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# Smart Charging Strategies for Electric Vehicle Charging Stations

by

***Zeinab Moghaddam***

This thesis is presented in fulfilment of the requirements for the degree of

***Doctor of Philosophy***

SCHOOL OF ENGINEERING

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# USE OF THESIS

The Use of Thesis statement is not included in this version of the thesis.

# ABSTRACT

Although the concept of transportation electrification holds enormous prospects in addressing the global environmental pollution problem, consumer concerns over the limited availability of charging stations and long charging/waiting times are major contributors to the slow uptake of plug-in electric vehicles (PEVs) in many countries. To address the consumer concerns, many countries have undertaken projects to deploy a network of both fast and slow charging stations, commonly known as electric vehicle charging networks.

While a large electric vehicle charging network will certainly be helpful in addressing PEV owners' concerns, the full potential of this network cannot be realised without the implementation of smart charging strategies. For example, the charging load distribution in an EV charging network would be expected to be skewed towards stations located in hotspot areas, instigating longer queues and waiting times in these areas, particularly during afternoon peak traffic hours. This can also lead to a major challenge for the utilities in the form of an extended PEV charging load period, which could overlap with residential evening peak load hours, increasing peak demand and causing serious issues including network instability and power outages.

This thesis presents a smart charging strategy for EV charging networks. The proposed smart charging strategy finds the optimum charging station for a PEV owner to ensure minimum charging time, travel time and charging cost. The problem is modelled as a multi-objective optimisation problem. A metaheuristic solution in the form of ant colony optimisation (ACO) is applied to solve the problem.

Considering the influence of pricing on PEV owners' behaviour, the smart charging strategy is then extended to address the charging load imbalance problem in the EV network. A coordinated dynamic pricing model is presented to reduce the load imbalance, which contributes to a reduction in overlaps between residential and charging loads. A constraint optimization problem is formulated and a heuristic solution is introduced to minimize the overlap between the PEV and residential peak load periods.

In the last part of this thesis, a smart management strategy for portable charging stations (PCSs) is introduced. It is shown that when smartly managed, PCSs can play an important role in the reduction of waiting times in an EV charging network. A new strategy is proposed for dispatching/allocating PCSs during various hours of the day to reduce waiting times at public charging stations. This also helps to decrease the overlap between the total PEV demand and peak residential load.

## Keywords

Plug-in electric vehicles (PEVs), charging stations (CSs), smart charging strategies, pricing model, portable charging stations (PCSs), EV network.

# DECLARATION

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**به راه بادیه رفتن به از نشستن باطل**
**و گر مراد نیابم به قدر وسع بکوشم**
**"سعدی"**

**Going down the path of a wasteland is better than sitting idly**
**Even though I might fail my desire, I would try my best.**
**"Saadi"**

**The greatest challenge to any thinker is stating the problem in a way that will allow a solution.**
**"Bertrand Russell"**

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Last but not least, I would like to express my profound gratitude to my Mom, all my sisters and brothers, and my beloved Mehrdad in Iran for their unconditional love, encouragement and support. Although I have been physically far away from them, their positive energy has been continuously in my mind.

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# LIST OF SYMBOLS

| | |
|---|---|
| $t$ | Current time |
| $M$ | Total number of PEVs |
| $N$ | Total number of charging stations |
| $o$ | Charging option (o = 1: swap battery; o = 2: DC charging and o = 3: AC charging) |
| $T^{drive}(s, j)$ | Driving time from current location of $PEV_i$ to the charging station $j$ |
| $T^{drive}(j, dst)$ | Driving time from the charging station $j$ to the destination $dst$ |
| $D^{max}(t)$ | Maximum driving distance with the remaining energy |
| $E^{ca}$ | Battery capacity of PEV |
| $E_j^{ca}$ | Maximum power capacity of each charging station $j$ |
| $E_g^{max}$ | Maximum capacity of grid g |
| $E^{Travel}$ | Energy consumption per unit driving distance for each PEV |
| $SoC(t)$ | State of charge of the battery of PEV at current time |
| $\lambda_j$ | Arrival rate at the charging station $j$ |
| $\mu_j$ | Service time at $FCS_j$ |
| $\mu_i$ | Service time at $PCS_i$ |
| $P_i(t)$ | Power consumption of PEV $i$ at the current time |
| $L_j^k(t)$ | Queue length at time $t$ for charging option $k$ at charging station $j$ |
| $\pi_j^R$ | Probability transition matrix for $R$ possible state at charging station $j$ |
| $W_j^o$ | Waiting time at charging station $j$ for charging option $k$ |

| | |
|---|---|
| $d_i$ | Driving distance for PEV $i$ |
| $v(s, j)$ | Average speed between source to a charging station |
| $Pr_k$ | Price of charging option $k$ |
| $C_j^{recharge}(o)$ | Cost to charge with charging option $k$ at charging station $j$ |
| $T_j^{max-wait}(o)$ | Maximum waiting time for charging option $k$ at charging station $j$ |
| $\chi_m$ | Correlation coefficient of iteration $m$ for the updated price vector of $CS_j$ |
| $\Delta t$ | Time slot (time interval) equal to one hour |
| $\gamma_j(t)$ | Uniform queue occupancy of $CS_j$ |
| $\kappa_j(t)$ | Actual queue occupancy of $CS_j$ |
| $\kappa_j^{max}(t)$ | Maximum queue occupancy of $CS_j$ |
| $\kappa_j^{min}(t)$ | Minimum queue occupancy of $CS_j$ |
| $\overrightarrow{\beta_j(t)}$ | Price coefficient vector of $CS_j$ |
| $\overrightarrow{g_j(t)}$ | Gain vector of $CS_j$ |
| $\overrightarrow{Q(t)}$ | Inverse correlation matrix of the price vector in the RLS algorithm |
| $\phi_j^{min}(t)$ | Minimum value for profit at $CS_j$ |
| $\pi_j^R$ | Probability transition matrix for the $R$ possible states at $CS_j$ |
| $\sigma$ | Charging price coefficient |
| $c_j(t)$ | Electricity purchase price [cents/kWh] |
| $d_j(t)$ | Charging demand at $CS_j$ |
| $dst$ | Destination of PEV |
| $e_j(t)$ | Prediction error of $CS_j$ |
| $E_j^{ca}$ | Maximum power capacity of charging station $j$ [kW] |
| $I_j(t)$ | Amount of incentive from the grid [cents/kWh] |
| $j$ | Index of a charging station |

