Double Demand Responsive Electric Bus Operation to Passengers and Power System

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A thesis submitted as fulfilment of the requirements for the degree of Doctor of Philosophy of Imperial College London

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October 2018
Declaration

The research that is presented in this thesis is my own words, except where the work of others is referenced.

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Acknowledgements

First and foremost I would like to express my sincere gratitude to my supervisors Prof John Polak and Prof Goran Strbac for their patience, motivation, and immense knowledge. Without their invaluable supports, I would not have advanced any parts of this research in transport and power system.

Besides my supervisors, my sincere thank goes to Dr. Fangce Guo, Dr. Jianlin Luan, Dr. Yujian Ye, Dr. Fei Teng, Dr. Dimitrios Papadaskalopoulos, Dr. Aruna Sivakumar and Dr. Konstantinos Gkiotsalitis for their insightful comments and guidance in their highly experienced field, but also for the hard question which incented me to widen my research from various perspectives.

In the happy moments and the difficult ones that punctuate a four year commitment, I had the privilege to be immersed in the affection of friends and family who may not have been all physically close, but they have been all felt so. And particular gratitude to me fiancee Wenhan, wholeheartedly for your patience and accompany.
Abstract

Recently the potential for the electrification of urban bus fleets has attracted considerable policy, industrial and academic attention. Although there are significant potential benefits in terms of reduced local emissions and operating costs, electric bus operations raise a number of new challenges – how electric bus fleets and electric network operators can optimally benefit from the synergetic interaction, both as consumers of electricity and providers of grid balancing services. Researches in the public transport field exhibit simplistic learning from isolated operations in the proof-of-concept projects without considering the dynamic in electricity supply, whilst the lack of understanding of the interdependence between electric mobilities and charging flexibility has limited power system researchers applicability of load management of electric bus fleets.

Against this backdrop, this thesis proposed, analysed and tested an analytic framework consist of two approaches that accommodates the interaction between the grid-integrated e-bus operation and demand side management in power system. At First, the classic frequency setting models are extended to incorporate the charging dimensions – charging duration and residual energy requirement - and embedded into a Stackelberg game model where the lower-level problem corresponds to the electricity pool market which generates distribution level location-specific prices. Secondly, in order to couple more complicated bus service patterns including short-turning and interlining options, a novel adaptive service scheduling approach is developed to embrace higher level of flexibility responding to the variation of passengers demand and electricity tariff. Extensive case studies using real-world transit data and IEEE test system, with different scenarios of operating conditions, are used to validate the theoretical properties of the proposed mechanism. This framework provides tools enabling the electric bus fleets operator to achieve cost-effectiveness by understanding the implication of dynamics in electricity supply and electric network operators to deliver efficient load management by utilising the flexibility of electric buses loads.
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List of abbreviations

$pp$  Planning period
$Z$  Feasible set of frequency
$\{L, S\}$  A bus network with bus lines $L = \{1, 2, ..., |L|\}$ and bus stops $S = \{1, 2, ..., |S|\}$
$S'$  Origin and Terminal stations in $S$ that have electric chargers
$CP_l$  Location index of Control Point in route $l \in L$
$J$  Junctions allowing bus transfers between bus routes which constituted by Origin, Terminal stations and Control Points
$A_{i, l}^{j+}$, $A_{o, l}^{j-}$  Section that have inbound/outbound bus arriving at particular stop which usually being a junction of several routes $j \in S$
$NB$  Total number of available bus
$h_l$  Headway in route $l \in L$
$T_l$  The round trip travel time required for completing the trip
$W_{i,j,l}$  $|S| \times |S| \times |L|$ dimensional matrix denoting the combined view of passenger wait time for each stop pair $i, j$ in route $l$
$B_{i,j,l}^h$  Historical data of passenger boarding at stop $i$ and alighting at stop $j$ deduced from smart card data
$B_{i,j,l}$  Updated amount of passenger boarding at stop $i$ and alighting at stop $j$ that elastic to waiting time
$\rho_o$  Unit operating cost associated with bus travel kms
$\epsilon$  Fare per passenger.
$\theta$  Bus speed (km/hour)
$e, w_b$  elasticity and Benchmark wait time
$\tau$  Bus transit capacity (p)
$ct_{l,s'}(f)$  Charging duration at station $s'$ of bus line $l$
$\eta$  Grid-to-vehicle charging efficiency (p)
$L_{l, t, s'}(f, x)$  Charging load (kW) at station $s'$ in hour $t$ of bus route $l$
$\varrho$  Energy consumption ratio (kWh/km)
$\phi(k, T_n, f_n)$  Accumulated travelling time of bus $k$ according to the trip assignment based on $f_n$
δ Charging rate (kW)
ρb, ρc Unit battery capacity cost, unit charger cost
κ Battery capacity (kWh)
1, 2, ..., K A number of electric bus required to provide service
NC(t, s') Number of effective chargers in station s' at hour t
\( \sum_{k \in K} U(k) \) Total effective usage capacity of battery
\( \sigma_{t,n} \) Dynamic tariff rate at node n at time t
\{N, C\} A distribution network with N nodes and C feeders.
\( \rho^g_{t,n} \) Unit cost of generation at time t for generator at node n
\( D_{t,n} \) Inflexible demand at node n \( \in N \) at time t
\( f_l \) Bus dispatch frequency (decision variable) in route \( l \in L \)
x Charging control variables (decision variable)
\( P_n \) Net power imported or Generator dispatch at node n (decision variable)
\( R_c \) Impedance of power line/feeder c
\( PLoss \) Power loss estimated from iterative DCOPF
\( E^{FND}_{t,n} \) Fictitious Nodal Demand (FND) deduced from the estimated Ploss at node n at time t
\( PF_c \) MVA capacity of power line c \( \in C \)
\( SF_{c,n} \) Power transfer distribution factor coefficient of power line c w.r.t. to a unit injection at node n
\( DF_{t,n} \) Power transfer distribution factor coefficient of node n w.r.t. power line injection
\( LF_{t,n} \) Loss factor coefficient at node n at time t
\( \lambda \) Dual variable of total power flow balance constraints
\( \mu^+ \) Dual variable of power flow constraints
\( \alpha_t \) Weighting of congestion and lost component in dynamic tariff
\( M \) A population of M in GA algorithm
\( g, NG \) Gene and length of genotype of individuals in the population in GA
\( DLMP \) Distribution Locational Marginal Price
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<th>Abbreviation</th>
<th>Full Form</th>
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<tr>
<td>DT</td>
<td>Dynamic Tariff</td>
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<tr>
<td>EV</td>
<td>Electric Vehicle</td>
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<tr>
<td>e-Bus</td>
<td>Electric Bus</td>
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<tr>
<td>e-Mobility</td>
<td>Electric Mobility defined as the mobility of vehicle and mobility of e-Bus charging demand</td>
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<tr>
<td>FSP</td>
<td>Frequency Setting Problem</td>
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<td>FND</td>
<td>Fictitious Nodal Demand</td>
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<td>GA</td>
<td>Genetic Algorithm</td>
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<td>G2V</td>
<td>Grid to Vehicle</td>
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<tr>
<td>KKT</td>
<td>Karush-Kuhn-Tucker optimality condition</td>
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<td>LTDS</td>
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<td>SoC</td>
<td>State of Capacity</td>
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<td>SM</td>
<td>Serve Matrix</td>
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<td>ToU</td>
<td>Time-of-Use electricity tariff</td>
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Chapter 1

Introduction

1.1 Background

Announced in December 2015 and enforced in November 2016, the Paris Agreement set the objective of limiting the increase in the global average temperature to well below 2°C above pre-industrial levels. The transport sector is the second source of global energy-related carbon emission, and accounted for around half of the global oil consumption (ICCT, 2012). With increasing environmental concerns associated with the use of fossil fuels, the electrification of transport is expected to play a crucial role in the decarbonisation of the energy system. To be more specific, the Electric Vehicles Initiative (EVI) - a multi-government policy forum under the Clean Energy Ministerial - set the aspirational goal for all member countries of a 30% market share of Electric Vehicles (EVs) in the total of all passenger cars, light commercial vehicles, buses and trucks by 2030 (IEA, 2017).

Under such a stimulating environment that dedicated to accelerating the EV deployment, major global urban centres tend to witness growing interest in the use of battery electric buses. It is estimated that the number of worldwide electric bus fleet has reached approximately 173,000 in 2015. (ODonovan et al., 2018). At the same time, there is also increasing interest in the potential use of EVs as flexible resources in Demand Side Management (DSM). Growing energy
security challenges emerge over the wide deployment of Renewable Energy Resources (RERs) and increasing penetration of embedded EV customers. With the proliferation of proactive customers, the traditional passive operation mode of distribution utilities which only focus on the reliable power supply is inadequate.

However, the increasing number of electric bus connecting to the power system will add one dimensional complexity of the needs for grid support. First of all, the intuitive implication of uncoordinated EV charging is the intervention (upgrading or even complete replacement) in the distribution. If all buses in the UK were electrified, 850 MW of power, the same as one large nuclear reactor or two coal-fired turbine (Low carbon vehicle partnership, 2016), has to be coordinately managed. Another report of the ‘My Electric Avenue project’ delivered between 2012 and 2015 by the EA Technology on behalf of Scottish and Southern Energy Networks showed that, 32% of medium voltage (11 kV) and low voltage feeders, totalling 312,000 circuits, will require intervention (upgrading or even complete replacement) when 40 to 70% of households have EVs (EA Technology & Southern Electric Power Distribution (SEPD), 2016). Secondly, the conventional backup generation capacity and dedicated storable capacity are expensive in face the emerging energy security challenges. If the storage capacity of the batteries in EVs can be engaged in the demand response programme, such as for personal use (Faria et al., 2012), for buildings (Ioakimidis et al., 2018) and for aggregated application through Vehicle-to-Grid (Tan et al., 2016), there could potentially be significant benefits for both grid operators and EV owners.

Since buses are ubiquitous in many cities, if and when a significant proportion is converted to batter-based power trains they offer an especially attractive potential. Four specific features of electric buses make them particularly attractive to drive the engagement:

1. they offer a high degree of spatial predictability due to the limited choice of route;
2. they are also spatially extensive and collectively inter-connected by schedules;
3. they offer top-to-bottom control of a series of highly concentrated and charging infrastructure with large power;
(4) they offer access to a large number of standardised high capacity batteries.

However, although the technical feasibility has been investigated in numerous researches (Li, 2016; Mohamed et al., 2017a) and demonstration projects (Frontier Economics and Sustainability First, 2012), electric bus operations still raise a number of new challenges. In the context of operational study, it consist of how best to integrate and optimise bus battery charging activities and bus services schedules. In the context of demand response, the main challenges consist of the prediction of the load profile, both temporally and spatially, and the mechanism to manage the load effectively. Therefore The multi-disciplinary feature of electric mobility has driven this research aiming at utilising the tempo-spatial load profile to maximise the benefits of transportation electrification to both bus operations and power system operations.

1.2 Research gaps and motivation

As indicated by the above description regarding the challenges and potential of electric buses, the interaction between electric bus operation responding to the passenger commuting demand and the demand response requests attract increasing interests. Before the potential of electric mobilities can be realised, here are four critical research gaps that found in the literature.

First, the bulk of the existing work on EVs and their potential synergetic interaction with the power grid has focused on modelling the energy demand of light duty vehicles (i.e. passenger cars) in a simplistic linearity, rather than distinguished load patterns by vehicles types. The EVs integration necessitates a demand responsive load in the power system. From this derivation, the travel behaviour has not been explicitly modelled but represented as the image of the pre-determined constraints and scenarios. In this way, it makes the approach to appear as a less sensitive model to the test of the effectiveness of using the electric bus to support the grid operation.

Second, although there are increasing numbers of practical trials of electric buses operation in the UK (e.g. Milton Keynes), Switzerland (e.g. Geneva) and China (e.g. Shenzhen), the princi-
pal focus of these trails has on methods to the challenges in achieving effective operational range for electric buses in the context of isolated single bus route operation. In particular, whilst a wide variety of charging strategies have been explored in literature including opportunity charging (Miles and Potter, 2014a), rapid charging (Filippo et al., 2014), continuous charging (Leemput et al., 2012a) or charging station planning (Wei et al., 2018), the focus has on supporting existing vehicle duty cycles. The practicability of electric buses in more complicated operations has not been investigated and demonstrated.

Thirdly, existing literature solving bus scheduling problems focus exclusively on satisfying demands from the transportation market (i.e., passenger demand) rather than jointly considering demands from the transport and energy market together. The conventional approach to bus scheduling, dating back to Mohring (1972), seeks to optimise the allocation of resources such as vehicles and drivers to each service line of a transport network according to passenger demand only. There is a need to extend the existing scheduling approach to take into consideration the grid-integrated electric bus operation.

The final limitation in the existing literature is that electric buses have not been directly involved in an grid-support manner. Hence, the research gaps motivate a re-design of the EV-grid integration mechanism to include the demand response of bus operation models that based on bus travelling activities and automatic responding scheme minimising the systematic balancing cost.

In a nutshell, the lack of EV-grid integrated studies make the SoA works unable to realise the full potential of EV, either because they overestimated the vehicle flexibility or underrated the return of electrification. These intellectual and practical challenge that has not yet been addressed in the literature shape this research in an exclusive way that incorporate the tempo-spatial characteristics generated by dedicated e-bus service with the electricity markets requiring particular service. A framework is pivotal to quantify the impacts of the dynamic in one side market when supply/demand price is affected by the system operation condition of the other. It is capable to improve the electric bus fleets operations with enhanced control over charging that responds to both the passenger demand and load management signals.
1.3 Thesis scope

This thesis aims to answer the question: what’s the main impacts on the service in the shift to electric mobility within a smart energy system. It will contribute to the work on the integration of electrified transportation and smart grid operation by the first time accounting for the dynamic in the tempo-spatial characteristic of electric bus mobility within the power system. This objective is achieved by developing a methodology to investigate electric bus charging and operation in technological scenarios that enable interactive smart grid operations. To be specific, the objectives for the electric bus operators include:

1. To Identify the extension of capability that has not fully realised in the scheduling of traditional bus service and the potential application brought by the electrification of power-chain;

2. For an inherent connection of bus travel activities and charging loads regarding the location, timing and magnitude, through the comprehensive depict of the decision-making process of bus service patterns;

3. To analyse how external factors such as electricity tariff, batteries cost and opportunity charging could sustain the electric bus operation in more complicated operational conditions

and the objectives for power system include:

4. To derive a pricing mechanism of electricity revealing the systematic balancing cost that influenced by the location, timing and magnitude of electric bus charging, and could respond to the change of loading instantaneously;

5. To demonstrate the market structure with equilibrium problem in simulate the interaction between electric bus charging loads and the power systematic balancing. needs

The first objective is achieved by reviewing the realised feature of bus operation in the development of electric bus demonstration projects and research as well as the application of EV in
the power system. The chapter of literature review filter the numerous markets to fit in the particular characteristic of electric bus demand that differs from those private EVs.

The second objective is achieved by modelling the bus service patterns into two mechanism, namely the classic approach that schedule the service independently and multiple service patterns that capable of incorporating the short-turn and interlining into the bus operation planning. However, due to the computational complexity, two mechanism are introduced into same framework to deal with different public transit problem.

The third objective (analysis of external factors) and the fifth objective (effectiveness of market structure) are conducted under a framework of simulation or bi-level equilibrium programme, with the framework dedicated to quantify the interaction between electric bus and power network.

The forth objective, i.e. the first objective for the power system side, is achieved by the deduction of marginal cost from a Lagrange-relaxation based model representing the electricity market clearing process. The power network operational condition is converted to the constraints and then relaxed as complementary condition in supplementary to the supply and demand balancing.

The overall methodology adopted in the research formulate the interaction of electric bus fleets with electricity market to a number of optimisation problems for the particular subjectively valued purposes, with multiple criteria that contain the information about the realistic operational conditions. Each mathematics model depicts the states of electric bus operation or power network condition. The response of each side to the other in equilibrium ensure the opposite dynamics in operation can be taken into consideration. As a outcome of this process, the optima in the jointly scheduling of dynamic bus service and battery charging as well as the electricity price can be used as the indicator to evaluate the implications of internal factors such as trading mechanism and external factors such as battery costs.

The first mechanism provides an analysis platform to investigate the optimal reaction as a trade-off between multi-factor operational cost and passenger patronage, by combining the jointly
scheduling of classic bus operation and opportunity charging with the dynamic pricing of cost-based electricity tariff into a bi-level cooperative model. For bus operators, the model benefits the understanding of how electricity price in congested hours would affect the range extension by opportunity charging. Because of that, the loads in different feeders are interconnected by the bus mobility, the DNOs will be able to use this platform to investigate the inter-temporal and inter-spatial mitigation of flexible demand. In the second mechanism, the optimisation is based on a simulation of multiple service patterns including short-turn and interlining, which have higher efficient but are more complicated in the use of vehicle resources. The fluctuation of electricity tariff, which is the output in the first mechanism, together with the passenger variation at the stop level are employed to test the feasibility of electric bus operating in a complex condition.

1.4 Thesis outline

The thesis is structured as follows:

Chapter 2 provides a review of the literature on the common practice of electric buses. A deeper understanding of the critical challenges from the perspective of transit agencies and power system operators is needed before informing any methodologies to achieve the objectives of this thesis. One should note that the review of the literature that is relevant to this thesis is not only contained within this chapter. Other chapters of the thesis also contain literature reviews of modelling techniques that is useful for the specific purposes of the specific chapters.

Chapter 3 first reviews the classic methods in bus planning. Then the conceptual planning model of electric bus operation and charging, and the DCOPF-based market clearing are introduced respectively. In particular, the pricing of electricity in congested periods that derived from the sensitivity of network balancing cost with respect to the unit change of electric bus loads are defined. Lastly, a bi-level framework for the joint analysis of electric bus operation and load management is introduced with preceding structures of providing high-quality solutions.
1.4. Thesis outline

Chapter 4 applies the first bi-level mechanism proposed in this thesis to a case study based on the real-scale ridership data in Shenzhen, in order to validate its theoretical properties and analyse and compare impacts of interactive operation. A number of scenarios and sensitivity studies have been built. The theoretical properties examined through the case study include the effectiveness of frequency setting to practical case, and the efficiency of proposed DLMP regarding the mitigation of peak loads of electric buses. The sensitivity of bus operation with respect to battery cost, electricity tariff and unit vehicle running cost is presented.

Chapter 5 extends the classic frequency setting model to the adaptive frequency allocation in segment level, in order to incorporate more complicated service pattern. Numerical examples have been employed to illustrate the benefits and identify the complexity below the novel approach. For the cases where charging loads model introduced in Chapter 3 is affectless, a simulation based approach is then introduced to replace the previous model. Finally, the last section in this chapter develops a problem-specific heuristic method providing near-optimal feasible solutions in face of non-convexity and complying with the adaptive frequency allocation philosophy.

Chapter 6 describes the implementation of the framework developed in Chapter 5, using improved high granularity data processed from the same data source in Chapter 4. This is used to demonstrate the applicability of the multi-pattern planning framework in catering to spatially and temporally disaggregated passenger demand. The various scenario with different electricity tariff including the DLMP derived from Chapter 4, Time-of-Use and flat rate are employed to test the reaction of bus operation in terms of flexibility, sustainability and economics.

Chapter 7 provides a summary of the research reported in the previous chapters, highlighting the main concluding remarks and contributions. Suggestions for further work aiming at improving the modelling of interactive electric mobility are also provided, in light of the limitations that this research bears.
Chapter 2

Literature Review

2.1 Introduction

The expected outcomes of integrating electrified public transport with power networks are not only limited to de-carbonise the transport, but also to improve the operation of both grid and electric buses without under-evaluating the cost-effectiveness brought by grid-integrated service. Despite the reduced operational costs because of low electricity price, a lesson learned in the real world trials is the necessity of improving the operation of electric bus in facing the shortage of energy. For example, Miles and Potter (2014a)’s work points out that two battery electric buses would be vital to replace one diesel bus to avoid violating the same pre-defined timetabling, while battery swapping station as the range remedy method in Shanghai (Cai, 2012) is an costly but reliable solution to retain the original arrangement as well as sustainable energy storage for the grid support. The main reason beyond this is the different solutions to the low energy density of batteries, which result in different level of inconvenience when charging activities are not considered in the tactical planning. On the other hand, different range remedy technology leads to various vehicle range and tempo-spatial characteristics of charging loads in the power network. Therefore, the benefits of the transition from conventional diesel to electric driven-train depend on how the integration can be realised in the charging process. A investigation into the unresolved challenges and unrecognised features exhibited in the electric
bus trials could facilitate the identification of research gaps, and the summary with respect to the prevailing EV-grid integration could provide a good direction to follow.

In general, there are two types of studies commonly used to analyse the effects of vehicle-grid integration, namely evidence-based models and mathematical models. The increasing number of literature raised from the trials of the electric bus in place has presented a road-map about the development of electric bus so far as well as the technical challenges that travel agencies faced in pilot projects (Li, 2016), allowing us to capture the key characteristics of electric bus operation to nurture path-breaking innovations. On the other hand, compared to the large amount of literature that stimulate the application of charging demand of light duty electric vehicles within the low carbon smart grid (see socio-technical review (Sovacool et al., 2017), techno-economic review (Niesten and Alkemade, 2016; Tan et al., 2016) and interview-based expert advice (Kester et al., 2018)), the efforts of integrating electric bus loads within the smart grid based on actual works is relatively limited. Due to the scarcity of proof-of-concept trials of the well-known concept of Vehicle-2-Grid (V2G) ¹, theoretical models need to be reviewed to assess impacts of grid-integrated bus operation in a situation that do not entirely coincide with those trials.

Motivated by the first objective described in the first chapter, namely the need to identify the applicable Vehicle-Grid-Integrated (VGI) operation of electric bus fleets, this chapter has to find the distinctive characteristic of fleets operation and how they fit into the needs in the deployment of electric bus for the transit agency.

The structure of this chapter is summarised as follows. At first, section 2.2 gives an introduction to the development of electric bus projects which put into practice for the demonstration purpose. By reviewing the state-of-art electric bus trials and the literature regarding the challenges have faced by the agencies, this section sorted out the unresolved problems in the operational research for electric bus. The second section 2.3 identified the importance of charging technology as the connection between operational sustainability and grid-support capability. There is a need in the operational research to quantify the trade-off between costs on range remedy

¹V2G is defined as the ”technology that allows for the retrieval of stored electricity in electric vehicles for the benefit of the electricity networks” (Kempton and Tomi, 2005a)
2.2 Research gaps in electric bus trials

Electric Vehicle (EV) is not a new technology; the history of EV began from the 1880s and the first battery electric bus occurred in London in 1907 (Economist, 2007), where the lead-acid battery-powered EV was in a dominating position in the automobile market in the mid-19th century. Battery swapping was also firstly used in place during lunchtime in order to extend the one-charge range of 60km. Eventually, the dis-economies of expensive cost, low top speed (up to 20 MPH) and short range, compared to the Internal Combustion Engine (ICE) vehicles, had forced the electric bus to give ways to its competitors. Although the energy crisis in the 1970s and 1980s has brought a short-lived interest in electric cars, it was not until the 21st century that concerns about increasing oil prices and climate change have promoted the advancement in methods and dependence on battery. Followed by the comparison of charging technologies, section 2.4 distinguished the feature of load profile between bus fleets and private EVs. More importantly, this review identified the gap of integrating the distinctive feature of electric bus with the markets to overcome those challenges that group charging may bring. Finally, a thorough review to categories of V2G service and the theory in the design of market-based demand side management are presented.

It should be noted that the reviews of the literature that is useful for specific purposes are not limited to this chapter. The review of literature here is intended to present the advancement and requirement of integrating electric bus and grid, and to identify the gaps in two mainstream fields. Some other chapters of the thesis that contain a summary of existing works for the specific purposes of the specific chapters are listed here as well, specifically:

- Chapter 3 has also review the mainstream methods in modelling the electric bus operation from the transport perspective only.
- Chapter 4 has also review the emerging methods that incorporate the flexibility in the tactic level frequency setting to match the imbalance passenger demand.
batteries and power management as well as the adoption in the mass market of electric vehicles technology. Since the mid-2000s, electric bus manufacturers emphasise on the development of heavy-duty electric buses, and fast-charging technologies have also been developed which made the sustainable operation of electric bus more likely feasible (Li, 2016).

Lead-acid batteries that most commonly used before the mid-2000s are then gradually replaced by LiFe/Li-Ion batteries, which help to extend the operational range from 40-80km to more than 150km. Table 2.1 has compared five major electric bus manufactures by the products launched before and after 2015. Most electric buses support fast charging that can re-energise the bus within 1 hour. While the major advancement before and after the mid-2000 is the development of fast charging technologies and battery technologies, the latest model provided by major electric bus manufacturers offers higher transit capacities and longer operational ranges by employing larger batteries. Since battery costs continue to drop from 1,000 per kWh in 2010 to $227 per kWh in 2016 (McKinsey & Company, 2017), 76% in 6 years, this in turn allows electric buses made to be considerably cheaper than before, although equipped with an increasing capacity of batteries to suit the customised needs.

In 2009, Optare introduced Solo EV, a battery-electric bus with 9.0 to 9.7m long and 28 to 37 seats. Solo EVs can be fully charged by being plugged into a standard three-phase outlet in less than 8 hours (drive for future, 2013). Solo EV has been used in Nottingham (eight vehicles), Durham (three vehicles), and Poundbury (two vehicles) (Department of Transport, 2009). Another electric bus developed by Optare, the Versa EV, can achieve between 120 and 153 km after a full charge in less than 2 hours (Low carbon vehicle partnership, 2016). The charging infrastructures are supported by Wampfler & Partners, a Germany company, who developed a novel charging technique named inductive power transfer, which can allow bus charging during passengers’ boarding and alighting. Conductix-Wampfler’s product has been deployed and tested in some European countries, such as Italy, Netherlands and UK.

The motivation and situation to develop a viable design for electric buses are complex. North America, Asia-Pacific and Europe have a tremendous amount of pilot/demonstration projects with all kinds of buses and supporting infrastructure. European trials tend to achieve a trade-off
### Table 2.1: Summaries of main electric buses manufacturers

<table>
<thead>
<tr>
<th>Company/Vehicle</th>
<th>Length</th>
<th>Seats</th>
<th>Range</th>
<th>Price</th>
<th>Battery Capacity</th>
<th>Charger</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ebus USA (EBUS, 2017; Li, 2016)</td>
<td>6.7m</td>
<td>22</td>
<td>72 km</td>
<td>$295K</td>
<td>NiCad 28 KWh</td>
<td>Regular/Fast</td>
</tr>
<tr>
<td>Proterra USA (Li, 2016; Proterra, 2016)</td>
<td>10.7 m</td>
<td>37</td>
<td>48 km</td>
<td>$1.2M</td>
<td>LiTi 72 KWh</td>
<td>Regular/Fast</td>
</tr>
<tr>
<td>Optare UK (Optare, 2016a,b)</td>
<td>11 m</td>
<td>34</td>
<td>150/320 km</td>
<td>-</td>
<td>LiFeMgPO4 92/180 kWh</td>
<td>Fast/Wireless</td>
</tr>
<tr>
<td>BYD China (BYD, 2016, 2017, 2018)</td>
<td>12 m</td>
<td>44</td>
<td>350 km</td>
<td>$395K</td>
<td>LiFeMgPO4 276.5/327.7 kWh</td>
<td>Regular/Fast</td>
</tr>
<tr>
<td>Hentong China (HengTong, 2017; Li, 2016; Tat, 2015)</td>
<td>12 m</td>
<td>45</td>
<td>150 km</td>
<td>$250K</td>
<td>LiTi 77.8 kWh</td>
<td>Regular/Fast</td>
</tr>
</tbody>
</table>
between the battery size for a whole day operation and fast charging supporting infrastructure to refuel quickly, while the US trials spend more interest on the rapid charging technology that re-energise the buses even faster. Although not all the information can be found in details and accessed to the public, a summary of trials in Europe based on information provided in Berhan et al. (2013); Ekström (2016); Frenaj (2014); Li (2016); Low carbon vehicle partnership (2016); ZeEUS (2016) are presented in table 2.2 with respect to bus ranges, capacity, charging techniques and routes. Several projects with a lack of relevant information are illustrated by an '-' symbol inside an empty cell in the overview. In general, the summary indicates that the dependence on the battery has a reversional relationship as the power charging facility increases and driving distance shrinks. However, there lacks a quantitative study to unveil to what extent and in what situation would the charging techniques facilitate the reduction of dependence on large batteries.

It is estimated that the number of worldwide electric bus fleet has reached approximately 173,000 in 2015. China is leading this global mass deployment, with more than 170,000 buses (98.3% of the global total) operating in Beijing, Shanghai, Shenzhen, Hangzhou, Tianjin, Xian, Nanjing, Changsha, Dalian and other cities. For example, all of the Shenzhen’s buses have been fully electrified by the end of 2017 reaching a total of 16,493 electric buses. These developments are strongly endorsed by an official programme new energy buses launched by the Chinese government, which aims to produce 1.67 million EVs (including E-buses) (ODonovan et al., 2018). In Europe, the Zero Emission Urban Bus System (ZeEUS), funding 60 European electric pilot projects, aims to be the flagship EU project to extend the fully-electric solution to the core part of the urban bus network. Most of the electric buses are procured from Optare, a UK based bus manufacturer and BYD, a Chinese bus manufacturer.

