies. An interaction model in [95] was proposed to solve the unbalances of the charging demand and load deviation with considerations of time-of-use (TOU) pricing. The study aims to find mutually beneficial charging scheduling to satisfy the different interests of the system operators and the EV users. However, it is under the assumption that all EV plug-in events and tariff are known in all scenarios. In practical, the assumption is not convinced as it is not realistic to obtain this information in advance. An online scheduling study can be found in [86], in which the EV charging process was coordinated with renewable source to minimize daily market cost with uncertain electricity price. In this way, the strategy is developed to satisfy economic goals of the aggregator while ignoring the EV users' interest. A decentralised method on scheduling of EV charging loads was carried out in [57] to mitigate over-current situation while reducing the charging cost. It should be noted that, in this research, there is no guarantee that all EV would be fully charged because the priority of the charging strategy is to adjust the charging rates of PHEV chargers to prevent violation of the network constraints.

Afterwards, the prediction of data knowledge was adopted in the online charging scheduling as it plays a dominant role in improving the system practical performance [87]. As proposed in [96], the data knowledge such as spot/intraday prices could be forecasted by an Extreme Learning Machine (ELM). The correlation between electricity price and EV charging demand has been investigated in [83] by carrying out price-

responsive charging control, in which the online scheduling was developed to minimise charging costs for EV users based on the known tariffs. Apparently, the design of tariff is the key point to successfully implement economic EV scheduling. With respect to economic EV integration, some authors devoted to minimize the operating cost [97] while others intend to maximize the operational profit [98]. By only considering the unilateral interest of either DNOs or EV users, the charging tariff may result in the failure of load shifting, thereby posing a threat to profitability of charging service. Therefore, the repetitive iterations over times between the charging operators and PEV users are necessary to reach the equilibrium for satisfying the interests of both of them [88]. It is expected that there is a point, wherein, both the DNOs (relieving loads) and the EV users (saving costs) are satisfied with the mutually beneficial arrangements. In order to achieve mutual benefits, [99] proposed a rolling multi-period optimisation to control EV charging processes. The basic idea of rolling horizon scheduling is to split the whole time horizon and operation problem into multiple slots which are solved in sequence as different sub-problems [100]. These rolling horizon strategies had ideas in common that they acquire EV charging data over a fixed time step in the past and make charging decisions based on forecasting electrical price or other required information [80]. During the execution of the algorithm, the knowledge of EV charging data and solutions were updated in a moving horizon pattern. In this field, [101] developed a rolling horizon optimisation framework for the simultaneous energy supply and demand planning in microgrids consisting of solar, wind power systems and storage units. The duration of the energy consumption tasks was updated at each time-step to maximise profit. The rolling EV scheduling

strategy was proposed in [102] to suppress the known 24-hour load profile. Another similar work can be found in [84], model predictive control (MPC) based approach was suggested to verify the difference between near-optimal solutions and the optimal solutions.

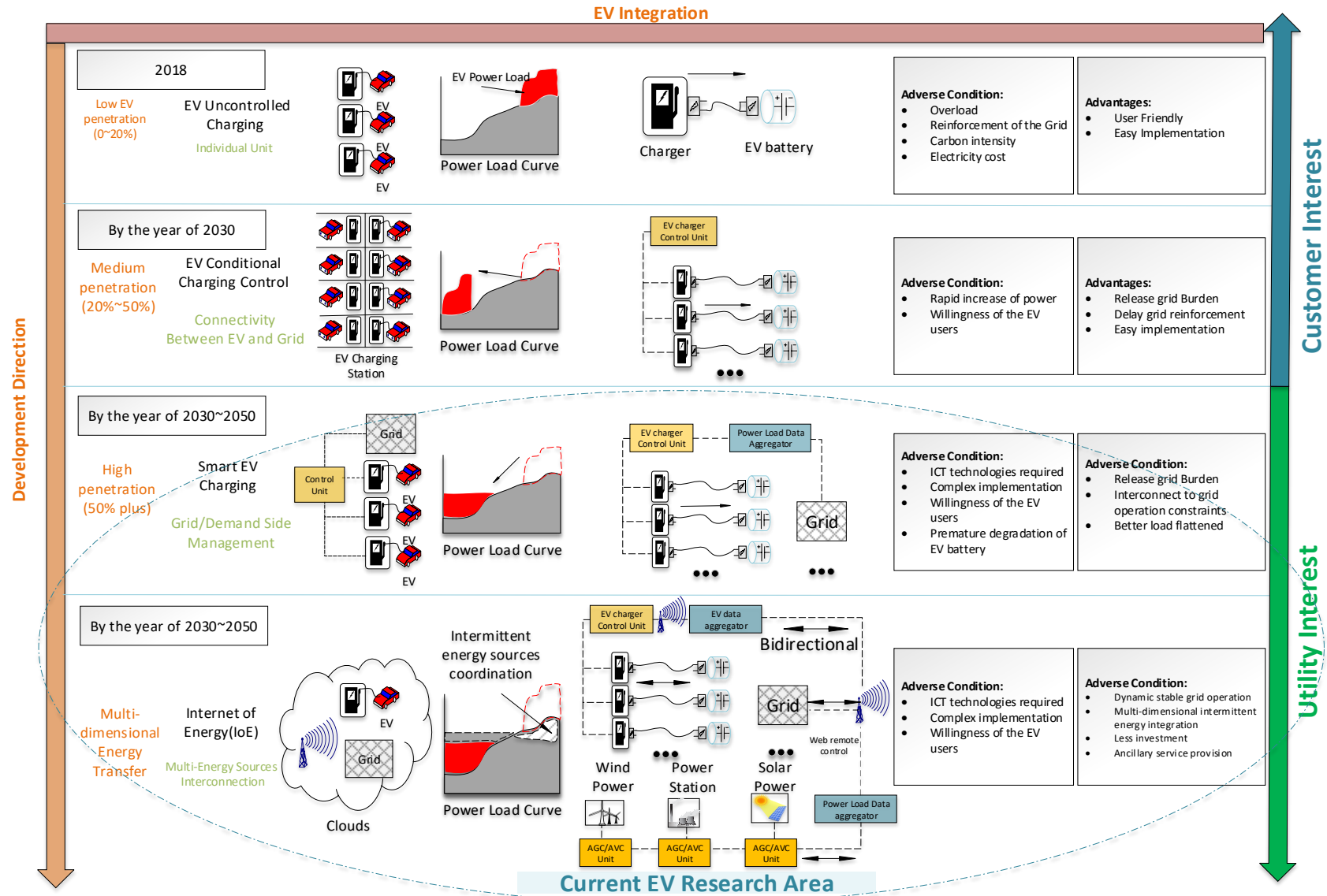


Fig. 1 The pictorial representation of current research outline on EV integration

In the current literature, the EV management strategies are classified in the integration of prediction, operational planning and operation control. The research work primarily focused on the effectiveness of optimization methods that are deployed for EV integration with pre-determined charging data. Few papers elaborated the solutions with uncertain charging data and examined their feasibilities in the energy trade market. As such, this paper aims to build up an online economic scheduling strategy, which can be used to coordinate energy trading between DNOs and EVs for the win-win ecosystem. The main contributions of this article can be summarised as follows:

- Both EVs and DNOs that are participated in the energy market can benefit from the proposed rolling horizon scheduling strategy by satisfying expected cost-effective goals.
- Specific tariff plans can be determined toward possible values in a rolling prediction basis to obtain load-shifting effect for DNOs and the lower charging cost for EV users.
- In the rolling horizon framework, Genetic Algorithm (GA) is integrated into scheduling strategy to solve optimisation problems that are derived from EV availability, predicted tariff plan and voltage profile at each time interval until the end of the day.

The rest of this paper is organised as follows. Section 2 describes the roll-scheduling conceptual framework and the major existing challenge for its practical implementation. Then, the proposed optimisation model, in terms of the mathematical model and computation flow chart, is presented in Section 3. Next, Section 4 mainly introduces the

application of the rolling horizon scheduling strategy into a case study. Then, the results and discussion are presented in Section 5, and the paper is concluded in Section 6.

2. Problem Statement

The objective of the proposed rolling horizon scheduling is to make sure that the charging service can be carried out with a certain profit margin in the presence of uncertain wholesale electricity prices and random EV charging behaviours. The rolling horizon method utilises Mixed Integer Linear Programming (MILP) for optimising the EV charging schedule in the distribution network. The variable sets used for model characterisation need to be introduced first because these sets represent base framework suitability for the implementation in the modelling language. The set T of hours of the day: $T = \{1, 2, 3, 4, \dots, 96\}$ with the subscript t indicates the variable or parameter corresponding to the t period (15 mins) of the day. The set K of 320 EVs fleet: $K = \{1, 2, 3, 4, \dots, 320\}$ with the superscript k indicates the variable or parameter corresponding to the EV. The following parameters have different values for each time period t being affected by k EV charging events:

- C_t : charging fees of the tariff in time period t , with $t \in T$.
- CP_t : wholesale electricity prices in time period t , with $t \in T$.
- D^k : daily travel distance of k EV at time period, with $k \in K$.
- H_t : future 8-hour rolling horizon period of the day in time period t , with $t \in T$, that is represented by the vector $\{t, t + 1, t + 2, t + 3, \dots, t + 32\}$
- MC_t : pre-set 8-hour charging fees of the tariff in time period t to $t+32$, with $t \in T$, that is represented by the vector $\{C_{t+1}, C_{t+2}, C_{t+3}, C_{t+4}, \dots, C_{t+32}\}$

- MCP_t : predicted 8-hour wholesale electricity prices set in time period t to $t+32$, that is represented by the vector $\{CP_{t+1}, CP_{t+2}, CP_{t+3}, CP_{t+4}, \dots, CP_{t+32}\}$, with $t \in T$.
- σ_t : the sum of k EVs plug in time period t , with $t \in T, k \in K$.
- P_t^k : charging power of k EV at time period, with $t \in T, k \in K$.
- $\sum_{k=1}^{\sigma_t} P_t^k$: aggregated EVs charging power in time period t , with $k \in K, t \in T$.
- t_c^k : charging duration of k EV, with $k \in K$.
- t_{in}^k : plug-in time of k EV in time period t , with $k \in K, t \in T$.
- t_{out}^k : plug-out time (charging completion) of k EV in time period t , with $k \in K, t \in T$.
- t_s^k : start charging time of k EV in time period t , with $k \in K, t \in T$.
- t_{park}^k : parking duration of k EV in time period t , with $k \in K, t \in T$.
- SoC^k : battery state of charge k EV at time period t_{in}^k , with $k \in K, t \in T$.

Due to the stochastic characteristics, a high degree of uncertainty is related to when and how many EVs start charging. The modelling of EV charging demand is done by the Monte-Carlo Simulation (MCS) that was previously developed by authors in [85]. In the MCS, $t_{in}^k, t_{park}^k, D^k$ and SoC^k are independent stochastic variables for k^{th} EV, which are generated based on the modelling parameters in Table 3. Then, the aggregated EVs charging power $\sum_{k=1}^{\sigma_t} P_t^k$ in time interval t can be calculated.

In this work, the wholesale electricity price MCP_t is considered as future knowledge (FK) that is generated from ELM. In the energy trade market, the DNOs would announce an optimised tariff C_t in advance to sell power to EV users, then, carry out the EV scheduling based on predicted wholesale electricity price CP_t with a specified time horizon vector H_t . The profit margin in the rolling horizon is represented by the price difference between

the tariff and upstream electricity price, which is represented by $MC_t - MCP_t$. Once above charging data is obtained in MCS, the DNOs aims to shift the EV charging loads to the period when the future profit margin is as high as possible. However, the EV users are only willing to attend the scheduling if charging cost will not get higher. This becomes a competing situation in which the rolling horizon scheduling is required to generate a win-win solution for all participants. In this optimised problem, the decision variable is start charging time t_s^k for k EV. It should satisfy the constraints that every EV should be fully charged to $SoC^k=0.95$ at the plug-out time t_{out}^k . With the time rolling forward, all these variables need to be updated and imported into the scheduling algorithm to generate an optimised solution for time interval t . Then, the resultant charging power $\sum_{k=1}^{\sigma_t} P_t^k$ could happen in any busbar i of a distribution network model to verify the proper tariff that brings the most obvious load-shifting effect.

As mentioned in [103, 104], MPC was known as an established technique for dealing with different complex control problems under uncertainty. In this paper, MPC is used to solve an online EV scheduling problem that provides the optimal decisions about the start charging time t_s^k of deferrable EV charging loads, whilst minimising the energy trading cost of the distribution network in the given rolling horizon. As specified in Table 1, at time t the online scheduling strategy is computed for a relatively short future time horizon H_t . The forward-looking objective function (14) is repetitively executed at subsequent time slots $t + 1, t + 2, \dots, \in T$, and every time the variables of the first time step are implemented as the optimal decision variables in accordance with the rolling horizon concept.

Table 1 Computation flowchart of rolling horizon scheduling strategy

| Rolling horizon scheduling strategy |
|---|
| Predefined tariff inputs: MC_t |
| EV fleet charging data from MCS: $\{t_{in}^k, t_{out}^k, SoC^k, P_t^k, D^k\}$ |
| Procedure: |
| 1 Set $t \leftarrow 0$ |
| 2 iterate |
| 3 Get forecast data vector MCP_t based on ELM |
| 4 Update user constraints parameters $\{t_{in}^k, t_{out}^k, SoC^k, P_t^k, D^k\}, k \in \sigma_t$ |
| 5 Solve the optimisation problem for H_t by using GA |
| 6 apply solution $t_s^k, k \in \sigma_t$ |
| 7 Set $t \leftarrow t + 1$ |
| Outputs: $\sum_{k=1}^{\sigma_{t+1}} P_{t+1}^k$ |

The rolling horizon strategy consists of three sets of knowledge at time t , constructing the basic rolling horizontal framework as shown in Fig. 2 . The Future knowledge (FK) represents the predicted 8-hour prices of the wholesale electricity MCP_t , and the past knowledge (PK) and solution knowledge (SK) are referred to charging information $t_{in}^k, t_{out}^k, SoC^k, P_t^k, D^k$ of k^{th} EV and the optimised start charging time t_s^k in time interval t , respectively. These three sets of knowledge are included in the time rolling horizon with a time step t of 15 minutes. In such way, uncertain parameters, such as the external variability in EV charging requests σ_t and wholesale electricity prices MCP_t , could be updated with the same pace rolling horizon H_t .

The operation of the online charging system is based on event-driven architecture (see Fig. 3). The main event in this system is the occurrence of EVs plug-in and plug-out at time t . The rolling process is characterised in terms of the following step:

- (i) A period of T (24 hours) is divided into 96 of equal-size time intervals $t \in T$.
Also, the three sets of knowledge.
- (ii) Once an EV plugged in a charger during time slot $\Delta t = t_2 - t_1$, the EV owner will be requested to provide total parking duration t_{park}^k . Then, the EV charger transmits battery SoC^k and requests a start charging time t_s^k for charging duration from t_{in}^k to t_{out}^k .
- (iii) As displayed in Fig. 3 , the local server acts as an EV aggregator to collect PK within its domain at each time slot Δt .
- (iv) The prediction of future 8-hours wholesale electricity prices MCP_t needs to be done during the current time slot Δt to produce FK . Normally, the time length of the rolling horizon H_t needs to be defined the same length as FK 's to keep synchronisation.
- (v) Meanwhile, the load-flow and economic calculations need to be carried out to evaluate scheduling effectiveness.
- (vi) The main server executes the optimal charging strategy based on GA, generating SK , as shown in Fig. 2 .