| | |
|---|---|
| $L_j^o(t)$ | Queue length for option $k$ in $CS_j$ (Number of PEVs in a queue) |
| $p_j(t)$ | Charging price at $CS_j$ |
| $p_j^{max}(t)$ | Upper bound of the charging price at $CS_j$ |
| $p_j^{min}(t)$ | Lower bound of the charging price at $CS_j$ |
| $r(t)$ | Residential load [MW] |
| $src$ | Current source of PEV |
| $t$ | Time consisting of 24 time slots; t = $\Delta t$, $2\Delta t$, $3\Delta t$, 24hours |
| $T_j^{wait}(o)$ | Waiting time for charging option $k$ at $CS_j$ |
| $x_j$ | Price coefficient for price vector at $CS_j$ based on the actual and uniform queue occupancy at$CS_j$ |
| $E_N^{ca}$ | Capacity of the EV network |
| $E_g^{ca}$ | Maximum capacity of grid assigned to a charging station [kW] |
| $\alpha$ | Weight of pheromone and heuristic values in ACO |
| $\beta$ | Weight of pheromone and heuristic values in ACO |
| $E_i^{ca}$ | Maximum power capacity of portable charging station $i$ [kW] |
| $E_j^{ca}$ | Maximum power capacity of fixed charging station $j$ [kW] |
| $w_i^{max}$ | Maximum waiting time of $PCS_i$ [min] |
| $w_j^{max}$ | Maximum waiting time of $FCS_j$ [min] |
| $\eta$ | Heuristic information of ACO |
| $\lambda_j^o$ | PEV Arrival rate at charging station $j$ with charging option $o$ |
| $\lambda_i$ | PEV Arrival rate at portable charging station $i$ |
| $\phi$ | Permutation matrix |
| $\rho$ | Charging capacity of FCSs |
| $\sigma$ | Evaporation coefficient in global pheromone update |
| $\tau$ | Pheromone intensity of ACO |

| | |
|---|---|
| $\varrho$ | Evaporation coefficient in local pheromone update |
| $E(W_j^o)$ | Average waiting time [min] at $CS_j$ for charging option $o = 1, 2, 3$ |
| $E_k^{ca}$ | Battery capacity of the PEVs [kW] |
| $F$ | Feasible neighborhood of two noes in ACO |
| $i$ | Index of a portable charging station |
| $j$ | Index of a fixed charging station |
| $k$ | Index of a PEVs |
| $r$ | Charging rate |
| $s$ | Number of servers at FCSs |
| $\mathcal{J}$ | Set of FCSs |
| $\mathcal{I}$ | Set of PCSs |
| $\mathcal{K}$ | Set of PEVs |
| $\mathcal{L}$ | Set of locations to allocate PCSs |
| $\lambda_{old}^j$ | Arrival rate of $FCS_j$ without using PCSs |
| $\lambda_{new}^j$ | Arrival rate of $FCS_j$ with using PCSs |
| $\Delta_\Lambda^j$ | Arrival rate reduction at charging station $j$ |
| $wt_{old}^j$ | Waiting time of $FCS_j$ without using PCSs |
| $wt_{new}^j$ | Waiting time of $FCS_j$ with using PCSs |
| $\Delta_{wt}^j$ | Waiting time reduction at charging station $j$ |

# LIST OF ACRONYMS

| | |
|---|---|
| **PEV** | Plug-in electric vehicle |
| **CS** | Charging station |
| **FCS** | Fixed charging stations |
| **BSS** | Battery storage system |
| **SoC** | State of charge |
| **ACO** | Ant colony optimization |
| **ICE** | Internal combustion engine |
| **QAP** | Quadratic assignment problem |
| **NP-hard** | Non-deterministic polynomial-time hardness |
| **DeFS** | Depth First Search |
| **RLS** | Recursive least square |
| **UP** | Uncoordinated pricing |
| **BrFS** | Breadth First Search |
| **UnCS** | Uniform Cost Search |
| **BeFS** | Best First Search |
| **BeS** | Beam Search |
| **IEA** | International Energy Agency |
| **CEA** | Community Energy Association |
| **AS** | A star |

# List of Publications

## Published

1. **Z. Moghaddam**, I. Ahmad, D. Habibi, and Q. V. Phung, “Smart charging strategy for electric vehicle charging stations,” IEEE Transactions on Transportation Electrification, vol. 4, no. 1, pp. 76–88, 2018.

2. **Z. Moghaddam**, I. Ahmad, D. Habibi, and M.A.S Masoum, “A Coordinated Dynamic Pricing Model for Electric Vehicle Charging Stations,” IEEE Transactions on Transportation Electrification, vol. 5, no. 1, pp. 226–238, 2019

3. **Z. Moghaddam**, I. Ahmad, D. Habibi, and M.A.S Masoum, “Portable Charging Stations in Electric Vehicle Networks”, IEEE Transactions on Sustainable Energy, submitted, under the first revision.

*Dedicated to my Mom . . .*

# Chapter 1

# INTRODUCTION

Plug-in electric vehicles (PEVs) powered by electricity from low carbon emission grids can provide significant benefits in terms of reducing transportation impact on climate as well as minimising a transport grid's reliance on oil-based fuels. PEVs provide a cleaner and quieter environment, and reduce operating costs at the same time [10]. PEVs can potentially operate as flexible electric loads to support the operation of power systems and the integration of renewable energy sources [11]. The concept of using parked PEVs as storage devices for renewable energy has also attracted increasing interest from both utility and PEV owners in recent years [12, 13, 14]. PEV owners enjoy many social, environmental and economic benefits associated with owning PEVs. Fuel and maintenance costs of PEVs are significantly lower than standard gasoline cars. PEVs are also known to provide stronger torque, smoother acceleration and a quieter driving experience.

Despite offering some clear advantages, the market penetration of PEVs has been relatively low. Among other reasons, potential PEV owners identify a lack of public charging infrastructure as one of the key reasons for low uptake of technology. Driver's range anxiety is a major contributing factor. The other major concern is the long recharging/waiting time. To increase the uptake rate of PEVs, governments and automotive industries in most developed countries have been working together, and have undertaken projects to deploy a network of electric charging stations, commonly known as EV networks [15]. EV networks are anticipated to play a critical role in coming decades as the forecast for PEV market growth looks very promising (Figure 1.1), primarily associated with increasing support from governments and automotive industries.