However, except the increasing amount of permanent operations in China endorsed by the government policy, most progress in the rest of world remains in the trial and most transit providers believe it is not for implementation at present. It is evident that major research and transit agencies hold an affirmative attitude towards electric vehicle technique. Several advantages, such as the comforts, low level of noise and vibration have made manufacturers
## Table 2.2: Summaries of electric buses trials in the world

<table>
<thead>
<tr>
<th>Place(city)</th>
<th>Bus Spec.</th>
<th>Charging</th>
<th>Route</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Nottingham</strong></td>
<td>110 – 150 km (31 seats or 45 w. standee)</td>
<td>Slow charging 7.5 kW (8 h)</td>
<td>Medilink Park &amp; Ride, 41 min round trip, length of 10.8 km</td>
<td>(drive for future, 2013; Low carbon vehicle partnership, 2016) length measured in Google Map</td>
</tr>
<tr>
<td><strong>Milton Keynes</strong></td>
<td>305 km (31 seats or 45 w. standee)</td>
<td>Inductive charging 120 kW for 10 min and 20kW overnight</td>
<td>Medilink Park &amp; Ride, length of 24 km</td>
<td>(Low carbon vehicle partnership, 2016; Miles and Potter, 2014a)</td>
</tr>
<tr>
<td><strong>York</strong></td>
<td>120 – 150 km (34 seats Optare Versa)</td>
<td>Slow charging 7.5 kW (8 h) and 50 kw fast charging</td>
<td>Medilink Park &amp; Ride, 32 min single trip, length of 5.3 km</td>
<td>(Li, 2016; Low carbon vehicle partnership, 2016) length measured in Google Map</td>
</tr>
<tr>
<td><strong>Neitherland (Hertogenbosch)</strong></td>
<td>288 km (-)</td>
<td>Inductive charging 120 kW for 2mins and 20kW overnight (6h)</td>
<td>70 and 80, length of 5 km</td>
<td>(Wechlin, 2012; ZeEUS, 2016)</td>
</tr>
<tr>
<td><strong>Germany (Berlin)</strong></td>
<td>230 kWh (34 seat 41 standee)</td>
<td>Inductive charging 120 kW for 5mins and 50kW overnight (4h)</td>
<td>204, length of 6 km</td>
<td>(ZeEUS, 2016)</td>
</tr>
<tr>
<td><strong>USA (Pomona)</strong></td>
<td>30 – 40 km (-)</td>
<td>Rapid charging 500 kW</td>
<td>291, length of 25.9 km</td>
<td>(Eudy et al., 2016)</td>
</tr>
<tr>
<td><strong>USA (KingCountyMetro)</strong></td>
<td>30 – 40 km (38 seat 16 standee)</td>
<td>Rapid charging 500 kW less than 10 min</td>
<td>-</td>
<td>(Zero-Emission Transit Bus Evaluations, 2015)</td>
</tr>
<tr>
<td><strong>Korean (Seoul)</strong></td>
<td>48.6 kWh</td>
<td>fast charging 3*110 kW</td>
<td>35.3 km</td>
<td>(Kim et al., 2015a)</td>
</tr>
<tr>
<td><strong>China (Beijing)</strong></td>
<td>150 km</td>
<td>fast charging less than 2 hour</td>
<td>90 single trip 2 hours</td>
<td>(Li, 2016)</td>
</tr>
</tbody>
</table>
and transit planner think electric vehicle technology is a viable future technology that fits the nature of transit operation. Literature (Li, 2016; Mohamed et al., 2017b) indicates seven main barriers that hinder the adoption of the electric bus in the public transport field, in which three operation-relevant challenges are highly motivative to drive the innovation of operational models:

1. First of all, and was neglected in most studies, the **incompatibility between current electric bus characteristic and transit network.** Specifically, the short operational range has limited the use in medium to long range route as well as ”interlining” that is commonly efficient for resource allocations. From table 2.2 we can observe that most electrified routes are short routes, with over 15 min layover time and/or a maximum of 18 hours of operation. The particularity of electric bus has build barriers for extending the operational model to other conventional routes. Such an absence of operational flexibility in moving bus from a specific route to the other routes requires bus operators of extensive works on selecting suitable routes, thus need the exploration of bus operational models to fit in the characteristic of the electric bus.

2. The **short operational range** is the major argument that transit service operators hold against the adoption of the electric bus, although extensive works have discussed how to locate and use charging facilities (see Xylia et al. (2017)’s, Xylia and Silveira (2018)’s and (Li, 2016)’s work) to support normal operations. For example, it has been argued that the current electric bus technologies are unable to provide reliable services within reasonable charging time unless more electric buses or extreme larger capacity of battery to be put in a diesel-based transit network, which inevitably adds several financial and operational burdens on service providers (Miles and Potter, 2014a). This is more an issue of lack of operational innovation for integrating the charging activities within operation planning than a sole technical challenge. A promising example comes from the trial of electric freight vehicles in the Gnwet project (Nesterova N, 2015), in which the concept of micro-consolidation centre has been developed for small area delivery to comprise the issue of range, instead of delivering goods to customers directly from the suburban depot.
2.2. Research gaps in electric bus trials

with longer journeys. Such theoretic operational innovation and proof-of-concept trials would enrich the real-world operational data and encourage the adoption of the electric bus.

3. The assessment of feasibility is another key factor in the decision-making of electrification, which usually incorporates a comparison of maintenance, fuel consumption and investment costs with diesel buses. Technology review Bayindir et al. (2011); Khne (2010); Mohamed et al. (2017b), life cycle cost (LCC) models Lajunen (2014, 2018); Lajunen and Lipman (2016), environmental assessment Ou et al. (2010); Ribau et al. (2014), and operational feasibility Filippo et al. (2014); Kontou and Miles (2015); Miles and Potter (2014a) have been the prominent research domains in the overall assessment of feasibility. For example, Lajunen and Lipman (2016) and Lajunen (2018) have broken down the existence cycle cost of BEB by assessing buy costs, power utilisation, upkeep costs, battery framework substitution expenses, and conceivable carbon emanation costs. Lajunen (2018) have developed a specific simulation tool that involves factors influencing electric bus operations, such as weather condition, charging methods and route characteristics measured from existing bus routes in Finland and California, USA. The results show that the purchase costs of the electric buses, especially overnight charging buses due to the crucial role of high energy capacity of the battery system, are much higher than the costs of diesel or hybrid buses. But then, the operating costs are lower, especially the energy costs are much lower when comparing to diesel buses. Moreover, when an average 12 years life span is considered, the end station opportunity charging electric buses can have slightly lower LCC than diesel buses in some routes but on average they have 7% higher LCC. Except these works, only few studies (Noel and McCormack, 2014; Shirazi et al., 2015) explore the advantages to LCC from the point of view of earning excess incomes by giving V2G service, in which they indicated scientifically a V2G-capable electric transport fleets could turn into a net present advantage after five years of operation. However, such V2G-capable benefits have not been considered in any operational studies of electric buses.
2.3 Load profile by operations and charging techniques

The increasing EV deployment would lead to the increase of peak load, for example, the whole conversion of UK fossil fuel vehicles to electric will result in doubled transmission and distribution cable capacity (Strbac et al., 2012). The future grid has to cope with this additional loads and thus require good knowledge about the mobility and the load profile.

The load profile of EVs depends on the operational environment, which includes the journey information and route characteristic for buses specifically, the charging techniques and the times that EVs requires recharging. The route length, road grade, weather condition, driver’s performance and battery’s state of health are key factors influencing the routine consumption and hence the total energy demand (Kontou and Miles, 2015). While the distribution of the demand along the day depends on the charging rate, location, drive cycle and vehicle use plan (Rios et al., 2014), the effectiveness of range remedy is a result of controlled charging by the grid. In other words, the charging approach with smart charging strategies is the connection between transportation activities and smart grid. With millions of single-family homes, load controlling for personal electric vehicles is complex and highly uncertain. On the other hand, load controlling for buses will be simpler since a limited number of bus fleets will be deployed at a limited number of bus depots and stations.

In the trials, there are four types of charging technologies that pose different impacts on range remedy effects and operations: 1) Slow (Regular) Charging overnight 2) opportunity (fast) charging during layover time 3) Battery Swapping/Extra energy storage 4) Continuous charging en-route.

Regular Charging

Regular charging is performed with a moderate charging power up to 3 kW, which is mostly used and discussed in the project for overnight charging. It has been employed in the demonstration projects in Santa Barbara (Griffith, 1995), Shenzhen (She, 2013), some cities in the UK (Department of Transport, 2009), and other cities in the worldwide (Frenaij, 2014). The cost accounting for the land use is relatively low because the depot for buses to stay overnight
is often located out of the central business district. In addition, the electricity price in most worldwide cities fall into the range of off-peak time, which further reduce the recharging cost. The main disadvantage is that a bus has to return to the charging station before its batteries completely exhausted. Although the latest model of electric bus is capable to operate at a range of 250 km on a single charge (e.g. BYD K9/C9 (Magazine, 2018)), another bus has to be dispatched to serve remaining trips in the case that insufficient energy to operate a full day of service. Fig. 2.1 has compared the range and added range per charge, from which we can see the reason why overnight BEB are argued less able to provide similar performance to the diesel counterpart. Therefore the regular charging is often deployed together with other type of range remedy technology.

![Figure 2.1: Comparison of drive range and added range per charge figure from (Mohamed et al., 2017b)](image)

**Opportunity Charging**

With the end station and opportunity charging, the onboard battery capacity of opportunity BEB does not need to be very high (Tammi and Lajunen, 2016); they often have a shorter operational range compared to overnight BEB. As a consequence, the battery has to be recharged at layover frequently by using a fast charging method from 10 to maximum 90% SoC in 10 min depending on the power of the chargers. As early as 2010, "Foothill Transit Ecoliner Electric Bus Program" (Eudy et al., 2016) has trial an automatic fast charger (500 kW) to sustain the
2.3. Load profile by operations and charging techniques

operation of 12 Proterra electric buses with 30-40 km operational range in 21 routes in Pomona. As of December 2015, the BEB fleet operated reliably with minimal issues, none of the fast chargers resulted in downtime for the buses. The wireless opportunity charging could provide more convenience and has been demonstrated in the Milton Keynes project in the UK, where a fleet of 8 BEB operate along a busy route of 25 km long (Miles and Potter, 2014a). Two inductive chargers with a maximum of 120 kW power output were installed under the roads, as illustrated in the right figure in Fig. 2.2. The wireless inductive charging can deliver high power ratings with an efficiency between 80-95% (Jung et al., 2012) and has been a crucial component for any viable electric bus system design (Tzeng et al., 2005), but the expense of these types of chargers could be twice higher (Elin, 2016). However, the amount of studies that have consider the restricted time availability in the joint scheduling of operation and charging during is the least among all, which leave a significant research gap in modelling the load profile during the duty cycle.

Figure 2.2: Fast charger on top in Pomona (left) and Inductive charging system in Milton Keynes (right) figure from (Bowdler, 2014; Eudy et al., 2016)

Continuous Charging

While normal opportunity charging enables electric buses to refill the battery at the end station of routes, a recently emerging technology focusing on charging-while-driving (CWD) that enables drivers to recharge their EVs while they are on the move (e.g. Siemens eHighway (Herron, 2017)). Leemput et al. (2012b) assessed similar ideas on electrifying trucks and Chen et al. (2017) applied this concept to the operation of electric buses. They established mathematical models to investigate the optimal deployment of various charging facilities along the transit
2.3. Load profile by operations and charging techniques

line and determine the optimal size of the electric bus fleet, as well as their batteries, to minimise total infrastructure and fleet costs while guaranteeing service frequency and satisfying the charging demand of the transit system (Chen et al., 2018). Nevertheless, the authors also pointed out that the CWD technologies are costly competitive for those transit systems with high service frequency and low operating speed, but it indeed expects yield higher operational and maintenance costs than charging and swapping stations.

Battery Swapping

Battery swapping or exchange systems (BSS) are easier to implement as a solution to the range anxiety, while could reduce the interruption of bus services to the least level. Better Place in 2012 installed multiple stations that can handle a specific type of EVs. In 2013, Tesla Motors introduced battery swapping technologies for their customers' EVs. The pilot infrastructure of BSS and the respective electric bus route was built and experimented on the Pohang public road under the real world traffic situations in Seoul, Korean Kim et al. (2015b). The BSS has battery storage for 8 batteries and is able to facilitate the 3 high-speed chargers (110 kW/unit) to recharge the batteries stored in the BSS. In China, BSS projects are gradually adopted in major cities such as Beijing, Chongqing (Li, 2016), Shanghai (Cai, 2012; Chao and Xiaohong, 2013) and Qingdao (Zhou, 2012). The weakness of battery swapping methods is obvious that a certain amount of extra batteries are maintained at the stations to ensure the availability of batteries when buses return to the BSS. Another issue refers to the land use, for instance the battery swapping stations in Qingdao occupy an area of 5800 m2(Zhou, 2012), which is less possible in most city central areas. The major advantages of the battery swapping technology are the fast speed of replacement -which usually takes less than 12 minutes (Chao and Xiaohong, 2013)- and the possible utilisation of the stored batteries as a mini scale energy storage system for power shaving in peak hours. Fees charged for battery swapping are not the only source of revenue; BSS seeks to maximise its profits by participating in electricity markets to provide services such as voltage support, regulation reserves, or energy arbitrage. Sarker et al. (2015) proposed a typical commercial model for a universal BSS in addition to the battery swap service, in which the BSS can purchase electricity and charge batteries during the
2.3. Load profile by operations and charging techniques

low-price periods of a day, and sell electricity back to the grid during the high-price periods by discharging batteries. Hence the standby amount of batteries and the service capability is the primary concern of BSS, which have direct influences on the feasibility of the BSS investment. The figure 2.3 makes a comparison of the mainstream fast refuelling solutions to the range anxiety:

![Figure 2.3: Morphological box for the systemic description of charging infrastructure, from (Kley et al., 2011)](image)

By reviewing the prevalent charging technologies at the time being, it is evident that charging methods play an important role in the implementation of electric city bus operation. While both the continuous charging and battery swapping require extreme high initial cost, battery swapping attracted more attention in research because of its potential in the grid-integrated operation as energy storage. On the other hand, the opportunity charging, which though considered in many projects (Miles and Potter, 2014a; Qin et al., 2016a; Rogge et al., 2018a; Tammi and Lajunen, 2016), has not been fully investigated to model the interactions in bridging the demand for energy and needs for smart grid service.

Wei et al. (2018) introduced an innovative spatio-temporal analytical framework to assist transit agencies to identify the optimal deployment of on-route charging stations and overnight in-depot
2.3. Load profile by operations and charging techniques

charging stations, without interference with current operation routes and schedules. Rogge et al. (2015) analysed to what extent the entire bus networks can be electrified with the increased power of fast opportunity charger at end stations, without affecting the existing bus routes and schedules. They correlated the power requirement of fully charging with the static dwell time between pre-determined vehicle schedules, and thus showed that 50% of the service trips can be electrified with a charging power capability of 300 kW and a usable battery capacity of 220 kWh. Recently, Rogge et al. (2018a) proposed a framework for the cost-optimised planning of bus fleets and their opportunity charging infrastructure, in which a vehicle schedule adjustment was monetised and investigated with the fleet composition, and the optimisation of charging infrastructure. The result shows that the total energy consumption differs between lightweight bus and high range bus, although the total ownership costs for operating both bus types are relatively close, due to the rise of crew and vehicle expenses required for the lightweight bus system with larger fleet size.

However, those studies mainly focus on the adaption of the fixed predetermined timetables and the special configurations of electric buses, without considering the particular load controlling needs from the grid. Li (2016) even treated the intermittent charging along the day as one of the drawbacks of opportunity charging because the lower electricity rates are often applicable at night. This review argues that the cost-effectiveness of opportunity charging will be greatly improved when the new value-added architecture manages to promise suitable benefits (Kley et al., 2011), such as reduced reliance on large battery packs and the auxiliary market. In addition, the idea of incentive electricity pricing, which also defined as demand response in smart grid concept, involves awards for load shifting by deviating from the typical electricity consumption in response to changes in the electricity price offered to consumers (Albadi and El-Saadany, 2008). This is one of the forms that the well-known concept of Vehicle-2-Grid (V2G) are applied in power system demand side response for electric vehicles, which offers an additional dimension of income. The arbitrage strategy based on the fast charging station for electric buses is a good example of business model innovation that utilising the fluctuating electricity rates (Ding et al., 2015) and can be introduced in the research.
Collectively, even though most transit service providers lack the education of charging technologies, utilising layover time at stops or end stations to sustain bus operation is an interesting field of research but lack of consideration. Whilst a supply of large-power charging stations have been proofed capable of help reduce the reliance on large battery capacity, special attentions have to be paid to the proper integration of charging process into operation planning, as frequent recharging will yield delays to operations. Otherwise a larger size of bus fleet will be needed to guarantee the original service frequency. Besides, the outrageous power output will prompt expanded electric system blockage troubles on the power network, especially in metropolitan areas, which is also considered a roadblock for the implementation of electric bus with any type of high power charger. Further research should mull over needs from power systems to deviate excess load at peak time. From the view of bus operators, how and to what extent could electric buses utilise charging technology to reduce total ownership cost without causing downtime to the routine duties is another unexplored area in electrified public transport.

2.4 Grid-integrated application of electric bus

Compared to electric bus specifically, EV as the entirety has drawn remarkable attention in power system research. Many industry corporations, organisations and countries invest millions of dollars to move forward EV technology as well as exploiting its potential. However, it was also found that almost all the EV-grid researches have not differentiated into the potential for passenger EVs and commercial EVs. This gap raises particular concern since companies fleets, especially bus operators, might able to provide significant diversity in electric mobility from individuals. Existing management of individual electric vehicles has proposed temporal, spatial and communications requirement to the integrated electric vehicles that may not be suitable for electric bus operators. Hence, due to the limited literature on electric bus integrated power system research, this section will first identify key features influencing grid stability of aggregated individual EVs, then summarise underlying application for electric buses.

The increasing deployment of electric buses is often chosen accompanied with a rising amount
of fast charging station where the charging power is 10 to 100 times higher than the regular charging power. This imposes an additional burden on the power grid as the high charging loads will degrade the operating parameters of the distribution network. In general, the penetration level, charging techniques and rates associated with EV operation cause degraded power quality from at least five aspects: increase in peak load (Habib et al., 2015; McCarthy and Wolfs, 2010; Strbac et al., 2012), voltage instability (Das and Aliprantis, 2008) and imbalance (Li et al., 2012; Shahnia et al., 2011; Shareef et al., 2016), harmonics distortion (IEEE Standards Coordinating Committee 22 on Power Quality, 1995; Onar and Khaligh, 2010) and power loss (Fernandez et al., 2011; Papadopoulos et al., 2010).

The extent of negative implication are considered relevant to the load profile on three aspects: charging technology, penetration levels and consumer patterns. High power DC charging has significant adverse effect on weaker networks due to the high value of current Melo et al. (2011), but this topic is out of scope and will not be expanded further. More relevantly, as the penetration level rises, which can also be considered as the number of EVs connecting to the network increases, EVs will cause severe voltage harmonics, deviations, power losses and transformer overloading (Moses et al., 2010). These impacts of grouped charging is not a linear summation of total distortion (Zamri et al., 2013), but depend on the type of vehicle use and charging patterns. Weiller (2011) demonstrated that uncontrolled PEV charging leads to peak load in the early evening at residential sites, in the morning at the workplace and the afternoon at commercial sites. K et al. (2009) considered the vehicle energy requirement by different driving cycles for family or jobholder users, but lack of commercial vehicles. Rios et al. (2014); Ros et al. (2014) used Monte Carlo simulations and route characteristics to compute the load demand profiles from a large charging station with four to six slots. The peak demand as shown in the right figure of 2.4 occurred during 11 am to 12 pm and 2 pm to 3 pm, which have significant difference from the residential load profile in the UK and Europe that illustrated in the left figure. It is apparent that these distinctive features of electric bus fleets loads, such as the magnitudes and distribution of demand among charging stations, has not been recognised and fully researched in existing works.
2.4. Grid-integrated application of electric bus

Distribution Network Operators (DNOs) could handle the aforementioned issue caused by grouped EV charging by either reinforcing the infrastructure (Rahman and Shrestha, 1993) or employing Demand Side Management (DSM) for flexible power consumers to alleviate the negative impacts (Biegel et al., 2012). The goals of alleviating voltage security problems (Li et al., 2012), reducing power loss (Clement-Nyns et al., 2010) and coordinating nearby distributed generation (Sadeghi-Barzani et al., 2014) or photovoltaic (Ye et al., 2014) are often integrated in the DSM in scenarios of large adaptation of EVs. DSM provides a way to influence the consumption pattern to follow the generation pattern while contribute to increasing the efficiency of the system investment. As a result, consumers will be compensated for interrupted power consumption based on the amount or the time the services are provided (Richardson, 2013). Again, neither did the state-of-art DSM works have incorporate the distinctive features to compromise different level of degradation in different parts of networks.

For EV technology, the concept is extended to the concept of Vehicle-to-Grid, which is one of the most auspicious opportunities to embrace EVs in power systems. The V2G concept does not necessarily mean that the power flow must come from the vehicle to the grid (operated as energy storage), since vehicles with only a controlled unidirectional charging mode may also provide V2G services. In this unidirectional charge, the electric vehicle is capable of reducing or increasing consumption under a dispatch control signal and responds proportionally to frequency changes (operates as a grid controllable load) (Tan et al., 2016). Through the V2G system, the battery in electric vehicles is considered with great potential to stabilise grids in
terms of peak load shaving (Drude et al., 2014), to mitigate voltage fluctuation to subsequently moderate the use of voltage regulators, to achieve protective relay tripping (Wade et al., 2009), and contribute to the improvement of power quality as well as frequency control (Arita et al., 2006; Sasaki et al., 2004). Ma et al. (2013) also demonstrated that V2G could considerably reduce power system operating costs and secure distribution networks. Keep the V2G as impetus, Noel and McCormack (2014) made an effort to fill in this gap by using electric school buses to achieve additional revenue for providing V2G services. From an economic view, their conclusion stated that a 24-seat V2G-capable electric bus would save $6,070 per seat and becomes a net present benefit after five years of operation. The higher initial purchase price for the electric school bus is more than offset by V2G revenues, as well as lower fuel, maintenance and externality costs. Although their findings are argued overlooking several substantive issues, for examples electrical losses from V2G and reduced V2G availability during cold weather (Shirazi et al., 2015), the approach to involve service in the concept of smart grid has provided a novel direction to follow.

Ehsani et al. (2012); Kempton and Tomi (2005b) suggested three groups of V2G service that can be enabled within the broader paradigm of smart grids: peak load shifting, spinning reserves through back-feeding, and regulations to ensure power quality.

1. **Load Shifting** is the basic and universal functionality can be achieved by either type of EVs. Smart charging or coordinated charging strategy with special purposes is therefore developed and expected to alleviate these adverse impacts by utilising the surplus power at rush hour to the lower-demand hours with the help of the so-called valley filling - peak shaving algorithm. The earliest research on the controls of EVs for valley filling start from Ford (1994) in Southern California Edison, where limited charging to times of low utility power demand were applied rather than charging whenever plugged-in. Jian et al. (2017) defined capacity margin index and charging priority index in the valley-filling algorithm to centrally optimise the temporal loads of large scale EVs. According to Lopes et al. (2011)’s work, the application of coordinated charging strategies allows attaining the highest EV penetration level without violating voltage lower limit. A congestion
level caused by integrating 10% EVs with dumb charging is equivalent to an integration level of 54% EVs with coordinated charging strategies aiming at assessing the maximum EV integration capacity of the grid. Although the coordinated charging approach will only be effective while the grid has enough capacity to provide all the power required by EVs, it can significantly release the reinforcement stress before the moment the inevitable upgrade comes.

Except for the implement of coordinated charging which somehow requires a direct control infrastructure, there is another business model driven by the distinct in peak and off-peak electricity price and the temporal charging flexibility of EVs. Using energy storage or battery swapping station BSS to mediate between electric grid and charging stations for electricity price based arbitrage can be grouped in this type. Ding et al. (2015) has advances the limited literature regarding the excessive benefits of electric buses. A more commonly discussed approach is to build a mini scale energy storage system based on BSS, such that the BSS can operate "either as an energy source when the batteries are fully charged or as an electrical load when the batteries need to be charged"(Lombardi et al., 2010; Zheng et al., 2014). Kempton et al. (2001) computed the economic potential of having battery, fuel cell, and hybrid EV to sell power back to grid in 3 years of Californias electricity market. Results show that the cost of electricity injected into the electrical network were found too high to be competitive for base load power, e.g., the Honda EV plus has a cost of $0.446/kWh while the base load power price is around $0.1/kWh. Wang (2008) analysed the potential impact of the plug-in hybrid vehicle on locational marginal prices (LMP). The results for a PJM five-bus example (with empirical data) show that as load increases from 0 to 10% due to EV recharging, both mean and standard deviation of LMP would increase substantially (more than 26 and 62%, respectively). Therefore, charging during off-peak hours for selling at peak hour may not be economically attractive, but charging for daily usage does. On the other hand, and it is not recognised in existing works, the spatial differences of LMP create an opportunity for battery stations to reduce their cost by choosing low LMP locations.

2. Active Power Regulation in the concept of V2G would requiring EVs under direct
real-time control of the electric network operator for increasing or decreasing generation/consumption of active power to maintain the power quality (voltage or frequency). Regulation is called for only a few minutes at a time, but the number of times can be up to 400050 times per day. EV is paid for having available and synchronised a given capacity (e.g., $/MW) and receives additional payments for energy delivered to the network ($/MWh) (Bessa and Matos, 2012). Therefore, the battery will only charge and discharge slightly and alternating, and the battery charge will only oscillate around the initial charge state.

The early research shows that battery EV is particularly promising for regulation service, with a net income between $8442 and $3162. Kempton (2009) tested a single battery EV operating under real-time dispatched by PJM (regional transmission organisation). The test shows that power provided by the EV tracks the regulation signal very closely, and in contrast to conventional generation units, the energy is stored and injected during the provision of regulation service. In addition, Due to the presence of EV charging stations in the distribution system, EVs are possible local source of reactive power for the distribution system. EV charging stations can be used as shunt active filter to improve power quality of girds integrating wind generation (Islam et al., 2011). Similar to the requirement of active power regulation, Reactive regulation is required frequently during power system operation hence equipment that allows bidirectional power flows between vehicles and the grid are necessary.

3. **Spinning Reserve** is typically called 20 to 50 per year and the duration time is typically around 10 min but the source must be able to last up to 1 hour (Ehsani et al., 2012). The utility pays spinning reserves sources for just being available, i.e. per hour availability with a market value of $10/MW per hour at 2012 (Kempton, 2009). Some relevant analysis estimated that most of the EV could deliver this service with a positive net income. The battery EV can provide at an average net income from tens of dollars to $700, while the hybrid EV in motor-generation can provide at a net income of around $2000 (Bessa and Matos, 2012). However, this type of service requires a generation capacity to respond in case of equipment or power supplier failures and hence the quick response capability
that can back feed power to the grid immediately and reach full capacity within 10 min is extremely important. In other words, the spinning reserve market is well suited for battery electric vehicles that have bi-directional communication and supporting infrastructure and deferrable energy.

In this section, it is found that neither did the load profile of electric bus fleets distinguished from the individual EVs in the analysis of potential impacts on power network, nor did the electric buses directly involved in the operational research with various V2G markets. These research gaps have to be filled in with an ad-hoc design for integrating the distinctive feature of electric buses with the markets to overcome those challenges that grouped charging may bring. Based on the content reviewed in the literature, there are three points shall be paid particular attention in the design of interaction mechanism: (1) The mechanism shall automatically respond to the dynamic in the bus charging load profile, since the number of buses connecting to the grid varies at diverse locations along the same day; (2) The changes of vehicle use plan and charging patterns have to been revealed instantaneously in the load profile; (3) The mechanism have to be selective and effective on the grid-support objectives, since different V2G markets have different requirements on supporting infrastructure.

2.5 Market design for grid-integrated electric buses

For passengers of electric vehicles, "Aggregator" plays as the crucial inter-mediator between vehicle owners and the utility. It commonly assumes that electric vehicle owners cannot, as individual entities, have transactions with the electrical utilities nor bid in the electricity market due to the low power transactions(Bessa and Matos, 2012). In such content, aggregator need to attract and retain electric vehicles so as to result in an MW capacity that can proactively impact the grid with direct control(Guille and Gross, 2009). In terms of electric bus fleets, bus operators who manage the charging duration, power and locations in a similar way, have instinctive advantages in playing the role of aggregator for the V2G.

The approaches that electric bus can offer the Demand Side Management (DSM) services can
be categorised as **physical-based** and **market-based** demand response (Gelazanskas and Gamage, 2014). To help understand how electric vehicles and grids interact, Tan et al. (2016)’s classification is introduced as well. In Tan et al. (2016)’s dividend, the service that vehicles can provide could either be unidirectional or bidirectional depending on the direction of power flow. Functionality that requires EVs to consume electricity, such as preventing grid overloading are grouped in the unidirectional type, whilst any services that request a bidirectional energy exchange between the EV battery and the grid are sub-group in the other type. Most of market-based contracts are done a day ahead because such marketplaces are not arbitrarily quick. One can refer to Kirschen (2003)’s work for a comprehensive view of different contracts. Reference (Huang et al., 2015; Li et al., 2014b; OConnell et al., 2012; Singh et al., 2011) showcase the examples of extending the centralised marking clearing process to involve the demand side response. The market operator in this case has to achieve or predict the economic and technical characteristics of flexible demand participant and then clears the market through the solution of a global optimisation problem. At last, the LMP at each busbar can be updated and broadcasted to participants so that they can submit their bids in the distribution market with the energy plans solved by their own problems.