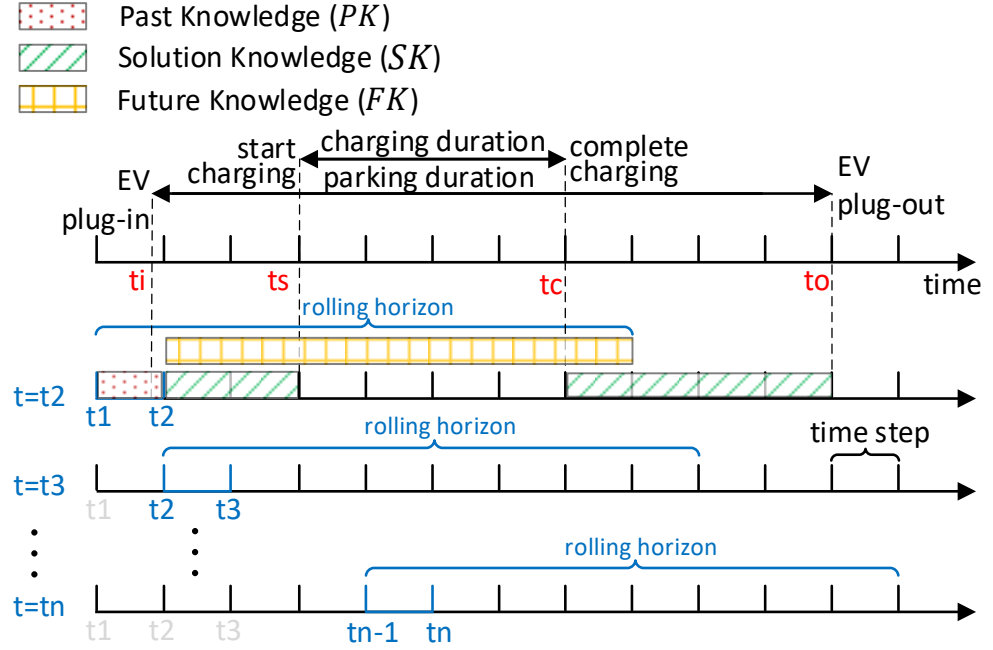


Fig. 2 Framework of EV rolling horizon scheduling

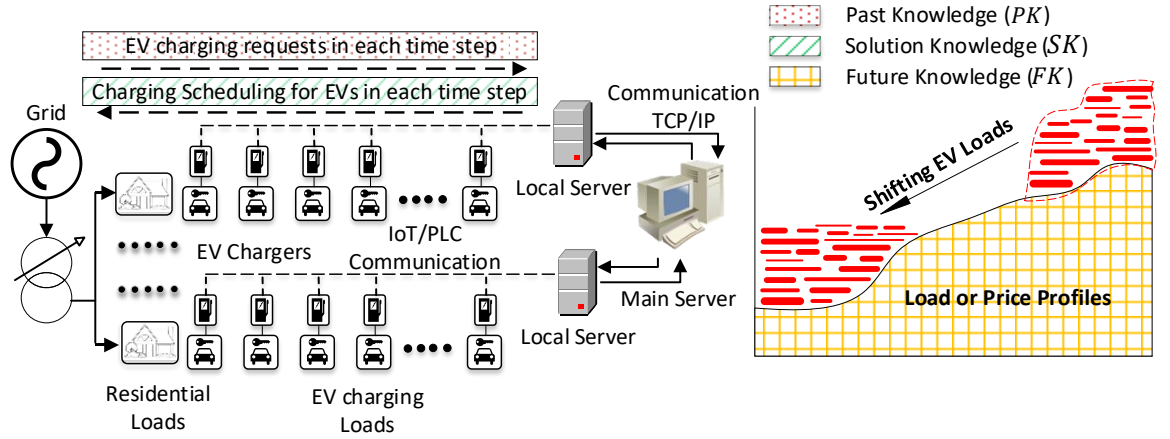


Fig. 3 Schematic structure of an online smart EV charging system [85]

3. Mathematical formulation

3.1 Modelling of EVs charging loads

The modelling of EV charging demand was derived from our previous work [85], in which a temporal EV charging demand is generated based on the multivariate probabilistic model. The developed methodology based on MCS is utilised to generate results close to the real use-cases daily power demand, which can be

further utilised in the analysis of EV charging strategies. In this paper, EV model is parameterised according to Nissan-Leaf specifications, as presented in Table 2.

Table 2 Charging parameters of EV models

| Manufacturers Model | Battery Capacity (kWh, Cap^k) | Charging Power (kW, P^k) | | Full endurance mileage (km, D) |
|------------------------|--|--------------------------------|-------------------|--|
| | | Slow Charging | Quick Charging | |
| Nissan-Leaf | 24/40 | 6.6 | 11 | 150/250 |

The household travel survey in [62] indicated that the daily travel distance of private EVs was 23.2 km on average. Therefore, for private EVs, the mean value μ_D and deviation value σ_D in log-normal distribution function are assumed to be 3.2 and 0.92, respectively, which are applied to Eq. (1) [85].

$$f_D(D^k) = \frac{1}{\sigma_D \sqrt{2\pi}} \exp \left[-\frac{(\log D^k - \mu_D)^2}{2\sigma_D^2} \right], D^k > 0 \quad (1)$$

$$SoC^k = 1 - \frac{D^k}{D}, 0.1 \leq \frac{D^k}{D} \leq 0.95 \quad (2)$$

where D^k represents the daily travel distance of k^{th} EV, which is a random variable derived from Eq. (1). All vehicles need to be fully charged before the next journey starts. Given the full endurance mileage D^k , the initial state of charge SoC^k can be estimated by Eq. (2) [85].

For k^{th} EV, plug-in time t_{in}^k , plug-out time t_{out}^k and state-of-charge SoC^k of battery are independent stochastic variables, which are generated from authors' previous work [85].

As real EV charging data is not publicly available, a multivariate probabilistic model is developed in [85] to estimate aggregated EVs charging loads with the consideration of randomness and heterogeneity based on transportation statistic data. As displayed in Table 3, it is assumed that 80% of private EVs would plug in the chargers from 07:00 to

09:00 and from 16:00 to 18:00; the remaining 20% will be recharged evenly across working hours from 09:00 to 24:00. In Eq. (3), it is assumed that each EV immediately starts charging once t_s^k is assigned. Charging power P^k keeps constant until the charging process completes at time t_{out}^k . The P_t^k denotes the power charging demand of k^{th} EV at time slot t aims to make sure charge completion (SoC=0.98) for all EVs, as described in Eq. (4).

$$\begin{cases} P_t^k = P^k, & t_s^k \leq t \leq t_{out}^k \\ P_t^k = 0, & \text{other time} \end{cases} \quad (3)$$

$$t_c^k = (0.95 - SoC^k) \times \frac{Cap^k}{P^k} \quad (4)$$

The parking duration t_{park}^k of k^{th} EV is defined by a random function in Eq. (5). The parking duration t_{park}^k is rounded to the nearest integer towards infinity in the calculation. The sum of EV charging requests in the time slot is indicated by $\sigma(t)$. The decision variable for start charging time t_s^k is defined in Eq. (6). Aggregated EV charging loads in each time step t can be expressed as $\sum_{k=1}^{\sigma(t)} P_t^k$.

$$t_{park}^k = t_{in}^k + rand(-1,1), t_{park}^k \in N \quad (5)$$

$$t_{in}^k \leq t_s^k \leq t_{park}^k - t_c^k \quad (6)$$

Table 3 Charging Parameters of Private EVs for MCS [85]

| Plug-in Period | Charging Power (kW, P^k) | Probability | Initial SoC^k Distribution | Plug-in time t_{in}^k |
|----------------|-----------------------------|-------------|---|-------------------------|
| 07:00~09:00 | 6.6 | 40% | Equation (1) based on log LogN (3.2,0.92) | N(8,0.5) |
| 16:00~18:00 | 6.6 | 40% | | N(17,1) |
| 09:00~24:00 | 11 | 20% | | Even Distribution |

3.2 Power Flow Calculation

Once the EV charging loads $\sum_{k=1}^{\sigma_t} P_t^k$ is obtained, it could be placed at any busbar i of a distribution network model, in addition to the existing load power P_{Li} , Q_{Li} and generation power P_{Gi} , Q_{Gi} . For n -nodes ($i = 1, 2, \dots, n$) distribution network model, there are $2n$ power balance equations to be solved in the Newton-Raphson algorithm. The uncertainty in EV charging loads is one of the input variables for the power flow problem. The aggregated EV charging loads $\sum_1^{\sigma_{i,t}} (P_i^k)_t$ in busbar i was integrated into power flow calculation, which can be represented by a set of nonlinear equation represented in Eq. (7).

$$\begin{cases} (P_{Gi} - P_{Li})_t - \sum_1^{\sigma_{i,t}} (P_i^k)_t = V_i \sum_{j \neq i} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \\ (Q_{Gi} - Q_{Li})_t = V_i \sum_{j \neq i} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) \\ i = 1, 2, \dots, n \end{cases} \quad (7)$$

The variables in Eq. (7) must satisfy the constraints in Eq. (8) to enable the distribution network to operate in a stable condition.

$$\begin{cases} P_{Li,min} < P_{Li} < P_{Li,max} \\ Q_{Li,min} < Q_{Li} < Q_{Li,max} \end{cases} \quad (8)$$

The power generation in the distribution network is zero in this research so that $P_{Gi} = Q_{Gi} = 0$. P_{Li} and Q_{Li} will be specified by the case study in Section 4, where a typical residential load profile is introduced.

In Eq. (9), the voltage of each node i should meet the power quality requirement of the system, and it must be limited to a certain range, i.e $V_{i,min} = 0.9 \text{ p.u.}$, $V_{i,max} = 1.1 \text{ p.u.}$ Similarly, the voltage phase difference in Eq. (10) between some nodes i, j should not

exceed a certain range as well, i.e $|\theta_i - \theta_j|_{max} = 10^\circ$. The relevant variables shall be modified and recalculated until the solution can satisfy the constraint conditions.

$$V_{i,min} < V_i < V_{i,max} \quad (9)$$

$$|\theta_i - \theta_j| \leq |\theta_i - \theta_j|_{max} \quad (10)$$

3.3 Rolling Prediction of Electrical Price

In each time interval t , future wholesale electricity prices MCP_t needs to be predicted as the input data for the proposed online scheduling strategy. In order to assure the accuracy of the prediction, an 8-hour horizon, defined as FK in Section 0, is set up in ELM and kept rolling forward in the same pace with scheduling iterations.

The forecasting of MCP_t is done by a time series model based on ELM. For a single hidden feed-forward neural networks (see Fig. 4), it is assumed that there are n historical wholesale electricity price samples (X_i, CP_i) collected from the wholesale market, in which time series slots $X_i = [x_{i1}, x_{i2}, \dots, x_{in}]^T \in R^n$, price series data $CP_i = [cp_{i1}, cp_{i2}, \dots, cp_{im}]^T \in R^m$. The neural networks with L hidden layer nodes can be expressed by Eq. (11) [105].

$$\sum_{i=1}^L \beta_i g(W_i \cdot X_j + b_i) = o_j, j = 1, \dots, N \quad (11)$$

In Eq. (11), $g(x)$ acts as activation function; $W_i = [w_1, w_2, \dots, w_L]^T$ and β_i describes input and output weights respectively; b_i is the offset of i^{th} hidden layer element. The o_j denotes output vector. The goal of the single hidden layer neural network learning is to minimize output errors, which can be expressed by Eq. (12) [105].

$$\sum_{j=1}^N \|o_j - CP_i\| = 0 \quad (12)$$

Therefore, there are β_i, W_i and b_i to make Eq. (13) true. It can also be rewritten as the matrix $H\beta = T$, in which H is the hidden layer output matrix, β is output weights respectively, T is expectation outputs [106]. In the ELM, once β_i, W_i are randomly confirmed, H, β can be uniquely identified as well [105].

$$\sum_{i=1}^L \beta_i g(W_i \cdot X_j + b_i) = CP_i, j = 1, \dots, N \quad (13)$$

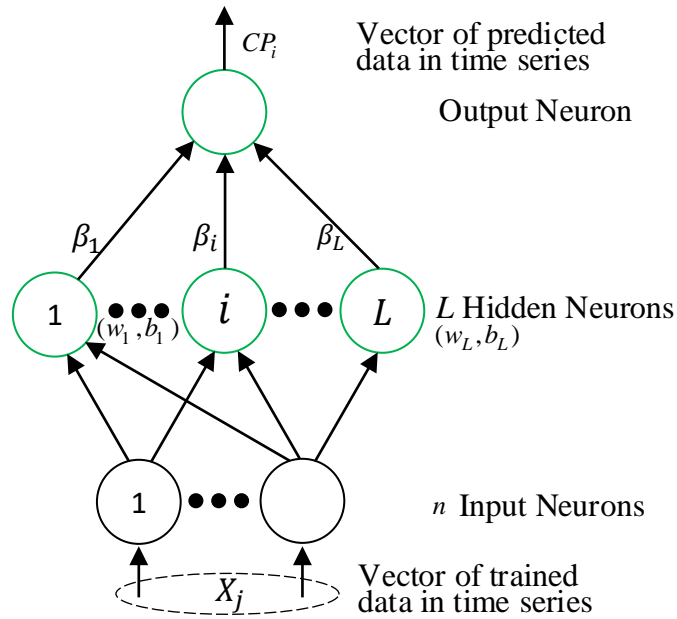


Fig. 4 Architecture of an ELM [105]

3.4 Objective Functions

In DNOs' point of view, aggregated EVs is reckoned as a tremendous source of controllable loads that could be used to make peak-shaving and valley impact. In order to enhance participation, the forward-looking objective function needs to be designed to comprise the commercial interest among EV users and DNOs. As illustrated in Fig. 5, the original EV charging tariff C_t obtained from Vector Network Ltd [107] is applied to the case study. The wholesale electricity prices CP_t displayed by the black line is downloaded

from the NZ electricity trading system in [108]. Two different EV charging tariffs are set up for the scheduling. The objective function is clarified in Eq (14).

$$f_t = \max \sum_{t=1}^{t+32} \sum_{k=1}^{k \in \sigma_t} (P_t^k \times ((0.8 - C_t) - CP_t) \times \Delta t) \quad (14)$$

The forward-looking objective function is subject to constraint functions Eqs. (3)-(6), (8)-(10), (12) and (13). The charging requests of k^{th} EV in time interval t (15 mins) of a day D is aggregated to form $P_{EV_i}^k$ in a busbar i of distribution network. The predicted wholesale electricity prices MCP_t is generated by ELM models, detailed by Eqs. (11)-(13). It covers the future 8-hour price knowledge and keep rolling forward every 15 minutes. The formulation $((0.8 - C_t) - CP_t)$ aims to schedule EV charging requests in Δt to maximise profit margin for DNOs. The constant 0.8 denotes load-shift factor to postpone EV start charging time to low price period. The elaborated objective function has the following three characteristics:

1. The wholesale electricity price and tariff are employed as a transitive signal of define profit margin displayed in Fig. 5.
2. The energy trading mechanism is considered by updating $((0.8 - C_t) - CP_t)$ in the rolling prediction algorithm mentioned in Section 3.3.
3. It involves checks and balances between EV users and DNOs, which naturally creates dynamic equality in the energy market.

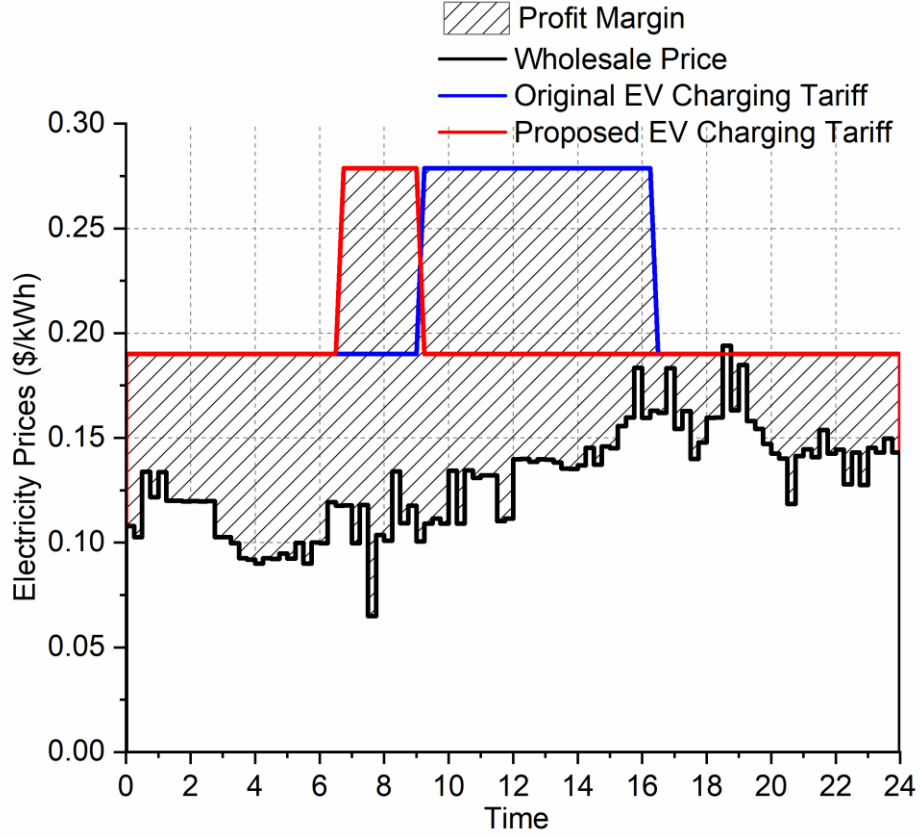


Fig. 5 Wholesale electricity price for test

4. Case Study

The application of the rolling horizon, in which the EV charging problem is solved iteratively, can produce fast responses to price changes in the tariff. This is contributed by the introduction of the three sets of information FK , PK , SK . As introduced in Section 0, the rolling information is comprised of EV modelling data, charging tariff, forecasted wholesale prices and network parameters. An 8-hour length of the prediction horizon has been considered in this case study because it is considered an adequate optimization horizon to ensure that EV charging would be completed within parking duration. Additionally, it is an appropriate horizon to forecast wholesale electricity price MCP_t with an acceptable error because long term prediction normally comes with high errors.

In the scheduling, the forecasting errors should be maintained within a certain level to generate satisfying solutions.

The predicted wholesale price MCP_t will be compared with the tariff price MC_t in the future 8-hour horizon to find the durations that give maximum profit margin for DNOs, as presented in Fig. 5. Then, the EV scheduling strategy will start to calculate whether or not the scheduled results save charging costs for EV users. If not, the EV will be excluded from the scheduling. As described in Fig. 7, the purpose of the exclusion arrangement is to ensure customers interests while maximising profit for DNOs.

To demonstrate the proposed EV scheduling strategy, a numerical case study is performed to verify the improvements of rolling-horizon EV scheduling. The one-line diagram of the IEEE 33-bus system [109] is chosen to represent synthetic distribution system as shown in Fig. 6. A charging station with a total number of 320 chargers is placed at the busbar 33 of the network in order to illustrate the worst condition. In the case study, it is assumed that the load profile is composed of 500 households with after diversity maximum demand (ADMD) 1.3 kW per household. The load demand data produced by the Electricity Association data show that the minimum and maximum demand are 0.16 kVA and 1.3 kVA, respectively [110]. Two different charging tariffs are considered in the case study to verify the effectiveness of the proposed strategy.