As the expectations for future PEV sales increase, there is a growing research focus on the development of charging infrastructure. Charging infrastructure is broadly divided into three categories based on PEV charging speeds. According to community energy

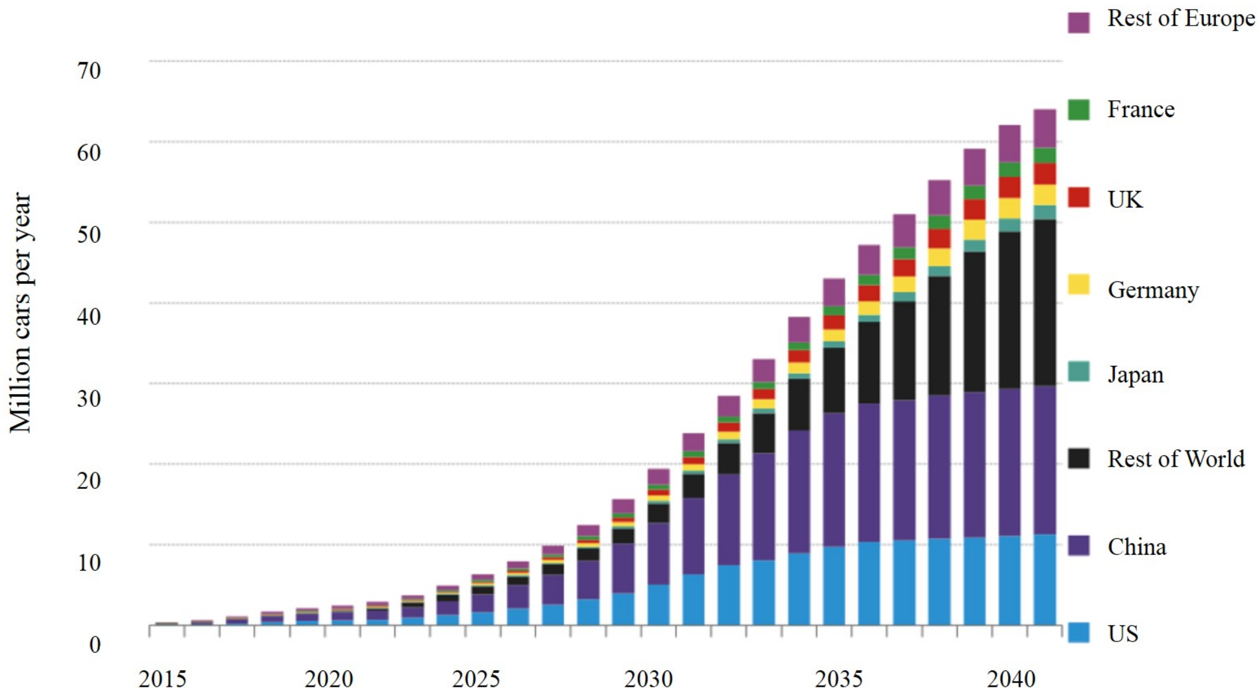



Figure 1.1: Global Electric Vehicle Market [1].

association (CEA), different levels of PEVs charging are AC level 1, AC Level 2 and DC fast charging. AC level 1 typically takes 10-20 hours to charge and the long charging time makes Level 1 chargers suitable only for home usage. AC Level 2 can be used for both commercial and home charging purposes. PEVs will take 4-8 hours to reach a full charge; and DC charging, also called fast charging, provides the fastest way of charging PEVs and can achieve full charge in 10 to 15 minutes [16, 17].

An EV network as presented in Figure 1.2 provides an opportunity for quick recharging on-demand; thereby, significantly addressing consumers' range anxiety problems. In addition, EV networks can play a critical role in peak load-shaving by offering charging facilities during off-peak hours. However, utilities have major concerns over the negative impacts of such stations on the stability of the power grid [18]. For instance, simultaneous charging of too many vehicles at CSs can substantially increase the power demand at that station and impose detrimental impacts on grid components. However, intelligent routing of PEVs can turn this challenge into an opportunity by viewing vehicles as mobile storage devices with charge/discharge capabilities [12].

It is anticipated that EV networks will address a number of key concerns currently raised by utility and potential PEV owners. Firstly, driver's range anxiety must be managed by better communication between PEVs and the smart grid interfaces to facilitate timely and

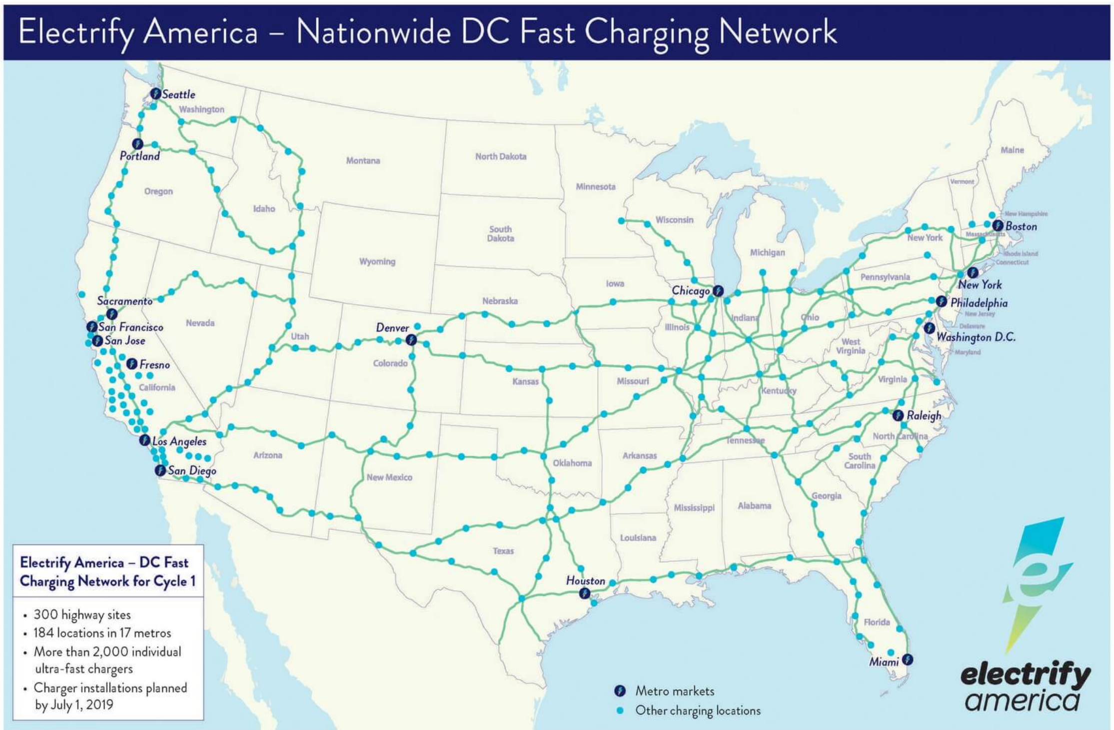



Figure 1.2: Example of an EV network [2]

fast recharging at public charging stations. Secondly, the average waiting/recharge time needs to be minimised. Thirdly, the PEV charging load needs to be smartly managed so that PEVs do not contribute to a significant increase in peak demand.