Hence the way calculating the dynamic tariff is crucial in differentiating the performance of EV demand response. A typical example of dynamic pricing could translate the cost of energy at the substation i.e. the transmission level LMP, and could capture the real objectives and cost in the distribution network(Heydt, 2010). Similarly, OConnell et al. (2012)’s work broadcasted the LMP derived from transmission level, particular the congestion component, to EV fleets aggregator in the distribution network. The latter optimised the concentrated charging schedules to avoid congestion to the grid while minimising the charging cost. However, since the same price signal is received by all domestic controllers, all the shifted events are rescheduled according to the same forecast, resulting in unexpected spikes of demand. Such avalanche effects are also observed by Gottwalt et al. (2011), who analysed the effects of the demand response based on time-of-use tariffs. Furthermore, the electric loads at each loading point are often considered by the occupancy time and mutually independent in their charging behaviours, which is however not the case that EVs indeed have the freedom to charge at neighbouring available
2.5. Market design for grid-integrated electric buses

charging infrastructure which belongs to another loading point. From the works that use EVs as power source/sink (Huang et al., 2015; Li et al., 2014b; Liu et al., 2018; OConnell et al., 2012; Papadaskalopoulos et al., 2013), one can observe the key expectation from power system is the ”rebound effect” that EV load can be shift from peak period/zone to off-peak time/zone. Such ”rebound effect” can take place in neighbour district as well rather in the preceding or succeeding time horizons only.

To overcome the barrier observed in past works, Li et al. (2014b) explored the market-based demand response by extending the concept of transmission-level locational marginal price (LMP) to distribution level (DLMP), where only the congested feeders are updated with a high price to shift the loads. The DLMP has been shown to be efficient for the congestion management in parts of the distribution networks with a high penetration level of EVs. However, there are at least two drawbacks in the application of EVs. Firstly, as Liu and Wen (2014) pointed out that there are infinite numbers of optimal solutions if the aggregator solves its benefit function in the form of continuous linear programming, which gives multiple plans with the same cost. Huang et al. (2015) then improved the multi-solution issues by replacing the aggregator objective function with quadratic programming based on a prediction of spot price. Secondly, in both methods but not limited to these literature listed, the results of market clearing model significantly depend on the way that DNO predicts the energy consumption of EVs. The elasticity between energy consumption and price are built based on a sensitivity matrix method proposed in Verzijlbergh et al. (2012), rather than transportation activities or preference of EV owners.

Since the decomposition of LMP/DLMP is able to reflect the physical power loss and economic cost to balance the supply at different loading points, the outcome of market clearing process provides a market place for bus operators to arbitrage if and only if such behaviours are beneficial. There does not exist similar business model for electric buses that utilise the fluctuating DLMP generated in the process congestion management, which is similar to the work (Ding et al., 2015) of using batteries in a fast charging station for historical-price-based arbitrage. Therefore, these research gaps drive innovations in the design of a market-based load
management mechanism to include the demand response of bus operation models based on bus travelling activities.

2.6 Summary

In this chapter, we have reviewed more than 200 literature relating to the operation of electric vehicles and the integration of electric vehicle demand into power system, from the state-of-art research of electric bus operation, charging infrastructures and range remedy methods, to a general summary of the involvements of electric vehicle loads in demand side management in the power system, which including numbers of auxiliary service that electric vehicle able to provide and the market structure to achieve the vehicle-grid service.

Among those studies, 66 works discussed the operation, feasibility and experience about battery electric buses; 53 studies about the characteristic of electric vehicle and the management of its load; 64 of 90 works in power system research have presented valuable reference to integrate the electric vehicle load into demand side management. It is noteworthy that the participation of electric bus load through V2G has been considered in two works only; in most cases, they are perceived without a distinct with other type of electric vehicles. In the review of electric bus trials in Europe by 2013, we found that 15 projects (36%) solely adopted regular charging while 18 projects (43%) has adopted fast charging as the complement to slow charging, and 1 project employed wireless fast charging to sustain the operation. Contrasting to other types of charging technologies, the fast charging is identified as the most popular technology to energise electric bus fleets while keeping the investment on infrastructure to an acceptable level.

To sum up, for the purpose of analysing the comprehensive interactions between electrified public transport network and the power systems, existing works have exhibited many limitations, including but not limited to:

1. Although many charging technologies have been researched and employed to remedy the range, the trade-off between the effectiveness of range remedy methods and the depen-
dence on the large battery is still unclear. Notwithstanding the importance of research in devising a way to integrate the charging process into the vehicle scheduling problem, analysts’ understanding of the extent to which attributes of electricity price structure would facilitate the operation of electric bus still needs expanding. Existing approaches have to interrupt the service after every few trips in order to not fully deplete the battery capacity. But for the sake of vehicle utilisation, it is very considerate to device a way in which the charging technology could reduce both service interruptions and reliance on large batteries.

2. The feasibility of operating electric bus in the single short-range route has been studied and demonstrated in many trials, but quite limited research has exploited the reliability of electric bus to a bus network. Such an absence of operational flexibility in moving bus from a specific route to the other routes requires bus operators of extensive works on selecting suitable routes. The present-day works lack of a methodology to compromise the feature of electric buses into more complicated operation conditions so that the feasibility can be thoroughly evaluated.

3. Instead of downscaling the annual use of the electric bus to hours of use periods, the lifecycle cost models, which is most commonly seen in the evaluation of the feasibility of electric bus operation, cannot solve the challenges of complex load pattern and electricity rate invariance. The benefits for innovated business models, such as providing grid support services, have not been realised in the existing models.

4. Both the load management model in the power system and the life cycle cost model of the electric bus were analysed in a simplistic linearity. The bulk of research do not distinguish the load patterns by the vehicle types. The EVs integration necessitates a demand responsive load in the power system. From this derivation, the travel behaviour has not been explicitly modelled but represented as the image of the pre-determined constraints and scenarios. In this way, it makes the approach to appear as a less sensitive model to the test of the effectiveness of using the electric bus to support the grid operation.

5. Another assumption that characterises most models is related to the charging patterns.
There are at least three factors affecting the effectiveness: first, the correlation to the consumption, it is often assumed linear to the route characteristics; second, the objective that the charging strategies coherent to; and the consistency of objectives between vehicle owners and electricity price makers. It was found in the literature that the goals of charging strategies assumed in the operational research differ from which in the power system research. The former could apply the charging process control or charging management within vehicle scheduling to ensure the smooth operation of electric buses, whereas the objective of charging in the major power system research of electric vehicle are just minimises the charging cost.

6. It is found a gap that electric buses have not been directly involved in an integrated manner of scientific operation and service market to support the power network. Hence, the research gaps motivate the innovation in the design of a market-based load management mechanism to include the demand response of bus operation models that based on bus travelling activities and automatic responding scheme minimising the systematic balancing cost.

The rest of this dissertation will first introduce a bi-level modelling framework for the joint analysis of electric mobility representing the electric bus network as well as the load management to alleviate congestion in power system. Then, on the basis of the improved understanding of to which extent will electric mobility and loads been affected by the distribution locational price, an enhanced bus dispatch planning model will be introduced to improve the flexibility of electric bus operation to capture both the variations in passenger transit demand and electricity price.
Chapter 3

Grid-Integrated Electric Bus Operation in Bi-level model

3.1 Introduction

This chapter aims to develop a mathematical model that could depict the responsive process regarding to electric buses' movements and charging activities, thus enabling the distribution network operators (DNO) to understand how EV load management mechanism can be designed to affect the location, timing and duration of charging along the city. EV load management has been discussed in a large amount of power system literature, in which a common practice is the inter-temporal demand shifting at the same node. By assuming a completely full cycle control of EV chargers, this type of scheme - also called interruptive charging - aims to minimise the charging cost by shifting loads to low priced period without causing inconvenience to the next trip. The inter-temporal continuity beyond this assumption is guaranteed by acquiring information about the EV availability, but the independent spatial inter-correlation before and after the movement of EV has been attenuated to the least level.

For electric buses, the heavy duty cycle has restricted the duration of availability that electric buses could be connected to the grid. Several works (e.g. Rogge et al. (2018a); Xylia et al.
(2017)) employed a similar approach that can interrupt the allocated service trips in the vehicle scheduling by inserting the charging events as a trade-off to low power chargers. This approach, therefore, needs the cost-optimised planning of charging infrastructure to minimise the deadheading time of vehicles to the charging station. In most cases, one charging station with multiple chargers is designed to satisfy all the demand, and that is the reason why electricity tariffs are often assumed at a flat rate there. However, the electric mobility depicted by this approach has the temporal characteristics only, without the ability to consider the differentiated electricity rates that relevant to the power network condition in different zones.

This chapter propose a novel framework to analyse the impacts on bus operations from a grid-integrated manner, which distinct from existing works on three aspects. First, the bus dispatch frequency as the decision variable in the classic bus timetabling problem are first time unified to link the bus movement, availability of vehicles and the charging loads. Second, contrasting to existing demand response in power system that requests the EV to schedule a change on temporal charging sequence, the approach proposed in this chapter use aggregated loads at multiple zones with different bus operational characteristics to respond to the grid. Since the bus stations of same route locates in different zones, nodes aggregating the loads of opportunity chargers are able to coordinate the operation of different parts of distribution network. This is build on an automatic pricing based mechanism. Thirdly, the inter-dependence between battery requirement and range remedy approach has incorporate one more dimension of the benefits received by participating in the dynamic electricity market. It is a field that none of the existing works has discussed before.

In general, the electric buses and power market are placed in a hierarchical bi-level game that the DNO (leader) moves first to give an initial price to the follower, and then the bus operator (follower) moves sequentially with the optimal allocation of bus minimising the cost. They compete on the quantity of goods, which is the electricity traded in the plan period, until reaching an equilibrium that neither the bus operators nor the DNOs could further improve their performance function by changing their strategies of the supply and demand of electricity.

At first, the proposed upper level approach is based on the tactic planning of bus operation,
3.2 Assumptions on examined e-bus operational model and electricity market model

Before proceeding further into the presentation of the model, one should understand that the bus service is difficult to remain stable because of the uncertainty in passengers boarding and alighting the vehicles, and the variability in traffic conditions. As a result, the less predictable travel time would contribute to the uncertainty in the tempo-spatial characteristics of electric mobility that affect when and where the demand is shifting. Modelling such an accurate depiction of electric mobility is out of scope in this thesis. Hence the following assumptions have to be made in order to reduce the complexity of the problem as well keep the computational
cost at an acceptable level.

For electric buses, the required assumptions made in this thesis are:

1. Due to the uncertainty in the demand of passengers, the boarding and alighting time as well as the time consumed in bus holding strategies used to prevent bus bunching are not considered in the model.

2. For the same reason, the road condition is assumed freeflow and uncongested in this thesis, i.e. the arrival time can be deterministic estimated after departure.

3. The plan periods in the practical operation are often categorised into peak, off-peak and night hours, which has a large inconsistency in the planning resolution of the power market. For the sake of intensive analysis, the plan period for buses are assumed to every 3 hours of the day that was empirically found to exhibit a relatively stable ridership pattern, and is ensured to complete a round trip of the longest bus route in the case study. In practice use, neighbouring decisions can be combined to manage the fleets at a stable frequency for a period longer than three hours.

4. Opportunity charging (or referred flash charging) facility are installed at the start and end station of each bus route.

5. Buses are assumed running bi-directional in each bus line, and only able to recharge when they are arriving at the stations at the end of the route.

6. By assuming the passengers arrive randomly, the waiting time for each passengers can be estimated as the half of the headway.

7. In the most real-scale power system market, a capacity threshold exists for demand participant to enter. This thesis assumes that the bus operators that aggregate and manage all the charging demand of electric buses fleets, are capable of insufficient capacity to participate in the day-ahead market and adjust the charging loads through the dwell time in response to the dynamic tariff rate.
8. Due to the differentiated policies over the world, there could have several situations that several bus companies compete in the same bus routes. This situation is, however, ignored in this thesis, which means all the bus routes in the models and case studies are fully operated by an oligopolistic bus company.

For the DNOs, in addition to the topological arrangement of the location of feeder connecting the charging stations which will be presented in the case study, the power market model has the following assumptions.

1. Electrical energy is the only commodity traded in the examined power market, since other commodities such as electrical capacity and ancillary service need specific customisation in a market-based system design (Kirschen and Strbac, 2004), this dynamic market is designed to use differentiated price to attract EVs to provide load shifting service.

2. The trading architecture used in this thesis is assumed as pool-based. There are two types of trading architectures that have been widely implemented around the world, market-based and pool-based (Kirschen and Strbac, 2004). In the former, the trade of electricity can be arranged directly between the buyer and seller, with the price of the transaction set independently by them without interference from a third party. In the pool-based markets, generators submit bids for the supply of energy and consumers submit offers for the demand to the third party, which often indicates as market operators to facilitate the transactions based on a mechanism. Such a mechanism would determine a trade price as a result of the dispatch of each participant.

Given that the focus of this chapter is to investigate the response of electric bus mobility based on the changing price, the bi-lateral interactions have to be revealed in the price. Moreover, the most significant feature of the clearing mechanism applied by the pool market is the scheme employed for the pricing of the traded commodities.

3. The objective of the market clearing is set to maximise the social welfare, which constitutes the most representative global indicator of the market state efficiency, while ensuring the safe operation of the whole system. The problem is also referred as Security Con-
strained Economic Dispatch (SCED). In real-scale distribution-level power systems, the participants of electricity markets are located in different geographical areas and attached to different nodes/feeders of the network. Some specific constraints regarding the limits on line capacity, voltage and reactive power characterise the market clearing process to secure the safe operation of the system. These effects of the network, as well as the non-linear loss have enhanced the complexity of market operation. However, in order to limit the computational requirements of the problem, especially the bi-level framework, the model used for the market clearing is based on the common DC load flow approximation.

4. The nodal marginal price derived from the pool-based market clearing process constitute the major component in the dynamic tariff for electric buses. Among the numerous approaches to account for the effects of congestion (power system) and power losses, the one incorporating the relevant network constraints explicitly in the SCED problem solved by the market operator and yielding location-differentiated prices depending on the condition of network lines, is widely accepted as the most efficient (Kirschen and Strbac, 2004). Under this scheme, the price of electrical energy to recharge electric bus at period $t$ depends on the node from which it is extracted, when network congestion (power system) or losses apply.

5. The market is assumed to be set based on an hourly resolution in the day-ahead horizon. It is impractical to assume a very long horizon when considering the loss of accuracy due to the uncertainty in predicting their demand/generation over a long period. On the other hand, a market design with a very short horizon will not fully enable the participant to exhibit their inter-temporal characteristics. The selection of day-ahead horizon will ensure a trade-off between the prediction uncertainties and computational burdens, and give sufficient flexibility for participants to adjust their allocated energy due to unexpected imbalances. In respect to the trading resolution, higher resolution markets capture more accurately the characteristics of generation and demand but would introduce a heavier computational burden. This thesis involves the most common design of hourly resolution for the market clearing process, which sufficiently captures the basic properties of most generation and demand participants.
3.3 Literature review of bus planning problem

Bus planning decisions are typically made at the strategic, tactical and operational planning level (Ibarra-Rojas et al., 2015). At the strategic level, the traditional route design problem is addressed where the layout of bus routes and space between stops are determined. For instance, Szeto and Wu (2011)’s work minimised the transfer times and travelling times of passengers with the consideration of fleet size. For green buses, consideration of operational constraints inevitably poses new challenges on routing models (Lin et al., 2014) as well as operation models (Miles and Potter, 2014b). Beltran et al. (2009) allowed commuters to choose from the green fleets but with the limited size and non-green sub-networks as normal in the city of Rome. Modifying bus routes for fitting the characteristics of electric buses is not practical because passengers heavily relies on the pre-defined routes even if they are properly communicated (Kepaptsoglou and Karlaftis, 2009).

Subsequently, at the tactical planning level, the sub-problems of bus frequency settings (Gkiot-salitis and Cats, 2018), timetable design (Ceder et al., 2001), vehicle scheduling (Ming et al., 2013) and driver scheduling (Wren and Rousseau, 1995) are typically addressed in a sequential order. Tactical decision associated to the FSP is often related to balancing the passenger demand with the operational cost of given fleet size and characteristics: operators need to provide a good quality of service to attract non-captive users at an affordable cost. Reducing the vehicles assigned to service will decrease the operational cost but will result in a loss of passengers and revenues, and vice verse.

However, the operation of public transport is dynamic; frequency is requested to be adjusted to the passenger behaviour, resource capacities and operational limitations more often. In those works containing the scheduling of charging process, both the sequence of duty-cycle and the fleet size are given in advance. Recently, with the aim of solving vehicle scheduling of electric buses, Rogge et al. (2018b) integrated the total cost of ownership of charging infrastructure into the scheduling problem of vehicles trips and charging events. The defined problem covers a monetised cost of vehicle schedule, the investment of chargers per depot, and fleet size and composition investment in a joint process.
3.4 Formulation of bus operation as frequency setting problem

There are several methods to handle the demand in the problem determining the frequencies of the service. One of them sets the frequency based on the maximum loading point or loading profile in each line (Ceder, 1984; Mohring, 1972). The demand in this approach can be assumed unchanged or elastic to service quality or fares (see Paulley et al. (2006)). In the second type, the fixed demand-line assignment of origin-destination (OD) pairs is embedded as the lower-level problem in the bi-level optimisation (Constantin and Florian, 1995; Han and Wilson, 1982; Schele, 1980), and the frequency is set by solving the up-level FSP. Recently, Hadas and Shniderman (2012)’s work considered the demand uncertainty in the form of probability distribution on the basis of Automatic Vehicle Location (AVL) and Automatic Passenger Counting (APC) data. The implement of the minimisation of total cost based on not-served demand and empty seats has shown that the low-level of service contributes to the most significant cost reduction. The development of new technologies has provided new forms of higher granularity mobility data that allows bus operators evaluate the demand at the stop level. Thereby a third type of bus scheduling for several line patterns are launched in recent years Gkiotsalitis et al. (2019); Verbas and Mahmassani (2013); Verbas et al. (2015).

The afore-mentioned works highlighted a broad range of elements and concerns in the form of the planning of electric buses; however, it is apparent that there is a gap in the integration of charging scheduling with frequency setting in the tactical phase. Frequency setting problem differs from the vehicle schedule of minimising costs based on vehicle usage in that its objectives are to balance passenger demand with all type of resources, including charging expense. The spatial deployment of batteries along a day is significantly influenced by setting different frequency because the total number of electric buses that aligned with each bus route are determined at this stage.

3.4 Formulation of bus operation as frequency setting problem

Before proceeding, the abbreviation used in the formulation are given as below:
3.4. Formulation of bus operation as frequency setting problem

\( pp \) Planning period

\( Z \) Feasible set of frequency

\( \{L, S\} \) A bus network with bus routes \( L = \{1, 2, \ldots, |L|\} \) and bus stops \( S = \{1, 2, \ldots, |S|\} \)

\( S' \) Origin and Terminal stations in \( S \) that have electric chargers

\( h_l \) Headway in line \( l \in L \)

\( T_l \) The round trip travel time required for completing the trip

\( B_{i,j,l} \) Updated amount of passenger taking the transit service in line \( l \) that is elastic to waiting time

\( \rho_o \) Unit operating cost associated with bus travel kms

\( \epsilon \) Fare per passenger.

\( \theta \) Bus speed (km/hour)

\( \tau \) Bus transit capacity (p)

\( ct_{l,s'}(f) \) Charging duration at station \( s' \) of bus route \( l \)

\( L_{l,t,s'}(f, x) \) Charging load (kW) at station \( s' \) in hour \( t \) of bus route \( l \)

\( \varrho \) Energy consumption ratio (kWh/km)

\( \delta \) Charging rate (kW)

\( \rho_b \) Unit battery capacity cost

\( \sigma_{t,n} \) Dynamic tariff rate at node \( n \) at time \( t \)

\( \{N, C\} \) A distribution network with \( N \) nodes and \( C \) power lines.

\( \rho_{t,n}^g \) Unit cost of generation at time \( t \) for generator at node \( n \)

\( D_{t,n} \) Inflexible demand at node \( n \in N \) at time \( t \)

\( f_l \) Bus dispatch frequency (decision variable) in line \( l \in L \)

\( x \) Charging control variables (decision variable)

\( P_n \) Net power imported or Generator dispatch at node \( n \) (decision variable)

\( PLoss \) Power loss estimated from iterative DCOPF

\( E_{t,n}^{FND} \) Fictitious Nodal Demand (FND) deduced from the estimated Ploss at node \( n \) at time \( t \)

\( PF_c \) MVA capacity of line \( c \in C \)
3.4. Formulation of bus operation as frequency setting problem

$SF_{c,n}$ Power transfer distribution factor coefficient of line c w.r.t. to a unit injection at node n

$DF_{t,n}$ Power transfer distribution factor coefficient of node n w.r.t. line injection

$LF_{t,n}$ Loss factor coefficient of node n at time t

$\lambda$ Dual variable of total power flow balance constraints

$\mu^+$ Dual variable of power flow constraints

Most works in transportation studies set the optimal bus frequencies as an exercise of balancing the passenger demand with the available supply of buses (Ceder (1984); Cipriani et al. (2012); Furth and Wilson (1981); Jansson (1980) represent the four classic methods in determining the frequency).

In this thesis, the bus operational planning problem is extended by correlating the charging cost with the operational decision as an outcome of the frequency setting problem. The objective function consists of four components:

1. operational cost relating to vehicle travel distance
2. revenue collected from passengers who is sensitive to the service quality
3. recharging costs that relate to the dwell time between arrival and departure time
4. the opportunity cost of not charging which is associated to the daily battery usage cost per kWh

3.4.1 Formulation of charging load and cost

Since the optimisation of bus operation is done in batches; in other words the decision value regarding to the frequency is piece-wise constant within planning sub-period, the formulations are presented within a sub-periods only. Now consider a bus network \{L, S\}, each with a number of stops $s$ and two stations $s'$ (Origin and Terminal). A set of variables $f$ depict the bus dispatch scheduling in each line, thus giving the headway as the reverse of frequency: $h_i = 1/2f_i$ and
3.4. Formulation of bus operation as frequency setting problem

The total required number of bus to that line as: \( T_{lfs} \). In this way, we have to ensure that the number of buses allocated to that line is an integer number. However, this is rarely the case and we need to round upwards the number of buses \( NB_l = \lceil T_{lfs} \rceil \):

For a bus route that has a round trip time of \( T \) and dispatching frequency of \( f \), buses will be scheduled to leave every \( \frac{1}{f} \) minutes, i.e. from the start of planning period \( t = t_0 \), the timetable for each bus \( n \in NB \) to leave is:

\[
t_0 + \frac{n}{f}, \quad \forall n = 0, 1, 2, 3 \ldots NB
\]  

(3.1)

The bus that has completed its journey will arrive at the origin station by

\[
t_{arr} = t_0 + T + \frac{n}{f} + \xi, \quad \forall n = 0, 1, 2, 3 \ldots NB
\]  

(3.2)

where \( \xi \) represents any delays caused by passenger boardings/alightings and other traffic conditions. For the sake of maximising the vehicle use efficiency, the bus has to be ready for the next duty-cycle after returning to the origin station. One should note that the arrival time often subjects to some factors, such as the road condition and the total boarding/alighting time affected by the passengers. Although many other works in public transportation research, such as holding control (Cats et al., 2012) and arrival prediction (Yu et al., 2016), are applied to improve the efficiency in vehicle scheduling, electric bus operators have to provide extra buses in order to maintain the original timetabling (Miles and Potter, 2014b). Since there are many factors affecting \( \xi \), it was relaxed by adding one more bus in the estimation of layover between arrive time and the next departure time. This research only considers the planning in the tactical phase with the assumption of an uncongested road network, and the total boarding and alighting times are neglected in the modelling. The total request number of buses to operate in this bus route becomes \( N = \lceil T_{lfs} + 1 \rceil \) and thereby yielding the timetables for the next round of dispatch:

\[
t_{next} = t_o + \frac{N + n}{f_l}, \quad \forall n = 0, 1, 2, 3 \ldots N
\]  

(3.3)

A second rule is introduced so that if the layover time \( I_l(f) \) is less than 3 minutes, operators
3.4. Formulation of bus operation as frequency setting problem

will not use this short period to recharge the buses, i.e. the charging time \( c_{il}(f) \) is 0. Hence, the layover which represents as the time interval between the first departure and the next departure is:

\[
I(f) = \left\lceil \frac{T_{lf} + 1}{f_l} \right\rceil - T_l \quad (3.4a)
\]

\[
c_{il}(f) = \begin{cases} 
0 & \text{if } I(f) < 0.05 \text{ hour}, \\
I(f) & \text{if } I(f) \geq 0.05 \text{ hour}
\end{cases} \quad (3.4b)
\]

The above function is piece-wise linear and hence undifferentiated at the point; another drawback of the above equation is that the output will fluctuate along the value in several intervals of inputs and will drop to 1 when \( T_{lf} \) reaches an integer. In order to take into consideration of the case that more precise data of arriving time to be integrated into the model, the author introduce a least square method to approximate the mapping of bus dispatching frequency to the maximum charging time for each bus route, while preserving the convexity of both the function of charging time and charging loads. The new charging time function is expressed in Equation. 3.5:

\[
c_{il}'(f_l) = \frac{\theta_1}{f_l} + \theta_2 \quad (3.5)
\]

Where \( \theta_1 \) and \( \theta_2 \) are parameters depending on the measures of lay over time and service frequency.

To illustrate the characteristics of the new charging time function, a bus route (a) which has outbound and inbound length of 64 minutes and 60 minutes respectively and a bus route (b) which has outbound and inbound length of 235 minutes and 251 minutes respectively are presented in Figure 3.1.

By introducing the second set of decision variable for controlling the charging process, \( x_{l,s'} \) represents the percentage of charging in the dwell time which can be achieved by either shortening the duration connected to the electric grid or adjusting the charging rates. The loads \( L_{l,s'}(f, x) \)
3.4. Formulation of bus operation as frequency setting problem

3.4.1 Formulation of the opportunity cost of flash charge

Figure 3.1: Charging time function plotted by Equation. 3.4 and fitted curve by Equation. 3.5 for line (a) and (b)

submitted to the DNO become the multiplication of charging time and charging power times the percentage of charging; and the charging cost for bus operators can be expressed as the summation of nodal demand times the instantaneous electricity rates:

\[
L_{l,s'}(f, x) = \delta * x_{l,s'} * cl_l'(f_l)
\]

\[
\text{cost}_\text{charging} = \sigma_{t,n} * \delta * x_{l,s'} * cl_l'(f_l)
\]

(3.6)

3.4.2 Formulation of the opportunity cost of flash charge

Opportunity charging - the rare range remedy approach that able to minimise the disruption to the original service to the least level - is used in this thesis to complement the depleted battery during bus operation, thus reducing the initial cost on battery. Theoretically speaking, if the charging power is high enough to complement the energy consumed in one service trip in a short time, the required battery capacity should equal to the energy consumption along this trip. Contrasting to the case that bus operator schedules all the charging events to overnight and requires a large battery capacity, the savings on the battery investment cost are achieved at a cost of increased investment on high power charging infrastructures.

The common approach that use a pre-set constant battery capacity exhibit an inter-temporal discontinuity of residual State-of-Charge (SoC) that restricts the optimisation. Instead, a new
definition is introduced in this section. The difference between the add-up energy per flash charge and the energy consumed on roads would require the same amount of battery capacity to support so that this difference can be charged in the next planning period or overnight. This difference accumulated along time is defined as the battery capacity deficit:

\[
\text{Deficit}_{\text{battery}} = \theta \cdot \varnothing \cdot T_l \cdot f_l - L_l(f_l, x)
\]

where \( \theta \) is the bus speed and the \( \varnothing \) represent the energy consumption rate per Km.

Hence, the opportunity cost of not using flash charging is defined as the levelised ownership cost of battery per unit per day, i.e. the unit cost of battery per KWh \( \rho_b \) times the total deficit of battery capacity in the planning horizon. In this thesis, the battery is conservatively assumed with a five year lifetime and a zero second hand value after degradation, i.e.:

\[
\text{Cost}_{\text{opportunity}}(f_l, x) = \rho_b \cdot (\theta \cdot \varnothing \cdot T_l \cdot f_l - L_l(f_l, x))
\]

Finally, the operational availability that restricted by the battery is relaxed in the planning period overnight. Because of the extreme low demand overnight, the operational frequency in this period is often set to the minimal level depending on the regulation policy and would allow sufficient time to recharge the battery to the full level.

\[
\sum_{n=0}^{pp-1} \text{Cost}_{\text{opportunity}}(n) + \rho_b \cdot (\theta \cdot \varnothing \cdot T_l \cdot f_{l,t} - L_{l, t}(f_{l,t}, x_l)) = 0, \text{ if } t = pp
\]

### 3.4.3 Formulation of the elastic passengers loads to service quality

For simplicity and according to the practical guide for bus planning (Balcombe et al., 2004), the parameter of elasticity is used to depict the correlation between the demand for bus service and the dispatching headway. This could help to retain the convexity in the cost function while restoring the sensitivity of passengers to the bus service quality.