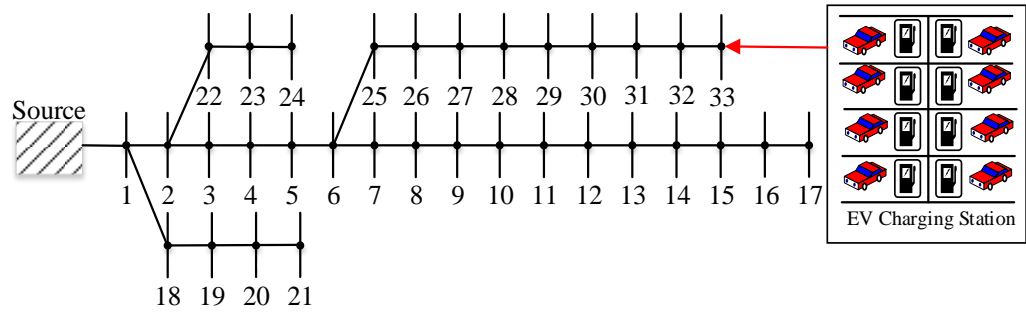


Fig. 6 IEEE 33-bus distribution system with an EV charging station

The proposed scheduling problem is introduced into an iterative rolling horizon framework. The flowchart of the rolling horizon approach is illustrated in Fig. 7 , as specified in the following steps:

- Initially, generate EV charging data by MCS that was developed in [85]
- Next, set the initial horizon of EV charging requests (PK) and predicted electricity wholesale price (FK), as well as the impedance of the distribution network
- Optimise start charging times for those requests. Then, run the load flow in order to get voltage and power loss profiles for the charging node in the distribution network
- Use GA to evaluate these solutions, and find out the solution with the highest fitness
- Review scheduled solutions to ensure the charging cost is reduced, otherwise, exclude the EV from the scheduling
- Finally, move to the next time slot and repeat executing PK and FK until reaching the end of time scale

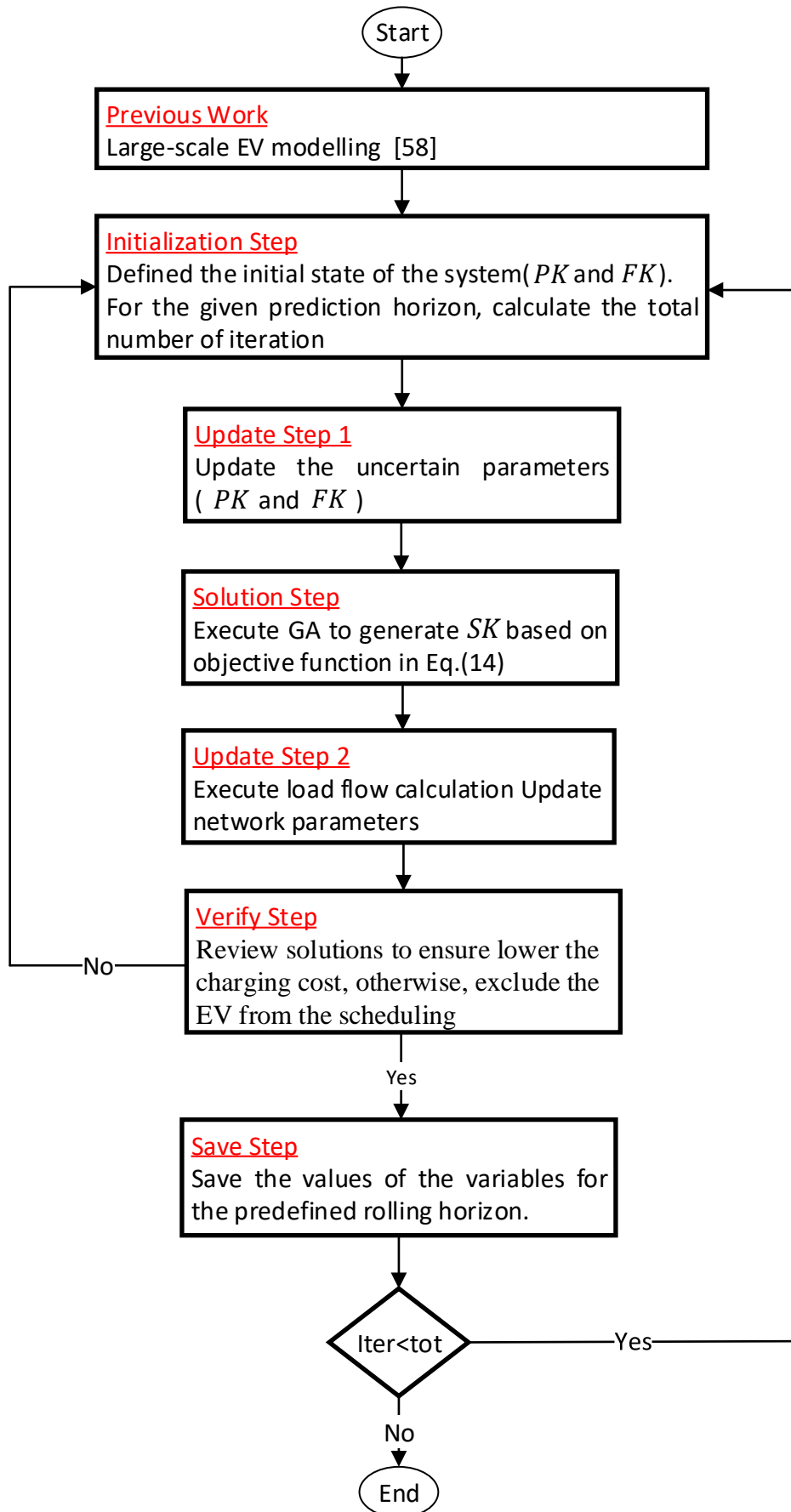
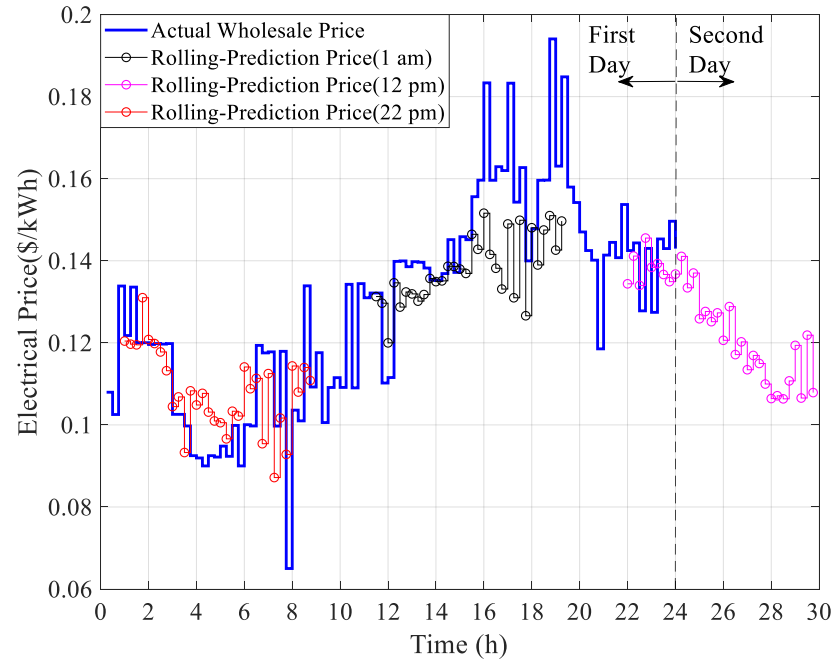


Fig. 7 Flowchart of the rolling horizon approach

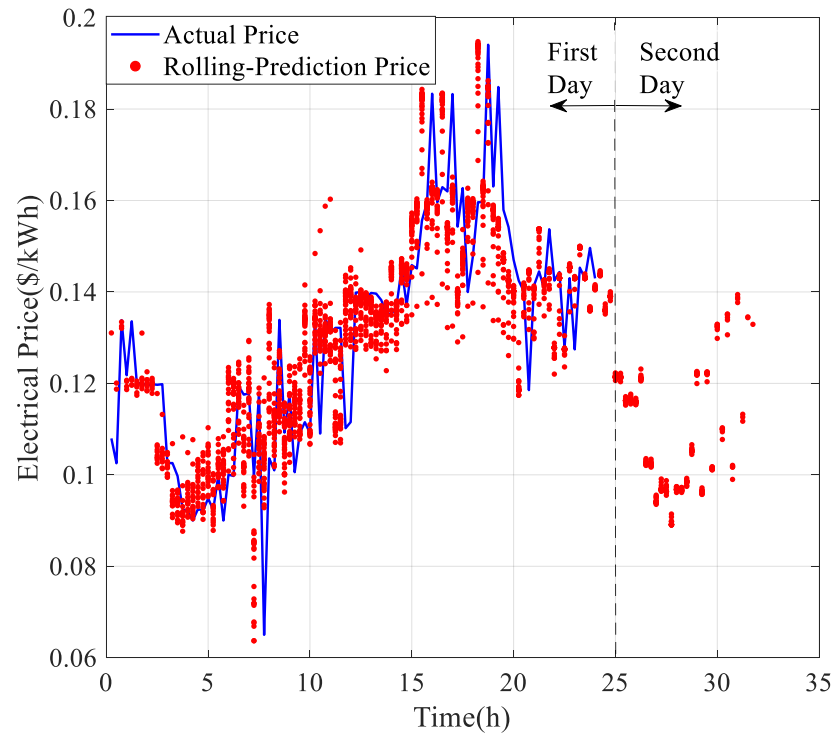
5. Results and Discussions

The rolling-horizon model has been done in Matlab 2019b with a Pentium Intel® Core™ CPU 7700 @3.6 GHz. The resolution of the model provides the online optimal schedule for EV users and DNOs. The rolling horizon approach is used to address the presence of EV plug-in uncertainty, allow updating information related to forecasted wholesale electricity price at each 15 minutes time interval in a day.

The historical data of the wholesale electricity price (X_i, CP_i) is collected from NZ Wholesale information Trading System [108]. A daily example of the wholesale electricity price is presented by the blue line in Fig. 8. For each repetition of the forecasting, a set of prices data composed of 32 dots is generated according to Eqs. (11)-(13) to represents the predicted wholesale electrical prices MCP_t in the future 8-hour horizon. As the intra-day forecasts updated iteratively, the EV scheduling decisions (defined as SK in Section 0) are made according to the assigned starting charging times t_s^k to response EV charging requests in each time interval t . Within a day, a total number of 96 sets of predicted prices are produced in the ELM model. R-square errors of the rolling predictions are recorded in Fig. 9. Although, R-square values in some iterations are under 0.6, the rolling optimisation is still able to generate satisfied solutions SK as long as the price trending is accurately foreseen.



(a) Selected time slots



(b) Full time slots

Fig. 8 The comparison of actual and predicted 15-mins electrical price in the wholesale market

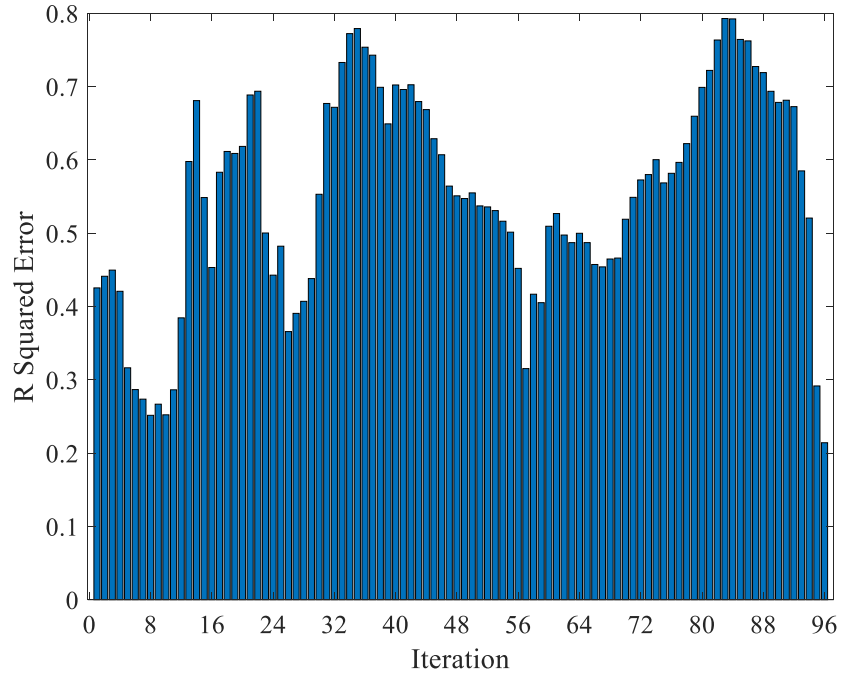


Fig. 9 R-square error values of predicted results among 96 iterations

The temporal distribution of the uncontrolled EV's charging demand is conducted in the probabilistic model introduced in Section 3.1. Fig. 10 displays the EVs' plug-in time t_{in}^k and initial SoC^k that are generated from MCS, as formulated in Eqs. (1)-(2). In the proposed scheduling strategy, the plug-in time t_{in}^k can be used to figure out the total number of the charging request in each time slot t . As all EVs are guaranteed to be fully charged, the initial SoC^k can be used to calculate charging duration based on constant charging power P^k and battery capacity Cap^k . Then, the charging data is applied to define constraints in Eqs. (3)-(5) and Eqs. (7)-(10) and decision variable in Eq. (6) for the charging optimisation. It can be seen that most EVs are recharged in early hours of on-work and off-work periods. In the uncontrolled scenario, it is assumed the EVs immediately start charging once plug-in. The charging processes are displayed in Fig. 11 with a Gantt chart. It records charging and parking durations of 320 EVs by red and green bars, respectively. In most of the time, EVs are parking on spot without charging processes. The charging duration is calculated based on

the Eq. (1) –(3), as described in Section 3.1. It can be seen that charging times only take up a minor fraction of total parking durations. This kinds of driving and parking patterns give significant feasibility for scheduling strategy to shift deferrable EV charging loads.

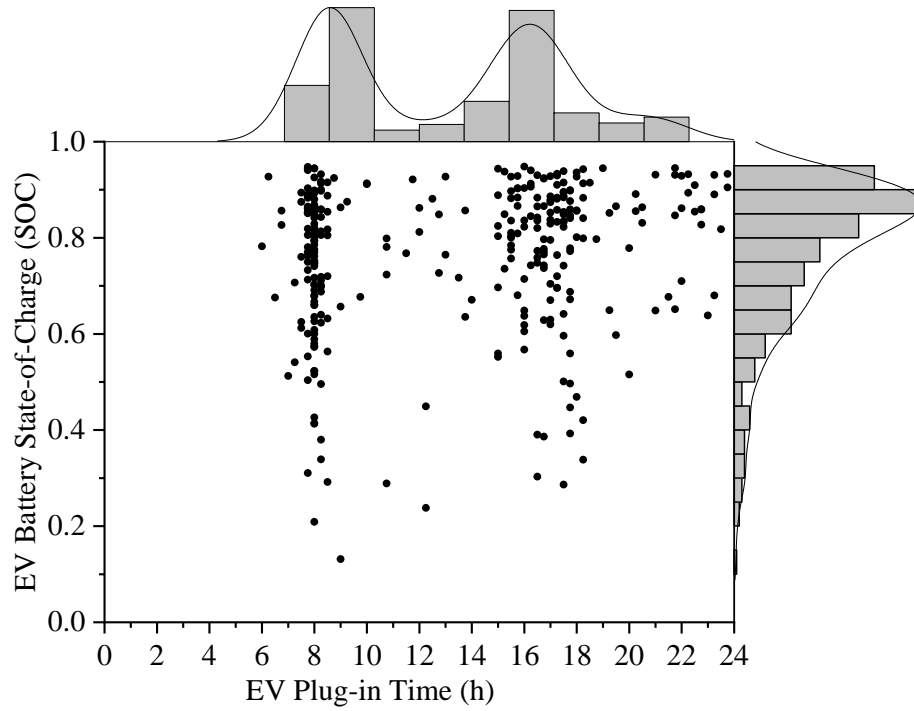


Fig. 10 Scatter plot between EV plug-in time and initial SoC

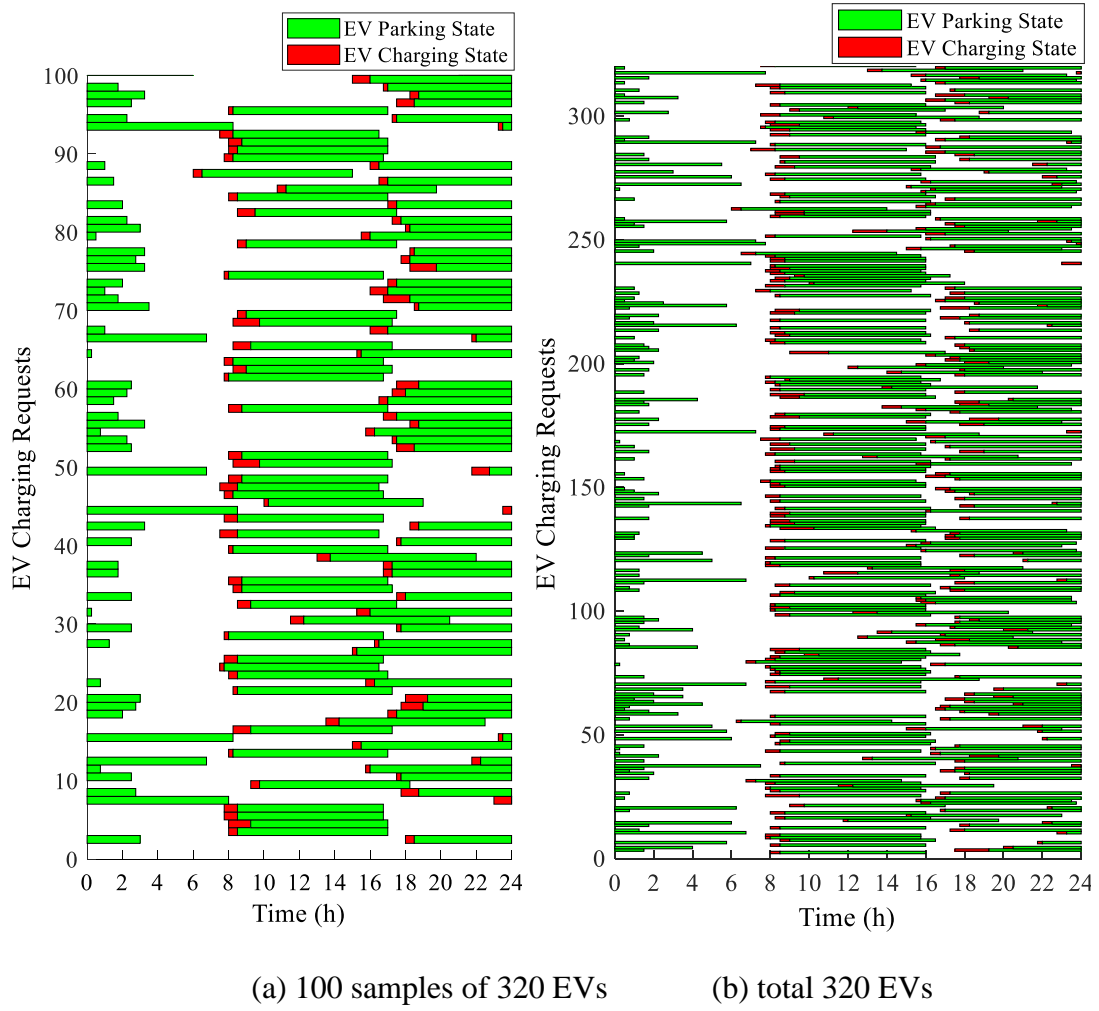


Fig. 11 EVs charging information in Gantt Chart

For individual EV users, the economic incentive is reckoned the most effective factor to enhance participation of scheduling if their departure is not affected. As presented in Fig. 12, two different EV charging tariffs are suggested for energy trading with respect to the 320 EVs fleet. The uncontrolled scheme (grey bars) indicates that EVs start charging immediately after they plug in. It results in severe peaks on power load at 08:00 and 17:00 respectively, with a value of 1100 kW and 500 kW, respectively (see Fig. 13).