Charging strategies, which influence the way the resources are utilised in an EV network, can play a critical role in achieving the above mentioned targets. Using a smart charging strategy, PEVs can optimise their decisions; for example, when to recharge, where to recharge, and what amount to recharge. Charging strategies however, come with their own set of challenges. For example, uncoordinated charging strategies in a limited charging infrastructure can increase the average recharge time [19] and contribute to an increase in peak loads [18]. As more PEVs join the grid, the waiting time at CSs in combination with actual road traffic can constitute a major challenge. During peak hours, CSs may end up with long queues that can directly impact the comfort of PEV owners. To resolve these challenges, there is the need for a systematic PEV-scheduling technique, which not only takes into account the distribution of electricity load, but also reduces traffic congestion and waiting times at CSs. Currently, charging infrastructures are not widely available in all major cities, and because of long waiting times at charging stations, the recharging process can cause significant delays [20, 21].

The temporal PEV charging load profile of an EV network is also expected to follow a pattern where the PEV load is high in the late afternoon [5]. Unless properly managed, the peak PEV load period can extend and overlap with peak residential load periods. Utilities have already expressed their concern over the possibility of facing this overlap between PEV and daily residential loads periods. An extended overlap period is likely to put significant stress on both the generation and distribution sides of the energy industry [5].

In order to accelerate the rate of uptake of PEVs, smart charging strategies that address some of the above mentioned challenges can play a significant role. This thesis presents one such smart charging strategy, one that reduces waiting times and charging costs for PEV owners. The proposed strategy also reduces overlap between the PEV load and daily residential load periods.

## 1.1 Research significance and motivation

The total number of PEVs in the world is currently over 3.5 million, and all of them have the potential to become important elements within smart grids [22, 23]. The international energy agency (IEA) sees the potential of 220 million electric vehicles by 2030, providing the world takes a more aggressive approach to fighting climate change and cutting emissions than currently planned [24]. Increasing the number of PEVs results in a significant reduction in emission up to 30% [24].

All PEVs can apply a two-way communication strategy to enable real-time monitoring and transmission control in the energy distribution grid to improve coordination and usage of renewable and available energy resources [25]. Ideally, PEVs can be recharged outside of peak demand periods so that, grid capacity does not have to be increased, renewable energy can be fully utilised, and charging costs may be reduced within a real-time energy management regime. Smart charging strategies can significantly help to achieve this target. Using a smart charging strategy, PEVs can optimise their own charging decisions to meet the dual goals of minimising the grid's peak hour load and drivers anxiety/waiting times [26].

Motivated by the need to develop a smart charging strategy, this research investigates the mentioned challenges with regard to PEV charging in EV networks. In particular, this research seeks answers to the existed challenges by exploring ways of managing PEV charging loads across various charging stations in an EV network so that both utility and PEV owners can enjoy benefits in the form of reduced peak demand, short waiting times and low recharging costs, respectively.

## 1.2 Aims

The main aim of this thesis is to present a smart charging strategy that provides benefits to both PEV owners and energy providers with the expectation that this ultimately promotes the uptake of PEVs. More specifically, the aims of this research include:

- developing a smart charging strategy that minimises travel times, waiting times and charging costs for PEV owners.
- developing a coordinated dynamic pricing model that can be used by within smart charging strategies to distribute PEV loads uniformly across all charging stations in an EV network so that overlap between PEV load and residential load can be minimized.
- developing a strategy to dispatch/allocate portable charging stations (PCSs) so that waiting times at charging stations and overlap between PEV load and residential peak load can be minimised.

## 1.3 Research contributions

The contributions of this thesis arise in proposing a new smart charging strategy and associated models including a dynamic pricing model and a PCS dispatch model to overcome the limitations of existing charging strategies . The main contributions of this thesis are as follows:

- As the first contribution, Chapter 3 present a smart charging strategy for a PEV network that offers multiple charging options, including AC level 2 charging, DC fast charging and battery swapping facilities at charging stations. For a PEV requiring charging facilities, The issue of finding the optimal charging station is modelled as a multi-objective optimization problem where the goal is to find a station that ensures minimum charging time, travel time and charging cost. Then the model is extended to a meta-heuristic solution in the form of an ant colony optimization. Simulation results show that the proposed solution significantly reduces waiting time and charging costs.
- As the second contribution, a new coordinated dynamic pricing model is introduced to reduce the overlaps between residential and CS loads by inspiring temporal PEV load shifting during evening peak load hours. The new idea is to dynamically adjust

price incentives to guide PEVs toward less popular/underutilized CSs. A constraint optimization problem is formulated and introduced a heuristic solution to minimize the overlap between PEV and residential peak load periods. Our extensive simulation results indicate that the proposed model significantly reduces the overlap and PEV load during evening peak hours.

- As the third and final contribution, the concept of dispatching portable charging stations (PCSs) is introduced to reduce waiting times for PEVs during an EV network's busy hours. In the proposed PCS management system, the strategy of dispatching PCSs in implemented at the right time to the right locations in order to ensure efficient management of PEV load. An optimization model with the aim of minimising total waiting times is defined. Considering the time complexity of the optimum solution, using a heuristic solution to implement the PCS dispatching strategy. Simulation results show that the proposed model can significantly help to reduce the average waiting times during peak hours.

## 1.4 Thesis outline

This thesis is organized into six chapters as follows:

- **Chapter 2** discusses the background and literature review of integrating PEVs into the power grid and their impacts. This chapter presents all relevant smart charging strategies along with both their advantages and disadvantage. Finally research gaps are identified and the research questions are proposed .