Several studies, such as Ibarra-Rojas et al. (2015); Paulley et al. (2006)’s work suggested an
average value of elasticity to be -0.64 for long-term operations, and Furth and Wilson (1981)’s work suggested a differentiated value for the off-peak and peak period since demand elasticity with respect to waiting time is higher during off-peak periods. By assuming the value during the peak period to be -0.2 and off-peak to be -0.64, i.e. we have a 0.2/0.64% decrease in passengers’ load if 1% waiting time increase. Equation. 3.10 shows that the expected passengers’ demand $B_l(f_l)$ for bus services per line will increase because they are sensitive to the service improvements:

$$\Delta B_l(h_l) = e \cdot \frac{0.5 * h_l - w_b}{w_b}$$

$$B_l(h_l) = B_l^h * (1 + \Delta B_l)$$

Or:

$$B_l(f_l) = B_l^h * \left(\frac{e}{2w_b * f_l} + 1 - e\right)$$

and the revenue collected from the ticketing can be expressed by following equation, if assuming a constant value of fare $\epsilon$:

$$Revenue_{passenger} = \sum_{l \in L} \epsilon \cdot B_l$$

### 3.4.4 Formulation of total bus operational cost

Given the above notations and assumptions, the first part w.r.t. the frequency setting in the objective function for bus operation planning for a round trip journey can be expressed as:

$$\varphi_{bus}(f) := Cost_{vehicle}(f) + Cost_{charge}(f) + Cost_{opportunity}(f) - Revenue_{passenger}(f)$$

$$= \sum_{l \in L} \rho_o * \theta * T_l * [T_l f_l] - \epsilon * B_l$$

$$+ \sigma_{t,n} * \delta * x_{l,s'} * c_l'(f_l) + \rho_b * (\theta * \theta * T_l * f_l - L_l(f_l, x))$$

subject to: $\sum_{l \in L} [T_l f_l] \leq \Gamma$  

$$B_{s,l}(h_l) \leq \sum_{l \in L} \tau f_l, \forall s \in S, l \in L$$
3.5. Formulation of lagrange-relaxation based market clearing model

\[ \forall f \in Z : f_{\min} \] 

\[ \forall x \in (0, 1) \]

(3.12d) 
(3.12e)

where \( \rho_o \) is the unit operating cost per vehicle-kms. For simplicity, bus speed \( \theta \), fare \( \epsilon \) and maximum charging rate \( \delta \) are assumed constant for each ride.

Bus operators commonly have to conform to a set of constraints. First, the number of buses allocated to the bus routes should not exceed the total available number of vehicles Equation. 3.12b, and constraint Equation. 3.12c guarantees the sufficient transit capacity for the passenger demand. In addition, there can be minimum and maximum requirements for the service frequency due to the regulation of service. Feasible sets \( Z \) can be defined by the bus operators according to the lowest and highest frequency that is permitted for each line.

### 3.5 Formulation of lagrange-relaxation based market clearing model

#### 3.5.1 Lossless electricity pool market

Based on the framework and assumptions, this section describes the day-ahead market clearing model. The LMP in the wholesale transmissions level is extended to distribution level due to the increasing needs of active control in the smart grid concept (Sotkiewicz and Vignolo, 2006).

According to the spot prices at the relevant transmission buses - which is usually transmission-level LMP calculated by solving DCOPF at national level (Litvinov, 2010) - the DNO solves the SCED problem based on flexible demand subjecting to network constraints. In our proposed framework, the dynamic tariffs are notified to bus operators based on the derivative DLMP so that the bus operators carried their optimisation of planning to bid in the day-ahead market.

There are several approaches in the literature for generating the DLMP. Bai et al. (2017) and Yuan et al. (2016) decomposed the DLMP for active and reactive power based on the linearised
3.5. Formulation of lagrange-relaxation based market clearing model

power flow with many approximation and relaxation of non-convex constraints. OConnell et al. (2012) proposed a step-wise structure to determine the dynamic tariff, where the energy balance components in the LMP and congestion component are calculated separately based on lossless DCOPF. Li et al. (2014b) and Liu et al. (2018) adopted a similar lossless DCOPF but in an integrated manner to alleviate the congestion caused by EVs. However, as Liu and Wen (2014) and Li et al. (2014a) argued, in the discussion with respect to the inaccuracy in a distribution network with higher resistance and lower voltage level, some modifications are necessary for the LMP methodology to fit in the distribution network.

Notwithstanding, DCOPF is still the most commonly used methodology for LMP, due to its high computational efficiency and good accuracy. ACOPF is much slower in computation and requires special care in input data to make it converge (Li and Bo, 2007). Considering the large number of nodes in a distribution network and the loss caused by the low voltage, we employ DCOPF with an iterative process of evaluating power losses and Fictitious Nodal Demand (FND) (see Yuan et al. (2016)) to improve the accuracy while keeping the convexity of the whole problem traceable.

First, for each time resolution \( t \in pp \), the optimal generation and demand dispatch are achieved by optimising social cost function \( J \) (objective function Eqn 3.13a, which excludes the information submitted by bus operator to reduce the complexity). The DCOPF problem without losses is constrained by nodal balance 3.13b and power flow limits in branch 3.13c. The voltage magnitudes are assumed to be unity and reactive power is ignored.

\[
\begin{align*}
\text{min} & \quad \sum_{n \in \mathbb{N}'} \rho_{t,n}^g * P_n \\
\text{subject to:} & \quad \sum_{n \in \mathbb{N}} (P_n - D_n) = 0 \quad \ldots \lambda \\
& \quad \sum_{n \in \mathbb{N}} SF_{c-n}(P_n - D_n) \leq PF_c^{max} \quad \ldots (\mu_c^+ \geq 0)
\end{align*}
\]

Where \( \rho_{t,n}^g \) is the purchase price of electricity from the bulk grid, \( P_n \) and \( D_n \) represent the total imported power and inflexible demand respectively. \( SF_{c-n} \) is the sensitivity factor of power
3.5. Formulation of lagrange-relaxation based market clearing model

flow at power line branch \( c \) with respect to the net injection at \( n \).

### 3.5.2 Approximation of power loss and Loss Factor (LF)

There are two main methods to estimate the power loss. The direct method that uses voltage angles throughout the system is the most accurate but can be computationally intensive and time-consuming (Cardell, 2007). In the second method, a co-efficiency is built to approximate the actual loss with a series of line information, such as voltage angle in the AC system and the power flow in the DC OPF. This method is more conceptually accessible to a wider audience and easier to implement. When considering a modification to the lossy network based on Equation 3.13, the energy balance constraint in 3.13b enforces that the total generation should be greater than the total demand by the average system loss, which results in a mismatch that absorbed in the slack busbar only. Therefore, fictitious nodal demand \( E_{n}^{FND} \) is introduced to distribute the total system loss to each line. By applying the FND approach, the power loss is equally halved and attached to both connector of the line, which is:

\[
E_{n}^{FND} = \sum_{c=1}^{M_{n}} \frac{1}{2} \times (PF_{c}^{*})^{2} \times R_{c}
\]  

(3.14)

where \( E^{FND} \) is applied at each end of the individual line to avoid the situation that most mismatches of power loss are absorbed in the slack busbar and \( L_{s,n} \) represents all the bus routes connected to the loading point. With * indicate a constant value of power flow obtained from the previous iteration of Equation. 3.13. Now the line flow can be viewed as the aggregation of the contribution from all power sources minus the power consumed by the FND, yielding:

\[
PF_{c} = \sum_{n=1}^{N} SF_{c-n}(P_{n} - D_{n} - \sum_{l \in L} L_{s-n} \times L_{l,n}(f, x) - E_{n}^{FND})
\]  

(3.15)

\[
Ploss = \sum_{c \in C} PF_{c}^{2} R_{c}
\]  

(3.16)
Loss factor $LF_n$ is defined as the sensitivity of system loss to the change of net injection at feeder:

$$LF_n = \frac{\partial P_{loss}}{\partial L_n} = \sum_{c=1}^{M} R_c \times 2PF_c \times \frac{\partial PF_c}{\partial P_n}$$

$$= \sum_{c=1}^{M} 2 \times R_c \times SF_{c-n} \times (P_n - D_n - M_{s-n}L_{l,n}(f,x) - E_n^{FND})(\sum_{n=1}^{N} SF_{c-n}) \quad (3.17)$$

Where the $M_{s-n}$ is the mapping matrix that connect the loads $L_{l,n}$ at bus stations $s$ and the loading node $n$. The deliver factor can be rewritten as $DF_n = 1 - LF_n$. Finally, the new iterative DCOPF formulation, which replaces the Equation. 3.13 can be expressed as:

$$\min \sum_{n \in N'} \rho_{i,n}^{g} \times P_n \quad (3.18a)$$

subject to:

$$\sum_{n \in N} DF_n P_n - \sum_{n \in N} DF_n (D_n + \sum_{l \in L} M_{s-n} * L_{l,n}(f,x)) + P_{loss} = 0 \quad \ldots \lambda \quad (3.18b)$$

$$\sum_{n \in N} SF_{c-n} (P_n - D_n - E_n^{FND} - \sum_{l \in L} M_{s-n} * L_{l,n}(f,x)) \leq PF_{c}^{max} \quad \ldots \mu_c^+ \quad (3.18c)$$

Note $P_{loss}$ is positive and used to offset the doubled system loss caused in the calculation of loss factor, such proof can be found in Li and Bo (2007) as well.

### 3.5.3 Derivative of distribution locational marginal price (DLMP) for e-bus

The LMP is defined as the sensitivity of total marginal cost (Lagrangian function) with respect to the change of demand at the load points. Therefore, after obtaining the optimal solution of
DCOPF, the LMP at any point can be calculated with the Lagrangian function, shown as:

\[
\Psi = \sum_{n \in N'} \rho_{t,n} P_n - \lambda \left( \sum_{n \in N} DF_n P_n - \sum_{n \in N} DF_n(D_n + \sum_{l \in L} L_{s-n} * L_{l,n}(f,x)) + P\text{loss} \right) \\
- \sum_{c \in C} \mu_c^+ \sum_{n \in N} SF_{c-n}(P_n - D_n - E_{FND} - \sum_{l \in L} L_{s-n} * L_{l,n}(f,x)) - PF_{c}^{\max}
\]

(3.19)

The formulation of DLMP at the load point \(n\) can be written as:

\[
DLMP_n = \frac{\partial \Psi}{\partial L_n} = \lambda \cdot DF_n + \sum_{c \in C} \mu_c^+ \times SF_{c-n}
\]

(3.20)

The loss component and the congestion component have to be passed to the bus operators and times a co-efficiency to constitute the dynamic tariff, i.e.:

\[
\sigma_n = \lambda + \alpha_t \cdot (\lambda \cdot (DF_n - 1) + \sum_{c \in C} \mu_c^+ \times SF_{c-n})
\]

(3.21)

where \(\alpha_t\) is set to 1 by default, adjusting this parameter will enable the policy makers to investigate the sensitivity of mobility to the charging cost.

### 3.6 Bi-level problem and MPCC reformation

In the proposed bi-level framework, both the function representing the electric bus operation and the function representing the market clearing process are convex, followed by the linear equality and inequality equations. In addition, either the decision of electric bus operators and balancing for the DNO depends on the information given by rival. Bus operators require the latest price to decide the amount and locations of charging events while these decisions are also necessary for DNOs to predict the loads and hence yielding the DLMPs. Therefore, the upper
level is set to represent the cost minimisation objective of electric bus operator and the lower level represents the energy market clearing model.

The overall expression of bi-level problem in our case is:

\[
\varphi_{\text{bus}}(f, x, p) := \sum_{l \in L} \rho_o \ast \theta \ast T_i \ast [T_i f_i] - \epsilon \ast B_i^h \ast \left( \frac{e}{2w_b \ast f_l} + 1 - e \right) \\
+ \sigma_{t,n} \ast \delta \ast x_{l,s} \ast c_l(f_i) + \rho_b \ast (\theta \ast g \ast T_i \ast f_i - L_i(f_i, x))
\]

s.t.:

\[
B_i(f_i) = B_i^h \ast \left( \frac{e}{2w_b \ast f_l} + 1 - e \right)
\]

\[
B_i(f_i) \leq \sum_{l \in L} \tau f_i, \ \forall s \in S, l \in L
\]

\[
\sum_{l \in L} [T_i f_i] \leq \Gamma, \ \forall l \in L
\]

\[
\sigma_{t,n} = \lambda + \alpha \ast (\lambda_t \cdot (DF_{t,n} - 1) + \sum_{c \in C} \mu^+_t,c \ast SF_{c-n})
\]

\[
\rho^\phi_{t,n} + \lambda \ast DF_n + \sum_{c \in C} \mu^+_c \ast SF_{c-n} = 0, \ \forall n \in N
\]

s.t. : min \sum_{n \in N} \rho^\phi_{t,n} \ast P_n

s.t.: \sum_{n \in N} DF_n P_n - \sum_{n \in N} DF_n (D_n + \sum_{l \in L} M_{s-n} L_{i,n}(f, x)) + Ploss = 0

\[
\sum_{n \in N} SF_{c-n}(P_n - D_n - E^{FND}_n - \sum_{l \in L} M_{s-n} \ast L_{i,n}(f, x)) \leq PF_{c}^{max}
\]

\[\forall f \in \mathbb{Z} : f_{\min}\]

\[\forall x \in (0, 1), \ \lambda > 0, \ \mu^+ \leq 0, \ \forall t \in pp\]

(3.22)

Bard (1991) proved that the bi-level problem is NP-Hard, but a classical method is replacing the lower level problem with its Karush-Kuhn-Tucker (KKT) optimality condition. Since for any optima \(y^* \in \mathbb{R}\), it must follow the KKT condition, i.e. KKT condition is the necessary step
3.6. Bi-level problem and MPCC reformation

To test if $\bar{y}$ is one of the optimal solutions, thereby the bi-level problem is transformed as:

$$\min_{x,y} f_u(x,y)$$
$$\text{s.t. } g_u(x,y) = 0,$$
$$h_u(x,y) \leq 0,$$
$$\frac{\partial f_l(x,y)}{\partial y} - \lambda \frac{\partial g_l(x,y)}{\partial y} - \mu \frac{\partial h_l(x,y)}{\partial y} = 0$$
$$g_l(x,y) = 0$$
$$h_l(x,y) + w = 0$$
$$\mu \ast w = 0$$
$$x, y, \lambda, w \geq 0 \text{ and } \mu \leq 0$$

where $w \in \mathbb{R}^{n_{PL}}$ is slack variable, $\mu \in \mathbb{R}$, $\lambda \in \mathbb{R}^{n_{PL}}$ is dual variable.

Thereby, the original bi-level problem is solved after converting to a Mathematical Program with Complementary Constraints (MPCC) when the Lagrange multipliers are introduced, and followed by simplification that replace the lower level problem with its equivalent Karush-Kuhn-Tucker (KKT) optimality conditions.

The KKT conditions of Equation 3.18 are:

$$\rho^g_{l,n} + \lambda \ast DF_n + \sum_{c \in C} \mu^+_{c} \ast SF_{c-n} = 0 \quad \forall n \in N$$ (3.23a)

$$\lambda \perp (\sum_{n \in N} DF_n P_n - \sum_{n \in N} DF_n (D_n + \sum_{l \in L} L_{l,n}(f,x)) + Ploss) = 0$$ (3.23b)

$$\mu^+_{c} \perp (PF^{\max}_c - \sum_{n \in N} SF_{c-n}(P_n - D_n - E^{FND}_n - \sum_{l \in L} L_{l,n}(f,x))) = 0, \quad \forall c \in C$$ (3.23c)

$$\sum_{n \in N} DF_n P_n - \sum_{n \in N} DF_n (D_n + \sum_{l \in L} L_{l,n}(f,x)) + Ploss = 0$$ (3.23d)

$$\sum_{n \in N} SF_{c-n}(P_n - D_n - E^{FND}_n - \sum_{l \in L} L_{l,n}(f,x)) \leq PF^{\max}_c$$ (3.23e)
Finally, the expression for the equation 3.12 can be rewritten as the following form:

\[ \varphi_{bus}(f, x, p) := \sum_{l \in L} \rho_{b} \times \theta \times T_{l} \times [T_{l} f_{l}] - \epsilon \times B_{l}^{h} \times \left( \frac{e}{2 w_{b} \times f_{l}} + 1 - e \right) \]

\[ + \sigma_{t,n} \times \delta \times x_{l,s'} \times c_{l}^{l}(f_{l}) + \rho_{b} \times (\theta \times g \times T_{l} \times f_{l} - L_{l}(f_{l}, x)) \]

s.t.:

\[ B_{l}(f_{l}) = B_{l}^{h} \times \left( \frac{e}{2 w_{b} \times f_{l}} + 1 - e \right) \]

\[ B_{l}(f_{l}) \leq \sum_{l \in L} \tau f_{l}, \forall s \in S, l \in L \]

\[ \sum_{l \in L} [T_{l} f_{l}] \leq \Gamma, \forall l \in L \]

\[ \sigma_{t,n} = \lambda + \alpha \times (\lambda \cdot (D_{F_{t,n}} - 1) + \sum_{c \in C} \mu_{t,c}^{\epsilon} \times S_{F_{c-n}}) \]

\[ \rho_{t,n}^{\epsilon} + \lambda \times D_{F_{n}} + \sum_{c \in C} \mu_{c}^{\epsilon} \times S_{F_{c-n}} = 0, \forall n \in N \]

\[ \lambda \perp \left( \sum_{n \in N} D_{F_{t,n}} P_{t,n} - \sum_{n \in N} D_{F_{t,n}}(D_{t,n} + L_{l,n}(f_{l}, x)) + \text{Ploss}_{t} \right) = 0 \]

\[ \mu_{t,c}^{\epsilon} \perp (P_{F_{c}}^{\text{max}} - \sum_{n \in N} S_{F_{c-n}}(P_{t,n} - D_{t,n} - E_{t,n}^{F_{ND}} - \sum_{l \in L} L_{l,n}(f_{l}, x))) \right) = 0, \forall c \in C \]

\[ \sum_{n \in N} D_{F_{t,n}} P_{t,n} - \sum_{n \in N} D_{F_{t,n}}(D_{t,n} + \sum_{l \in L} L_{l,n}(f_{l}, x)) + \text{Ploss}_{t} = 0 \]

\[ \sum_{n \in N} S_{F_{c-n}}(P_{t,n} - D_{t,n} - E_{t,n}^{F_{ND}} - \sum_{l \in L} L_{l,n}(f_{l}, x)) \leq P_{F_{c}}^{\text{max}} \]

\[ \forall f \in Z : f_{\text{min}} \]

\[ \forall x \in (0, 1), \lambda > 0, \mu^{\epsilon} \leq 0, \forall t \in pp \]

(3.24)

### 3.7 Implementation process

Due to the inconsistency of the planning horizon, in which the resolution of lossy DCOPF is an hour whereas the resolution of bus planning is the time to complete the maximum trip length. It is imperative to include a nested conversion of the DCOPF problem into the MPCCs and increase the computational burdens to satisfy all the network constraints.
Since the simplified charging load function (Equation 3.6) is linear to the bus dispatch frequency in the whole planning horizon, the variable in upper level problem as well as the charging load can be treated as constant in the lower level problem. The DCOPF in each hourly resolution can be converted to the MPCCs independently in the same process by introducing $pp$ times more dual variables. After the conversion of the multi-period DCOPF problem, the bi-level problem now becomes a single level problem that stands at the level of electric bus operators. Searching for the optimal solution set that includes the $(f, x)$ in the upper level problem and the $p$ in the lower level problem as well as an additional set of variables of the dual variables $(\lambda, \mu)$ associated with the power system constraints would result in an effort to gradually minimise the electric bus operational cost and hopefully satisfying the relaxed power system constraints.

If the power system constraints are satisfied, the dual variable along with the latest bus dispatch and generation responses constitutes a market equilibrium according to the relevant definition, since each party maximises/minimises their economic surplus/cost and system constraints are satisfied. The fact that this solution maximises the social welfare according to the properties of the duality theory (sub-section 2.4.1) is justified by the economic theory, according to which market equilibrium solutions constitute a subset of social welfare maximising solutions. The implementation process is shown in Figure 3.2.
3.7. Implementation process

**Bus Operation Model**
- charging control
- charging cost
- battery opportunity cost
- elastic demand

**Market Clearing Model**
- system constraints satisfied
- termination

**Generation/Net import**
- lossless DCOPF
- PLoss*, LF*, DF*

**Lagrangian Multiplier**
- convergency stop criteria
- PLoss, LF, DF
- network constraints
- resolution t

**MPEC**
- NLP solver

Figure 3.2: Implementation process of optimisation
Chapter 4

Case Study I: Impacts Of Dynamic Tariff On E-Bus Operation

4.1 Introduction

The previous chapters of this thesis present and analyse the modelling, mathematical, algorithmic and implementation aspect of the proposed bi-level model. In order to comprehensively validate the applicability and hence understand the implication of differentiated locational price generated in the mechanism, the first part of case study using real-world passenger data collected from the smart card and General Transit Feed System (GTFS) data in Shenzhen, China and a distribution level IEEE test system are developed and analysed.

In general, the case consists of two networks: bus transit network that constituted by 8 bus route and their attached road characteristics such as stops, departure and return journey length, as well as the radial distribution network constituted by 7 feeders and 38 loading points. The scope of this case studies was limited to the electric mobility, loads and locational price in the distribution network only. From the views of DNOs, the flexible demands of electric bus fleets examined in the presented case studies spread over the 7 feeders with differentiated amount of stations (charging facilities). The coupled inflexible demand would vary along the day and
results in different power line condition in hours.

Several scenarios regarding the different level of power line limits, as well as the dynamic tariff are examined. In addition, the performance of bus operation that responding to the same network condition in off-peak and peak hours are necessary to be compared due to its different fulfilment to regulations.

This chapter is organised as follows. Section 4.2 briefs the scale, challenges and pre-processing of raw data, as well as section 4.3 laid out the topology, input data, assumptions and simulation tools employed. Section 4.4 present results associated with the case that no network operational constraints applied and analysis of the theoretical properties of the proposed mechanism. Section 4.5 would indicate the variation of locational price in the case of load congestion and the impact of dynamic tariff on bus operation. At the end of this chapter, the sensitivity of system with respect to the parameter of bus operational cost and bus battery usage cost and dynamic tariff rates and presented in section 4.6.

4.2 Data pre-processing

4.2.1 General description of data and the objective of pre-processing

The raw data are highly vulnerable to missing, noisy and inconsistent because of the huge size, and the heterogeneity embodied in different collecting methods and multiple resources. Data mining is an imperative step in Knowledge Discovery in Database (KDD) to extract knowledge from large amount of data to an understandable format. Figure 4.1 shows the process steps to select the target data. After data pre-processing which aims to enhance the reliability, several procedures such as clustering, classification and regression will be applied to derive the desired patterns.

There are two series of data-sets collected from the city of Shenzhen, China. The first series represents the records of automatic ticketing system, which consists the labels of tickets, fare
4.2. Data pre-processing

![Knowledge Discovery in Databases steps](Source from Bhaya (2017))

before and after discount, the date and time of transactions, name of the bus company, the bus routes in which the ticket was issued and the number plates of vehicles. The example of this smart card dataset is shown in Figure 4.2. The second series represents the Global Positioning System (GPS) data collected during the movement of buses, which consists of the position information (longitude, latitude and altitude), the date and time of records, the type of data which specified the arriving at, leaving from each stop, the bus routes that the vehicle scheduled to serve, speed and angle of sensor, and the number plates of vehicle license is recorded in the last column, as shown in Figure 4.3.

However, the information of the name, position of stops and the distance between stops in each bus route has not been provided in the data-sets. An additional web crawler in python is developed to capture the relevant bus route information available online, thus constituted the third series of data-sets.

The objective of data pre-processing is to generate a set of patronage patterns including the information of bus stops, length of trips in each direction and the number of passengers boarding at each stops on an hourly basis.
4.2 Data pre-processing

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Figure 4.2: Example of smart card data

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Figure 4.3: Example of GPS data
A total number of 820 bus routes has been recorded and analysed in this chapter, in which most lines have a poor data quality to compose a reliable pattern that could provide traceable passenger demand patterns by stops and directions. Hence several steps of data implementation are processed to select bus routes that have sufficient records of both patronage and GPS locations in each planning horizons. In order to filter out the useless and noisy data, the following rules are introduced for data filtering, cleaning and filling of missing data:

1. Because the records of operation span from 5 am in the morning to 1 am the next day, the selected bus route shall have transaction recorded in at least 7 planning horizons, if the planning horizons are assumed 3 hours. For bus routes that absent the records of movements and patronage before 11:00 pm are viewed as incomplete records and thus discarded. Bus routes that have intermittent ticketing records before 11:00 pm but absent data after 11:00 pm are kept and this vacant horizon is treated as zero demand periods.

2. For the same reason of selecting routes with abundant trajectory history data, a similar method of Rule 1 is applied to the GPS data, in which the bus routes with adequate records of the time are retained into a list of candidates.

3. Target lines must have records both in the first and second series of data-set, since lacking any parts in the transaction of tickets or the positioning information along the trajectory will not be able to provide a completed image about the variation of passenger demand along the day.

4. The time of transaction in the smart card data, the time of movement in GPS data, the bus routes that transactions affiliates and the number plates of the vehicle are considered as the criterion to correlate the position of patronage to the specific stops in bus routes.

5. Movements that take place within a small horizon of minutes are grouped into the same cluster, of which the K-means of distance measures is used to affirm the closest bus stops. Same rule is used to detect outliers, since it grouped similar points into a cluster, any
points fall out the cluster need extra smoothing. In the case of missing GPS data in the trajectory along the routes, a linear smooth based on neighbouring GPS position is employed to approximate the trip length. The technique is illustrated in Figure 4.4.

6. For the smart card data consist of the patronage and time of transaction, the clusters are inherited from the clustering process of GPS data with the same horizon of time. In this way, the magnitude of passenger demand and positions where the transaction occurred are paired with the GPS data along the bus trajectory.

![Figure 4.4: Illustration of data clustering and pairing of demand data](image-url)
After the step of data pre-processing, a total number of 51 bus routes have been retained for further selection. The name, amount of allocated buses in real-scale operation and the amount of patronage are listed in Appendix A. Despite the bus routes with allocated bus less than 10, 8 from the rest 47 bus routes are manually selected by their geospatial topology considering the further application of adaptive operation in Chapter 5 and 6. They share the following specifications:

1. Bus concentration, which is defined as a situation that buses in different lines oriented to the same area due to the intensive deployment of bus stations in the area. Given the assumption of opportunity charging, a higher amount of bus laid over in this zone would result in the higher rate of power distracted from the grid. A further assumption is made that the grouped bus stations in this zone receive power from the same feeder that connects the inflexible consumers with the 11 kV substations.

2. There exists at least one transfer stop that could provide seamlessly interlining to one of the other lines. This feature is particular important in the adaptive operation for its minimised deadheading cost. However, it falls beyond the scope of this chapter, and will be discussed in Chapter 5.

4.2.3 Target data: Line level passenger demand

As presented in Figure 4.5, the selected 8 bus routes comprise 304 bus stops and 14 bus stations. Among those bus routes, 3 west-to-east and 1 north-to-east long-distance bus routes take over 5 hours to complete a round-trip journey; 4 medium-distance routes take less than 3 hours to completed the service. Major parts of original service cover a compact geographical area that enables an evident clustering of bus stations.

To apply the bus network to the case study, the average round-trip length, and travel time by direction are presented in Table 4.1. The eight originally planned bus routes are operating at a high frequency less than 15 minutes, with an total number of available buses for operating the service equal to 271.
4.2. Data pre-processing

Table 4.1: General information of cleaned target data

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<th>Round-trip length (km)</th>
<th>Departure travel time (min)</th>
<th>Return travel time (min)</th>
<th>No. of bus</th>
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<td>77.4</td>
<td>15</td>
<td>7118</td>
<td>10</td>
</tr>
<tr>
<td>204</td>
<td>55</td>
<td>146.3</td>
<td>155.9</td>
<td>56</td>
<td>24418</td>
<td>6</td>
</tr>
<tr>
<td>383</td>
<td>46</td>
<td>124.4</td>
<td>126.6</td>
<td>20</td>
<td>7605</td>
<td>12</td>
</tr>
</tbody>
</table>
From Figure 4.6, it can be seen that though the demand diverse over lines, the average bus demand in general can be significantly higher than the other direction at a specific hour period (6 - 9 am). For optimally utilise the vehicle, there might be a major part of bus routes that not necessary running at the under-utilised high frequency for 75% of the time. Hence the actual dwell time that enables electric bus connected to the grid will be longer than expected. Considering the tremendous amount of fully electrified bus fleets in Shenzhen, the proposed mechanism are expected of great potential to shift demand both inter-spatially and inter-temporally.
4.3 Description of case

4.3.1 Distribution system topology

Based on the passenger demand profile generated in the previous section, the plan period for bus is considered to 3 hours that can be empirically found to exhibit a relatively stable ridership pattern in Figure 4.6 and is sufficient for any bus to complete at least a single-trip service. Furthermore, for simplicity the plan horizon is set from 6:00 am in the morning to 3:00 am in the next day where the ridership can be found positive. The developed case studies simulate the application of electric bus load at bus stations using opportunity charging on the power system, those buses that return to the depot for overnight charging will not be counted in this study. For the power system topology, the case in Shenzhen is replaced by the Bus (power system) 4 distribution network of the Roy Billinton Test System (RBTS) (Allan et al., 1991; Billinton et al., 1989) instead, due to the absence of available data.