In the scheduling scenario, the first stage is to apply original tariff into the rolling horizon strategy. By comparing grey and blue portions in Fig. 12, it can be found that most of EV charging requests at dusk are delay by three hours, while, the charging requests in the early

morning remain unchanged because the charging strategy considers the delayed charging will result in higher charging cost to users. Indeed, in the original EV charging tariff, the charging fees raises from \$0.18/kWh to \$0.26/kWh in the early morning, forcing the charging strategy to abandon scheduling for the sake of saving cost. This logic judgement explained in Section 0 plays a significant role in producing win-win solutions for EV users and DNOs. Even though the peak power demand is decreased by 100 kW in the early evening, it still peaks at as high as 1100 kW in the early morning (see Fig. 13). In order to obtain better scheduling results, the tariff might need to be revised to enhance participation of EV users.

Thus, a new tariff is proposed and depicted by red lines in Fig. 12 and Fig. 13 . The high price duration starts from 06:00 to 10:00 when it is coincident with rush hours of charging requests. This tariff allows the charging strategy to obtain lower charging cost by shifting peak charging demands. The red portions in Fig. 12 and Fig. 13 displays that a considerable curtailment on peak power demand is experienced in the early morning, which drops from 1100 kW to just over 400 kW. It dramatically saves network investment in terms of substations and cables.

More importantly, the elaborated objective function Eq. (14) aims to schedule EVs within periods when the profit margin is large. By comparing the low-price duration of two tariffs, the large profit margins are highlighted by green dash lines in Fig. 12 and Fig. 13 . These are exactly the same durations when two scheduled results reach peak charging demand. Apart from achieving peak-shaving and valley-filling effect, the strategy is also trying to maximise profit.

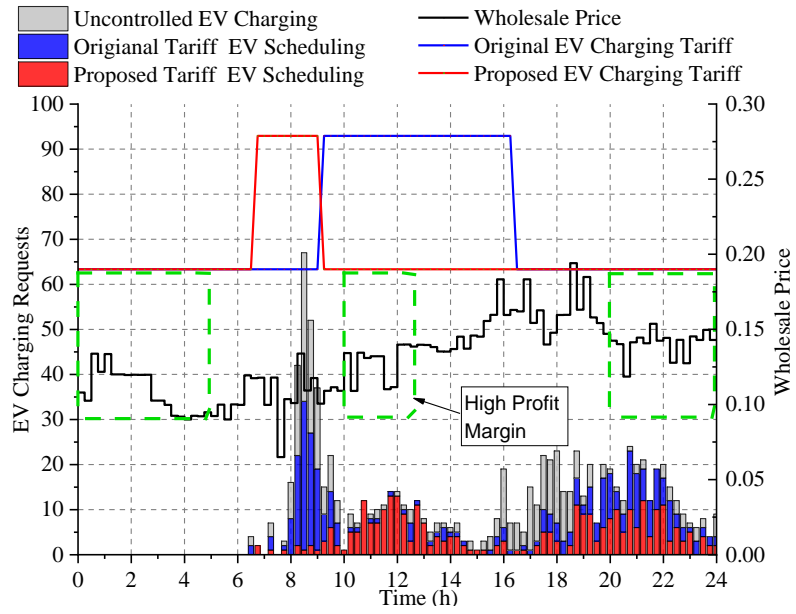


Fig. 12 EV charging requests based on different tariffs

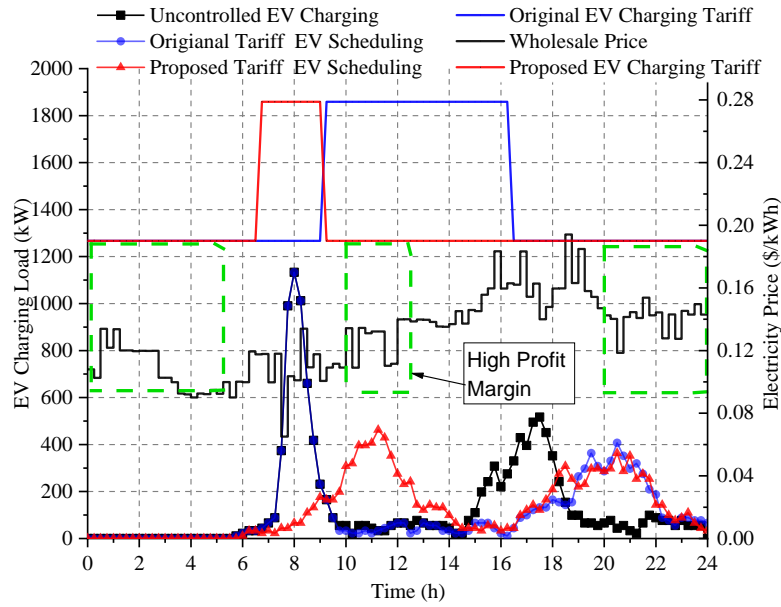


Fig. 13 EV charging loads based on different tariffs

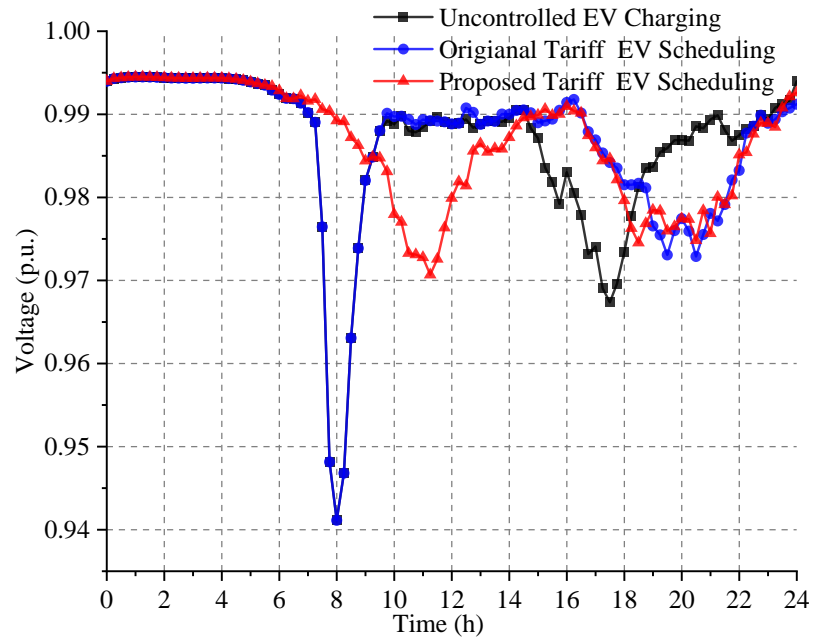


Fig. 14 Voltage profile at node 33 under different scenarios

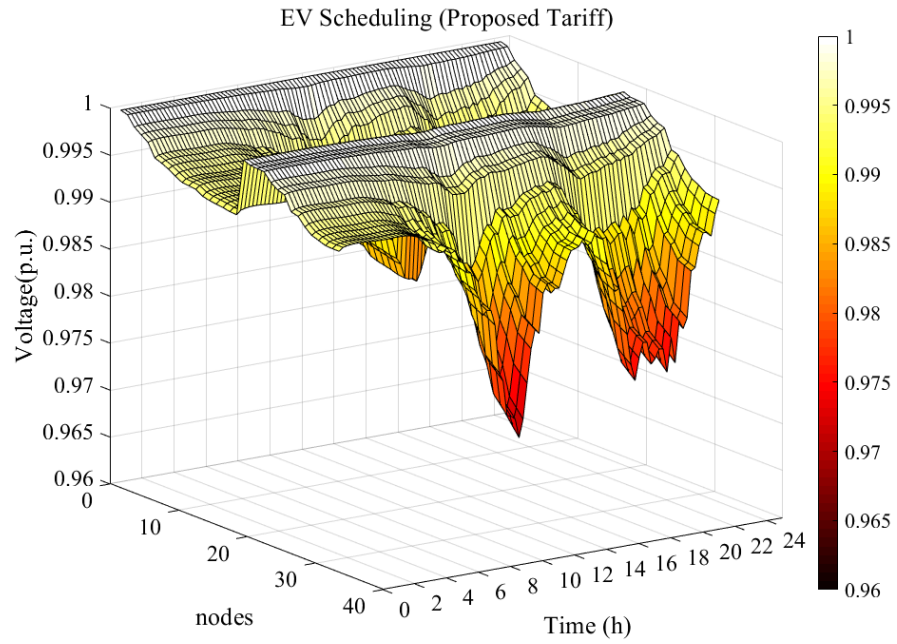


Fig. 15 Voltage profile (proposed tariff) in the IEEE 33-node network

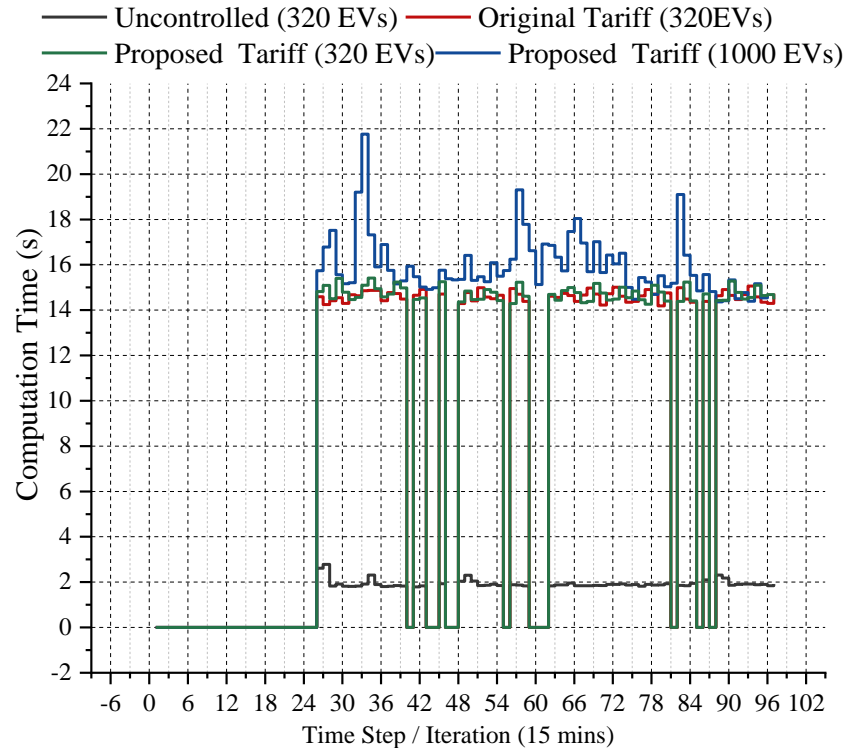


Fig. 16 Computational time of each time step

The rolling-horizon algorithm maintains the voltage magnitude at the far end of the feeder. To demonstrate the scheduling effect, the EV charging station is located at the furthest end of the feeder as the worst scenario of network operation. (see Fig. 6). The voltage magnitudes at node 33 for the 320 EVs fleet are displayed in Fig. 15 . Once again, power flow results shown in Fig. 14 and Fig. 15 correspond to the rolling horizon charging strategy mentioned above. Recall that the minimum voltage magnitude of the system is set at 0.9 p.u in (9). In Fig. 14 , the uncontrolled scenario with original tariff scheduling cause significant voltage magnitude drops in the morning, under 0.95 p.u. With the proposed tariff, voltage magnitudes stay above 0.97 p.u. even though some EVs start charging during rush hours. As shown in Fig. 15 , the charging strategy effectively enhances the voltage profile of all nodes under proposed tariff. In the uncontrolled scenario, the running times are just about 2 s when it comes to updating the EV plug in or out events (see Fig. 16). With *FK* and *SK* being applied,

the running times of optimisation are increased to roughly 14 seconds. Under all conditions, the running times are well within the time step of the scheduling 15 minutes, therefore, there is no overtime issue in the optimisation process. With the proposed tariff being applied, the number of EVs is reset to 1000 to verify the calculation performance of the algorithm regarding the scalability. The computational times (blue line) merely slightly grow by 1-5 seconds in each time step, which means the dimensionality of the variables will not have an obvious impact on the calculation capability of the proposed algorithm.

Finally, several key indexes are concluded in Table 4. The comparison of scheduling results demonstrates that EV users experience lower charging costs in both tariffs. The aggregated demands of 320 EVs decrease from 1133 kW to 462 kW in the proposed tariff. Similar effects are noticed in the load standard deviation, which falls from 214 kW to 206 kW, and finally bottoms at 128 kW. The peak demand is considered a major driver of investment in the distribution network. It means the DNOs only need to invest 500 kW installed capacity to meet the EV charging demand that originally required 1200 kW. Based on information from DNOs [111], reinforcing the lines to increase capacity by 920 kVA costs €67,000 (approx. NZ\$123,000), while reinforcing the substation costs €3 million (approx. NZ\$ 5 million). Although, in the scheduling scenario, the daily profit drops from NZ\$212 to NZ\$175, DNOs are more interested in the use of a smart charging strategy that could lead to reduced capital expenditure and social costs in comparison with the uncontrolled case. The scheduling results reveal potential investment decisions for distribution networks regarding trade-offs between capital costs and profits.

Table 4 The comparison of scheduling results

| | Peak Load(kW) | Load Standard Deviation(kW) | Charging Cost (NZ\$) | Profit (NZ\$) |
|-----------------------|------------------|--------------------------------|-------------------------|------------------|
| Uncontrolled Scenario | | | | |
| Original tariff | 1133 | 214 | 655 | 233 |
| Proposed tariff | 1133 | 214 | 707 | 285 |
| Scheduled Scenario | | | | |
| Original tariff | 1133 | 206 | 608 | 212 |
| Proposed tariff | 462 | 128 | 598 | 175 |

6. Conclusions

In this paper, the online economic scheduling problem considering both the availability and status of EVs, and the uncertain upstream electricity price has been solved. The rolling horizon approach has been introduced in the formulations to address the uncertainties inspired by the realistic EV charging scenario. The approach takes into account not only the EV charging time (beginning and end) but also the profit margin of the electricity tariffs for DNOs. The forecast of electricity price plays a significant role in the decisions of opportunity charging for EVs so that all charging requests can be satisfied as long as the EV users do not make an earlier departure. The significant improvement was found in the voltage profile of the IEEE 33-node test network. Also, the charging strategy integrates a fast convergence power flow calculation to provide technical insights for DNOs to evaluate the tariff that will encourage EV deployment under the energy trading market. The scheduling results derived from the proposed tariff demonstrates that high-price durations coincident with charging rush hours obtains better performance than the original tariff regarding peak loads shifting. The rolling prediction of wholesale electricity prices gives the charging strategy a certain level of perception capability to make proper decisions on the opportunity charging. Although the accuracy of the rolling prediction is not always satisfied, it still can produce good scheduling

results as long as the price trend can be foreseen correctly. Overall, the simulation results verify that the proposed method does contribute to cost-saving for EV users and profitability for DNOs while ensuring each EV to be fully charged before desired usage time. Opportunity charging based on the market mechanism is considered as the win-win strategy for main participants within distribution networks.