- **Chapter 3** proposes a smart charging strategy for a PEV network that offers multiple charging options at charging stations. A multi-objective optimisation model is introduced where the goal is to reduce charging time, travel time, and charging costs. In the proposed model a queuing model is used to estimate the delay at various charging stations. To mitigate the challenge of longer waiting times and potential overlap between peak PEV and residential load periods, also the concept of partial charging is introduced during peak load hours. Finally, the research question is solved using an ACO-based metaheuristic solution. This research [5] is published in the ***IEEE Transactions on Transportation Electrification, vol.* 4*, no.* 1*, pp.* 76–88, 2018.**

- **Chapter 4** implements a new coordinated dynamic pricing model that encourages temporal PEV load shifting to reduce overlaps between PEV and residential peak load periods. The dynamic pricing model is formulated as a constrained optimisation problem. This chapter, also presents a rule based heuristic solution to address the dynamic pricing challenge in real-time. The proposed solution is included in the proposed charging strategy, which is then implemented using an ACO model for bench-marking. The findings of this study reveal significant benefits to both consumers and utilities by minimising waiting times at CSs and by shifting the charging demands to reduce overlaps. This research is published in the ***IEEE Transactions on Transportation Electrification , vol. 5, no. 1, pp. 226–238, 2019.***

- **Chapter 5** introduces a new model to dispatch portable charging stations in order to minimise waiting times at busy fixed charging stations. The research question is modeled as a constrained optimization problem where a heuristic solution is provided to solve the problem in real-time. This research has been submitted to ***IEEE Transactions on Sustainable Energy*** and is under the first revision.

- **Chapter 6** presents the conclusion from this research, followed by suggestions for future works.

## 1.5 Publications resulting from this research

1. Z. Moghaddam, I. Ahmad, D. Habibi, and Q. V. Phung, "Smart Charging Strategy for Electric Vehicle Charging Stations", ***IEEE Transactions on Transportation Electrification***, vol. 4, no. 1, pp. 76–88, 2018 .

2. Z. Moghaddam, I. Ahmad, D. Habibi, and M.A.S Masoum, "A coordinated Dynamic Pricing Model for Electric Vehicle Charging Stations", ***IEEE Transactions on Transportation Electrification***, vol. 5, no. 1, pp. 226–238, 2019.

3. Z. Moghaddam, I. Ahmad, D. Habibi, and M.A.S Masoum, "Portable Charging Stations in Electric Vehicle Networks", ***IEEE Transactions on Sustainable Energy*** (Submitted, under the first revision).

# Chapter 2

# BACKGROUND AND LITERATURE REVIEW

This chapter aims to provide a background to PEVs, charging infrastructures and their impact on the power grid. Smart charging strategies are also investigated as a solution for providing an optimal and effective way of charging electric vehicles whilst preventing negative impacts on the power grid. Solutions are currently being developed with related work, and different methodologies.

This chapter begins with Section 2.1 which includes an overview of integrating of PEVs into electric power grid, introducing charging infrastructures and discussing the impact of PEVs charging on the power grid. A brief discussion on charging standards and infrastructures are then presented in Section 2.2. In Section 2.3, smart charging of PEVs in the EV network is investigated. Also in this section, three smart charging strategies with their related works are reviewed. Based on the findings of different charging strategies and identifying the existing gaps for improving the solutions, the author presents the relevant research questions for this thesis in Section 2.4. Finally, Section 2.5 concludes the chapter.

## 2.1 PEVs integration into electric power grid

The integration of increasing PEVs into the electric power system is an important issue that needs to be assessed and observed in terms of economic impacts, operation and control benefits under optimal conditions. There are many existing studies that analyzed the impact of the PEVs on the power grid [27, 28].

Generally, using PEVs increases domestic electricity consumption and if their owners charge their cars synchronously, for example overnight, demand patterns are not uniform over a 24 h cycle [29]. Costs increase if PEVs are recharged during peak demand periods and if a real time charging regime exists. PEVs can be considered as the centrally controlled generators with the concept of V2G in the high voltage side and loads at the low voltage side. Therefore, power flows from the generators, which are connected, to the low voltage side of the network, to the high voltage side [30, 31]. Researchers [28] have argued that using various distribution and generation models with bidirectional power flows can affect power supply quality and voltage levels. Other impacts of PEVs on the distributed grid include increasing fault currents leading to bugs in the network protection system and phase imbalances (specific to single-phase applications). Using a power electronics controller, PEVs can communicate with a power system. These controllers usually include an on-board a.c to d.c converter which is coupled to the grid via a single or three-phase connector. In the power grid, PEVs are active loads in charging process that create extra demand on the network but also as generators when operating in regeneration mode. Therefore, the behaviour of PEVs in both modes, charging from and discharging to the power grid, should be analyzed further. As the number of PEVs grow they will significantly impact the grid, so well-designed PEV interface devices will be needed to minimise the effects of PEVs on the power grid's fault and security system [30].

A major concern associated with charging PEVs is the potential of exceeding the grid power and grid infrastructure capacities. In the case of a large amount of uncontrolled PEV charging, like a large number of PEVs charging concurrently, there is a substantial increase in power demand, which can be higher than the available local transformer power supply. This could cause transformer overload or higher than the current capability of the transmission and distribution grid infrastructures, leading to thermal over loading of conductors. Therefore, these impacts need to be quantified in order to preserve the reliability of the grid. Increased power harmonics related to PEV charging can create an additional impact on distribution grid transformers, which are widely distributed across different parts of the power grid. Thus, future distribution network planning needs to assess the PEV market uptake scenarios and adapt the local grids accordingly [32].

## 2.2 PEV charging standards

One of the fundamental entities in electric vehicle's applications is PEV charging. There are several charging levels for PEVs based the power capability and charging duration. These levels of charging identify slow or fast charging scenarios [27]. As Table 2.1 shows, there are three AC charging types based on their power level which are known as slow charging and there are two power levels for DC fast charging [33, 34].