The RBTS was designed following the general utility principles and practices regarding topology, ratings and load levels. In this network, 38 groups of consumers are connected to the load point via transformers, and received power from 7 feeders (11 kV) that connected to 3 supply points at medium voltage level (33 kV). The feeders are operated as radial feeders but connected as a mesh through normal open sectionalising. The impedance per km length is assumed uniform for all connectors on a 100 MVA p.u. base, thus yielding the impedance for each line by its length, voltage rate and type of use. The single line diagram of the distribution system is shown in Figure 4.7 and the parameters of connecting cables (or overhead lines) are summarised in Table 4.2. The detailed data used in this thesis by loading points, supplier points, connector and the cable length and impedance can be found in the Appendix B.

By combining two networks, the power using to charge electric buses is assumed distracted from the three supply point separately. The allocation of aggregated charger in each station was carried out through the mapping presented in Table 4.3, in which $O$ represents the originating station of direction 1 and $T$ represents the originating station of the opposite direction.
4.3. Description of case

Figure 4.7: Single line diagram of bus 4 distribution system of RBTS (Allan et al., 1991) and connection of e-bus loads

<table>
<thead>
<tr>
<th>Connection line type</th>
<th>Line Rate</th>
<th>Line length (km)</th>
<th>Line number</th>
<th>Impedance (p.u./km, 100 MVA)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.6</td>
<td>2, 6, 10, 14, 17, 21, 25, 28, 30, 34, 38, 41, 43, 46, 49, 51, 55, 58, 61, 64, 67</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>11 kV</td>
<td>0.75</td>
<td>1, 4, 7, 9, 12, 16, 19, 22, 24, 27, 29, 32, 35, 37, 40, 42, 45, 48, 50, 53, 56, 60, 63, 65</td>
<td>0.2538</td>
</tr>
<tr>
<td>3</td>
<td>0.8</td>
<td>3, 5, 8, 11, 13, 15, 18, 20, 23, 26, 31, 33, 36, 39, 44, 47, 52, 54, 57, 59, 62, 66</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>33 kV</td>
<td>10</td>
<td>SP1 - SP2, SP2 - SP3</td>
<td>0.0114</td>
</tr>
<tr>
<td>5</td>
<td>15</td>
<td>SP1 - SP3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.3: Assumption of the affiliation between bus stations and load point

<table>
<thead>
<tr>
<th>Supply point</th>
<th>Feeder</th>
<th>Load point</th>
<th>Bus station</th>
<th>Bus routes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>7</td>
<td>1 - 4</td>
<td>383(T), 320(T), 82(O&amp;T), 101(O), 204(T)</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>25</td>
<td>5 - 11</td>
<td>212(O&amp;T), 287(O&amp;T), 352(O&amp;T)</td>
</tr>
<tr>
<td>3</td>
<td>7</td>
<td>33, 34, 38</td>
<td>12 - 14</td>
<td>101(T), 204(O), 320(O)</td>
</tr>
</tbody>
</table>
4.3. Description of case

Table 4.4: Customer data

<table>
<thead>
<tr>
<th>Number of load points</th>
<th>Load points</th>
<th>Customer type</th>
<th>Load level per load point (MW)</th>
<th>Number of customer</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>1-4,11-13, 18-21,32-35</td>
<td>Residential</td>
<td>0.545 0.8869</td>
<td>200</td>
</tr>
<tr>
<td>7</td>
<td>5,14,15,22, 23,26,37</td>
<td>Residential</td>
<td>0.5 0.8137</td>
<td>200</td>
</tr>
<tr>
<td>7</td>
<td>8,10,26-30</td>
<td>Small user</td>
<td>1.0 1.63</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>9,31</td>
<td>Small user</td>
<td>1.5 2.445</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>6,7,16,17, 24,25,38</td>
<td>Commercial</td>
<td>0.415 0.6714</td>
<td>10</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td><strong>24.58 40</strong></td>
<td><strong>4779</strong></td>
</tr>
</tbody>
</table>

Figure 4.8: Electric load profile of inflexible demand by seasons (Subcommittee, 1979)
4.3.2 Inflexible demand

The RBTS defines the customer types, number of customers of each type, average and peak load at each load point, several of which are considered as the same type. Table 4.4 summarised the assumption that the demand of those 4779 customers are inelastic to the price and must be satisfied by the importation of power from the bulk grid. In addition to the average load that carried on at the load point, the author also suggested a simulation of hourly demand variation that differs in seasons, as provided in the IEEE reliability system (Subcommittee, 1979). Curves in Figure 4.8 describe the peaking system in the percentage of the daily peak by winter, summer and spring week, from which one can observe that the daily loads rise at 7 am and maintained at a relatively high level until 22:00. The allocation of the hourly inflexible demand was carried out according to the respective percentages in this profile.

4.3.3 Cost of generation system

The RBTS has 6 generators locating at busbar 1 and 5 locating at busbar 2, totalling 11 generators deliver energy to 6 busbar system through the transmission system. However, due to the scope of this case study, the bus 4 distribution system is examined without generators so that all the energy consumption has to be imported from the bulk grid referenced at supply point 1. Hence a wholesale price (NORD POOL, 2018) in the UK day-ahead market is taken as the cost of importing electrical energy from other suppliers. The hourly day-ahead price (data can be found in Appendix D) published by the Nord Pool represented a typical price that the buyer, typically a utility, willing to pay for the electrical energy volume to meet customers’ demand. The price has the lowest rate at the period of 1:00 am to 7:00 am in the morning and 13:00 to 17:00 in the afternoon, while culminated at 10:00 am, as described in the Figure 4.9.

Given the above assumptions, the objective function in Eqn 3.13a can be simplified and rewritten as:

\[
Objective function : \min \rho_{t,0} * P_{t,0}
\]  
(4.1)
where \( P_{t,0} = \sum_{n \in N}(D_{t,n} + \sum_{l \in L} M_{s-n} * L_{t,n}(f, x)) + P_{loss}, \) for \( t \in pp. \) Since the demand of 38 load points is inflexible, the nature of the objective function becomes minimising the incremental cost caused by the network power loss and congestion. As discussed in Section 4.1, different scenarios regarding to the power flow limits are considered and will be analysed in Section 4.5.

![Figure 4.9: Plots of day-ahead electricity price on 1 June 2018, available at NORD POOL (2018)](image)

### 4.3.4 Electric bus

The fully electrified bus fleets are examined in this thesis, features characterising the electric mobility include the travel time described in Section 4.2, energy consumption rate, the battery and the specification of chargers.

The energy consumption rate varies subject to very complicated operational conditions, especially for heavily-used electric buses. It was indicated that the theoretical performance for the electric bus deployed in the Milton Keynes project is estimated to be within a range of 1.06 kWh/mile and 1.33 kWh/mile. Severe weather condition would result in consumption increasing. For instance, the electric bus has to turn on the air conditioner in hot weather or has to turn the lights on during darkness. Kontou and Miles (2015) has suggested an average rate
of 1.5 kWh/per mile should be estimated for practice in the UK’s case. Based on the similar consideration of the weather condition in Shenzhen, this rate was set to 2 kWh/mile, i.e. 1.25 kWh/km.

The grid-to-vehicle charging rate is the parameter combining the charging efficiency and the power of charger. This parameter is used to translate the available charging time and charging requirement to respective electric load. Miles and Potter (2014b) also provided a valuable reference for the assumption of flash chargers, in which two inductive charging systems are installed with a grid-to-vehicle efficiency 80%. Based on this demonstration project, the charger power is set to 140 kWh and the grid-to-vehicle charging rate is 112 kWh.

Furthermore, as discussed in Section 3.4.2, the opportunity cost of not charging is estimated based on the levelised daily usage cost of batteries. From 2010 to 2016, battery pack prices fell roughly 80% from $1000/kWh to $227/kWh, and McKinsey & Company (2017) forecasts that the current projections will put EV battery pack prices below $190/kWh by the end of the decade. Hence, the opportunity cost for requiring unit kWh battery at current stage is set to £0.1/kWh, the values of 0.08 based on 2020 case and 0.16 on past years will be conducted as a sensitivity analysis.

As the benchmark, the fuel cost of diesel bus operation is considered in addition to the variable cost associated with the vehicle travel kms for service. According to Smith (2013)’s report about alternative fuel cost for bus operators, on average each bus travels approximately 40000 miles (64000 kms) with fuel consumption of 5 mpg for a double deck bus. Taking the current diesel price at 130 pence per litre into consideration, the equivalent variable fuel cost associated with km is £0.62 per km. Since the fuel accounts for 9% of the total running cost and 27% of all non-labour costs respectively, thus the $\rho_{bh}$ (variable cost per km associated with the total vehicle travel kms for service) is estimated as £2.3 per km based on total non-labour costs. The rest parameters are summarised in Table 4.5.
4.4 Validation of the proposed framework

Table 4.5: Parameters used in the case study I

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Gamma$ (total number of available bus)</td>
<td>300</td>
</tr>
<tr>
<td>$\tau$ (transit capacity by standing per bus)</td>
<td>70</td>
</tr>
<tr>
<td>$\rho_o$ (unit km value associated with the total vehicle travel kms for service)</td>
<td>2.30</td>
</tr>
<tr>
<td>$\rho_b$ (unit kWh value associated with the battery usage cost)</td>
<td>0.08</td>
</tr>
<tr>
<td>$\rho'_o$ (unit km value associated with the total vehicle travel kms of diesel bus)</td>
<td>2.92</td>
</tr>
<tr>
<td>$\delta$ (power rate of charger)</td>
<td>140</td>
</tr>
<tr>
<td>$\eta$ (grid to vehicle charging efficiency)</td>
<td>80%</td>
</tr>
<tr>
<td>$w_b$ (benchmark of passenger wait time in minutes)</td>
<td>5</td>
</tr>
<tr>
<td>$\varrho$ (energy consumption rate kWh/km)</td>
<td>1.25</td>
</tr>
<tr>
<td>$\epsilon$ (fare per patronage)</td>
<td>1</td>
</tr>
<tr>
<td>$\theta$ (bus average speed)</td>
<td>10</td>
</tr>
</tbody>
</table>

4.3.5 Implementation

The proposed bi-level model was implemented in Python, Version 2.7, in a 64-bit computer with a 4-core, 2.83GHz processor and 8GB RAM. To solve the nonlinear convex problem, a commercial solver IPOPT in the package Pyomo (Hart et al., 2017, 2011) widely used in Python is employed. Pyomo supports an object-oriented style of formulating optimisation models, which are defined with a variety of modelling components: scalar and multidimensional parameters, decision variables, objectives, constraints, equations, disjunctions and more importantly the MPCC constraints.

The Daily bus scheduling problems are broken down to 8 3-hourly scheduling problems, which embedded 3 hourly market clearing problem with fixed demand. There are 424 decision variables, 136 equality constraints and 321 inequality constraints in total, of which 104 are complementary constraints.

4.4 Validation of the proposed framework

The objective of this section is the validation of the theoretical properties of the bi-level model. Two scenarios will be examined and compared with the target data given in Table 4.1. These properties include the effectiveness of scheduled frequency, the required number of buses, effectiveness of charging to complement the energy consumption and finally the diversity of DLMP.
4.4. Validation of the proposed framework

Two scenarios that were built are:

a. Operation planning of diesel bus, which is used as the benchmark scenario.

b. Bi-level model including the bus operation planning under uniformed price tariff and market clearing under an uncongested power network, i.e. the power flow limit of each cable in this scenario will be set to infinity and the $\alpha_t$ is set to zero.

The scheduled headway of 8 bus routes in the case study (1) are shown as the blue curve in Figure 4.10, in which a total number of 250 buses were employed for the service, Which is close to the total number of 271 that recorded in the data. The total bus travel distance in the first case is 34123.5 km.

Table 4.6: Comparison of theoretical optimal frequency and headway for each bus route

<table>
<thead>
<tr>
<th>bus route</th>
<th>Diesel</th>
<th>Electric</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>f(bus)</td>
<td>h(min)</td>
</tr>
<tr>
<td>320</td>
<td>7</td>
<td>8.5</td>
</tr>
<tr>
<td>352</td>
<td>11</td>
<td>5.5</td>
</tr>
<tr>
<td>82</td>
<td>11</td>
<td>5.5</td>
</tr>
<tr>
<td>212</td>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td>101</td>
<td>11</td>
<td>5.5</td>
</tr>
<tr>
<td>M287</td>
<td>7</td>
<td>8.5</td>
</tr>
<tr>
<td>204</td>
<td>10</td>
<td>6</td>
</tr>
<tr>
<td>383</td>
<td>10</td>
<td>6</td>
</tr>
</tbody>
</table>

In Scenario b., the total dispatched number of buses increased to 276 to provide more attractive service to passengers, which was stimulated by the reduced cost on alternative fuels. As a result the total bus travel distance increased to 36253.1 km and attracted theoretically 8802 more patronage in 24 hours. The cost associated with the vehicle running distance took the highest proportion in the total cost, which is 96%, followed by the cost incurred in the opportunity charging. Contrasting to the diesel case, the cost on diesel took 21% of total non-labouring operational cost. Figure 4.11 compared the proportion of each composition in the total operational cost.

Table 4.6 gives an comparison of the frequency of dispatched bus in the peak period (6:00 to 9:00 am), from which it can be observed a slight difference of one more bus in the frequency
4.4. Validation of the proposed framework

Figure 4.10: Scheduled headway of diesel bus and electric bus in 8 bus routes
4.4. Validation of the proposed framework

Figure 4.11: Proportion of compositions in the total operational cost in scenario 1 and 2

setting to specific routes. The scheduled headway for electric bus are shown as the orange curve in Figure 4.10. Compared to the rest bus routes, the consistent patronage of passenger in bus route 82 has left less space for the improvement of bus service. The bus operation in the rest bus routes are encouraged to be run at smaller headway. Because of the increased service frequency that stimulated by the reduced cost on alternative fuels, the total operational revenue has been improved by 17.8 %, increased from £104,295.92 to £122,866.27.

The bus operation activities in scenario b. resulted in a total charging demand of 46687.6 kWh and 58.16 MW load distributed in three feeders along the 24 hours. As depicted in Figure 4.13, a great proportion of loads were distributed in periods between 13:00 to 18:00 and 21:00 to 8:00 the next day when the price is relatively lower than those in other periods. At peak hours of 21:00 - 22:00 in feeder 1, the charging load from electric bus resulted in the 40% additional loads on the basis of inflexible demand, which took a proportion of 28.67% of the total loading. For feeder 4 and 7, the additional loads required to charge buses took 41.64% and 19.55% of inflexible consumer loads respectively. Nevertheless, since the wholesale price applied from the Nord Pool only contain the supply-demand information on the national level, the impacts of additional loading caused by electric bus charging on distribution network request more detailed analysis and will be disclosed in the next section with 3 more scenarios.
4.5 Implication of power network congestion

As discussed in the last section, the 20% to 40% additional charging loads caused by electric bus charging would more likely lead to the congestion at the network bottlenecks. Grid congestion
4.5. Implication of power network congestion

(a) Aggregated load at feeder 1

(b) Aggregated load at feeder 4
4.5. Implication of power network congestion

Figure 4.13: Hourly load at feeders connected with e-bus station in Scenario b.

Figure 4.14: Hourly tempo-spatial distribution of e-bus load in Scenario b.
that induces power flows exceeding design limits depends on a number of factors including local grid rating and topology, charging loads and the spatial distribution of electric buses. The additional two scenarios in this section are designed to unveil the implication of electric bus loading as well as the mobility by given three levels of congestion, specifically:

c. One of the cables connecting the 4th feeder with load points was applied with a lower limit of power flow (7 MW in this section). However, this scenario optimises the total operational cost and dynamic tariff that bus charges the batteries irrespective of the congestion on feeder 4.

d. One of the cables connecting the 4th feeder with load points was applied with a lower limit of power flow (7 MW in this section). With the bi-level model, the bus operation is optimised to minimise cost while alleviating load to a low-priced period under the dynamic tariff ($\alpha_t = 1$).

One of the results in the case of uncoordinated charging in Scenario c. was the extremely high DLMP price. The highest price of £136.18/MWh occurred at 13:00 pm on feeder 4 when a significant proportion of charging activities are scheduled during this period. From a combined viewing of the tempo-spatial distribution of DLMP shown in Figure 4.15 and the power flow analysis shown in Figure 4.16, the spike of this extreme high price came with the exceeding power flow of cable limits due to the difficulty to shift other inflexible loads and will force the bus stations connected to feeder 4 to reduce the charging activities until the total loading declined to an acceptable level.

By applying the load management through DLMP in Scenario d., the value of DLMP price at 13:00 pm was reduced to £76.76/MWh, while the spike was shifted to the time 10:00 am with a price £94/MWh, which is still 30% lower than the case of uncoordinated charging. Figure 4.17 depicts the distribution of DLMP along supply points, from which it can be seen that the area of high-priced area concentrated at the feeder with a more strict limit on capacity - i.e. feeder 4 in this scenario - and the time with a higher percentage of load variation. The variety embodied in the rest district can be accounted for the power loss in the whole network, which
4.5. Implication of power network congestion

Figure 4.15: The variation of DLMP along supply point in Scenario c.

Figure 4.16: Loading of cable connecting feeder 4 and LPs in Scenario c.
is approximately 5.2% of total loading in the network on average. The highly priced DLMP when the network congestion occurs will drive the bus operators to reduce the charging loads until the total loading declined below the limit. In this way, the total charging demand has dropped by 8.17%.

![Figure 4.17: The variation of DLMP along supply point in Scenario d.](image)

However, the loads of bus stations connected to the congested feeder were reduced but not able to be shifted to other time horizons in the daytime, since the availability of electric bus was restricted by the optimal schedule. The only method to control charging activities is the interruption of charging that reduces the loads at high-priced time, such as 13:00 to 14:00 pm and 16:00 to 17:00 pm, but some intervals between two spike-prices such as charging loads at 15:00 pm was found to be the same as those in Scenario c.. The charging loads of bus station 5 to 11 and the power flow of the congested cable connecting feeder 4 and stations are shown in Figure 4.18 and Figure 4.19 respectively. As the add-up range per dwell time reduced, the maximal level of battery capacity deficit increased from 67 kWh in scenario b. to 74 kWh of which in Scenario d., which indicates that 10.4% larger batteries would be necessary to prevent from the shortage of energy in case of highly rated congestion price.

To sum up the comparison between Scenario b., c. and d., the practicability of opportunity
charging as a range remedy approach in electric bus operation depends on the power network that bus stations affiliated to. The high power rate of opportunity charger would cause significant balancing burdens at the bottleneck of power line capacity when congested. The proposed DLMP methods could promise effectiveness in removing the exceeding loads from electric buses instead of inter-temporal shifting. For power network operators, due to the restricted availability of heavy-duty bus operation, the unmet charging demand will not rebound to periods with lower price but may occur in the depots when electric buses completed their daily duties. For electric bus fleets operators, the electricity price, as well as the electric loading condition of the power network where the bus station is located, should be taken into consideration in the design process of electric bus batteries. The extremely high electricity rate under congestion would inevitably increase the daily requirement of battery capacities.

![Loading of Line connecting feeder 4 with LPs](image)

Figure 4.18: loading of cable connecting feeder 4 and LPs in Scenario d.

### 4.6 Sensitivity of electric mobility to cost parameters

As discussed in 4.4, the vehicle running cost takes the largest proportion in the total operational cost, while the decision of charging is affected by the battery cost. The planning periods of peak time between 6:00 am to 8:00 am in the morning and the off-peak time 9:00 pm to 11:00 pm are taken as examples to underline the trade-off between the battery related cost and vehicle-
4.6 Sensitivity of electric mobility to cost parameters

Figure 4.19: The distribution of charging loads and the DT price for station 5 to 11 in scenario d.

running related cost. The power network was set with a cable capacity limit of 7 MW on the
cable connecting feeder 4 and the loading points.

First, for the peak period only, the unit value of daily battery usage cost is set to 8 p/kWh
and 16 p/kWh. For each of the three generated scenarios, including the scenario of \( \rho_b = 10 \)
p/kWh in scenario d., the bi-level problem was solved and the results with respect to the total
operational surplus, total travelling vehicle-kms, charging loads and battery capacity deficit are
compared and summarised in Figure 4.20.

The main observations from Figure 4.20 are:

1. The reduction of 37.5% cost on battery before the year 2016 contributed to an extension
   of vehicle running distance by 13.5% as well as an improvement of operational surplus by
   10.87%.

2. The further declining battery cost from 10 p/kWh to 8 p/kWh by the end of 2020 was
   found to have minor impacts on the economic vehicle-running distance. The optimal
   frequency in each scenario was identical.

3. The charging loads and battery capacity deficit to the reduction of battery cost is more
4.6. Sensitivity of electric mobility to cost parameters

Figure 4.20: Sensitivity to changes of $\rho_b$ associated with battery daily usage cost in peak period sensitive when battery cost declined below the 10 p/kWh. The reduction of charging load was 34.17 % in the range of 10 p/kWh to 8 p/kWh and 1.6 % in the range of 16 p/kWh to 10 p/kWh respectively, while the increased needs for battery capacity is 108.94 % in the range of 10 p/kWh to 8 p/kWh and 51.14 % in the range of 16 p/kWh to 10 p/kWh respectively.

Three similar scenarios were optimised for the off-peak period, of which the same indicators are summarised in Figure 4.21

The main observations from Figure 4.21 for the off-peak period planning are:

1. The vehicle running distance and operational surplus is more sensitive to the reduction of cost on battery before the year 2016, since the same reduction of 37.5 % contributed to an extension of vehicle running distance by 20% as well as improvement of operational surplus by 81.7 %.

2. Similar to the trend of peak time, the further declining battery cost from 10 p/kWh to
4.6. Sensitivity of electric mobility to cost parameters

8 p/kWh by the end of 2020 was found to have minor impacts on the economic vehicle running distance in off-peak time.

3. Since the bus routes during off-peak time is operating at a low frequency, the battery capacity deficits hereby remained negative to complement energy consumed but yet added up in previous trips. However, when the battery cost declined below the 10 p/kWh, the reduction of charging loads and increased needs for battery capacity were 74.3% and 434.32% higher respectively.

The above findings can facilitate the decision-making process of the bus operators by providing information regarding the economic operation distance when the power network congestion is considered. Furthermore, as the cost on battery declining in the future, this analysis can also facilitate the power system analysis since most charging activities may not rebound as expected in the same location when the DLMP is applied to alleviating network congestion.

![Graphs](a)  (b)  (c)  (d)

Figure 4.21: Sensitivity to changes of $\rho_b$ associated with battery daily usage cost in off-peak period

Second, the sensitivity of bus operation to the $\rho_o$ which is associated with the unit vehicle
4.6. Sensitivity of electric mobility to cost parameters

Figure 4.22: Sensitivity to changes of $\rho_o$ associated with vehicle travel distance in peak period travel times is analysed when more importance is to reduce bus running times. Three scenarios where $\rho_o$ was replaced by 1.15 and 4.6 £/v-km respectively, and the unit daily battery usage cost remained the same. The four indicators: the total operational surplus, total travelling vehicle-kms, charging loads and battery capacity deficit in the peak time and off-peak time are compared and summarised in Figure 4.22 and Figure 4.23.

The performance of bus operation in vehicle running distance was approximately linear to the cost that associated with the travelling distance, since the cost with respect to providing service to passengers takes the dominating proportion in the total operational cost. The lowest total operational cost/surplus, which is £ -2961, was occurred during the off-peak time when a less frequent service was required as a trade-off to cover the low-demanding passengers. Apart from the labour cost that is not included in the analysis, higher vehicle travel cost incurred more pressures to sustain good profitability.

The needs for batteries followed a similar trend to the operational performance in the peak period. Higher weight to the vehicle travelling cost, $\rho_o$, reduced the needs for larger batteries.
4.6 Sensitivity of electric mobility to cost parameters

Figure 4.23: Sensitivity to changes of $\rho_o$ associated with vehicle travel distance in off-peak period

However, the needs for batteries reduce more slowly during the off-peak period than those in the peak period, as can be observed by the value of the slope. In other words, the requirement of energy in the off-peak time can be more likely complemented by a larger range per add-up, due to the less frequent operation and hence better availability of charging time.

Another interesting observation is the changes of the charging loads. In peak periods, as the cost to providing more service declines, the loads remained the same at first and then dropped because of the less dwell time to recharge buses. However, the charging loads in off-peak time are more unpredictable, which was raised to a higher value as the cost of vehicle travelling declined to 0.1, but then decreased to a lower level than which it was in the scenario of $\rho_o = 4.6$. To explain the difference in charging loads, another comprehensive comparison was made between the total number of buses employed and the average charging time per stop at the bus station, as presented in Figure 4.24.

A rational explanation is the differentiated sensitivity of charging time to the bus operation
4.7 Concluding remarks

This chapter develops a framework that jointly considers the trade-off within the bus operation among providing services to passengers, optimising cost structures and alleviating power congestion to local networks at the bottleneck. More importantly, the spatial distributions of electric bus opportunity charging loads are connected by the bus operation via solving a frequency setting problem. Following the problem formulation, an MPCC based approach is developed and applied to a multi-layer network with the data extracted from Shenzhen and RBTS. While the electrification of bus fleets is demonstrated to beneficially support the bus operation for a higher duty service, the uncoordinated charging would evidently bring increasing pressures and costs to balance the electricity supply and demand in distribution network at transmitting capacity bottleneck. Through a in-depth analysis of price and cost parameters, there are several noteworthy remarks for policymakers and bus operation planners:

Figure 4.24: The comparison of total number of buses employed and the average charging time per stop at bus station.

in peak and off-peak period. Since the charging time soared faster in peak than which in the off-peak time, when the cost of vehicle travel distance was increased to the doubled value. The multiplication of these two factors leads to a flatter performance regarding the charging loads. In the off-peak time, however, the total number of the employed buses is far less than those in the peak time, and the charging time is less sensitive to the vehicle travel time cost, the charging loads was thereby reduced contrasting to the scenario that $\rho_o = 2.3$. 
1. The power network capacity that the bus stations affiliated to should be taken into consideration in the design of battery capacity required for bus operations. The congestion price imposed on the electricity price would affect the add-up range per charging. The analysis shows that 10.4% larger batteries would be necessary to prevent from the shortage of energy in case of highly rated congestion price.

2. The magnitude of opportunity charging loads is determined by multiple factors including operation frequency, number of buses employed on road, price and battery cost. It is noteworthy that the alleviated loads by highly priced electricity rates may not rebound to other time periods at the original locations.

3. The battery cost with a downward tendency has gradually declined impacts on promoting operational performance in terms of travel distance and operational cost. But the implication on charging loads and requirements for battery capacity has an inversely soaring tendency. As the battery cost dips by the end of decades, it proved more economical to equip bus with a large battery if the congestion rate is applied.

However, the proposed framework also exhibits some limits in numerous aspects. First, due to the limitation of the opportunity charging model that is based on a tactical level of frequency setting, only the buses employed on the road for providing service were included in the modelling of electric mobility. Vehicle optimisation is a very complicated problem in which idle buses that complete their trips from the peak periods will not just park in the depots and out of service. In a more often practice to maximise the utilisation of vehicles, they were allocated to different bus routes where face a short of transit capacity. The unmet charging demands that was expected in the original stations will be moved to the new location that is belonging to new bus routes. Furthermore, the other efficient way of using vehicles, interlining also known as crossovers, cannot be included in the model. Interlining is a technique involved in bus scheduling where a single bus is scheduled to perform multiple bus routes. A great challenge embodies in the modelling of the tempo-spatial characteristics of electric mobility, both in operation and charging loads, along with uncertainty in multiple routes.

For the power networks, although the problem of significant power loss has been estimated
4.7. Concluding remarks

through an iterative FND process, and the inter-spatially and inter-temporally differentiated feature in DLMP has been realised through the loss factor and power transfer distribution factor, the linearised DC power flow model employed in this work has great limitations on the accuracy in the low-voltage distribution system. Because the stability influenced by the voltage and reactive power problems are critical features in ensuring the transmission of real power in distribution system operation (Momoh et al., 2008). Further works can be organised to develop a more rigorous pricing structure that involves the voltage constraints and reactive power flow constraints as well as the full restoration of the dynamics in bus scheduling.

In the next chapter, this thesis will propose a novel bus frequency setting methodology that could incorporate more complicated service patterns that employed in the real-world operation, such as bus interlining and short-turnings. Due to the non-convexity in the new methods, the bi-level framework will not be able to be extended to the new approach.
Chapter 5

Electric Bus Multi-Service Modelling
Via Adaptive Scheduling

5.1 Introduction

The previous two chapters presented two critical elements in the electric mobility of electric bus fleets: mobility of vehicles and mobility of electric bus charging loads. As a classic model of bus operation, the planning for each bus route was conducted at the level of round trip duty cycle separately. However, as discussed in the literature review, one of the most important factors that hinder the adoption of electric buses is the compatibility to fit in more complicated bus operation. The interlining and short-turn are two typical examples of service patterns that are commonly used to improve the vehicle utilisation at the tactical planning and operation phase, and hence should be incorporated in the extension of the bus planning model.

Both short-turn and interlining are reliable solutions to the problem that existed in the scheduling inefficiencies. A short-turn is the earlier terminus of scheduled trips where there is a lower demand for service along the part of the route. Interlining can be used to connect two routes if it is not cost-effective to allocate more buses to each. For example, considering two bus routes A and B with a headway of 20 minutes each, and a round trip length of 30 minutes and 25
minutes. Rather than allocating two buses to each bus route with a 10 or 15-minute layover respectively, the schedules of interlining would only require a bus performing one round of each service continuously, a total of 55 minutes, followed by a 5-minute break. This is similar to the scheduling of one route with 55 minutes journey duration and usually manually combined in the problem of frequency setting.