In the future work, the proposed approach could be used as the basis for solving further problems with higher complexity by combining proactive technique to take into account the feasibility of Vehicle-to-Grid mode. The rolling horizon could be made with dynamic durations to actively solve EVs scheduling problems in a smarter way. Another direction for future work is to investigate other robust MPC techniques that could be applied to the EV integration, so as to investigate convergence characteristics; and whether or not rolling horizon scheme can provide solutions as good as global optimisation scheme.

Chapter 4 Manuscript 3

This manuscript addresses the closed-loop control problems regarding imbalanced EVs charging power among adjacent feeders in the distribution network. The modelling of EVs charging demand developed in Chapter 2 has been used in this manuscript as an uncertain input variable. The distributed PV generation is considered as another input variable. Due to the varying nature of EV and PV in the LV distribution network, this manuscript proposes a novel control system to manage the imbalanced power among feeders. In the proposed DPBS, unbalanced power can be transferred from the heavily loaded feeder to the neighbouring feeder that is lightly loaded through tie-line voltage source converters (VSCs).

The manuscript was published in the journal of ‘IEEE Transactions on Industry Applications’ under the title: “Integration of Electric Vehicles in Distribution Network Considering Dynamic Power Imbalance Issue”.

Integration of Electric Vehicles in Distribution Network considering Dynamic Power Imbalance Issue

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Abstract

The continuous growth of the number of electric vehicles (EVs) poses great challenges to distribution networks. Intermittent and stochastic EV access detrimentally affects the security of the power supply. In terms of unplanned events, EV users might dispersedly plug in or out at any available spot instead of ensuring identical distribution across feeders. This uneven deployment may lead to imbalanced loading conditions among adjacent feeders. The situation may become worse with an increased penetration of the distributed Photovoltaic (PV) generation due to the intermittent generation characteristic. This paper proposes a novel control scheme to manage the imbalanced power among feeders. In the proposed dynamic power balance system (DPBS), unbalanced power can be transferred from the heavily loaded feeder to the neighbouring feeder that is lightly loaded through tie-line voltage source converters (VSCs). The tie-line VSCs are designed to connect adjacent feeders at the low-voltage side of distribution transformers via an 800 V dc-link. In this way, the power variance caused by either EV or PV can be split into joint feeders and transformers, so as to mitigate fluctuations. The stochastic variations on EV charging loads are addressed using a Monte-Carlo simulation (MCS) technique. The effectiveness of the proposed scheme is demonstrated on a typical distribution network with integration of EVs and PV. It could be

used as a supplementary measure to obtain a fast demand balance response without restraining EV users, and to considerably curtail the risk of overloading the power distribution equipment.

Keywords: Distribution network, unbalanced power, voltage source converter, electric vehicle, photovoltaic

Nomenclature

Indices

| | |
|-----|----------------------------|
| i | Index of network equipment |
| j | Index of controller |
| k | Index of electric vehicles |
| t | Index of time intervals |
| $*$ | Index of reference values |

Parameters

| | |
|-----------------|---|
| C_{dc} | Capacitance of the VSC dc capacitor |
| D^k | Endurance mileage of k^{th} EV |
| $i_{a,b,c}$ | Phase current a, b, c at ac side of the VSC |
| i_{dc} | Current flowing towards dc side of the VSC |
| $i_{d,q}$ | Injected current at ac side of the VSC in dq -axis Framework |
| i_L | DC load current of the VSC |
| $K_{jd,q}^p$ | Proportional coefficient of the current proportional-integral (PI) controller in dq -axis framework |
| $K_{jd,q}^i$ | Integral coefficient of the current PI controller in dq -axis framework |
| $K_{jd,q}^{p'}$ | Proportional coefficient of the voltage PI controller in dq -axis framework |
| $K_{jd,q}^{i'}$ | Integral coefficient of the voltage PI controller in dq -axis framework |
| L | Inductance of RL filter for the VSC |
| M^k | Daily travel distance of k^{th} EV |
| P_C^k | Rated charging power of k^{th} EV |
| P_{ei} | Imported grid power in i^{th} feeder |
| $P_{gmax.i}$ | Maximum output power of the VSC in i^{th} feeder |
| P_{gi} | Output power of the VSC in i^{th} feeder |
| P_{xi} | Aggregated EV charging power in i^{th} feeder |
| R | Resistance of RL filter for the VSC |
| s | Laplace operator |
| S_i | Installed capacity of distribution transformer in i^{th} feeder |

| | |
|------------------|---|
| S_0 | Aggregated installed capacity of transformers within P - Q control scheme |
| SoC^k | Battery state-of-charge of k^{th} EV |
| T^k | Parking duration of k^{th} EV |
| t_i^k | Plug in time of k^{th} EV |
| t_{out}^k | Charging completion time of k^{th} EV |
| $u_{a,b,c}$ | Phases a, b and c voltage at grid side of the VSC |
| u_{dc} | Output dc link voltage of the VSC |
| $u_{d,q}$ | Grid voltage in dq -axis framework |
| μ_D | Mean value in logarithmic probability distribution function |
| σ_D | Standard deviation value in logarithmic probability distribution function |
| $v_{d,q}$ | Voltage at ac side of the VSC in dq -axis framework |
| $v_{gd,q}$ | New voltage vector of the VSC in dq -axis framework |
| $\Delta V_{d,q}$ | Outputs of PI control current loop in dq -axis framework |
| ω | Angular velocity of dq -axis framework |

1. Introduction

The expanded deployment of electric vehicles (EVs) will potentially reshape residential power consumption profiles as charging one EV is nearly equivalent to adding two houses to distribution networks [85]. Imagine what will happen when all EV owners living in the same residential area decide to recharge them after returning from work, which is almost the same time that households turn on their heating, ovens and other appliances. The risk of overloading distribution transformers or feeders is particularly high in specific periods of a day, such as early morning and evening. On the contrary, photovoltaic (PV) generation normally reaches peak output at midday, when demand for EV charging is relatively low [112, 113]. These two reversed cases expose a dynamic power imbalance issue between renewable distributed generation and EV charging demand. It is a challenge to get consumers to shift their EV charging times to periods when grid power consumption is relatively low or distributed generation reaches the peak output [114]. For distribution network operators (DNOs), EVs could be considered the controllable loads in scheduling strategies [115]. With scheduling strategies being applied, DNOs may need to provide incentives for their customers to change their charging behaviours for optimised objectives [116]. This could be done by providing various price tariffs that are designed to flatten power curves [83, 117, 118].

Various scheduling models in the integration of EVs and renewable energy sources have had their effectiveness demonstrated with respect to peak-shaving and valley-filling capabilities [119]. Such optimisation approaches would improve the grid's reliability and efficiency with a high share of intermittent loads and renewable generation [120-124]. Numerous algorithms

had been found in centralised, decentralised or agent-based charging strategies that manage EV charging processes to achieve optimisation targets [88, 125]. Most of the previously used strategies have focused on the management of a large group of EVs in order to produce significant changes on a systemic level. When it comes to high EV and PV penetrations, scheduling may not be sufficient to achieve the expected effectiveness as it does not accurately reflect the willingness of EV owners to undertake those charging strategies. Moreover, centralised control is not appropriate for managing a large number of EVs because it requires high computational capability and advanced communication infrastructure to avoid delays in real-time operation [126]. The significant network upgrade investment for peak charging demand can be expected either to have costly implications for consumers or to cause constraints preventing customers from charging their EVs anytime and anywhere [127]. Inevitably, the grid upgrade might eventually mean adding an energy management system (EMS) and power distribution equipment [128, 129]. In this instance, the EMS would control power flow by shifting the EV charging loads to meet scheduled targets [130, 131]. In general, the controllers are responsible for managing EV charging demand, thereby directly controlling the charging process of EVs [126]. Such studies can be found in [132-134], in which the EV charging process was shifted to the period when PV generation was excessive. With increasing penetration of distributed renewable energy, the complexity of EMS is increasing to maintain a proper operation of the grid. Due to this, a robust local controller for the voltage source converter (VSC) is necessary to deal with bidirectional power flows and power ripples. Therefore, it is essential to develop a dynamic power balance system (DPBS) as a supplementary measure to EMS to better manage EV charging loads and renewable generation.

A motor integrated converter was proposed in [135] to operate in the bidirectional power flow mode, wherein energy can be transferred between the vehicle and the dc or single-phase ac supply. A further study in [136] proposed a three-level dc-dc converter to integrate renewable energy, EV and storage altogether within the distribution network. The proposed dc power balance management centre was in charge of the power transition between EV charging and renewable generation, assisting the central converter in balancing power when the imbalanced power was out of its predetermined controllable zone. Similarly, a novel dc power electronic transformer topology was researched in [137] to obtain power conversion between a medium-voltage (MV) dc bus and a low-voltage (LV) dc bus, based on a series connection of full-bridge converters. Another advanced study can be found in [138], in which a multi-port dc-dc converter was adapted in EV integration with energy storage units. The effect of the load shedding was minimised to avoid power quality issues. Basically, a common dc-link based converter developed among the above literature has been utilised to manage the bidirectional power conversion in different scenarios. Most studies have intended to address the integration problem between EV and other types of energy resources, e.g. solar power, or storage units, while ignoring the integration problem between EVs and the grid. There has been little discussion on a power control scheme that can be applied to EV integration within adjacent feeders, which can be used to address the imbalanced power issues arising from coincidental charging behaviours.

The mobility of EVs means that high energy consumption may happen at any available spot within the LV distribution network [139]. From a power system point of view, EVs can be regarded as random moving loads. Uncertain factors, like how users drive, park and charge their EVs, may lead to varying load profiles in residential and commercial areas [140, 141]. The mobile and stochastic characteristics make EV charging loads highly unpredictable in

their spatial and temporal distribution. Such a dynamic scenario exposes a potential risk to the traditional radial LV distribution network, as it is quite likely to overload certain feeders while keeping other adjacent feeders lightly loaded. In this study, this issue is defined as a dynamic power imbalance issue. In the investigation of [142], the main topologies used to configure the LV distribution networks show that most LV networks are designed as radial networks because of the simplicity of analysis and design. The extent of power imbalance may become worse when more distributed PV generation and EVs are penetrated into LV radial distribution networks. To overcome this issue, there is an urgent need to reconfigure the conventional LV network to adapt it to the appearance of imbalanced power.

To address the aforementioned shortcomings, this study proposes a control scheme to incorporate EV and PV integration. It is designed to take into account not only the network constraints but also flexible EV usage. More importantly, the DPBS intends to regulate bidirectional power flow among adjacent feeders instead of direct control of charging processes. It further extends the current feature of tie-line VSCs by transferring EV charging loads and excessive PV power between neighbouring feeders. In this way, power deviations and peak demands should be suppressed within the threshold level. However, the challenge is designing a controller that coordinates parallel VSCs to transfer imbalanced power from the heavily loaded transformer to the lightly loaded one. The DPBS proposed in this study contributes to the issue in the following way:

- Examines the potential impact of coincidental EV charging behaviours by Monte-Carlo Simulation (MCS). This part was previously developed in [85].
- Obtains bidirectional power flow among adjacent feeders through the dc-link spanned across transformers.

- Transfers excessive PV power to local EV charging loads rather than feeding into the grid.
- Tests the robustness of the VSCs (in dq frame) through proper tracking of the reference power and current value. Moreover, multiple control schemes (P-Q and voltage control) are integrated into the DPBS.
- Specifies reinforcement arrangement regarding DPBS in a typical distribution network.

This article is organised as follows: Section 2 presents the overall DPBS system description; Section 3 explains the VSCs' control schemes and mathematical formulations for the DPBS system; Section 4 introduces the modelling of EV charging loads; Section 5 describes the solution method and procedure; the simulation results and discussion are detailed in Section 6; finally, Section 7 presents the conclusions.

2. System Description and Problem Formulation

The proposed architecture of the distribution network is displayed in Fig. 1. The network comprises of three branches with integration of the DPBS, EV, and PV. Each branch consists of a transformer, feeder and EV charging station with a specified number of charging spots. It is assumed there are 80, 80 and 40 available EV chargers allocated within these three feeders, respectively. The EVs will plug into these spots following a predefined probability density function (PDF). The modelling of EV charging demand was derived from the authors' previous work [85], in which the multivariate probabilistic model had been established and validated in MCS. In this paper, EV models are parameterised according to Nissan-Leaf specifications, as presented in Table 1.

Table 1 Charging Parameters of Nissan Leaf EV Model

| Brand | Battery Capacity (kWh, SoC^k) | Charging Power (kW, P_C^k) | Endurance mileage (km, D^k) |
|-------------|-------------------------------------|----------------------------------|-----------------------------------|
| Nissan Leaf | 24/40 | 6.6/11 | 150/250 |

As shown in Fig. 1, three parallel tie-line converters are spanned across LV buses of distribution transformers. P_{e1} , P_{e2} and P_{e3} represent grid power flowing towards EV charging loads P_{x1} , P_{x2} and P_{x3} through the corresponding LV buses. Whenever an EV is connected to the charger, its owner is required to set the charging power rate, plug-out time, and expected state-of-charge (SoC) of the battery (normally 100%). The configuration of the DPBS is depicted by the red dashed line in Fig. 1. The ac sides of VSCs connect to LV buses 1-3 through circuit breakers. They share a common dc bus with an interlinked capacitor.

The DPBS is designed to achieve bidirectional power flow among the three feeders. P_{g1} , P_{g2} , and P_{g3} represent the output power values of the VSCs that are determined by the corresponding controllers. The VSCs control the power flow in both directions according to different strategies. For VSC1 and VSC2, the amount of active power flowing in either direction can be assigned to a pre-set value. VSC3 works as a voltage regulator to maintain the dc-link voltage. In this distribution network, EV charging loads generated by MCS are randomly distributed into 200 chargers along with three feeders. Furthermore, a 73 kWp PV system is considered in a case study to verify the effectiveness and robustness of the proposed DPBS.

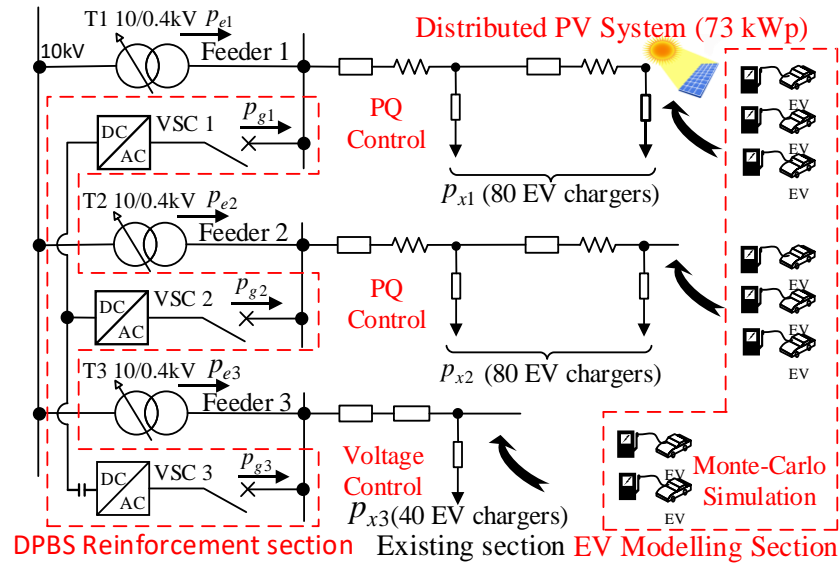


Fig. 1 The proposed DPBS reinforcement in the typical distribution network with integration of EV and PV

3. VSC Control Scheme

The configuration of the three-phase VSC is presented in Fig. 2. The transient mathematic model of the VSC has been widely discussed previously. For simplicity, its control block diagram under the dq synchronous reference frame is presented in Fig. 3 [143].

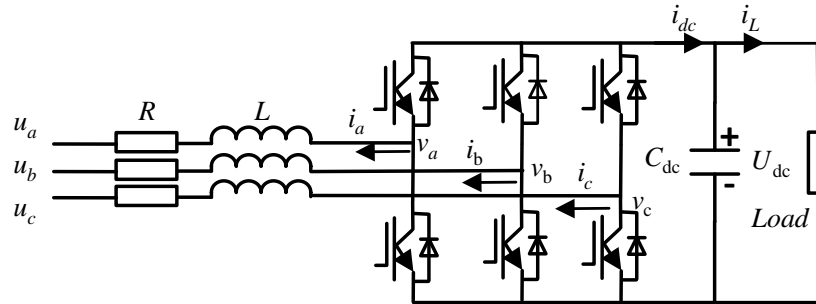


Fig. 2 The three-phase topology of the VSC

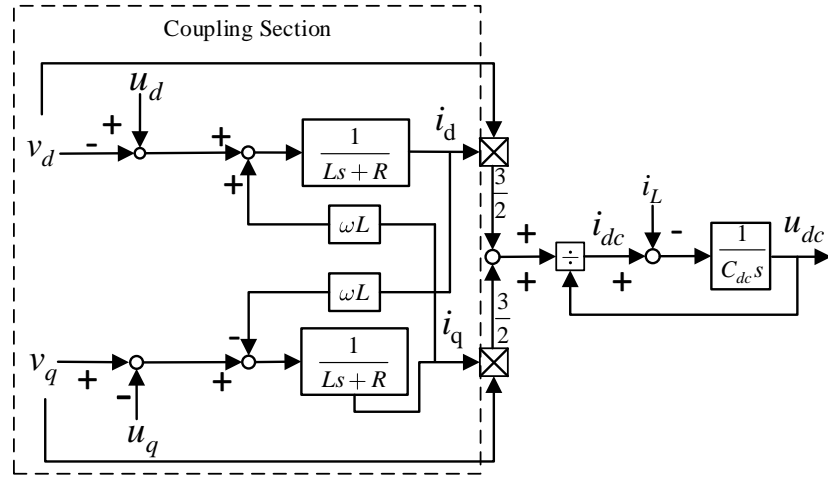


Fig. 3 The control block diagram of the three-phase VSC under the dq synchronous reference frame

A. P-Q Control

It can be seen from Fig. 3 that currents under the dq synchronous reference frame are coupled with each other. Such coupling components make it difficult to control the active power P and reactive power Q separately. Therefore, decoupling control needs to be adopted to eliminate cross-coupling terms ωLi_p , ωLi_q and u_d , u_q . As defined in Eq. (1), a new voltage vector is assigned to consist of v_{gd} and v_{gq} . In a decoupled feedback control strategy, the outputs of the proportional-integral (PI) control current loop are ΔV_d , ΔV_q in Eq. (2) [144].

$$\begin{cases} v_{gd} = u_{gd} + \omega L i_q - \Delta V_d \\ v_{gq} = u_{gq} - \omega L i_d - \Delta V_q \end{cases} \quad (1)$$

$$\begin{cases} V_d = (K_{jd}^p + \frac{K_{jd}^i}{s})(i_d^* - i_d) \\ \Delta V_q = (K_{jq}^p + \frac{K_{jq}^i}{s})(i_q^* - i_q) \end{cases} \quad (2)$$

where i_d^* , i_q^* are reference currents in dq frame, i_d , i_q are actual sampling currents.