Table 2.1: Charging level characteristics based on SAE J1772 standard

| Power level type | Voltage level | Current capacity [A] | Power capacity [kW] | Charging time for 100 km of PEV range |
|---|---|---|---|---|
| AC Level I- single phase | 120 V AC | 16 | 3.3 | 17 hours |
| AC Level II- single phase | 230 V AC | 32 | 7.4 | 3-4 hours |
| AC Level III- three phase | 400 V AC | 32 | 22 | 1-2 hours |
| DC Level I | 400-500 V AC | 100-125 | 50 | 20-30 minutes |
| DC Level II | 300-500 V AC | 300-350 | 120 | 10 minutes |

The charging time that each PEV can spend fully charging its battery depends on battery storage capacity and charging level characteristics (e.g. voltage and current rating). The recent development of a universal charging facilities by automakers in collaboration with the society of automotive engineers (SAE) integrates both AC charging and DC-fast charging solutions. In addition to the SAE standard, there is a charging standard known as CHAdeMO, developed by the Tokyo electric power company which has gained a considerable acceptance in the EV market [33].

For public charging of PEVs there is a need to establish charging infrastructure with structures, machinery, and equipment necessary and integral to support a PEV, including battery charging stations, and battery swap stations [35]. A battery charging station is defined as an electrical component assembly or cluster of component assemblies specifically designed to charge PEV batteries. A rapid charging station is defined as an industrial grade electrical outlet that allows for faster recharging of PEV batteries through higher power levels [35]. A battery swap station is defined as a fully automated facility that enables a PEV with an exchangeable battery to enter a drive lane and exchange the depleted battery with a fully charged battery through a fully automated process. In all the above infrastructure must meet or exceed any applicable state building standards, codes, and regulations [36].

Public facilities range from AC level 1 residential electrical outlets at local restaurants to DC fast charge facilities in a parking garage. These can be free to use or require payment. Distributed charging stations can be considered EV networks that are primarily owned and operated by private providers, but many local governmental entities have also installed chargers at libraries and other public facilities. According to the U.S. Department of Energy's Alternative Fuels Data Center, there are currently over 8,600 PEV recharging stations with over 21,000 charging outlets in the United States [36]. Finding the location of public charging stations is almost totally dependent on having access to the Internet or a smartphone with a location finder application. Some new PEVs with on-board navigation can display the location of charging stations, but the most up-to-date information is available on Internet websites or Internet-based smartphone applications.

Uncontrolled PEV charging in the EV network with the high penetration of PEVs can result in undesirable impacts on the stability of the power grid. In the next section smart charging schemes are discussed as an intelligent tool to control unexpected PEVs demands.

## 2.3 Smart charging

Smart Charging is a control mechanism that can be enabled by the grid, by charging point, or the vehicle itself, while a communication system interfaces with the charging process taking into account actual grid capabilities as well as customer preferences (Figure 2.1). As presented in [37], smart charging represents opportunities for the entire stakeholder group. For customers it can maximize convenience while reducing costs. Studies show that EV users prefer to charge their cars in a regular pattern, mostly at home or on the way back from work in the afternoon. If charging at home, they will probably use residential low-voltage grids as the primary charging point. However, PEVs have the potential to double household's power consumption in peak hours, so a significant and costly upgrade of the home grid may be required. If drivers charge their cars at public stations, a high-voltage power grid is likely to be preferred fast charging point, but during peak hours this may create an extra load on the power grid. However, in both scenarios, smart grid controlling, decrease extra peak hour loads on the power grid. To facilitate smart charging, customers should be informed about the role they can play in preventing excessive grid loads by adopting appropriate elastic/non-elastic charging behaviours. PEVs represent a new type of electricity load that will mostly be connected to the distribution grids at low/high voltage levels. As PEVs were not considered at the initial stage of network planning, they can cause serious network overloads. Smart charging considers network constraints in order to avoid overloading the grid [37]. If the charging is coordinated to make better use of the available grid capacity at off-peak hours, smart charging may reduce additional peak load to zero. It also has potential for optimizing the power grid utilization. Smart charging can also help to maximize their use of solar systems during the daytime before peak periods. This energy efficiency option could be very interesting for utilities [37].

As the area of the research in this thesis is about charging strategies for an EV network

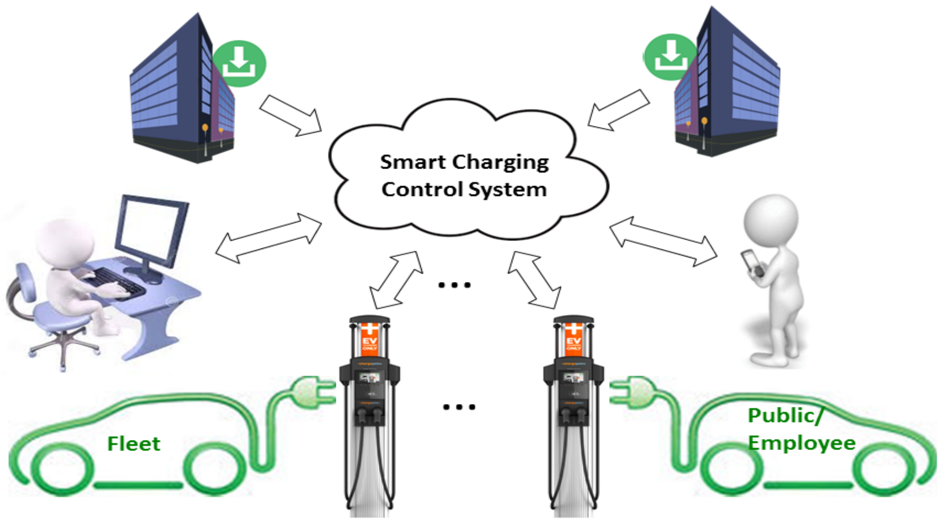



Figure 2.1: Smart charging control system overview [3].

of public charging stations, in the following sections some of the proposed smart charging strategies is reviewed.