The works of Verbas and Mahmassani (2013) and Verbas et al. (2015) provide the first step in the automatic planning of multi-service patterns by allocating bus frequencies at a segment level to a set of pre-defined short-turning options. Gkiotsalitis et al. (2019) extended the options by an ad-hoc rule-based virtual line generating mechanism, which can optimally select and set active lines with the optimal frequency to maximise the utilisation. However, the algorithm proposed in the presented works requires manual inputs of a set of line patterns and extension of the electric cost if applying to electric bus fleets. Moreover, none of the existing works has assess the compatibility of electric bus fleets for services patterns other than the isolated operation in the single line, especially from the perspective of bus planning.

The work presented in this chapter differs from previous work in that the line segments constituting the short-turn and interlining bus lines are inherently aligned with sub-line frequencies in the optimisation. Also, the decision components associated with the routine cost are customised with battery cost and charging cost that associated with the electric bus fleets. Finally, the flexibility embodied in this novel bus scheduling would facilitate the model to capture more inter-spatial e-mobility of buses from different routes. The energy consumption of each bus in the previous model is solely correlated to a single route. The load profile in this model consists of route characteristic and charger locations from couples of bus lines that interlined, since buses are allowed to transfer between bus lines to improve the utilisation. Such flexibility contributes to the diversification in the load profile submitted to the power network for the electric bus load management.

The contents in this chapter are structured as follows. Due to the lack of grid-integrated modelling of electric bus fleets in multiple service patterns, the literature review part of the relevant technique is replaced with the transport literature of flexible scheduling in catering with
the passenger demand imbalance. Followed by the literature review, the general implementation process and the relationship between modules in the model are presented in Section 5.3. Then the formulation and basic explanation can be found in Section 5.4 to Section 5.8. Finally, Section 5.10 gives a problem specific solution based on Genetic Algorithm (GA).

5.2 Review of approach for multiple service modelling

Incorporating the short-turn and interlining service into bus scheduling is one of the approaches to handle the inefficiency in matching the passenger demand with the available bus supply, since setting frequency based on demand counted in bus routes level does not always guarantee the optimal utilisation of vehicles. The reason is that buses are allocated to different lines according to the observed passenger demand at the line level and the classic approach does not cater for the demand variations at different segments of the line or at different directions.

Several works integrated the aims of maximising the efficiency into the classic planning approach. A number of works that solve together the strategic-level problem of route design and the tactical-level problems of frequency settings (Arbex and da Cunha, 2015; Yan et al., 2006; Zhao and Zeng, 2008). Re-designing the routes have the potential to reveal the complication of bus operation environment. However, models that modify bus routes on a regular basis corresponding to the time horizons of electricity market clearing is not practical for bus operators because such models cannot provide other guidance on daily operation. Bus operators are reluctant to modify the bus routes as it increases significantly the passenger inconvenience even if they are properly communicated (Kepaptsoglou and Karlaftis, 2009).

Another lines of studies in the operational planning phase, near real-time control measures such as stop-skipping (Chen et al., 2015; Sun and Hickman, 2005)) or bus holdings at specific stops (Hernández et al., 2015; Newell, 1974; Wu et al., 2017) are deployed. Real-time control is a short-term strategy for the benefits of reducing the total waiting time and its variability, improve the regularity of the system and the comfort for passengers. In terms of the application of electric buses, it can be used to adjust the loads accordingly on the traffic conditions, rather
than the demand estimation that is considered in this thesis.

The introduction of a flexible frequency setting is still in the tactical planning phase - where service frequencies are not set per line, but per line segment based on the automatically generated short-turning and interlining lines that serve those segments - thus enabling the accommodation of charging loads of multiple services in the day-ahead electricity market. The works of Cortés et al. (2011); Delle Site and Filippi (1998); Verbas and Mahmassani (2013) and Verbas et al. (2015) focused on generating short-turning lines for serving the demand variation at specific line segments. Verbas et al. (2015) and Verbas and Mahmassani (2013) split the routes into line patterns formed by sets of pre-defined sub-routes and define dispatching headway of pattern independently. However, their complexity has been greatly reduced by manually select a small amount of short-turn lines serving routes that are independent. Previous studies only considered the pre-defined short-turning lines that can cover the spatio-temporal demand variations at different segments of the service lines based on historical passenger demand data. In contrast, in the Gkiotsalitis et al. (2019)’s work, the sub-lines and inter-lines are generated automatically by introducing an ad-hoc framework that allows not only for short-turning lines but interlining options, which can optimally explore more bus line choice with the reasonable frequency to maximise the utilisation.

Given the scarcity of theoretical works that integrate grid support service in bus operation, the flexible scheduling of multiple line patterns that used to handle the passenger demand imbalances can be considered as the extension to the low-level problem. It falls into the same time horizons as the day-ahead electricity market and diversifies the bus operation environments for better estimation of load profile.

5.3 General overview of the implementation process

Before preceding to the detailed formulation, the notation for the adaptive methods has been extended as following:

\[ pp \] Planning period
5.3. General overview of the implementation process

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Z$</td>
<td>Feasible set of frequency (Integer) and Charging control (Continuous)</td>
</tr>
<tr>
<td>${L, S}$</td>
<td>Bus network with bus routes $L = {1, 2, ...,</td>
</tr>
<tr>
<td>$S'$</td>
<td>Origin and Terminus stations in $S$ that have electric chargers for opportunity charging</td>
</tr>
<tr>
<td>$CP_l$</td>
<td>Location index of Control Point in line $l \in L$</td>
</tr>
<tr>
<td>$J$</td>
<td>Junctions allowing bus transfers between bus routes which constituted by Origin, Terminus and Control Points</td>
</tr>
<tr>
<td>$A_{ib}^h, A_{ob}^j$</td>
<td>Section that have inbound/outbound bus arriving at particular stop which usually being a junction of several lines $j \in S$</td>
</tr>
<tr>
<td>$f_{l,n}$</td>
<td>Bus dispatch frequency (decision variable) for section $n \in A_l$ in line $l \in L$</td>
</tr>
<tr>
<td>$T_{l,n}$</td>
<td>Travel time required for completing the trip of section in $n \in A_l$ line $l \in L$</td>
</tr>
<tr>
<td>$W_{i,j,l}$</td>
<td>$</td>
</tr>
<tr>
<td>$B_{i,j,l}^h$</td>
<td>Historical data of passenger boarding at stop $i$ and alighting at stop $j$ deduced from smart card data</td>
</tr>
<tr>
<td>$B_{i,j,l}$</td>
<td>Amount of passenger boarding at stop $i$ and alighting at stop $j$ that elastic to waiting time</td>
</tr>
<tr>
<td>$\rho_o$</td>
<td>Unit operating cost of a bus (vehicle-kms)</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>Fare per passenger.</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Bus speed (km/hour)</td>
</tr>
<tr>
<td>$e, w_b$</td>
<td>Arc elasticity and Benchmark wait time</td>
</tr>
<tr>
<td>$\tau$</td>
<td>Bus load capacity ($p$)</td>
</tr>
<tr>
<td>$\text{NB}$</td>
<td>Maximum available number of bus in the fleets</td>
</tr>
<tr>
<td>$K$</td>
<td>An electric bus fleet $K = {1, 2, ...,</td>
</tr>
<tr>
<td>$\text{SoC}_k$</td>
<td>State of Charge (residual energy) in the battery of bus $k \in K$</td>
</tr>
<tr>
<td>$\phi(k, C_n, f_n)$</td>
<td>Accumulated travelling time of bus $k$ according to the trip assignment based on $f_n$</td>
</tr>
<tr>
<td>$x_{s',t,\nu}$</td>
<td>Percentage of charging power that control the charging process at each station (decision variable)</td>
</tr>
</tbody>
</table>
5.3. General overview of the implementation process

- **$ct_c(k, t, s')$**: Charging duration at station $s'$ in hour $t$ for bus $k$
- **$L_c(k, t, s')$**: Recharging load (kW) at station $s'$ in hour $t$
- **$P_c(k, t, s')$**: Charging strategy determining the likelihood to charging at station $s'$ at hour $t$
- **$\sigma_{t,n}, \sigma^{\text{min}}, \sigma^{\text{max}}$**: Electricity rate in hour $t$, Minimal charging rate and Maximum charging rate in the whole day
- **$\varrho$**: Energy consumption ratio (kWh/min)
- **$\eta, \delta$**: Charging efficiency, Charging rate (kW)
- **$\rho_b, \rho_c$**: Unit battery capacity cost, unit charger cost
- **$NC(t, s')$**: Number of effective chargers in station $s'$ at hour $t$
- **$\sum_{k \in K} U(k)$**: Total effective usage capacity of battery

As shown in Figure 5.1, the overall framework incorporates two modules - the frequency setting module and the vehicle scheduling module - and four key elements: the operational cost associated to vehicle running times, the revenue of served passengers that elastic to the service quality, total cost for re-filling the desired energy and the cost on batteries. The input data consists of the bus network topology, passenger demand patterns by Origin-Destination (O-D) pairs, dynamic tariff generated in Case study I and numerous assumptions regarding the parameters in operation.

As the first step, before the implementation of the frequency setting, the smart card data providing higher granularity mobility information are processed to generate passenger O-D matrix for each bus route. Using the O-D matrix, ridership with the geographical intersections between bus routes can facilitate the manual selection of the best control point to segment original lines and form interlining combination. There are three benefits of breaking the frequency of original decision into pieces:

1) Allowing buses transferred from less demanding sections to serve over-crowded sections;

2) Enabling buses to quickly adjust directions towards the nearest station when it is tactically necessary to respond to the ultra-low price;
5.3. General overview of the implementation process

3) Theoretically combining the headway control instinctively within tactical planning when more real-time data is integrated.

Theoretically, the number of control points can be as many as the number of stops, which is often seen as a method of stop-level headway controlling in an isolated line. The difficulties to find solutions in a transit network, however, will rise exponentially if more than one mutually contradictory constraints are correlated for each decision variable. In theory, buses are permitted to continue their trips in any other lines with deadhead time (dashed line in Figure 5.2). Hereby, in order to avoid the unpractical situation, the following rules have to be clarified before manually selecting the control points and restraining the improved flexibility for each bus route:

1) All transfer stops are considered as potential control points. Bus stops where a significant ridership change is observed are also considered as the candidates in the control points set. Thus, providing an opportunity for serving only the overcrowded segment with higher frequency;
2) The neighbouring stops are checked and compared with the stops with significant demand variation. The stop that has at least one intersect with other bus routes is more preferable;

3) Neighbouring bus stops, \( s \pm 2 \), of a confirmed control stop \( s \) that belong to the same bus route cannot be considered as control points;

4) Interlining lines can serve segments of at most two originally planned bus lines;

5) Interlining connections are required to return to the origin station after completing their trip, routes ending at the other terminus are added with an additional penalty of dead-heading time;

6) In the allocation of buses to segments devised from selected control points, the short-turning routes that cut the service at the control points have higher priority to the interlining routes;

Based on the above notation and rules, an exhaustive, rule-based graph search is devised for determining the control points of the bus network. The rule-based graph search for determining the control points is presented in Algorithm 1.

**Algorithm 1** Rule-based graph search for determining the control points

1: function **RULE-BASED GRAPH SEARCH**
2:    Initialize a set of switch points \( S^* \leftarrow \emptyset \);
3:    for each originally planned line \( l \in L_o \) do
4:        for each bus stop \( s \in S_l \setminus \{1, |S_l| \} \) do
5:            if bus stop \( s \) is a transfer stop and \( s \notin S^* \wedge s \notin S' \) then
6:                Set \( S^* \leftarrow S^* \cup \{s\} \);
7:                for each neighboring stop \( s' \in (s-2, s-1, s+1, s+2) \) do
8:                    if \( s' \in S^* \) then
9:                        \( S^* \leftarrow S^* \setminus \{s\} \);
10:                   end if
11:                end for
12:            end if
13:        end for
14:    end function
For simplicity, the maximum number of control points allowed for each original route is set to one. With the given control points, the route network is split into numerous segments with separate decision variables controlling the mobility of buses between junction. In order to restrict the unnecessary deadhead time in the situations that buses start the journey from the control point, the equality constraints of bus flow are applied to each control point associated with neighbouring decision variables. Hereby, various combination of segment service can be used to constitute the short-turning and interlining routes in addition to the normal operation. The single decision variable $f_n$ is physically meaningless without the decoding process into any known service pattern. An automated procedure for decoding is detailed in the algorithm 2 and explained using a simple numerical example in Section 5.4.

After the initialisation of decision variables, the bus dispatching frequency is set within a module depicting the objective cost associated with the vehicle running distance and revenues of the stop-level elastic passenger demand for service quality. Due to the complicated operation of electric buses, the estimation of energy consumption and lay over time based on the approximation function is not suitable in the adaptive method. Thereby, an agent-based micro-simulation module is established to schedule the vehicle trips with the service patterns decoded from the translation procedure. Energy consumption is accumulated by the routes that each bus served, while the lay over time is estimated by the interval between arriving time and the departure time of next trip.

The second set of decision variable is passed to each station for an hourly charging decision-making according to the rate of dynamic electricity tariff as well as the current State-of-Charge (SoC) level in each bus battery. The total charging costs generated by this module are accumulated and added to the final objective function. The daily usage cost of batteries for each bus and usage cost of charging infrastructure for each station, which is similar to the opportunity cost of not charging in Section 3.7, are estimated and accumulated as parts of the final objective function.

Finally, a series of operational constraints that bus operators have to conform are added to the problem statement, which incorporates the balancing equality of bus flows at each control
5.4 Formulation of adaptive frequency setting

5.4.1 Mathematics formulation and ad-hoc decoding algorithm

Consider a bus network \( \{L, S\} \) each with a number of stops \( s \) and two stations \( s' \) (Origin and Terminus). Let \( f_n \) represent the decision variable of bus trips aligned with each section and control the number of bus trips in total over a planning period \( pp \); the objective of optimisation in the adaptive method is the same as which in the classic method:
5.4. Formulation of adaptive frequency setting

\[
\begin{align*}
\min & \quad \sum_{l \in L} \sum_{n \in l} \rho_o \cdot \theta \cdot T_{l,n} f_{l,n} \\
\text{subject to:} & \quad \sum_{l \in L} \sum_{n \in l} [T_l f_l] \leq \Gamma \\
& \quad B_{s,l}(h_l) \leq \sum_{l \in L} \tau \cdot SM_{l,s} \cdot f_{l,n}, \forall s \in S, l \in L \\
& \quad \forall f \in \mathbb{Z} : f_{\min} \\
& \quad \forall x \in (0, 1)
\end{align*}
\]

where \(\theta\) and \(\rho_o\) represent the bus speed and unit operational cost respectively. SM is a new serving matrix defining the mapping of the sequence of frequency that passengers experienced in each stop, since the frequency along the whole line was split into \(2(n+1)\) segments in order to improve the flexibility for matching the demand variation along sections and directions of bus routes. \(n\), the number of control point, is manually selected based on the observed passenger loading patterns and geographic intersections. Depending on the O-D pair, the headway for each O-D pattern differentiates by the location of Origin and Destination. For example, the bus that passengers boarding at stop 1 and alighting at bus stop 10 takes is different from which passengers boarding at stop 1 and alighting at bus stop 40, if the control point was selected at bus stop 20. The mapping of service frequency experienced by the passengers and the \(f_n\) can be pre-determined and hence boost the optimisation speed.

In addition, the challenge to maintain consistency along all bus route is restrained by the balancing equation that the total number of coming bus should equal to the total number bus leaving at each junction \(J\):

\[
\sum_{l \in L} \sum_{n \in A_{ib}^n} f_{n,l} = \sum_{l \in L} \sum_{n' \in A_{ob}^{n'}} f_{n',l}
\]

where the outbound flow refers to any corresponding buses departing from junction (e.g. \(f_b\).
and \( f_d \) in Figure 5.2) and the inbound flow referred to any buses arriving at junction (e.g. \( f_a \) and \( f_c \) in Figure 5.2). Junction \( J \) is defined as the control point including the terminus that allows bus to transfer to other routes, for instance the control point (red circled) in Figure 5.2 and the origin station shared by route 2 and route 3.

Apart from the control points, the term of "outgoing" is defined for bus operating in consistence with pre-defined direction (e.g. \( f_a \) and \( f_b \) in Figure 5.2, from Origin to Terminus) and "return" for buses towards the opposite direction (e.g. \( f_c \) and \( f_d \) in Figure. 5.2, from Terminus to Origin). In practice, they are often expressed in a way such as "Route 1 towards Terminus A" and "Route 1 towards Terminus B". Thereby, there are three forms of operation that can be translated based on the correlations in the route:

1. Normal operation: when all bus dispatching frequencies in the lines are identical (e.g. \( f_a = f_b = f_c = f_d \))

2. Short-turns type I: when only part of lines are identical (e.g. \( f_a = f_c \neq f_b = f_d \) but still follow the constraint 5.6 in single line), this type of short-turn is an earlier terminus by the middle of a route and go back to the origin station in a similar operation to the "circular" route.

3. Short-turns type II: when only part of lines are identical (e.g. \( f_a = f_b \neq f_c = f_d \) but still follow the constraint 5.6 in single line), this type of short-turn is identical to a unidirectional full-length trip.

4. Interlining: when the equation is not balanced in an isolated route but balanced within several routes (i.e. summation of the total number of buses coming and leaving in route 2,3,4 surrounding \( \beta \) in Figure 5.2 should follow constraint 5.6).

The above operation types are translated by an automatic ad-hoc rule-based algorithm described in Algorithm 2. In more detail, the procedure of translation of the optimal frequency is similar to the mathematical technique "hill climbing", in which the frequency allocated to the "Normal Operation" is the easiest to find an initial solution by setting to the least value.
Then, a small incremental is added to the operation type "Short-turn type I" and "Short-turn type II" sequentially, because the "Short-turn type I" that have buses returning to the origin station has a higher priority in order to minimise the total dead-head time. Finally, remained elements in the optimal decision set \( f_n \) that cannot find the suitable type of short-turning will be allocated to the operation type "Interlining". The order of decoding, which is the priority of allocation at the meantime, is consistent with the cost of deadheading from the least to highest. As illustrated in Figure 5.3, the base of passenger demand are satisfied by the "Normal operation", while the spike in the demand variation is resolved by the short-turning and interlining.

**Algorithm 2** Rule-based translation for determined optimal frequency

1: function RULE-BASED TRANSLATION
2:  Given a set of frequency \( f^* \leftarrow \emptyset \);
3:  for each originally planned line \( l \in L \) do
4:  \hspace{1em} Set \( f_{Normal} \leftarrow \min(f_n) \);
5:  \hspace{1em} Set \( f_{translated} \leftarrow \text{Location of } \min(f_n) \);
6:  \hspace{1em} Set \( f_{residual} = f_n - f_{Normal} \);
7:  \hspace{1em} if \( f_{residual} \neq 0 \) then
8:  \hspace{2em} if Location of Normal operation \( f_{translated} \in \{a, c\} \) then
9:  \hspace{3em} Set \( f_{ST,a}, f_{ST,c} \leftarrow \emptyset \);
10:  \hspace{3em} Set \( f_{ST,b}, f_{ST,d} \leftarrow \min(f_{residual,b}, f_{residual,d}) \);
11:  \hspace{2em} else
12:  \hspace{3em} Set \( f_{ST,b}, f_{ST,d} \leftarrow \emptyset \);
13:  \hspace{3em} Set \( f_{ST,a}, f_{ST,c} \leftarrow \min(f_{residual,b}, f_{residual,d}) \);
14:  \hspace{1em} end if
15:  \hspace{1em} Set \( f_{residual} = f_{residual} - f_{ST} \); \hspace{1em} \(\triangleright\) Set the allocation to Short-turn Type I
16:  \hspace{1em} end if
17:  \hspace{1em} \(\triangleright\) Update the remained unallocated frequency
18:  if Location of Normal operation \( f_{translated} \in \{a, b\} \) then
19:  \hspace{2em} Set \( f_{STI,a}, f_{STI,b} \leftarrow \emptyset \);
20:  \hspace{2em} Set \( f_{STI,c}, f_{STI,d} \leftarrow \min(f_{residual,c}, f_{residual,d}) \);
21:  \hspace{2em} else
22:  \hspace{3em} Set \( f_{STI,c}, f_{STI,d} \leftarrow \emptyset \);
23:  \hspace{3em} Set \( f_{STI,a}, f_{STI,b} \leftarrow \min(f_{residual,a}, f_{residual,b}) \);
24:  \hspace{2em} end if
25:  \hspace{1em} \(\triangleright\) Set the allocation to Short-turn Type II
26:  \hspace{1em} Set \( f_{residual} = f_{residual} - f_{STI} \);
27:  end if
28:  \hspace{1em} if \( f_{residual} \neq 0 \) then
29:  \hspace{2em} Set \( f_{IL} \leftarrow f_{residual} \)
30:  end if
31:  \hspace{1em} \(\triangleright\) Set the allocation to Interlining
32:  end for
33: end function
5.4. Formulation of adaptive frequency setting

5.4.2 Numerical example

To illustrate the effects of adaptive scheduling, an example of bus route 2 and route 3 sharing the same control point $\beta$ - in which $T_{2,a} = T_{2,c} = 70$ mins, $T_{2,b} = T_{2,d} = 80$ minutes and $T_{3,a} = T_{3,c} = 80$ mins, $T_{3,b} = T_{3,d} = 50$ minutes respectively - is used to present the possible operational results. For simplicity, the bus frequency, which is determined by the optimisation in the later models and case studies, is determined by the well-known maximum loading principle instead in this numerical example. The loading data is based on a higher granularity passenger loading generated from a new data pattern pre-processing procedure described in Section 6.2 and plotted in the right two figures in Figure 5.2. Assuming a transit capacity of 100 for each bus, the total bus trips determined by the classic method based on line level are $f'_2=15$ and $f'_3=12$ respectively. Hence the average occupancy in the outgoing direction for the segment between bus stop 28 to 40 in bus route 2 is 45.8%, which is 31.4% under-utilised contrasting to the segment between bus stop 1 to 27.

By splitting the bus route 2 into two segments by $\beta$ and applying the adaptive method, the bus trips determined by the maximum loading are $f_{2,a} = 15$, $f_{2,b} = 15$, $f_{2,c} = 13$, $f_{2,d} = 13$. Since only the roue 2 is adaptive, the buses are not allowed to interline to other services at

![Figure 5.3: Graphic illustration of the multi-service pattern and passenger demand imbalance](image-url)
the control point $\beta$ until arriving at the terminus. However, adaptive methods could achieve a saving of $2 \times (T_a + T_b)$ vehicle-travel time by differentiating the headway in two directions. The final result of scheduling is 13 bus trips operating in the normal models and two bus operating in the model of short-turning. The passengers in the outgoing direction will still face an average waiting time of 6 minutes, whilst passengers in the opposite direction will see an average waiting time of 6.92 minutes.

Considering the situation that both route 2 and 4 are adaptive and allowing bus interlining at control point $\beta$, the optimal numbers of service trips are:

\[
\begin{align*}
  f_{2,a} &= 15, f_{2,b} = 10, f_{2,c} = 10, f_{2,d} = 13 \\
  f_{3,a} &= 4, f_{3,b} = 12, f_{3,c} = 5, f_{3,d} = 5
\end{align*}
\]

and the translated operation from optimal frequency are:

<table>
<thead>
<tr>
<th></th>
<th>Normal Operation</th>
<th>ST Type I</th>
<th>ST Type II</th>
<th>Interlining</th>
</tr>
</thead>
<tbody>
<tr>
<td>Line 2</td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Line 3</td>
<td>4</td>
<td>0</td>
<td>1</td>
<td>8</td>
</tr>
</tbody>
</table>

The total savings in this example by the adaptive method are 910 vehicle-mins and 1550 vehicle-mins for line 2 and line 3 respectively. The average waiting time for short trips, for instance between bus stop 1 to bus stop 20 in bus line 2, remains at 6 minutes while the average wait time in the next segment is increased to 9 minutes. Five buses originated from the origin station and three buses originated from the terminus in line 2 interlined to line 3 to serve the segment b in bus line 3 providing a total frequency of 4 bus per hour (totalling 12 trips in the plan period).

However, due to the increased complication of operation, the lay over time at the station can no longer be estimated by the approximation function given in section 3.4.1. As described in the introduction to the structure in section 5.3, the average layover time in the station for recharging is hence estimated in an upper level rule-based vehicle scheduling model, through the difference of vehicle arrive time and start time of the next trip.
5.5 Elastic passenger demand to service quality

Because of the service segmenting, passenger waiting time is sub-sequentially affected as a result of combined services. Here we assume the passengers arrive at stops randomly and followed the uniform distribution, resulting in a waiting time that is half of the headway at the stop. The average waiting time for those passengers boarding and alighting in the same section (i.e. boarding and alight before/after control point) are calculated by $1/2f_{i,n}$. Since the passengers that boarding and alighting in different sections experienced a different headway from a combined view of bus service patterns, their choices of buses are limited to buses covering their O-D stop pairs. Hereby we assume that passengers are well informed about the bus service so that no transfer is needed along the same route. As a result, this part of waiting time is dominated by the least frequencies in the neighbouring sections. Then, for each passenger O-D pair, their waiting time $W_{i,j,l}$ can be estimated by halving the observed headway according to the following expression:

$$W_{i,j,l} := \frac{1}{2\psi_{i,j,l}}$$

where $\psi_{i,j,l} = \begin{cases} f_{i,a} & \text{if } i < j \text{ & } j < CP_i \text{ & } i < CP_l \\ f_{i,b} & \text{if } i < j \text{ & } j \geq CP_i \text{ & } i \geq CP_l \\ \min(f_{i,a}, f_{i,b}) & \text{if } i < j \text{ & } j \geq CP_i \text{ & } i < CP_l \\ f_{i,c} & \text{if } i > j \text{ & } j < CP_i \text{ & } i < CP_l \\ f_{i,d} & \text{if } i > j \text{ & } j \geq CP_i \text{ & } i > CP_l \\ \min(f_{i,c}, f_{i,d}) & \text{if } i > j \text{ & } i \geq CP_i \text{ & } j < CP_l \end{cases}$$ \hspace{1cm} (5.7)

Using the expected value of the operational waiting time for each passengers, the new demand at each stop is assumed elastic to the service quality (waiting time), in which the elasticity is defined according to a modification of the transport planning guide (Balcombe et al., 2004):

$$e = \frac{\Delta B_{i,j,l}}{(W_{i,j,l} - w^b_l)/w^b_l}$$
5.6 Charging scheme by agent-based micro-simulation (AMS)

The difference is that the final patronage $B_{i,j,l}$ in the adaptive frequency setting has to be evaluated at each bus stop rather than the line level, yielding:

$$B_{i,j,l}(W_{i,j,l}) = B_{i,j,l}^h * (1 + e * \frac{W_{i,j,l} - w_{l}^b}{w_{l}^b})$$  (5.8)

Hence, the total revenue generated by the patronage of passengers is:

$$Rev_{passenger} = \sum_{l \in L} \sum_{i \in s} \sum_{j \in s} B_{i,j,l}^h * (1 + e * \frac{W_{i,j,l} - w_{l}^b}{w_{l}^b})$$  (5.9)

5.6 Charging scheme by agent-based micro-simulation (AMS)

As discussed in Section 5.3, the complexity is furthermore increased by the different type of bus operation embodied in the segmented frequency setting. During the charging scheduling, both the instantaneous price at the time of charging and available dwell time have to be taken into consideration with the trip-dependent energy consumption for deriving the mobility of electric loads. In the classic method, since the trip length between two stations, namely the two electric loads, is constant, the demand of charging for each bus is solely related to the cumulative energy consumption during each trip. The feature that making adaptive method differs from the classic methods of estimating the energy consumption fall in that buses are not travelling through a fixed length of trip in the planning. The final service patterns of trips are seen as a combined result of neighbouring frequencies (see Subsection 5.4.1), which make it extremely challenge to estimate the average energy consumption of a bus arriving at charging points solely according to the bus route itself running.

The lay over time of the electric bus at the station (a) not only relates to the complete single journey length that the station affiliates to, but also associates with the trip length of the interlined routes. Such an adjustment of operation for short-turn and interlining based on the distinguished frequencies has to be embodied in the estimation of electric mobility. Hence, a
rule-based micro-simulation that assigns trips and schedules opportunity charging according to the given frequency is introduced in this section.

Figure 5.4 sketches the Agent-based Micro-simulation (AMS) module that outputs the charging expense and battery cost. The vehicle scheduling is conducted within the same routes and between multi-routes following the policies of "first-in-first-charge" and "first-charged-first-out". In more detail, the trip assignment and decision-making of charging activities in the individual level is followed the logic described in Algorithm 3.

1) At first, the demanded numbers of buses \( K = \sum_{n \in l} T_n f_n \) are initialised at the start of planning period in both directions.

2) Given the initialised decision set \( f^* \), a timetable of dispatching is generated at each junction \( j \), including the bus stations and control points.

3) Then, in the original bus routes, trips in the timetable are assigned to buses in an order
of first-in-first-out by the sequence of arriving time. Unassigned trips will be stored into a multi-routes timetable to be matched with the idle buses in the interlined routes.

4) The process of 3) continues in iteration until all the trips in the same routes are assigned and idle buses are stored in another multi-routes availability list.

5) Due to the balancing equality constraints, the number of unassigned trips in the multi-routes timetable will certainly equal to the number of bus in the multi-routes availability list. With an embedded optimisation of minimising the deadhead time, then the idle vehicle will be informed by the updated departure time.

6) Finally, the dwell time that can be utilised to recharge can be estimated by the intervals between the arrival time and the departure times for the next trip. The SoC of battery are iteratively updated with the summation of energy consumption accumulated in served route segments and charging amount as a result of charging control variable at the station that bus laid over.