Substituting Eqs. (1) and (2) into (3), Eq. (4) can be obtained as follows:

$$\begin{cases} v_d = u_d + L \frac{di_d}{dt} + Ri_d + \omega Li_q \\ v_q = u_q + L \frac{di_q}{dt} + Ri_q - \omega Li_d \end{cases} \quad (3)$$

$$\begin{cases} L \frac{di_d}{dt} = -Ri_d + \Delta V_d \\ L \frac{di_q}{dt} = Ri_q + \Delta V_q \end{cases} \quad (4)$$

Eq. (4) can be rewritten as (5) by substituting (2) into (4). Based on Eqs. (1)-(5), currents in the dq frame can be controlled separately to solve the coupling issue.

$$\begin{cases} (Ls + r)i_d = (K_{jd}^p + \frac{K_{jd}^i}{s})(i_d^* - i_d) \\ (Ls + r)i_q = (K_{jq}^p + \frac{K_{jq}^i}{s})(i_q^* - i_q) \end{cases} \quad (5)$$

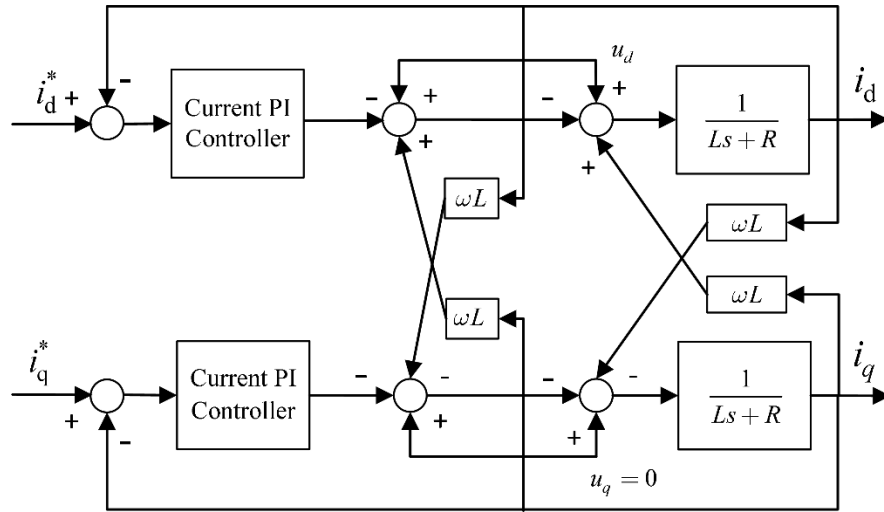


Fig. 4 The control block diagram of current decoupling of the three-phase VSC under the d-q synchronous reference frame [144]

As calculated in Eq. (5), the control diagram of the decoupled current control is displayed in Fig. 4. The introduction of voltage feedforward components, u_{gd} and u_{gq} , improves the dynamic response speed of the system. As a result, P and Q of the VSC are computed as follows [145]:

$$\begin{cases} P = \frac{3}{2} \times (u_d \times i_d + u_q \times i_q) \\ Q = \frac{3}{2} \times (u_q \times i_d - u_d \times i_q) \end{cases} \quad (6)$$

In the EV charging scenarios, the focus is active power rather than reactive power. As a result, the unity power factor is assigned in the P-Q control scheme so that i_q and u_q are equal to 0. Therefore, Eq. (6) can be simplified as follows:

$$\begin{cases} P = \frac{3}{2} u_d i_d \\ Q = -\frac{3}{2} u_d i_q \end{cases} \quad (7)$$

According to Eqs. (5) and (6), i_d and i_q can be calculated based on the pre-set values of P and Q . To do so, the reference values of P^* and Q^* determine i_d^* and i_q^* in the current inner loop (see Fig. 5). It eventually controls the output powers of VSC1 and VSC2 to manage imbalanced power flows coming from the EVs. In the steady-state operation, the reactive power output is assigned to 0; therefore, $Q^* = 0$.

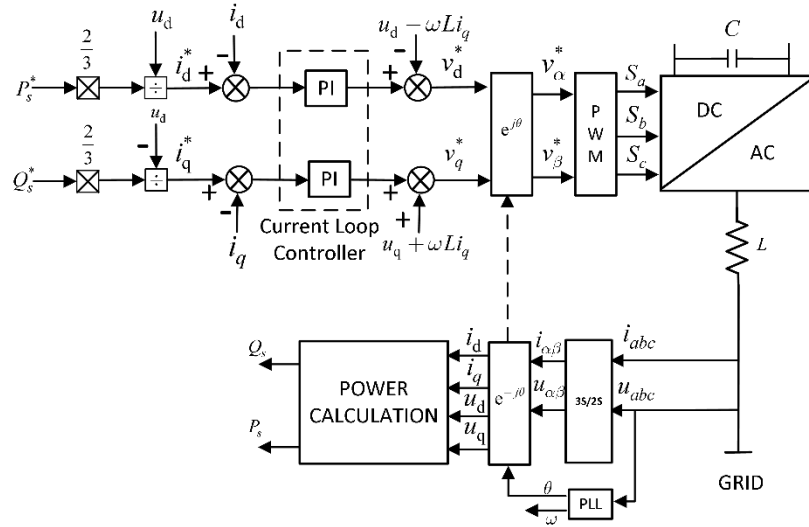


Fig. 5 The power decoupling control block diagram of the VSC

C. Control Strategy in the DPBS

In order to demonstrate the effectiveness of the proposed DPBS, VSC1, VSC2 and VSC3 are equipped in a radial distribution test system, as displayed in the reinforcement section in Fig. 77. Three tie-line VSCs are interconnected by circuit breakers in transformers' LV buses. A voltage-regulating capacitor was added to stabilise the dc-link voltage at 800 V and reduce the impacts on the power-switching bridge. The DPBS is installed as additional components to the existing system to minimise the network reinforcement.

In principle, DPBS balances P and Q transfer among feeders by adjusting the set values of P_s^* and Q_s^* for the tie-line VSCs under the P-Q control scheme. In steady-state operation, the Q_s^* is assigned to 0 to maintain operation with a unity power factor. The problem is how to figure out the reference values of P_s^* for the corresponding feeders to transfer the unbalanced power caused by EVs and PV integrations. The bidirectional power flow among feeders can only be obtained by measuring the voltage and the current signals at the LV bus of the distribution transformer. The targeted load power of each transformer is proportional to its size over the total installed capacity. The imported grid power of i^{th} distribution transformer P_{ei}^* shall be guaranteed as shown in Eq. (10).

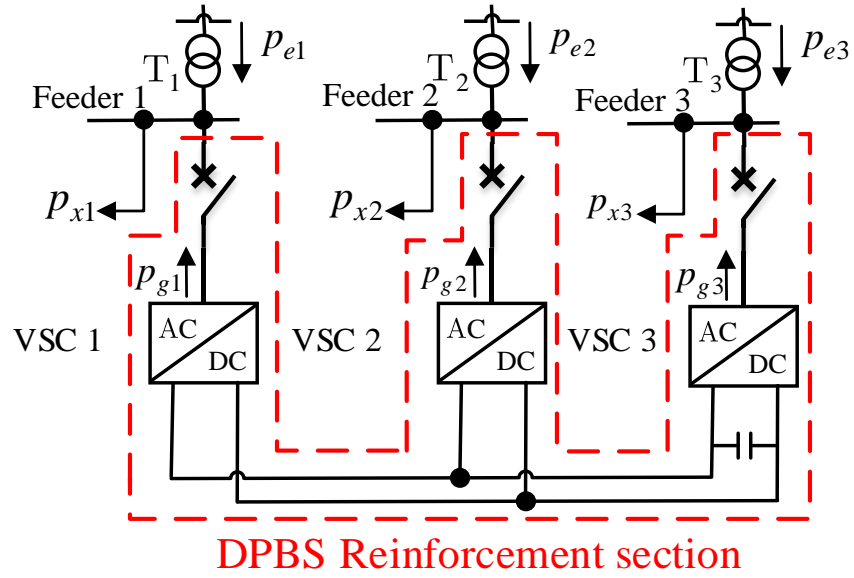


Fig. 7 Configuration of the DPBS

$$P_{ei}^* = \frac{S_i}{S_o} \sum_{i=1}^n P_{xi} \quad (10)$$

$S_o = \sum_{i=1}^n S_i$ describes the aggregated installed capacity of the total transformers within the P-Q control scheme. In this paper, $n = 2$.

According to the power-balance principle, the reference output powers of the VSC and transformer in i^{th} feeder should equal the power demand, as described in Eq. (11).

$$P_{gi}^* + P_{ei}^* = P_{xi} \quad (11)$$

Substituting Eq. (10) into (11), the reference transferred power P_{gi}^* of VSC under the P-Q controlled scheme can be obtained as follows.

$$P_{gi}^* = P_{xi} - \frac{S_i}{S_o} \sum_{i=1}^n P_{xi} \quad (12)$$

Similarly, the measured power values also satisfy the power-balance principle. It is defined as follows:

$$P_{gi} + P_{ei} = P_{xi} \quad (13)$$

Ignoring the power losses of VSCs, that is $\sum_{i=1}^n P_{gi} = 0$, the measured output power of the transformers satisfies:

$$\sum_{i=1}^n P_{ei} = \sum_{i=1}^n P_{xi} \quad (14)$$

By substituting Eqs. (14) and (13) into (12), the reference output power of i^{th} VSC is expressed as follows:

$$P_{gi}^* = P_{gi} + P_{ei} - \frac{S_i}{S_o} \sum_{i=1}^n P_{ei} \quad (15)$$

As calculated in Eqs. (11)-(15), the DPBS only needs to measure P_{gi} and P_{ei} to determine the reference P_{gi}^* for the related VSCs under P-Q control. When the surge load occurs, the reference output power of the VSC may be greater than the rated power. In order to protect the converters, the reference values should satisfy the following constraints:

$$P_{gi}^* = \begin{cases} -P_{gmax.i} & P_{gi}^* < -P_{gmax.i} \\ P_{gi} + P_{ei} - \frac{S_i}{S_o} \sum_{i=1}^n P_{ei} & |P_{gi}^*| \leq P_{gmax.i} \\ P_{gmax.i} & P_{gi}^* > P_{gmax.i} \end{cases} \quad (16)$$

The parameters of the VSCs in the DPBS are listed in Table 2. The P-Q control scheme is applied to VSC1 and VSC2, while VSC3 is operated under the voltage-control scheme to regulate the dc link voltage at 800 V.

Table 2 VSC Designed Parameters in DPBS

| VSC System Parameters | | P-Q Controller Parameters | |
|----------------------------|---------------|--|----|
| Rated Power $P_{gmax,i}$ | 80 kW | Proportional Coefficient $K_{jd,q}^p$ | 1 |
| Rated ac Voltage $v_{d,q}$ | 230 V | Integral Coefficient $K_{jd,q}^i$ | 10 |
| Rated dc Voltage u_{dc} | 800 V | Voltage Controller Parameters | |
| Frequency | 50 Hz | Proportional Coefficient $K_{jd,q}'^p$ | 10 |
| Component Parameters | | Integral Coefficient $K_{jd,q}'^i$ | 10 |
| Inductance L | 6 mH | | |
| Resistance R | 0.02 Ω | | |
| Capacitance C_{dc} | 6 mF | | |

4. Modelling of EV Charging Loads

The household travel survey performed by [62] indicated that the median daily distance travelled for a private vehicle was 23.2 km. Therefore, for private EVs, the mean value μ_D and standard deviation value σ_D in logarithmic probability distribution function are considered to be 3.2 and 0.92, respectively. These are applied to the PDF in Eq. (17) [85]. M^k represents the daily travel distance of k^{th} EV, which is a random variable derived from Eq. (17).

$$f_D(M^k) = \frac{1}{\sigma_D \sqrt{2\pi}} \exp \left[-\frac{(\log M^k - \mu_D)^2}{2\sigma_D^2} \right], \quad M^k > 0 \quad (17)$$

$$SoC^k = 1 - \frac{M^k}{D^k}, \quad 0.1 \leq \frac{M^k}{D^k} \leq 0.95 \quad (18)$$

All EVs need to be fully charged before the next journey starts. Given the full endurance mileage D^k , the initial state of charge SoC^k can be estimated by Eq. (18). As real EV charging data is not publicly available, it is assumed that 80% of private EVs would plug in the chargers from 07:00 to 09:00 and from 16:00 to 18:00; the remaining 20% will be recharged evenly across working hours 09:00 to 24:00. In Eq. (19), it is assumed that each EV immediately starts charging once plugged in at time t_{in}^k . Charging power P_C^k remains

constant until the charging process completes at time t_{out}^k . The $P_{EV,t}^k$ represents the power charging demand of k^{th} EV at time slot t .

$$\begin{cases} P_{EV,t}^k = P_C^k, & t_{in}^k \leq t \leq t_{out}^k \\ P_{EV,t}^k = 0, & \text{other time} \end{cases} \quad (19)$$

The parking duration T_k of k^{th} EV is defined by a random function in Eq. (20). It is rounded to the nearest integer towards infinity in the calculation.

$$\begin{cases} T^k = 5 + rand(-1,1), T_k \in N \\ T^k > t_{out}^k - t_{in}^k \end{cases} \quad (20)$$

In the MCS, t_{in}^k , M^k and T^k are independent stochastic variables for k^{th} EV, which are generated from the predefined Table 4. The MCS schematic process is presented in Fig. 8, specifying the following steps:

- Initiate EV modelling PDF parameters listed in Table 4
- Generate stochastic variables regarding EV charging information based on Eqs. (17)-(20)
- Aggregate EVs charging power

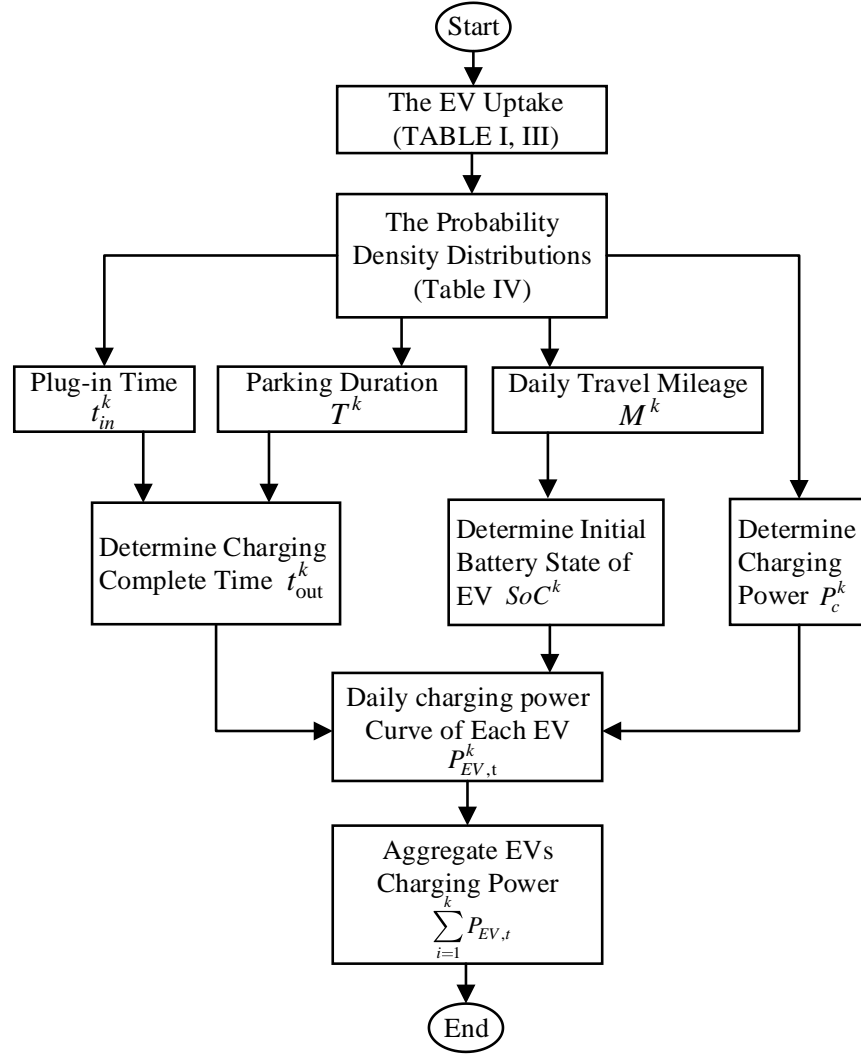


Fig. 8 Schematic process of MCS for EV charging demands [85]

5. Solution Method and Procedure

The flowchart of the proposed DPBS is generalised into steps in Fig. 9. Initially, the EV charging data is obtained from the MCS specified in Section IV. Then, the targeted EV fleets are distributed into three feeders within the typical distribution network. Next, two case studies specified in Table 3 are carried out to test the robustness and effectiveness of the control schemes in DPBS.