### 2.3.1 Smart scheduling

Figure 2.2 shows the average afternoon traffic distribution as a percentage of the total vehicle counts, and a typical residential load profile in an urban area in New South Wales (NSW), Australia [38, 39]. It is evident that the period between 2 p.m. and 6 p.m. is the busiest, when most of the vehicles are on the streets. The load profile for a PEV charging network is expected to follow a similar trend, as most of the PEVs are also expected to be on the roads during this period and would need to recharge. This is analogous to traditional gas stations, where the load is generally high in the late afternoon. Figure 2.2 also demonstrates that there is an overlap between the daily residential peak load and the PEV load. This overlap would be a major challenge for the power industry since an extended period of overlap can put significant stress on both the generation and distribution sides of the energy industry. An uncoordinated charging strategy can result in a long queue at hotspot areas during busy period, which would increase the charging time (i.e., waiting time at a station plus time to recharge) and the overlap period between the PEV and the residential load. This challenge can be mitigated by introducing a smart charging strategy where the smart grid can collect real-time information about loads at various charging

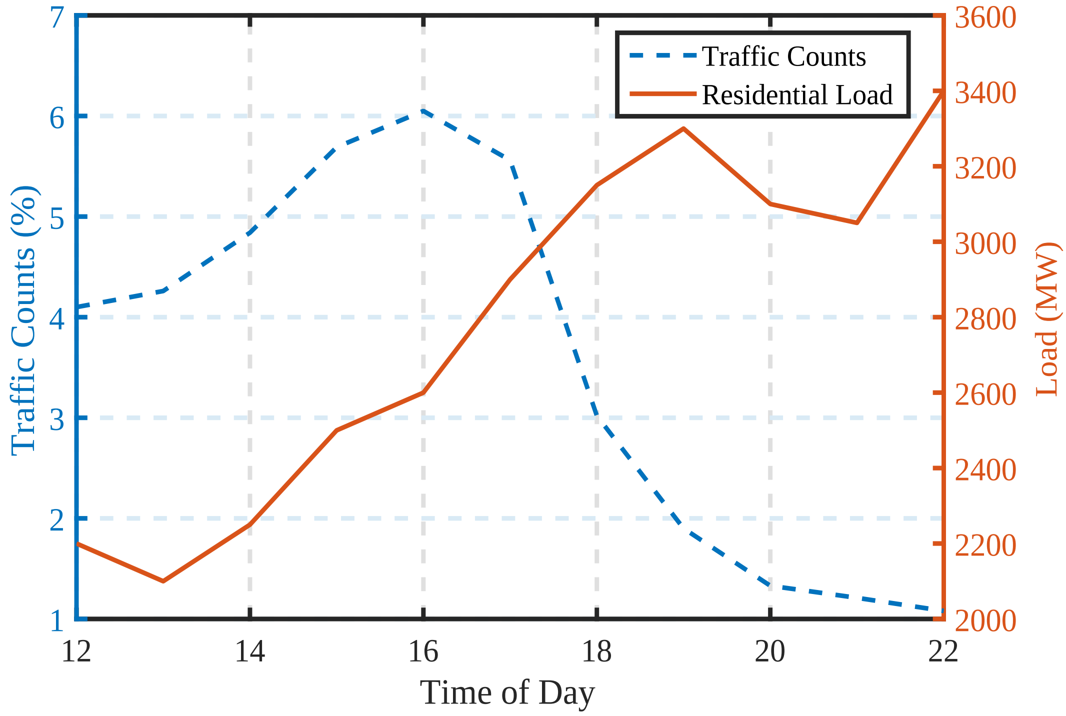



Figure 2.2: Traffic counts and residential loads in NSW, Australia

stations and pass this information to individual PEVs, enabling PEVs to come up with their charging plans (i.e., the optimum charging station along the route to the destination).

The relevant industries consider this delay to be a major challenge and are exploring all available options to reduce waiting time at public charging stations [40], commonly known as PEV networks. A smart charging strategy can make a major contribution to the efficient management of available resources in PEV networks. Recognizing the significance of smart charging in the context of PEV networks, researchers have investigated and presented various smart charging strategies in recent years, targeting the reduction of range anxiety and charging time [41]. However, a gap still exists in the literature as none of these previous works consider multiple charging and dynamic pricing options at charging stations in their PEV networks [42], [43]. In practice, a charging station, like a traditional gas station (selling petrol, diesel, LPG) can have multiple charging options with dynamic price information. A smart grid can collect important information about the current status (e.g., available number of sockets, queue status, price etc.) of every charging station in a PEV network. The grid can then provide this information in real-time to the individual PEV user [44], [45]. This information can be taken into account to calculate a path to the destination which would reduce both the time and cost of charging.

#### 2.3.1.1 Related research

Most of the established research [25, 46, 47, 48] on PEV charging strategies has focused on controlling residential charging patterns to avoid potential overloads, stresses, voltage deviations and power losses that may occur in distribution systems from domestic PEV charging activities. Some researchers [49, 50] have also investigated the simultaneous utilization of distributed renewable resources and PEVs to improve the performance of smart power distribution networks. Most recently, researchers have started to investigate charging strategies for public charging stations.

In [51], Amini *et al.* proposed a framework for interdependent power and electrified transportation networks that utilise the communication of PEVs with competing charging stations to exchange information such as electricity price, energy demand and time of arrival. While the framework solves an important problem in the area of optimal power flow and vehicle routing, Amini *et al.* do not consider multiple charging options and associated queuing models to address the problem of longer waiting times at charging stations. In [52], Shun-Neng *et al.* investigated the PEV charging problem and proposed two types of charging station selection algorithms: the first solution utilized only local information (e.g., SoC, geographical position etc.) relating a PEV and the second solution utilizing the global information obtained through interactions between the PEVs and charging stations server using a mobile telecommunications network. Their work demonstrated that the performance of the charging algorithm that used global information was better than an algorithm that used local information. However, their work focused on waiting time and did not consider the multiple charging option, cost and travel time.

In [53], Pourazarm *et al.* solved a path-finding problem within a graph of charging station nodes using a dynamic programming solution. They applied a grouping technique based on traffic flows with multi-vehicle routing to achieve the shortest path. This work, however, did not consider the waiting time and recharging cost at charging stations. Similar to the work presented in [53], Sweda *et al.* [54] introduced a recharging plan for PEVs to find a charging station with the shortest path. Their model was designed for an urban environment where the number of routes can be very large and the number of charging stations is limited. They proposed a pre-processing approach to save computations in an urban environment. Their work, however, focused on finding the shortest path based on the minimum travel time only. In [55], a distributed charging scheduling protocol was proposed to minimize waiting times in the charging stations. The authors used a theoretical approximation model which was based on the arrival rate of PEVs at each charging station and achieved a high performance in terms of waiting time. However, they did not consider a multi-server queuing system for different charging options. In addition, they did not consider the minimization of total travel time and recharging cost in their objective function. In [56], Gusrialdi *et al.* proposed an optimized charging strategy using a stochastic model for controlling the PEV arrival rate at charging stations in order to minimise the demand flow and the waiting time. However, they did not consider the impact of variable price and multiple charging options at a charging station.