7) Activities continues until all trips in the netor are aligned or iterations meet the end of planning.

Let $\sigma_{t,s'}$ and $SoC_{k,t}$ denote the electricity price at station $s'$ and the SoC of battery for bus $k$ at the time of use $t$, another set of decision variables $x_{s',t}$ as a percentage of charging rate is introduced to control the desired charging power. The situation that the dwell time is too less to be utilised for recharging is considered in the determine of electric loads. The required charging time $c(t(k,t,s'))$ for each charging event is determined by the maximum duration of dwell time (the period between arriving and matched departure time) and an upper limit avoiding overcharging:

$$c(t(k,t,s')) := \min(\frac{\kappa - SoC_{k,t}}{\eta \delta}, t_{k,departure} - t_{k, arrive})$$ (5.10)

The daytime charging load $L(t,s')$ and charging cost by hours are defined as correlated to the
charging controlling variable \(x_{s',t}\), the charging rate \(\delta\) and electricity price at each node \(\sigma_{t,s'}\):

\[
L(t,s') = \sum_{k \in K} \delta \cdot x_{s',t} \cdot c_t(k,t,s')
\]

(5.11)

\[
\varphi_{\text{charging}}(.) = \sum_{t \in 24/pp} \sum_{s' \in S} \sum_{k \in K} \delta \cdot \sigma_{t,s'} \cdot x_{s',t} \cdot c_t(k,t,s')
\]

(5.12)

Algorithm 3 Rule-based trip assignment within and between multi-routes

1: function RULE-BASED TRIP ASSIGNMENT
2: for each bus route \(l \in L_o\) do
3: for each bus station \(s' \in S_l\) do
4: Initialise a set of electric bus \(K \leftarrow \emptyset\);
5: end for
6: end for
7: for each Junction \(J\) including the station and control points do
8: Set the timetable \(q_j\) of departure trips by neighbouring outbound \(f_n\)
9: Set the arriving vehicles \(k_j\) by neighbouring inbound \(f_{n,e}\)
10: for each bus route \(l_j\) affiliated to junction \(j\) do
11: match the departure time in timetable \(q_j,l\) with the arriving vehicle \(k_j,l\)
12: if junction \(j\) is a transfer stop \& \(c_1(f_l) \neq 0\) then
13: if If number of trips \(q_j,l\) \& number of available vehicles \(k_j,l\) then
14: Set \(q_j' \leftarrow q_j,l \setminus k_j,l\);
15: else
16: Set \(k_j' \leftarrow k_j,l \setminus q_j,l\);
17: end if
18: end if
19: end for
20: if junction \(j\) is a transfer stop \& \(c_1(f_l) \neq 0\) then
21: match the unmet departure time in timetable \(q_j',l\) with the unmet arriving vehicle \(k_j',l\)
22: end if
23: end for
24:
25: end function

5.7 Usage cost of battery

Another advantage of using simulation is the records of buses operation by activities, from which we can derive the effective range of batteries in the individual level, rather than an average estimation of battery deficits. Let \(\varphi(T_n,f)\) denote the function depicted in Algorithm 3 estimating the travelling time, then the SoC is correlated with the consumption rate \(\varphi\), sectional travelling time \(T_n\) and charging load \(L(t,s')\). The charging rate, charging efficiency
and battery capacity are represented by $\delta$, $\eta$ and $\kappa$. The updating formulation is:

$$SoC_{k,t} = SoC_{k,t-1} - \varrho \phi(T_n, f) + \eta L(t, s')$$ \hspace{1cm} (5.13)

and subject to SoC constraints:

$$SoC_{k,t} \leq \kappa$$ \hspace{1cm} (5.14)

To replace the cost of battery deficits, the cost of battery is estimated depending on the highest level of discharging in terms of SoC over the whole planning period, as defined below:

$$U(k) := \kappa - \min(SoC_{k,t} : t = 1, 2, 3..., T)$$ \hspace{1cm} (5.15)

As the SoC varies along the time of day, the final cost of critical capacity for whole day operation is determined at the end optimisation.

To quantify the implication of large capital cost of battery, the life cycle is levelised to daily level, which in practice can be viewed as the daily ownership cost. In this thesis, the second hand value is assumed to zero after five years lifetime. Hence the periodical cost in the planning phase can be correlated to the effective range of batteries and the total cost of ownership is related to the maximum periodical cost. Let $\rho_b$ represent the daily ownership cost of batteries per kWh, yielding:

$$ \varphi_{usage}(\cdot) := \sum_{k \in K} \rho_b U(k)$$ \hspace{1cm} (5.16)

### 5.8 Final problem formulation: net cost minimisation

Given the cost functions described above, the objective functions 5.1, 5.9, 5.12 and 5.16 are composited into a net cost minimisation problem subject to constraints of Equation 5.3 to 5.2, 5.6 and 5.14. To be specific, the final expressions are:
argmin \( f, b \) \( \varphi(\cdot) := \sum_{t \in 24/pp} [\varphi_{\text{bus}}(f) - \varphi_{\text{rev}}(f) + \varphi_{\text{charging}}(f, x)] + \varphi_{\text{battery}}(\cdot) \)

\[ = \sum_{t \in 24/T} \sum_{l \in L} (\rho_{\theta} \sum_{n \in l} f_{n,l} T_{i,l} \]

\[ - \epsilon \sum_{i \in l,S} \sum_{j \in l,S} \left( \delta \sum_{s' \in S} \sum_{k \in K} \delta_{s',t} \right) \]

\[ + \sum_{k \in K} \rho_{\theta} \left( \kappa - \min(\text{SoC}_{k,t} : t = 1, 2, 3, ..., 24/pp) \right) \]

subject to:

\[ c_1(n) := \sum_{l \in L} \sum_{n \in A_{l}^{i}} f_{n,l} - \sum_{l \in L} \sum_{n' \in A_{l}^{i}} f_{n,l} = 0, \quad \forall s \in J \] (5.19)

\[ c_2(n) := B_{i,j,l}^{h} \left( 1 + e \cdot \frac{W_{i,j,l}}{w_{l}^{b}} \right) \leq \tau \cdot SM_{i,j,l} \cdot f_{n}, \quad \forall n \in l, l \in L \] (5.20)

\[ c_3(n) := \frac{\sum_{i \in l} \sum_{j \in l} W_{i,j,l} \cdot B_{l,i,j} \cdot f_{n,l}}{\sum_{i \in l} \sum_{j \in l} B_{l,i,j}} \leq w_{l}^{b}, \quad \forall l \in L \] (5.21)

\[ c_4(n) := \sum_{l \in L} \sum_{n \in l} f_{n,l} T_{l} \leq \Gamma \] (5.22)

\[ c_5(n) := \text{SoC}_{k,t} \leq \kappa \] (5.23)

\[ \forall f \in \mathbb{Z} : f \leq f \] (5.24)

\[ \forall x \in \mathbb{Z}' : 0 \leq x \leq 1 \] (5.25)

Apart from the equality constraints that balance the bus flow, the inequality constraints \( c_2 \) guarantee the sufficient transit capacity for the passenger demand, whilst \( c_3 \) introduces an upper limit service quality ensuring that the bus operator cannot reduce the operational costs to such an extent that the average waiting time for passengers is significantly compromised.

The inequality constraint of \( c_4 \) ensures that the total number of allocated vehicles should not exceed the number of available number of bus \( \Gamma \) in the fleets, while \( c_5 \) ensures the battery will
not be over-charged. Finally, the Equation 5.25 ensures that the optimal frequency of each line is selected from a discrete set of values determined by the transit agency and a minimal service of proposed by the regulator.

5.9 Solution methods and conversion of constraints

5.9.1 Untraceable feature of problem

The non-linear objective function in the constrained optimisation problem above has two non-convex components - revenue associated to the elastic patronage and recharging expense associated to the charging duration - and one fractional, non-convex constraint $c_3(n)$ associated with the waiting time along with other linear constraints. As stated by J. Nocedal (2006), a constrained optimisation program is convex if the objective function is convex, the equality constraints are linear, and the inequality constraints are concave. Hence, the optimisation problem is non-convex. In addition, the problem of allocating buses to lines is an integer programming problem since the number of buses allocated at each section can take values from the discrete admissible sets $\mathbb{Z}$, while the determine of charging controlling threshold is continuous within the range of one. The complexity has been further increased by the property of mix integer programming.

The dimension of this problem is $\frac{48L(N+2)}{pp}$ times the number of lines in $L$ (n is the number of control point) and the required number of computations for computing the global optimum is $|Z|^{L+2T(N+2)}$ if we set that $|Z| = |Z'|$ by discretising the second sets of decision variable. Therefore, the problem is computationally intractable given the exponential computational complexity even for small-scale networks. The existence of nonlinear, fractional components and mutual effects of segmented lines make the optimisation much more difficult, to the authors’ knowledge, classic optimisation techniques behaviour poorly in such problem. Instead, a meta-heuristic method based on Genetic Algorithm (GA) is chosen because its simplicity of operation and simultaneously search for a high quality solution (Tom and Mohan, 2003).
5.9.2 Approximating the constrained frequency setting problem using exterior point penalties

First of all, the continuous variable $x$ is converted into several levels of discrete variable depicting operators’ willingness to affect the charging decision. Similar approach that uses charging threshold from 20% to 80% to analyse charging strategy can be found in the literature (Qin et al., 2016b). Denoting $x$ subjects to bounds $(\underline{x}, \bar{x})$, a sampling $\nu$ was set so that $\nu \cdot \bar{x} = 1$.

For using the violation of constraints in order to converge towards an optimal solution, an exterior point penalty function is introduced to approximate the constrained problem of Equation 5.17 by an unconstrained one structured in such a way that its minimisation favours the satisfaction of all constraints. This penalty function adds to the objective function $f(n)$ several penalty terms that produce a high cost for violating constraints. Starting from our constrained optimisation problem, this thesis introduces the penalty function, $\varphi(n)$, which approximates the constrained optimisation problem by the following unconstrained one:

$$
\begin{align*}
\arg\min_{f,b} \varphi(\cdot) &:= \varphi(\cdot) + W_1(\min[-c_1(n), 0])^2 + W_2(\min[-c_2(n), 0])^2 \\
&+ W_3(\min[-c_3(n), 0])^2 + W_4(\min[-c_4(n), 0])^2 + W_5(\min[-c_5(n), 0])^2
\end{align*}
$$

subject to:
\begin{align*}
\forall f &\in \mathbb{Z} : f \leq f \\
\forall x &\in \mathbb{Z}'
\end{align*}

(5.26)

$W_1$, $W_2$, $W_3$, $W_4$ and $W_5$ are penalty terms that are used to penalise the violation of constraints and are positive real numbers that are defined in such a way that priority is given to the satisfaction of constraints.

The penalty function $\varphi(n)$ is equal to the score of the objective function $f(n)$ if at some points we reach a solution $n$ for which $w_1(\min[-c_1(n), 0])^2 + w_2(\min[-c_2(n), 0])^2 + w_3(\min[-c_3(n), 0])^2 + W_4(\min[-c_4(n), 0])^2 + W_5(\min[-c_5(n), 0])^2 = 0$, indicating that all constraints are satisfied for such solution. Composing the penalty function $\varphi(n)$ this way ensures that violating constraints $c_i(n) < 0$ penalise progressively the penalty function by adding their squared value $c_i(n)^2$ to its
Therefore, the penalty function is over-penalised if some violating constraints $c_i(n) < 0$ are far from zero.

In addition, adding different weights, $w_1, w_2, w_3, w_4$ and $w_5$, to the constraints is useful in the case of problem infeasibility because in such case all constraints cannot be satisfied simultaneously; therefore, with the use of different weight factor values, the planner can prioritise the most important constraints at the expense of others.

Finally, since the inherently contradictory Equation $c_1(n)$ has put great challenge to identify the chromosome/decision vector that best suits the problem. With equality constraints, the solution will lie on a manifold which satisfied the inequalities instead; i.e. use deterministic or stochastic descent to reduce the dimensionality of search space. Therefore, the best option we proposed here is:

1. Equality constraints in Origin and Terminus stations are relaxed as penalty to the objective function. i.e. $W_1C_i(\sum_{l \in L} \sum_{n \in A_{lb}} f_{n,l,s} - \sum_{l' \in L} \sum_{n' \in A_{lb}} f_{n',l,s})^2$. This penalty refers to the deadheading cost for transferring buses from other lines in any case of bus shortage.

2. Equality constraints around junction $j$ will be combined in a form of stochastic way within the process of initialisation and mutation, thus the decision vector structure is designed and guaranteed to search in a feasible space, any unfeasible genotype will be replaced by values satisfied the constraints.

5.10 Standard Generic Algorithm (GA)

To solve the unconstrained optimisation problem of Equation 5.26, one needs to explore a vast, discrete solution space resulting in a significant computational burden. As discussed in the last section, applying a classical exact optimisation method such as the brute-force algorithm requires an exponential number of problem evaluations in order to find a globally optimal solution. As an alternative to classical exact optimisation methods, heuristics from the area of evolutionary optimisation can be employed. Evolutionary algorithms perform fewer
calculations for finding a generally good (but inexact) solution to a combinatorial optimisation problem (Simon, 2013).

For combinatorial optimisation problems several evolutionary optimisation algorithms can be applied such as simulated annealing (Kirkpatrick et al., 1983) or tabu search (Glover, 1986). In Li et al. (2013)’s work, the solutions provided by GA are claimed providing better balance between the bus operational costs and the passenger satisfaction compared to traditional approach. In this chapter, a problem-specific algorithm that considers a pool of solutions rather than a single solution at each iteration is employed, although other heuristic optimisation methods might also be used for solving this problem.

The principles of Genetic Algorithms that analogous to the evolutionary process in nature were initially conceived by John Holland in the 1960s. Standard GAs consists of evolutionary of chromosomes known as population and selection pressure that force chromosomes competing for survival. Five stages are implemented until reaching the convergence after few generations where the diversity of gene is minimal:

1. encoding the initial population;
2. evaluating the fitness of each population member;
3. parent selection for offspring generation;
4. crossover between two parents in the population to generate off-spring;
5. mutation of each off-spring.

In the following sub-sections, we detail the stages of the problem-specific GA that yields a solution of the optimisation problem of Equation5.26.

### 5.10.1 Encoding

A typical GA contains a number of members which form the population at each of the iterations. Each member has a genotype length equal to the number of decision variables and represents a
potential solution to the optimisation problem. In this initialisation stage, the first decision that needs to be made about the parameter is the population size. To take into consideration of the solution space exploration and computational cost, this parameter is recommended between 40 and 100 for the best practice. Since a GA with a larger population size is expected to conduct a more comprehensive exploration of the solution space but also requires more time for evaluating all possible solutions and performing the corresponding crossover/mutation operations.

The general process of this stage is shown in Figure 5.5(a) and an initial population $M$ with $\{1, 2, ..., |M|\}$ members is introduced. Each population member, $m \in P$, is a vector $m = (m_1, ..., m_t, ..., m_s, ..., m_{|g|})$ with $g = |L \times 2(n + 1) + 2 \times L \times pp|$ elements (known as genes) where each element $m_l \in m$ represents the number of buses allocated to the corresponding line $l \in L$ and $m_x \in m$ represents the control points at station $s \in S'$ in case this solution is adopted. Each gene $m_l \in m$ of an individual $m$ is allowed to take an integer value from the set $Z$ or set $Z'$ in a random process generated by the platform (Python in this thesis).

![Figure 5.5: Initialisation, evaluation and selection process in GA](image)

5.10.2 Evaluating the fitness of individuals and selecting individuals for reproduction

Diffs from the classic methods, the GA requires merely the objective function which can be used to evaluate the fitness of each member and does not consider the properties of the function such as convexity, smoothness or existence of derivatives (Bakirtzis et al., 2002) as well as the constraints. In the evaluation stage, Each member (individual) is evaluated for the fitness by
computing the penalty function score with the constraints of $c_i(n)$ incorporated as a decorator that correct values to ensure the satisfaction.

In the parent selection stage the fittest population members (individuals) are selected for reproduction and they pass their genes to the next generation. At each parent selection, two individuals from the population are selected where individuals with better fitness values have a higher probability of being selected for producing an offspring. This can be achieved by using the well-known roulette-wheel selection method (Goldberg and Deb, 1991). In the roulette-wheel selection method, each individual $m$ has a probability of being selected which is proportional to its fitness value divided by the fitness values of all other population members.

After selecting one parent using the roulette-wheel selection method, another parent is selected with the same method and the two parents cross over to produce two off-springs. The same process is repeated until the number of parents which are selected for reproduction is the same as the population size $|M|$. The graphic illustration is presented in (b) and (c) in Figure 5.5.

### 5.10.3 Crossover and mutation

At the crossover stage, two parents exchange their genes at a randomly selected crossover point selected from the set $\{1, 2, ..., |g|\}$ for generating two off-springs. For instance, if the crossover point of two parents $m = (m_1, ..., m_l, m_{l+1}, ..., m_s, ..., m_{|g|})$ and $m' = (m'_1, ..., m'_l, m'_{l+1}, ..., m'_s, ..., m'_{|g|})$ which are selected for reproduction is $l \in L$; then, the two generated off-springs will have the
set of genes \((m_1, ..., m_l, m_{l+1}', ..., m_{|g|}')\) and \((m_1', ..., m_l', m_{l+1}, ..., m_{|g|})\). The procedure is shown in Figure 5.6(a).

As shown in Figure 5.6(b), after the crossover stage follows the mutation stage. The mutation can be potentially applied to any generated offspring after the crossover stage to facilitate the exploration of new information that is not contained in the pair of parents that were used at the crossover stage. In our case, a small probability, \(p_c\), is specified for replacing each gene of the generated offspring with a random value from the set \(Z\) if that gene corresponds to frequency and set \(Z'\) if it corresponds to a charging activity.

The procedure described above continues iteratively until a pre-determined number of population generations, \(NG_{\text{max}}\), is reached. The population member with the best performance is then selected as the final solution and its genes that represent the optimal frequency in each section of routes and charging controls are outputted as the solution.

The number of population members \(|M|\), the mutation rate, \(p_c\), and the maximum number of population generations, \(NG_{\text{max}}\), are parameters of the GA which should be externally defined and can affect the performance of the computed solution. For this reason, several scenarios with different parameter options can be conducted for increasing the probability of finding a solution which is more close to a globally optimal one.
Chapter 6

Case Study II: Plural Bus Service By Adaptive Scheduling And Dynamic Tariff

6.1 Introduction

As discussed in the second chapter, the particularity of electric bus in projects has built barriers for extending the operational model to other conventional routes. Such an absence of operational flexibility in moving bus from a specific route to other routes requires bus operators of extensive works on selecting suitable routes. To further demonstrate the applicability of electric buses in more complicated operational patterns, which constitutes the original motivation of this thesis, the proposed methodology in Chapter 5 for the frequency allocation to multiple service patterns is tested for the case introduced in Case Study I (Chapter 4). Apart from the operational complications, the modelling framework also captures the double-demand response to the variation in passenger demand and fluctuation in the dynamic tariff. The objective is to minimise the net cost of bus operation in the face of the trade-off between the vehicle running cost, the available energy stored in the battery, the charging duration and charging costs.
This chapter will address the challenge of applicability from three perspectives:

1. Gain insights into vehicle utilisation by analysing the average occupancy and waiting times over the adaptive segments;

2. Gain insights into the impacts of different service patterns on the electric bus charging loads as well as a connection of the location, time of the charging loads.

3. Gain insights into the requirement of battery capacity by analysing the observed heterogeneity in daily usage between scenarios of non-adaptive and different levels of adaptive improvement;

However, since the passenger count datasets lack the information of journey duration at an individual level, a new data process is necessary to enhance the quality of data sets corresponding to the spatial disaggregation in the demand pattern. Based on the survey data collected with respect to the daily rates in the London Travel Survey Data (LTSD), a multi-variate Gaussian distribution is employed to describe, at least approximately, the probabilistic distribution of the bus trip duration, and then used to infer the passenger alighting stops.

The following contents are structured as below: Section 6.2 explains the implementation of a multi-Gaussian distribution fitting to estimate the probability of journey length based on the LTSD. Section 6.3 provides a supplementary description of the improvements to the original case described in Chapter 4, including the selection of control points, modified network topology and details of high granularity passenger ridership.

### 6.2 Data pre-processing

#### 6.2.1 Characterise the trip length

There are three critical elements to construct the detailed time-dependent ridership patterns complying with the example shown in Figure 5.3: the length/duration of individual journeys,
the direction of the journey along the routes and the passenger counts at each stop. With the demand patterns, the bus loading is measured by an accumulation of seat occupancy knowing the individual boarding and alighting stop. However, since data generated from the Shenzhen smart card and GPS datasets in Section 4.2 could only provide patronage information about the passengers’ boarding choice and the direction of bus routes they took. Trip generation experiments have to be carried out to simulate the destination stops, in order to infer the desirability of bus capacity.

The trip generation is the first step in the conventional four-step transportation planning process, which forecasts the demand of travels originating in or destined for a number of traffic analysis zones. Conventional Origin-Destination (O-D) estimation approaches rely on surveys, traffic counts and estimation techniques such as maximum likelihood, generalised least squares and optimisation (Alexander et al., 2015). Once established, the trip assignment with O-D flows is often solved at the inner layer of the strategical level route (Gallo et al., 2011) and frequency planning (Han and Wilson, 1982). However, due to the absence of travel demand data on public transport in Shenzhen, the London Travel Demand Survey (LTDS) is used instead in the generalised least squares estimation model, in order to simulate the trips that passengers taken. The LTDS gives a picture of travel by residents in a typical day. 8,000 randomly selected households in London are interviewed each year, which consist of details captured regarding trip purposes, modes used, trip start and end times, and the locations of trip origins and destinations.

First of all, the data regarding the trip duration of buses, totalling 53154 samples over the past five years, are extracted from the raw data. The absolute frequency and their corresponding relative frequency is shown as the blue histogram in Figure 6.1. Major trips were made within a range of 20 minutes to 60 minutes over a maximum duration of 130 minutes. There are four left-skewed sharps and narrow peaks and one right-skewed gentle peak describing the frequency. It is assumed that the general distribution is a linear combination of five normally distributed components with different means and deviation. Hence a multivariate Gaussian distribution is employed to describe, at least approximately, the passengers’ choice of trips.
6.2. Data pre-processing

The 5-dimensional random vector \( \mathbf{X} = [X_1, X_2, \ldots, X_5] \) can be written in the following notation:

\[
\mathbf{X} \sim N(\mu, \sigma),
\]

(6.1)

with 5-dimensional mean vector: \( \mu = E[\mathbf{X}] \),

(6.2)

and covariance: \( \sigma = [\text{Cov}[X_i, X_j]; 1 \leq i, j \leq 5] \)

(6.3)

where the \( \mu, \rho \) are vector of the unknown parameters specifying the mean and deviations. By setting the correlation between each vector to zero, i.e. mutually independent, the overall Probability Density Function (PDF) can be written in the form of a simply summation of uni-variate Gaussian PDFs, shown as:

\[
f(x|\mu, \rho) = \sum \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(-\frac{(x - \mu_i)^2}{2\sigma_i^2}\right)
\]

(6.4)

Then, the generalised least square test (using the Scipy package (Jones et al., 2001–) in Python) is employed to compare the PDF of multi-Gaussian distribution with the relative frequency of samples. The result is shown as the green curve in Figure 6.1. The errors found between the

![Figure 6.1: Distribution of bus trip duration in the LTDS and the estimated PDF](image.png)
6.2. Data pre-processing

Table 6.1: Summary of parameters in the multi-Gaussian estimation

<table>
<thead>
<tr>
<th>Vector</th>
<th>Mean</th>
<th>Deviation</th>
<th>Offset</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>18.22</td>
<td>4.84</td>
<td>0.73</td>
</tr>
<tr>
<td>2</td>
<td>29.95</td>
<td>2.00</td>
<td>0.83</td>
</tr>
<tr>
<td>3</td>
<td>42.64</td>
<td>5.33</td>
<td>0.54</td>
</tr>
<tr>
<td>4</td>
<td>59.80</td>
<td>3.00</td>
<td>0.46</td>
</tr>
<tr>
<td>5</td>
<td>85.57</td>
<td>10.55</td>
<td>0.16</td>
</tr>
</tbody>
</table>

fitted result with the samples were manually calibrated by adding an offset parameter $\xi$ in front of the function. Each uni-variate Gaussian distribution is multiplied by the offsetting parameter to adjust the kurtosis between multimodals. In this way, the above equation can be rewritten as:

$$f(x|\mu, \rho) = \sum \xi \times \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(-\frac{(x - \mu_i)^2}{2\sigma_i^2}\right)$$ (6.5)

Through the process of estimation, the generated PDF can be observed with the good consistency with the sample relative distribution. The parameters are summarised in Table 6.1 and passed to the preceding process of trip generation.

Finally, to obtain the O-D matrix of bus trips, the data pre-processing stage of cleaning, clustering and matching described in Subsection 4.2.2 was implemented for the stop-level boarding counts in each bus line. Each passenger was attributed with the simulated trip duration using the given PDF in Equation 6.4 and tested parameters in Table 6.1. The trip duration generated by simulation is proportional to the total single-direction journey duration of the bus route, thus inferred the bus stops that passenger would alight. By iterating the bus-stop-specific O-D pair through every stops in every bus routes, the spatial and temporal characteristics are identified in the accumulated bus loads. The dis-aggregated passenger demand for transit is presented in Appendix E, from which some counter-intuitive features can be observed. Due to the limit of scope, this section uses bus routes 204 and 287 as the example to reveal the characteristics only.

In general, there is a good correspondence between the bus loads across all routes in the
6.2. Data pre-processing

Figure 6.2: Bus loads along a day by directions (a) departure of route 204 (b) return of route 287
morning peak periods. Passengers’ demand for transit capacity soared to and then remained at the highest level across half of the bus journey at least. However, the bus loads differentiated between stops even at the high demanding periods, probably due to the early termination of trips in specific route segments. Furthermore, different bus routes exhibit various skewness and kurtosis along the day. Some routes have bimodal distribution of loads, which occurred both in the morning and evening while some other routes do not have. Those features facilitate the selection of control points as well as enable transit operators to better serve their ridership by understanding how to reallocate resources as demand changes.

6.2.2 Control points and bus loads

Given the spatially and temporal varied demand patterns, Algorithm 1 is implemented within the most differentiated periods to select the control points. According to the discussion in Section 5.3, the features that characterise the suitability of control points including the geographic interlink as well as the stops observe the most significant demand variation. Since major bus scheduling are conducted for a period across several hours covering the peak, off-peak and night times, the hourly dis-aggregated demand pattern produced in the last section are aggregated by three hours for further analysis.

There are three control points selected to split the service network, as notated by 15, 16, 17 in Figure 6.3. Points 16 and 17 are at the busy corridors that are shared by three bus routes; the last point 15 is the origin/terminus station shared by two bus routes. Such classification could enable us to understand the difference of splitting the original planning into 4 and 2 pieces, and thus gain deeper insight into how service patterns are fitted in a better match with passenger ridership.

To start with, the first control point is analysed by an illustration of the bus loads, boarding counts and alighting counts of bus route 101, 204 and 320 between 6:00 pm to 9:00 pm, as shown in Figure 6.4. The locations of the control points were highlighted in Figure 6.3. The long range of bus routes operating in parallel has provided a great number of candidates for the
control point. The interlinked corridors served by three bus routes at the same time enable the bus easily interlined to other routes with minor deadheading cost. Hence, the demand variation became the dominating factors in selecting the control point. From a collective view, the section between stop 7 and stop 25 in route 101 and route 204 experienced a drop of passenger load of 25.9 percent and 49.8 percent respectively. Meanwhile, the peak value of section between stop 1 to 18 is 38 percent of the highest value of section between stop 19 to stop 43. Based on the above analysis, the selected control point "KeJiYuan", shared by three routes, segmented the service in presented routes into the high demanding section and low to medium demanding section.

Given the control point, for bus routes with a significant difference between sections, short-turning can be employed to provide service in high demanding segments only, while the interlining service can be inserted from inter-linked routes withstanding the impacts on residual passengers.

The same analysis process described in Algorithm 1 was implemented for the rest routes, and yields the summary of best control points as shown in Table 6.2. One should note that not
all the control points have the same bus stops names, some stops, for instance, the Longhua market in route 287 and Longhua Tianhong centre in 212 are close to each other and hence clustered into the same group.

Table 6.2: Summary of control points

<table>
<thead>
<tr>
<th>Route</th>
<th>Origin Station</th>
<th>Terminus</th>
<th>Control Point (CP)</th>
<th>Name of CP</th>
</tr>
</thead>
<tbody>
<tr>
<td>101</td>
<td>4</td>
<td>12</td>
<td>17</td>
<td>KeJiYuan2</td>
</tr>
<tr>
<td>204</td>
<td>13</td>
<td>4</td>
<td>17</td>
<td>KeJiYuan2</td>
</tr>
<tr>
<td>320</td>
<td>14</td>
<td>2</td>
<td>17</td>
<td>KeJiYuan1</td>
</tr>
<tr>
<td>212</td>
<td>10</td>
<td>6</td>
<td>16</td>
<td>Longhua Tianhong centre</td>
</tr>
<tr>
<td>352</td>
<td>11</td>
<td>9</td>
<td>16</td>
<td>Qinghu subway station</td>
</tr>
<tr>
<td>287</td>
<td>8</td>
<td>7</td>
<td>16</td>
<td>Longhua market</td>
</tr>
<tr>
<td>82</td>
<td>3</td>
<td>4</td>
<td>15</td>
<td>Shenzhen station</td>
</tr>
<tr>
<td>383</td>
<td>5</td>
<td>1</td>
<td>15</td>
<td>Shenzhen station</td>
</tr>
</tbody>
</table>

6.3 Case study description

The distinction of this case study from the first one in Chapter 4 is the adjustment of bus network topology, which enables the adaptive scheduling of multiple service patterns, and is followed by a simulation based capture of the charging duration and demand. It is emphasised again that there is no passenger assignment. From the passenger perspective, there is no links and paths to choose from the network; instead there are distinct routes that are heterogeneous spatially and temporally. The amount of service at a combination of patterns affects the number of boardings on the basis of the headway elasticity.