Case study 1: a basic charging scenario consisting of 200 EVs within three feeders.

Case study 2: case study 1 plus the installation of a 73 kWp PV system in feeder 1.

Table 3 Considered Case Studies for DPBS

| Case Studies | Feeder 1 | Feeder 3 | Feeder 3 |
|--------------|--------------------------------------|----------|----------|
| 1 | 80 EVs | 80 EVs | 40 EVs |
| 2 | 80 EVs Plus 73 kW _p PV | 80 EVs | 40 EVs |

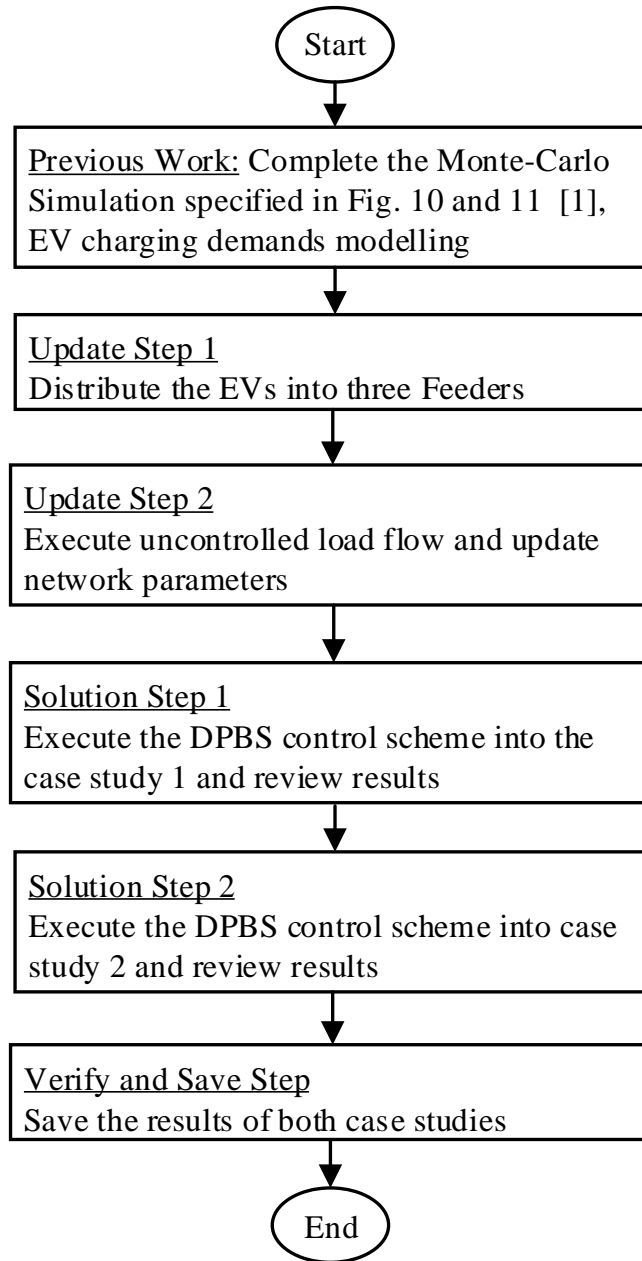


Fig. 9 Flowchart of implementation of the DPBS into the distribution network

6. Results and Discussion

The temporal distribution of the 200 EVs' charging profile is conducted in MCS. The PDFs defined in Table 4 are extracted from statistic data [62] to generate EV charging data. All results are rounded to the nearest 15 minutes' time slots towards infinity in the calculation, as it is easy to split 24 hours into 96 slots, and the time step is appropriate for recording vehicle parking events and PV generation.

As shown in Fig. 10, the charging profile of 200 EVs generated in MCS reveal that coincidental charging behaviours normally happen in the early morning and evening. According to the statistics in [62], private EV drivers prefer to recharge their vehicles during the early on-work and off-work period. The detailed charging durations are displayed in Fig. 11. The Gantt chart records the charging and parking durations of 200 EVs by red and green bars respectively. Based on usual driving habits, charging times only take up a minor fraction of the total parking duration.

The typical daily PV generation data is considered in case study 2 to validate the effectiveness of the DPBS. The realistic daily generation curve was gathered from a 73 kWp PV plant located in the University of Queensland, St Lucia campus (GP South), Australia [146]. As presented in Fig. 12, the PV generation peaks at nearly 50 kW around midday. The sharp power drop may be caused by clouds floating through the air.

The 200 EVs are randomly distributed into three feeders by three groups 80, 80 and 40 respectively. Whenever an EV is connected to the charger at time t , it will start the charging process immediately until SoC^k reaches 100%. The aggregated charging power curves are recorded in Fig. 13. Without installation of the DPBS, the identical numbers of EVs plugged in feeders 1 and 2 result in peak demands of roughly 230 kW. In the same periods, feeder 3

with 40 EVs makes its highest power point slightly below 100 kW. The red dashed line represents the power curves of feeder 1 in case study 2, which involves 80 EVs plus a 73 kWp PV generation system. As shown in Fig. 13, the additional PV generation reduces the peak power demand, to approximately 150 kW at 9:00, and feeds excess power into the grid from 10:00 to 15:00.

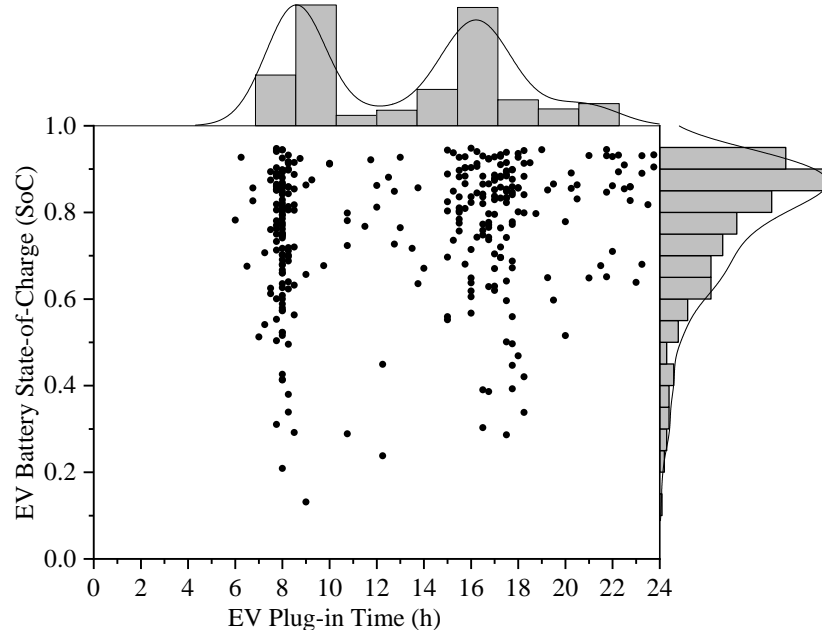


Fig. 10 Scatter plot between EV plug-in time and initial SoC

Table 4 Charging Parameters of EVs in MCS

| Plug-in Period | Charging Power (kW, P_C^k) | Probability | Initial SoC^k Distribution | Plug-in time t_{in}^k |
|----------------|--------------------------------|-------------|---|-------------------------|
| 07:00~09:00 | 6.6 | 40% | Equation (17) based on log N (3.2,0.92) | N(8,0.5) |
| 16:00~18:00 | 6.6 | 40% | | N(17,1) |
| 09:00~24:00 | 11 | 20% | | Even Distribution |

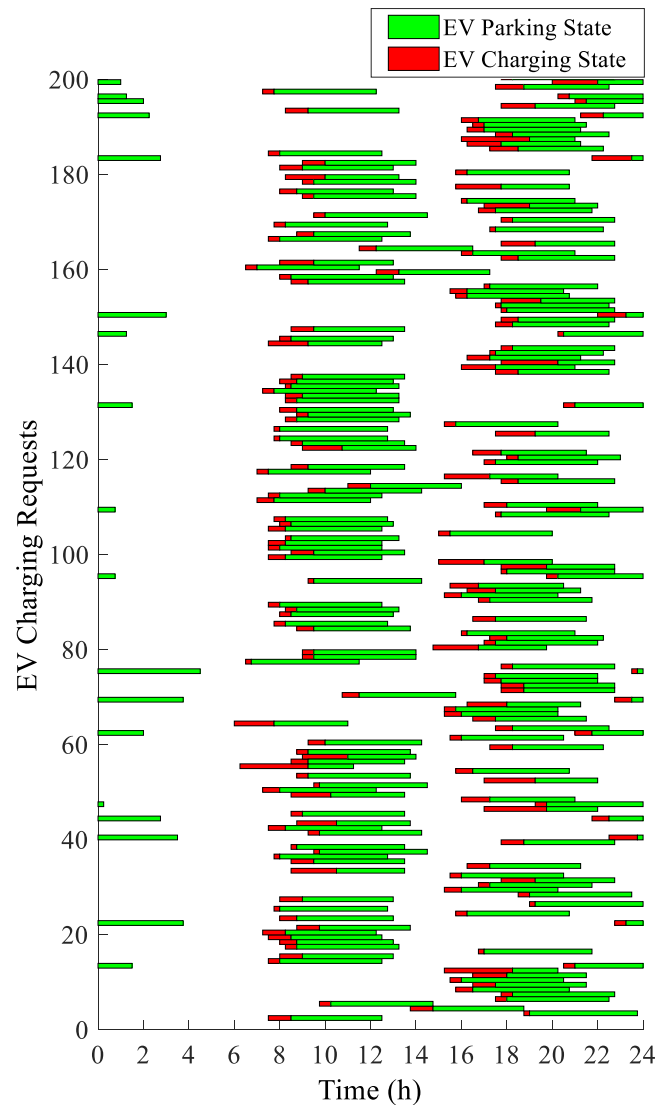


Fig. 11 EVs' charging information in Gantt Chart

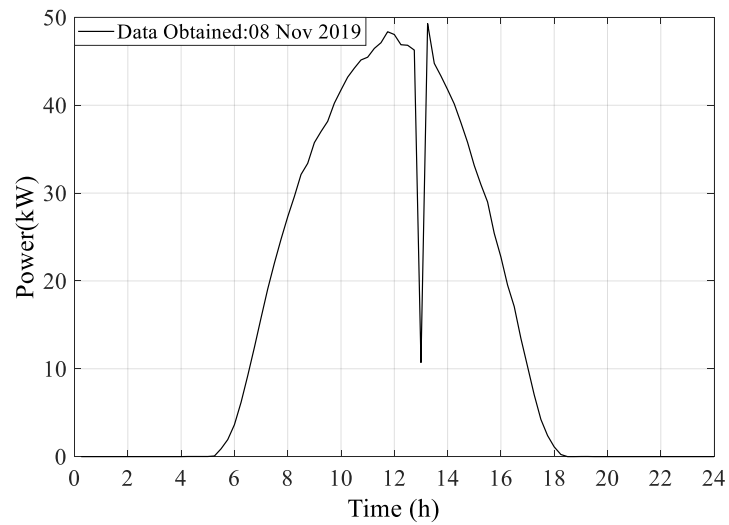


Fig. 12 Typical power generation curve of a 73kWp PV system [146]

The comparison of power curves demonstrates the power imbalance issue in feeders 1 and 2, and their corresponding transformers. With identical numbers of EVs and chargers being allocated, the resultant power curves have diverse shapes regarding peak power points and fluctuations. Such variation may become apparent if more EVs and charging spots are considered. In the case of 250 kVA transformers in feeders 1 and 2, the load factors almost reach as much as 90% without installation of the DPBS.

The load profiles of both case studies in Fig. 13 are imported into MATLAB/Simulink package. To do so, the 24-hour time horizon is mapped into 1 second in the Simulink environment. Then, two case studies are simulated with DPBS installed. Fig. 14 depicts the resultant charging power curves among the three feeders. Under the P-Q control scheme, feeders 1 and 2 illustrate almost the same variance and smooth effects on power curves. By comparing Fig.13 with Fig.14, it is clear that the peak power point drops from 230 kW to around 200 kW in both case studies. More importantly, when PV generation reaches spur power output, the renewable power is consumed locally in Fig. 14(b) rather than being fed into the grid in Fig.13. As all transformers have the same installed capacity of 250 kVA, the resultant power curves should be nearly identical according to the P-Q control schemes (see Fig. 14).

It can be seen from Fig. 15 that the transferring powers of VSC1 and VSC2 play an important role in balancing power consumptions within feeders 1 and 2. As presented in Fig. 14, feeder 2 experiences 60 kW more power demand than feeder 1 from 8:00 to 10:00. The controllers then assign reference power commands P_{g1}^* at around 30kW for VSC1 and P_{g2}^* at about -30 kW for VSC2, which means that the VSC2 is transferring the extra 30 kW load to VSC1 through the dc-link spanned across corresponding LV buses. The transferring power aims to compensate for the unbalanced EV charging loads among feeders 1 and 2. In the early

evening between 17:00 and 20:00, the transferring power flows in the opposite direction, from feeder 1 to feeder 2 to balance out the higher EV charging demand in feeder 1 (see Fig. 15).

The functionality of VSC3 in feeder 3 is to regulate capacitor voltage. It draws roughly 20 kW from the grid to maintain the dc voltage at 800 V (see Fig. 16). The voltage and current waveforms among feeders 1-3 under the DPBS are presented in Fig. 17. The resultant waveforms demonstrate that the currents keep precise track of the reference values assigned by P-Q and voltage controllers in the DPBS.

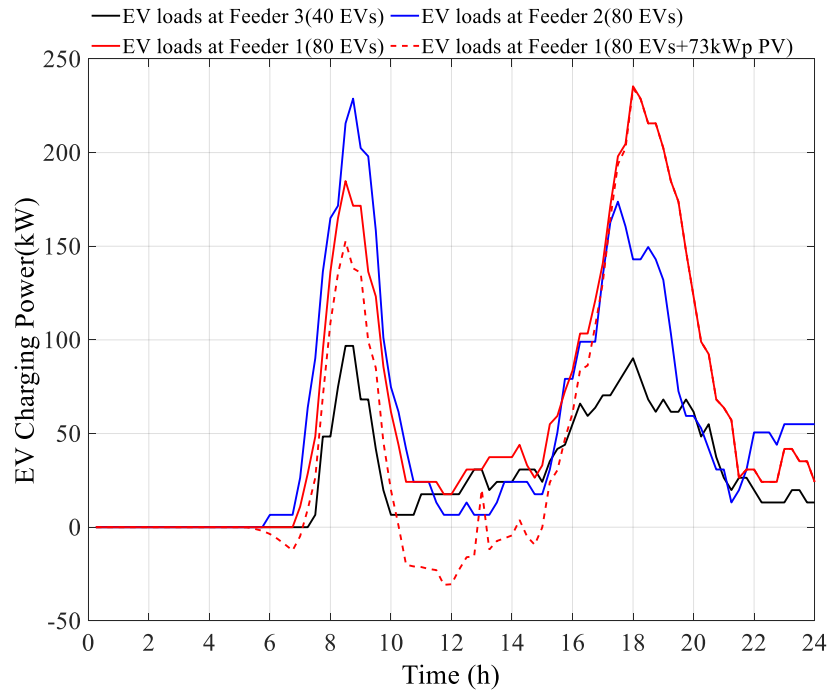
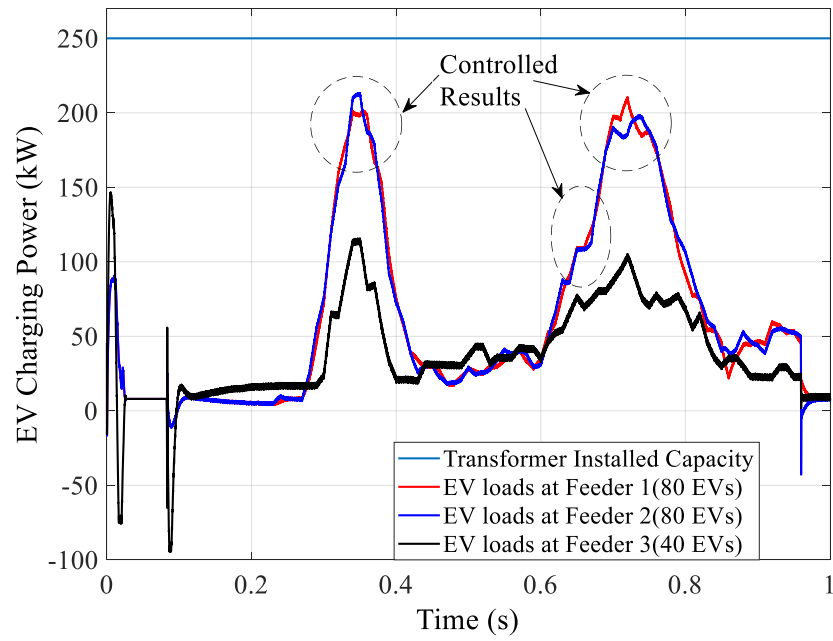
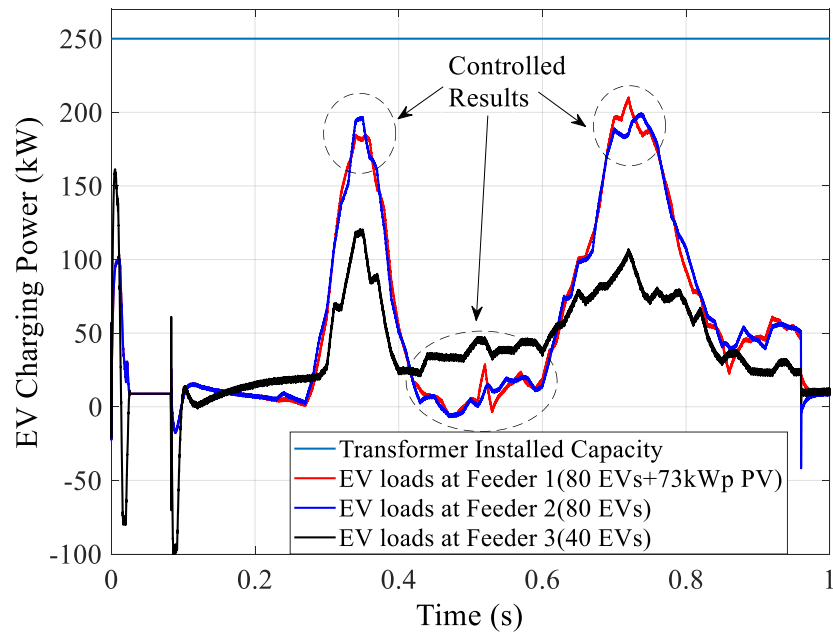