Table 6.3: Parameters used in the case study I

<table>
<thead>
<tr>
<th>pp (planning period in hours)</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Gamma ) (total number of available bus)</td>
<td>500</td>
</tr>
<tr>
<td>( \tau ) (transit capacity by standing per bus)</td>
<td>70</td>
</tr>
<tr>
<td>( \rho_o ) (unit km value associated with the total vehicle travel kms for service)</td>
<td>2.30</td>
</tr>
<tr>
<td>( \rho_b ) (unit kWh value associated with the battery usage cost)</td>
<td>0.08</td>
</tr>
<tr>
<td>( \rho_H ) (unit bus deadheading penalty associated with the imbalanced constraints ( c_1 ) in terminus)</td>
<td>10</td>
</tr>
<tr>
<td>( \delta ) (power rate of charger)</td>
<td>140</td>
</tr>
<tr>
<td>( \eta ) (grid to vehicle charging efficiency)</td>
<td>80%</td>
</tr>
<tr>
<td>( w_b ) (benchmark of passenger wait time in minutes)</td>
<td>5</td>
</tr>
<tr>
<td>( \sigma ) (energy consumption rate kWh/km)</td>
<td>1.25</td>
</tr>
<tr>
<td>( \epsilon ) (fare per patronage)</td>
<td>1</td>
</tr>
<tr>
<td>( \theta ) (bus average speed)</td>
<td>10</td>
</tr>
<tr>
<td>( W_1, W_4, W_5 ) (penalty coefficient associated with operational availability)</td>
<td>10000</td>
</tr>
<tr>
<td>( W_2, W_3 ) (penalty coefficient associated with improvements of service)</td>
<td>1000</td>
</tr>
</tbody>
</table>
6.3. Case study description

(a) Route 101

(b) Route 204

(c) Route 320

Figure 6.4: Accumulated bus loads, boarding and alighting of bus route between 6:00 pm and 9:00 pm
6.3 Case study description

As the duality gap between the non-convex problem and the linear programming problem would lead to loss of feasible solutions for the adaptive bus scheduling, the operation of electric buses is tested isolated without the interaction for load management. The majority of parameters remained the same, with additional parameters of GA relevant solvers. $W_1, W_2, W_3, W_4$ and $W_5$ are pre-set with a large value to guarantee the search for the Table 6.3.

Since the application of electric buses to boost the operational performance compared to the diesel buses has been demonstrated in Case Study I, this experimentation spent more concerns on the suitability of electric bus for complicated operations and the heterogeneity embodied in providing multiple service patterns. Numerous scenarios were built, including a series of assumption of a different level of adaptive operation under the uncongested dynamic tariff:

a. Operation of electric buses in consistence with frequency deployed in practice applying overnight charging;

b. Optimal operation of electric buses in which one route is adaptive;

c. Optimal operation of electric buses in which three adaptive routes share one control point;

d. Optimal operation of electric buses in which another set of three routes are adaptive;

e. Optimal operation of electric buses with full sets of adaptive routes;

The optimisation for an 18 hours operation was conducted in an 16 core CPU with 6 GB memory programming in parallel, and the total population and generation applied in the GA is 80 and 160 respectively. Depending on the level of adaptive operation, there are maximally 288 decision variables, 114 equality constraints, and 576 inequality constraints. The overall computing time for each case is approximately 779 minutes, which is extraordinary burdens and only can be carried out in the high performance computer.
6.4 Impacts of bus service quality

Based on the analysis of the outcomes in Scenarios a. to e., the following subsections explore the feasibility of adaptive scheduling and the impacts on passenger waiting time, crowding level and net cost. For the comprehensive reasons, only an example within a specific plan period is used to illustrate. The analysis starts with a translation of segmented frequency which is the necessary step to understand the service, followed by the improvements in service quality and overall operational performance.

6.4.1 First look at the service patterns by adaptive scheduling

In order to analyse the service patterns in detail, the morning peak period of 6:00 am - 9:00 am is selected as an example in this subsection.

First of all, the optimal frequency in Scenario a. is presented in Table 6.4, in which the total number of dispatched trips of routes 101,204,320 were 86, 60 and 33 respectively. Contrasting to the optima in of Scenario b. in Case study I, the headway has been reduced for approximately 58%, 45% and 27%. Because of the higher granularity data regarding the stop-level demand patterns, the constraints $c_2$ in the adaptive model can capture the bus loading rather than a line-level passengers patronages in the model introduced in Chapter 3. The total running distance was nearly doubled in Scenario a., which was 13189 compared to 8132 vehicle-kms in the case in Section 4.4. As a result, optima in Scenario a. tends to provide more services to prevent from overcrowding, while reduces the average occupancy.

For single route with adaptive operation, such as the route 383 in Scenario b, due to the restriction of bus flows in control points, there is no interactions with other routes. More trips are allocated to the service patterns of short-turns rather interlining. The optima [59,42,25,8] in Scenario b suggests a short-turn type I of 34 and short-turn type II of 17 trips, as shown in the Figure 6.5. The uni-directional trip (ST I) could provide sufficient transit capacity to satisfy the passenger demands along the out-going direction, while the shot-turn that break at
Table 6.4: Illustration of operation for 6:00 am - 9:00 am

<table>
<thead>
<tr>
<th>Route</th>
<th>Total dispatched trips</th>
<th>Adaptive (Scenario c)</th>
<th>Classic (Scenario a)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Service pattern</td>
<td>Service pattern</td>
</tr>
<tr>
<td>101</td>
<td>[89, 66, 3, 13]</td>
<td>Normal 3</td>
<td>86</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ST I 53 (Outgoing)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>ST II 10 (Ter. - CP)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>IL 33 (to 320)</td>
<td></td>
</tr>
<tr>
<td>204</td>
<td>[77, 79, 5, 10]</td>
<td>Normal 5</td>
<td>60</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ST I 69</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>ST II 5 (Ter. - CP)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>IL 3 (to 320)</td>
<td></td>
</tr>
<tr>
<td>320</td>
<td>[37, 31, 43, 1]</td>
<td>Normal 1</td>
<td>33</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ST I 36</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>ST II 0</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>IL 33 (from 101 &amp; 204)</td>
<td></td>
</tr>
</tbody>
</table>

| Total vehicle-kms | 10294.1 | 13189 |
| Total number of bus | 350 | 447 |

Control point (ST II) could well cater to the relatively high demand contrasting to the rest in the return direction.

Figure 6.5: (left) Service pattern suggested in S. b (right) Demand pattern observed during 6:00 -9:00 am

In Scenario c., a control point (the red dot in Figure 6.5) coordinates the bus short-turning and interlining among route 101, 204 and 320 using the algorithm described in Subsection 5.4.1. Table 6.4 summarises the service patterns translated from the decision variables. Collectively speaking, 9 trips were allocated to the normal round trip operation for servicing the base demand, while 206 bus trips were allocated to complementary patterns in consideration of the
significant uneven distribution of passenger demand, yielding an overall reduction of 22.0%
vehicle running cost. The total number of required buses in adaptive scheduling is 97 less than
those in the classic method.

For a lateral comparison across different levels of adaptive operation, the total running times of
buses and the total number of buses in use are compared in Table 6.5 and overall composition
of the cost structure is presented in Figure 6.6. Basing the comparison on the performance
of Scenario a, it shows that the adaptive scheduling that incorporating the short-turn and
interlining routes could reduce the costs that associated with vehicle running distance within a
range of 5.6% to 21.9% and a reduction of the number of bus in use ranging from 24 and 97.

<table>
<thead>
<tr>
<th></th>
<th>S.a: None</th>
<th>S.b: 1 route(320)</th>
<th>S.c: 1st set AR(3)</th>
<th>S.d: 2nd sets AR(3)</th>
<th>S.e: Full AR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle-mins</td>
<td>1318.96</td>
<td>1244.95</td>
<td>1029.21</td>
<td>1116.89</td>
<td>1126.22</td>
</tr>
<tr>
<td>No. bus in use</td>
<td>447</td>
<td>423</td>
<td>350</td>
<td>379</td>
<td>382</td>
</tr>
<tr>
<td>Improvements</td>
<td>-</td>
<td>5.6 %</td>
<td>21.9 %</td>
<td>15.3 %</td>
<td>14.6 %</td>
</tr>
</tbody>
</table>

Apart from the vehicle running cost, further reduction on the cost on battery, shown as the
grey bars in Figure 6.6, as well as charging cost (shown as the dark red and orange bars) are
achieved by comparing scenario a to e. The total surplus of ownership generally see a increase
with the increasing number of adaptive lines, from 17.6% in the scenario b to 74.5% in the
scenario c.

It is noteworthy that the total service performance measured by the vehicle running minutes
depends on the set of routes that selected for adaptive operation, since the demand patterns in
different set of routes would leads to different level of savings, as observed between the scenario
c. and d. Lastly, the adaptive operation of the whole set is a combined and complicated result
that contributed by cost-savings among three sets of adaptive routes. The overall optimal
service performance is not a simplistic linear correlation with the number of adaptive routes.
6.4. Impacts of bus service quality

6.4.2 Average passenger wait time by stops

Figure 6.7 summarises the potential benefits of the optimisation of adaptive operation in the morning peak time (6:00 to 8:00 am), when buses are allocated to round-trip routes, but also to short-turning/interlining. As the reference, the average passenger waiting time in route 101, 204 and 320 are 1.05, 1.5 and 2.73 minutes. In Figure 6.7, the area of the scatter represents the number of passengers at the bus stops and the darkness represents the concentration of bus loadings.

The optimal adaptive scheduling to three adaptive routes has demonstrated a potential benefits for major passengers. The proportion of passengers that benefited from a reduced waiting time exceed 50 % in all routes, which is 68.3 %, 77.8 % and 51 % as shows respectively. More specifically, route sections with majority passengers - which is the busiest sections - are provided
service with reduced waiting time, while passengers in less busy route sections experience longer waiting time. In route 204 and 320 the average improvement of waiting time for the whole line is 1.2 % to 6.6%, which is limited because of the waiting time in Scenario a is extremely small. For route 101, although the line-level improvement of waiting time is offset by the longer time for low-demanding section, the majority (68.3 %) of passengers in high-demanding section experience a reduced waiting time of 3.7 % to 1.01 minutes. From the perspective of patronage, the potential increase for the outgoing direction is 6393. As a trade-off, the decline in patronage along the direction of return is only 152.

A similar comparison is conducted for the off-peak time during 9:00 to 12:00 pm. The average passenger waiting time of three routes are presented in Figure 6.8, in which one can observe the differentiated waiting time across three routes. Table 6.6 summarises the increase or extension of waiting time. The reduction of waiting time of 0.16 minutes might too small for passenger to tell the difference. During the off-peak time, the average reduction of waiting time in the outgoing direction along route 101 is more than one minutes.
Table 6.6: Comparison of passenger waiting time across route sections between morning peak and night off-peak period

<table>
<thead>
<tr>
<th>Routes</th>
<th>Direction</th>
<th>06:00 to 09:00 am</th>
<th>Improvement</th>
<th>9:00 to 12:00 pm</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Avg. waiting time</td>
<td>S.a: None</td>
<td>S.c: A set AR</td>
<td>S.a: None</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1.05</td>
<td>1.22 -0.17</td>
<td>7.5</td>
</tr>
<tr>
<td>101</td>
<td>Outgoing</td>
<td></td>
<td>1.05</td>
<td>1.8 -0.72</td>
<td>7.5</td>
</tr>
<tr>
<td></td>
<td>Return</td>
<td></td>
<td>20.22</td>
<td>20.22 -18.32</td>
<td>7.5</td>
</tr>
<tr>
<td>204</td>
<td>Outgoing</td>
<td></td>
<td>1.33</td>
<td>1.41 0.11</td>
<td>4.5</td>
</tr>
<tr>
<td></td>
<td>Return</td>
<td></td>
<td>24.72</td>
<td>24.72 -15.48</td>
<td>4.5</td>
</tr>
<tr>
<td>302</td>
<td>Outgoing</td>
<td></td>
<td>2.73</td>
<td>2.85 -0.05</td>
<td>7.5</td>
</tr>
<tr>
<td></td>
<td>Return</td>
<td></td>
<td>0.00</td>
<td>0.00 0.00</td>
<td>7.5</td>
</tr>
</tbody>
</table>

Such an accumulated advantage that is similar to the Matthew Effect concludes that the higher demanding area has the advantage to receive more frequent services and on the contrary attracting more passengers. More importantly, from a combined view of vehicle utilisation in Table 6.5, the adaptive operation is able to serve more passengers with less number of buses.

Figure 6.8: Average passenger waiting time by route section during 9:00 - 12:00 pm
6.4.3 Vehicle utilisation

As aforementioned, because of the different measurement methods towards the bus load, the transit capacity provided in Case Study I may not be applicable in this case where the trip duration provides an in-depth measurement of seat occupancy. It is noteworthy that the transit agency will not make operation decisions merely based on the passenger counts, more reliability-based tools may be used in determining the optimal headway. This section aims to analyse the potential benefits of adaptive scheduling from the perspective of average occupancy, namely reduce the occupancy if it is over-crowding by providing more service, and increase the occupancy if the vehicle is under-utilised by reducing the service frequency.

Table 6.7 summarises the performance in terms of the average occupancy measured by the bus loading over the total transit capacity provided. The blank cells in the table which indicate a zero patronage in that route section are replaced by 0.00. It can be observed that the occupancy in the high-demanding route sections, such as two sections along the direction of outgoing, is reduced by employing adaptive operation. Buses in the ultra-low demanding sections along the direction of return are detached to serve other service patterns taking into consideration the 1% occupancy. For instance, the 33 trips originating from route 101 leave at the control points and interline with the route 302 (see Table 6.4).

<table>
<thead>
<tr>
<th>Time</th>
<th>Route</th>
<th>Direction</th>
<th>Avg. occupancy S.a: None</th>
<th>S.c: A set AR</th>
<th>Improvement</th>
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<td>0.97</td>
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However, it is also observed that the improvement on the extremely busy section (occupancy > 0.9) is relatively small, such as the direction of outgoing in Route 101. That is because any further few reductions of occupancy/waiting time in high-demanding sections would require more buses to be allocated to this area.

### 6.5 Impacts on charging demand and loads

Using the same power system network assumed in Case Study I, the origin and terminus stations of route 101, 204 and 320, which are notated as station 4, 13 and 14, are connected to the feeder 1 and 7 respectively. The aggregated electric bus charging loads are presented in Figure 6.9.

Due to the heavy duty cycle in the morning peak period, which is discussed in the previous section, the opportunity charging is less able to complement the energy consumed during the day. On average, the opportunity charging deployed in six bus stations is only able to add up 18.5% of consumed energy during the operation.

**Table 6.8: Summary of S.c. charging demand by opportunity charging and overnight charging**

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<tr>
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<th>kWh</th>
<th>Opportunity</th>
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<td>Origin</td>
<td>Terminus</td>
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<td></td>
</tr>
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<td>Total</td>
<td></td>
<td></td>
<td>2205.25</td>
<td>9717.47</td>
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</table>

Table 6.8 summarises the specific distribution of electric loads in stations and the magnitudes by opportunity charging and overnight charging. It can be observed that Station 4 connecting the bus route 101 and 204 takes the largest proportion (35.3%) of charging demand, while stations in route 204 share 38.44% charging demand during the operation.
6.5. Impacts on charging demand and loads

Figure 6.9: Aggregated e-Bus charging loads along a day at feeders (a) 101 and 204 at feeder 1 (b) 101, 204 and 320 at feeder 7
By combining the observation here with the service patterns derived in Section 6.4.1, a conclusion can be reached that opportunity charging could provide significant range remedy support to the normal and short-turnings, rather than interlinings. Because 36 of the total trips leaving from route 101 and 204 and interlining with route 320 have not contributed to a significant increase of charging demand in the stations affiliated to route 320, charging demand occurred in stations 2 and 14 still takes the smallest proportion of total daily opportunity charging demand.

6.6 Dependence of e-Bus operation on battery

As concluded in Chapter 4, the dependence of electric bus operation on the battery capacity, which was measured by the battery capacity deficits, generally influenced by the trade-off between electricity rate and battery cost, and subject to the layover in operations that can be used for opportunity charging. The merit of battery capacity deficits is that it enables a cost-effectiveness comparison within and across planning periods, such as peak and off-peak periods, to tell when would it be economical to achieve sufficient range add-up to support daily operation rather than rely on larger batteries, and vice versa. However, since battery capacity deficit is an average-based measurement, it is no longer able to provide in-depth information with respect to the heterogeneity in bus battery usage in catering diverse service patterns. The developed simulation module described in Section 5.6 is able to generate a series of datasets which has length equalling to the total number of electric bus used for service. Each set contains information about the initial SoC and the lowest level of SoC.

Figure 6.10 depicts the five-number summary of the effective range of batteries, both the average required battery capacity represented by the median line and the maximum value can be reduced in Scenario b to e comparing to the Scenario a. The interquartile range box between the first and third quartile represents the range of battery usage of the 50% buses. The longer the box, the more heterogeneous the bus fleets would be. In the case of a lopsided box plot, where the median cuts the box into two unequal pieces, the data in the smaller piece has a higher level of concentration. That indicates the median of battery capacity is less/great than the mean of
battery capacity in left-skewed/right-skewed distribution. By comparing the Scenario c, d and e to the classic operation in Scenario a, two conclusions can be made with the observations:

- Adaptive operation could reduce the reliance of electric bus on large battery capacity, since the maximum outliers, median and mean values are smaller than those in the isolated operation in Scenario a. It shows a gradual and slight reduction as the increasing number of route is integrated into the adaptive framework. For example, the mean value of effective battery usage range is 7.4% less in Scenario b to 11.46% in Scenario e.

- Electric bus in adaptive operation face more diversified battery requirements, which can be accounted for the multiple service patterns and exhibits a longer interquartile range box. Meanwhile, since the battery usage data is right-skewed, the median value of battery capacity that required for bus operation is smaller than the mean value.

![Box plot](image)

Figure 6.10: Distribution of effective range of battery by minimum, first quartile, median, third quartile, and maximum

Operators are able to configure heterogeneous electric bus fleets based on the distribution of effective battery capacity observed in this section. Most buses with large batteries can undertake the long-haul travel, such as normal operation and interlining, whilst buses with lower batteries can be allocated to short-turns and coordinate with the opportunity charging to
ensure a sustainable operational range. Using the same example of Scenario c, that is analysed in the previous sections, the effective battery usage capacity of 300 buses are plotted in Figure 6.11. One could get a brief image of the battery use in the electric bus fleets operating between different service patterns.

![Distribution of battery capacity in S. c](image)

Figure 6.11: An example of effective battery capacity usage range in the simulated bus fleets

### 6.7 Concluding remarks

This chapter demonstrates the application of adaptive scheduling approaches on fragmented and combinatorial routes segments in order to reduce passenger-related and the operational-related cost. Meanwhile, the suitability of electric bus in servicing highly complicated service patterns including the short-turns and interlinings have been analysed. The combinatorial and nonlinear nature of problem does not allow for the computation of optimal solution based on classic methods. The GA-based solving method is implemented on the converted problem of nonlinear non-convex integer programming and applied to a modified case study based on the data described in Chapter 4.
6.7. Concluding remarks

The foremost distinct finding is that flash charging may find less opportunity to provide intermittent range add-up for electric bus operating at peak time as the increasing number of routes integrated into the adaptive framework. Long-haul and heavy-duty cycle bus operation derived from the combinatorial route section is less able to embed a charging cycle of low-rated electricity. It appears that electric buses in use can not suspend the service just in order to charge with less cost. Comparatively speaking, bus operating in routes that encouraged to embrace a higher proportion of short-turn service tend to have a greater proportion of energy consumption fulfilled between trips.

Some other findings include:

1. Adaptive scheduling incorporating trip allocations to short-turns and interlining could achieve a potential 21.9% savings on the costs associated with the vehicle running times. It should also be noted that adaptive operation in a solely operated line that has less demand variation or time-costly intersection with others could only provide limited savings.

2. Interlining and short-turning proved very powerful in catering to the problem of vehicle under-utilisation caused by the spatially dis-aggregated passenger demand. Both the number of buses required for service, average bus seat occupancy are improved with the proactively scheduling of these service patterns.

3. The saving of usage cost on batteries capacity shows a gradual and slight reduction as the increasing number of routes integrated into the adaptive framework. The improved flexibility in multi-pattern bus operation could bring promising savings on operational cost and reduce the battery capacities that essential for an undisruptive full day operation. For example, the mean value of effective battery usage range is 7.4% less in Scenario b to 11.46% in Scenario e when compared with the value in Scenario a.
Chapter 7

Conclusions And Future Research

7.1 Summary

The emerging electric bus technology attracts continuously increasing interests. Bus operators dedicate to a long lasting electric mobility for viable bus service, whilst power system operators seek for the temporal flexibility which can be achieved by rescheduling the demand requirements. If the twofold characteristics - both spatial movability and temporal flexibility - are suitably exploited, it can induce significant economic and technical benefits.

In this thesis, the role of electric buses in the integration of bus service and power system safe operation is explored by developing a methodology to investigate the electric bus operation subjecting to numerous scenarios that enable mutually beneficial interactions. Electric bus operation as the bridge between two fields is required to respond to both the spatially distributed passenger demand, and the temporally varied electricity tariff.

The modelling framework for the joint analysis of bus movement and charging is presented. To fulfil the goal of better eBus-grid integration with complete tempo-spatial profile, the classic bus planning problem - frequency setting that capture trade-offs between vehicle running cost and passenger demand - is extended to incorporate the charging dimension and embedded into a bi-level game model. The decision of the upper problem - bus planning - followed sequentially the
decision made by the lower problem - the electricity market clearing problem. The latter enables precise pricing of electricity which unveils the systematic costs for providing service in electricity market. The above mechanism is mathematically founded on Lagrangian Relaxation principles and attempts to solve the bilevel convex optimisation directly by satisfying the KKT first order necessary optimality conditions of the lower problem. The complementarity constraint in the KKT conditions is what makes the whole problem an MPCC. To retain the convexity of the whole problem, any piece-wise linear/nonlinear components are approximated and replaced by a continuous expression using least square regression.

Analysis from the model application on a case study based on realistic passenger count data from Shenzhen coupling with the widely used IEEE test power system provides insights into the implication of electric bus load management policies. When the battery cost is relatively high, the high-rated congestion price would weaken the operational performance of bus operation, since the less cost-effective flash charging at the congested rate would lead to greater reliance on larger battery, and thus influencing the economic dispatch of bus operation. Given the significant cut on battery cost in the next decades, the impacts of high electricity price on the normal operation are likely seeing a declining trend but analysis also suggests the inter-temporal inflexibility would exist in the load shifting because of the limitation of bus operational constraints.

In the face of challenges of emerging needs for running electric bus in more complicated operations, which is not able to be captured in the classic model, another heuristic-based mechanism is developed to explore the heterogeneity in the service patterns that electric bus able to provide. The feature that make this work distinct from the state-of-art is that the service patterns including short-turns and interlining are endogenously and exhaustively generated and allocated with optimal frequency in the process of optimisation. This mechanism however require an extremely high granularity of passenger demand data, a series of data processing techniques are required to supplement the profiling of diverse passenger demand patterns. Given the combinatorial nature and the exponential complexity, the second mechanism proposes a meta-heuristic method that approximate the nonlinear constrained optimisation problem with exterior point
In the context of the scope discussed in Section 1.3, the original contributions of this thesis are associated with the development, analysis and testing of suitable models, methods, algorithmic approaches and examples of the electric bus operation under diverse market environment. These contributions are summarised below:

(1) This work has, for the first time, considered the charging scheduling in the duty cycle and off-duty charging at the same time, which contribute to the diversification of the
smart charging portfolio. With the opportunity charging embedded in the duty cycles, the challenges of coordinating the charging activities with the operational activities have been overcame by using an unified variable to correlate the charging demand with the optimised service schedule. In this way, the charging scheduling and operation scheduling are mathematically formulated with the same decision variables in the bus planning problem. Another distinctive characteristic of this approach with respect to respective works in EV load management is that it restrains the loads with operation activities rather than an assumption of availability of vehicles

(2) This work has developed a methodology to quantify the trade-off between achieving sufficient add-up range per charging and equipping large batteries to fulfil the service needs. Lack of relevant analysis in existing research will leads to the under/over-evaluation of the dependence on batteries. This work is ahead of the rest by differentiating the requirement of battery capacity and use of range remedy technique from the aspects such as vehicle use, service patterns, dynamic in electricity rates and charging network operational conditions.

(3) This work has developed a novel methodology to schedule the bus dispatch with improved efficiency that responds to the unevenly distributed passenger demand. Instead of pre-determining a limited set of sub-route choice as other works did, the heterogeneity of service pattern has been enhanced in the combination of the segment-level bus operation. The involvement of short-turns and interlinings in the electric bus modelling not only benefits the cost-effectiveness, but also contribute to the diversification of bus operation that fit in the loads profile of different range electric buses.

(4) The context of Locational Marginal Price (LMP) employed in the transmission-level market clearing is extended to the distribution-level (DLMP), which contribute to the gap in distribution level power network research that use pool-based market to attract and balance the demand response. Basing the electricity pricing on the Lagrange-Relaxian based formulation, the locationally differentiated price is able to re-balance multiple sub-networks at the same time. The corresponding analysis also provide unprecedented in-
7.3 Limitation and future work

The results of two case studies on a model of RBTS and Shenzhen bus network have indicated the very significant economic potential of electric bus in the load management - which reveals the beneficial potential in distribution network planning - and the applicability of electric bus in very complicated service in order to cater to the variation of passenger demand.

However, the connection between electric bus and power system is based on the opportunity charging that inserted into the duty cycle and regular charging during the overnight only. For this reason, the tactical planning problem of frequency setting is selected to model the electric mobility consist of the mobility of vehicle and mobility of electric charging demand. Other dimensions of charging or movement are intrinsically linked with the operational frequency. In this framework, only the tempo-spatial profile of vehicles in their duty cycle are included, whereas the number of buses for service varies along the day depending on the passenger demand pattern. The charging process of bus during the off-duty times are not captured in the first mechanism. Although this defect has been remedied in the second mechanism by introducing the simulation module, computational complexity has restricted the interactions between two markets.

A way to move beyond this limitation without substantially change the structure of the current model would integrate it with several fictitious bus stations representing the depots that enabling bus charging off-duties. This would be an essential step in future work intended to build a comprehensive and completed depict of the electric mobilities across planning periods.
and different service zones.

The second limitation of the works is the complexity in the approximation of charging loads, which implied by considering charging time as correlating to the service patterns. The uncertainty about service patterns in the optimisation process limits the deterministic response in the charging control function. There are possible two approaches to overcome this limitation. First, it could generate a number of pre-defined service patterns and embed the problem of vehicle allocation into the proposed bi-level framework. However, this approach proposes a tremendous challenge in the applicability and compatibility of generated service patterns. Alternatively, a trip assignment model is necessary to replace the module of simulation and constitute the whole problem within a tri-level framework.

Thirdly, the limitation of the interactive bi-level framework is the inaccuracy between DC-OPF and AC-OPF in the approximation of power flow. The reliability of the distribution network is significantly influenced by the power loss, but also the voltage and reactive power. One of the necessary work in the future is to consider the impacts of the error between network constrained DCOPF and ACOPF. To improve the accuracy in DLMP, the voltage, phase angle and reactive power have to be considered into the network constraints.

Last but not least, load management through electric bus could have broader applications in power system analysis. Some distributed resources such as photovoltaic and wind turbine are expected to be integrated into the interaction model, so that DLMPs are able to better reflect the values of the tempo-spatial characteristic of the service provided by electric bus fleets and other distributed energy resources.
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Appendices
## Appendix A

### Data Brief Of Case Study

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# Appendix B

## Power Line Data In RBTS

### Table B.1: Mid-voltage (33kV) Line data in RBTS

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## Appendix C

### Load Data in RBTS

Table C.1: Customer Peak Load Data By Type And LP

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Appendix D

Electricity Wholesale Data In Day-ahead Market

Table D.1: Electricity Wholesale Data in Day-ahead Market

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Appendix E

Spatial And Temporal Characteristics
Of Dis-aggregated Passenger Demand
Figure E.1: Bus loads in route 82 along a day by directions (a) departure (b) return
Figure E.2: Bus loads in route 101 along a day by directions (a) departure (b) return
Figure E.3: Bus loads in route 204 along a day by directions (a) departure (b) return
Figure E.4: Bus loads in route 212 along a day by directions (a) departure (b) return
Figure E.5: Bus loads in route 287 along a day by directions (a) departure (b) return
Figure E.6: Bus loads in route 320 along a day by directions (a) departure (b) return
Figure E.7: Bus loads in route 352 along a day by directions (a) departure (b) return
Figure E.8: Bus loads in route 383 along a day by directions (a) departure (b) return