Fig. 13 Power curves without installation of the DPBS

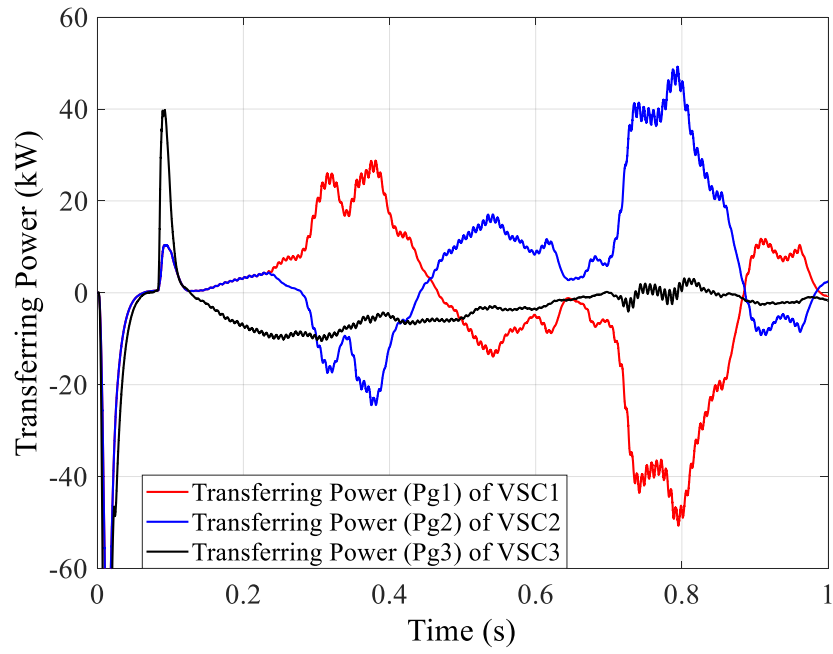


(a)

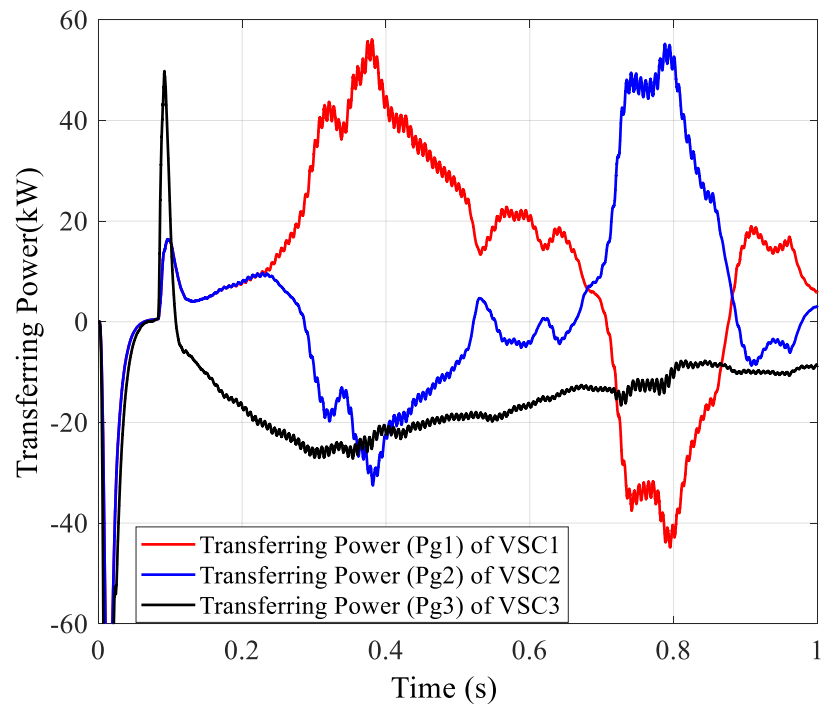


(b)

Fig. 14 Resultant power of feeders with installation of the DPBS: (a) case study 1 and (b) case study 2



(a)



(b)

Fig. 15 Resultant power transition of VSCs via the dc-link: (a) case study 1 and (b) case study 2

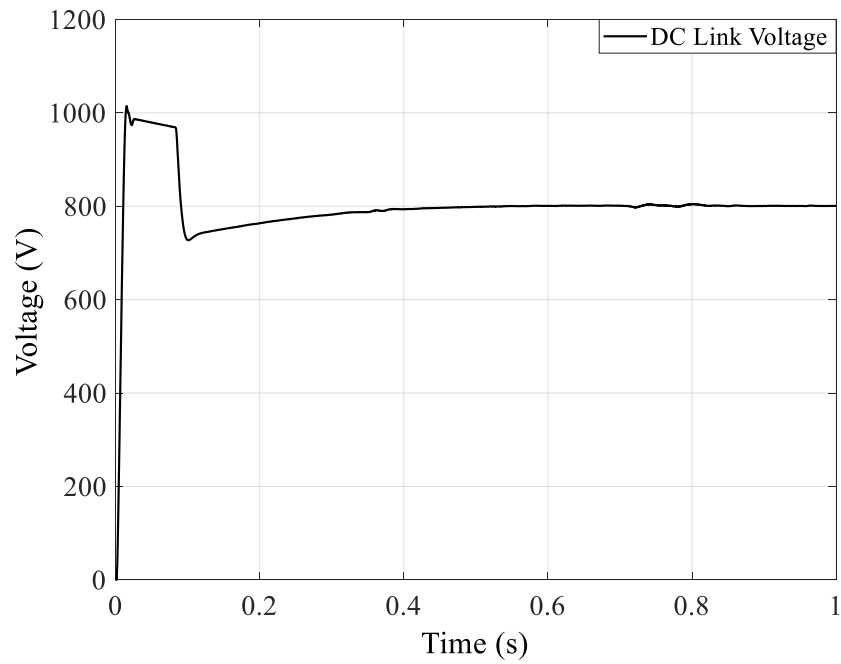


Fig.16 Voltage waveforms of dc-link in case study 2

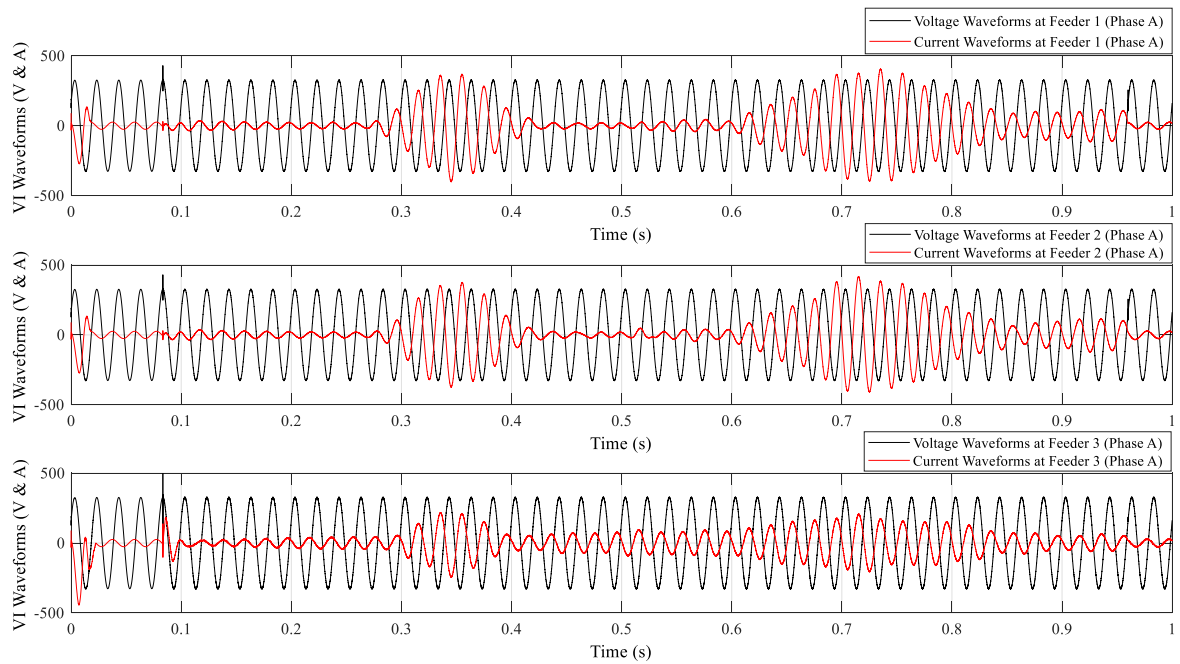


Fig. 17 Voltage and current waveforms among the three feeders in case study 2

7. Conclusions

In this paper, the proposed DPBS is presented to solve the dynamic power imbalance problem that originates from the integration of EVs and PV. The imbalanced power flow among adjacent feeders is investigated by modelling EV charging loads and PV generation into the distribution network. The aggregated EV charging loads are implemented in MCS, taking into account several factors that may affect the load profile.

Two elaborate case studies are adopted in the simulation in an attempt to demonstrate the effectiveness of the proposed control scheme. In case study 1, the peak charging demand as a result of the coincidental EV charging behaviours has been mitigated by the DPBS. At the same time, the power flow in feeders 1 and 2 is well managed to share fluctuation and unbalanced power, so as to smooth the power consumption curves. Furthermore, case study 2 demonstrates that the excess PV power could be consumed locally to charge EVs instead of being injected back into the network. With the DPBS installed, the bidirectional power flow is observed between the VSCs to transfer excess power to where it is needed. The effectiveness and robustness of the P-Q and voltage control schemes are verified in the two case studies. The simulation results validated that the coordinated control scheme achieves proper operation in the typical distribution network.

The proposed DPBS is installed as additional components to the existing distribution network to minimise network reinforcement. It provides a potential upgrading solution for conventional LV radial network. The control scheme could be used in the grid to adapt to the possible appearance of the imbalanced power in the future.

Chapter 5 Conclusions and Future Work

1. Introduction

This chapter concludes the thesis, outlines the contributions of this research and also discusses future work. The goal of this thesis was to investigate the optimisation and control techniques that could be applied to distribution networks to better manage EV charging loads. Elaborated scheduling strategies and control schemes were proposed to solve EV integration issues regarding both technical and economic aspects. First, Section 5.2 summarises the conclusions and contributions made in this study. Second, Section 5.3 discusses the future work needed to enable the adoption of EVs integration. Finally, Section 5.4 summarises the research statement of this study.

2. Conclusions and Contributions

In order to obtain the smart management of EV charging loads, it is vital to gain a comprehensive understanding of charging behaviours and desired control targets. The design process of scheduling strategies and control schemes have been conducted step-by-step in a research pathway, where it begins with modelling of large-scale EV charging loads, smart scheduling strategies, and then the control schemes for DPBS.

The following contributions have been made in this thesis:

- (1) In manuscript 1, a large-scale EV charging model was built to fill the gap in cross-sector analysis (transport and energy sectors) regarding the temporal distribution of charging behaviours and charging strategies. The modelling technique made use of MCS to estimate aggregated EV charging loads considering randomness and heterogeneity based on transportation statistics data. In this way, the problems of uncertainty regarding distribution network planning with the integration of EVs were addressed. The randomness and heterogeneous characteristics were detailed by the

proposed methodology. A case study consisting of four main EV fleets was carried out to test the effectiveness of non-smart and smart charging strategies regarding the impact of peak-shaving and valley-filling. The results demonstrated that the peak power points caused by the coincidence of EV charging demands were mitigated by the proposed coordinated charging strategies. These targeted EV fleets were rescheduled to flatten the load curve to enable the postponement of the investment into network reinforcement.

- (2) Manuscript 2 developed an online economic scheduling strategy according to manuscript 1's model, which could be used to coordinate energy trading between DNOs and EVs for a win-win ecosystem. The proposed online EV scheduling strategy enabled the plug-and-play system to optimise the aggregated EV charging parameters, i.e. charging power and charging costs. As a result, both EVs and DNOs that participated in the energy market can benefit from the proposed rolling horizon scheduling strategy by satisfying cost-effective goals. The online scheduling results based on the proposed tariff demonstrated that the interaction between price-based signals and charging behaviours is a key factor in the effectiveness of peak load shifting under market mechanisms. The rolling prediction of wholesale electricity prices offered a certain level of perception to the proposed charging strategy to make proper decisions on opportunity charging.
- (3) A novel control scheme was proposed in manuscript 3 to cope with the dynamic power imbalance issue that was derived from the integration of EV and PV in distribution networks. The control scheme was deployed in the DPBS to regulate bidirectional power flow among adjacent feeders with EV chargers and PV generation installed. The power transfer of EV charging loads and PV generation was performed through three tie-line VSCs installed in corresponding feeders. This enabled the suppression of power deviations and peak demands within a threshold level within

network operation limits. The proposed DPBS made use of multiple control schemes (P-Q and voltage control) to drive VSCs to mitigate the dynamic power imbalance issue so that excess PV power could be consumed locally to charge EVs instead of being injected back into the network. At the same time, the power flow among feeders was well managed to share fluctuation and unbalanced power so that the power consumption curves were smoother. The effectiveness and robustness of the proposed control scheme were verified by the two case studies. Simulation results validated that the coordinated control scheme achieves proper operation in the typical distribution network. The proposed DPBS provided a potential upgrading solution for conventional LV radial networks to adapt the possible appearance of power imbalance in the future.

3. Future Work

Based on the limitations of the current study, the following recommendations are made for the consideration of future study related to this subject area.

3.1 EV data analysis

This research makes use of ICEV travelling data to investigate EV travelling and charging demands because the realistic data of EV usage is not publicly available due to privacy concerns. To make a more realistic assumption, realistic EV charging data needs to be obtained to analysis charging behaviours. This requirement highlights the importance of data acquisition. It could be periodically retrieved from the real-time status information of each charger. Big data technology could be used in both the power and transport sectors to collect EV parking, travelling and charging data. After combining a variety of statistical and machine learning techniques to understand the demand pattern of electric vehicle charging, they can be used to develop policies for siting charging stations, evaluating the capability of the power grid and determining the market value for the services provided for EVs. It would be interesting to engage with leading stakeholders in the transport and

power sectors to collaborate on EV data so that all participants can reap the societal benefits of future EV uptakes identified by the government.

3.2 Vehicle-to-Grid (V2G)

Vehicle-to-grid (V2G) is considered one of the most advanced and valuable forms of smart charging in the distribution network, which further complicates the charging process by deploying bidirectional power flow. The focus of this research is mainly placed on one-way charging from the grid to the EV while ignoring the feasibility brought by V2G. Two-way charging allows batteries to discharge the power back to the grid when required, making the batteries an additional energy storage resource. The aggregated V2G capability could contribute to a virtual power plant (VPP) to enhance the stability of the power grid. With full V2G capability, EVs can potentially provide better peak-shaving and valley-filling as well as the possibility to control two-way charging, according to electricity tariffs, to gain more financial benefits for EV customers. Therefore, immediate future work will be developing an optimised scheduling strategy considering V2G in the energy trade market.

3.3 Three-phase imbalance charging

This research investigates the power imbalance issue among adjacent feeders because of the stochastic characteristic of EV charging behaviours. With the increased mixture of single-phase and three-phase loads, the phenomenon of voltage imbalance will be more severe in distribution networks. In a practical scenario, EVs as mobile single-phase loads will be randomly plugged in nearby residential, commercial and industrial areas where charging facilities are connected to either a single-phase or three-phase power supply in distribution networks. The three-phase imbalance problem may be further complicated by a massive single-phase distributed PV. It is a challenge to develop a control technique that could be utilised to alleviate the voltage imbalance with the integration of EVs and PV.

4. Summary

This research aimed to develop a smart charging strategy and control technique to prevent EVs from stressing distribution networks. It may provide insights for power system regulators to formulate and evaluate EV policies that will encourage EVs and distributed PV deployments. The possible business potential in charging services could be backed by various participants in the energy market. Within this Chapter, the conclusion and contribution of this research are provided. Furthermore, possible future work in continuum with this research are suggested.

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