Razo *et al.* in [6] proposed a smart charging approach to plan charging stops on highways with limited charging infrastructure. Using the coordination between the charging stations and PEVs, their approach focused on minimizing the waiting time at charging stations as well as overall travel time. Considering the complexity of the optimisation problem, they adopted a meta-heuristic (A* search) approach to find a solution. However, this work did not consider multiple charging options and price variation among charging stations in their model.

As discussed above, while researchers have introduced a number of smart charging strategies for PEVs, none of the existing studies presents an integrated solution that considers multiple charging options, waiting time, travel time and recharging costs. In Chapter 3, a smart charging strategy is introduced to focus on total travel time reduction, with different charging options at charging stations and also taking into account various prices for each charging option.

### 2.3.2 Dynamic pricing

Regarding the described challenge for the power grid represented represented in Figure 2.1, utilities have already expressed concerns over the possibility of facing an overlap between load and daily residential load periods. An extended overlap period is likely to put significant stress on both the generation and distribution sides of the energy industry [5]. The PEV load combined with increasing residential load during evening hours, commonly known as the "duck curve" problem, presents a major challenge (i.e., high peak-to-average demand ratio) for the energy industry. Researchers have been working to shift some loads from the evening hours to address the duck curve challenges [57, 58]. This motivates the researchers of this study to investigate charging strategies in EV networks, with mind to develop a coordinated dynamic pricing model for temporal PEV load shifting to reduce the PEV load during the evening hours.

Within the literature, various smart-charging strategies have been proposed to address the concerns raised by PEV owners and utilities. Most of these studies have been aimed at reducing the average waiting period and charging cost [59, 60, 6]. In our previous work [5], a solution is presented to reduce waiting time and charging costs. This in turn provides guidelines for PEV owners to assist them to select the best available CS based on the minimisation of distance, charging price and waiting time at the CS. The scope of the work presented in [5], however, does not include PEV load shifting and price coordination among CSs in an EV network. In this research, the authors show that price coordination among CSs can be an effective tool in balancing PEV load, which ultimately reduces the overlap between the PEV and residential loads.

The absence of price coordination within a charging station network leads to a non-uniform distribution of charging load across the CSs (e.g., long queues at hotspot areas whereas other CSs are not utilized to their maximum capacities). This results in under-utilization of the maximum capacity of the CS network; therefore, increasing the charging times and the overlap period between the PEV and residential loads. As a result, the PEV load during the evening hours can be high enough to cause network instability problem due to an increase in total load (i.e., residential peak load plus PEV load).

In a consumer-driven market, utilities are unable to directly deny services to PEV owners even when grid stability problems loom. However, PEV owner behavior can be influenced by adjusting the charging prices. Therefore, price incentives/signals can be used as important management tools in an EV network. Consequently, dynamic pricing has been an active area of research and researchers have made some important contributions in the literature such as [61, 62, 63, 64]. However, none of the existing solutions addresses the challenge of reducing the overlap between the PEV and residential load periods.

#### 2.3.2.1 Related research

In this section, previous studies related to the estimation of PEVs charging load, pricing models and PEV charging strategies is presented with emphasizes on reducing the overlap between PEVs charging and residential loads during peak hours. The authors of [21] presented a novel hardware design and implementation logic for a smart grid system to establish an interaction between PEVs and the power grid in order to ensure a safe and semi-stable load on the grid and minimize the cost. However, they focused on residential PEV charging without considering EV charging stations.

The electrification of transportation brings both opportunities and challenges to existing critical infrastructures [65]. For example, Wu *et al.* [66] addressed the challenges of energy scheduling in office buildings integrated with photovoltaic systems and workplace PEV charging for public users. They proposed to leverage day-ahead power market and time-of-use electricity, and used stochastic programming to address the uncertainties in PEV charging. They proposed a model to estimate the demands of charging a PEV at the workplace. However, there is limited flexibility for selecting a charging stations since they did not consider real-time pricing in their model and overlooked various charging options.

In [67], the authors presented a framework of PEV charging stations using the queueing model. They proposed a price strategy based on social optimal congestion which enforces the CSs prices to the customer in order to minimize the total latency of PEV users and total electricity costs of CSs. However, in their queueing model for CSs, they did not mention the charging rates and also they did not consider any load management of PEVs at peak hours.

There are also a number of industry projects [68] and research papers [69, 70] on fast charging stations with BSSs to store the purchased electricity from the grid at cheapest hours of a day and sell it to PEVs at peak hours. Sanzhong *et al.* [69] studied the power demand of the CS and proposed an optimum design of a fast-charging station equipped with BSSs. Similarly, Nargestan*i et al.* [70] have investigated the charging stations with BSSs but also estimated the optimum sizing of BSSs for controlling the charging demand. However, none of the existing literature discusses changing the price at CS and controlling the PEVs demand at peak hours.

Another important factor in managing a charging station is the power market. Similar to petrol stations, multiple CSs in the same area may belong to different owners, therefore competition between different CSs should be considered [71]. The authors of [72, 73, 74] have employed approaches based on game theory to model an interplay among multiple PEVs or between PEVs and power grid. They have established a competition system based on game theory for charging stations in terms of increasing CS profits; however, the impacts of traffic load of PEVs on the power grid at peak hours are not considered. Erol-Kantarci *et al.* [75] proposed a prediction-based charging scheme that receives dynamic pricing information via wireless communication, predicts the market prices during the charging period and determines an appropriate time of day to charge the vehicle at low cost. However their prediction-based charging scheme was based on a simple, light-weight classification technique which is suitable for implementation on a vehicle or a charging station. Therefore, they have not considered the impact of driving and charging patterns such as the increase in the demand for charging at peak hours in their charging scheme.

Junjie *et al.* in [76] presented two indirect methods for PEV management system in the power grid. They used market-based and price-based controls to minimize the communication cost and computational complexity. However, both control strategies have some limitations such as uncertainty of the price-based control strategy. Moreover, they did not present real-time verification of the proposed control strategies.

The authors in [77] developed an algorithm by controlling charging price and the number of vehicles to be scheduled as well as the charging/discharging of BSSs so that the charging station could achieve profit maximization. However, their work did not consider PEV load shifting. In [61], a price strategy for the economic operation of CSs equipped with the renewable resources has been proposed. In their proposed pricing model, they suggested a stochastic approach for dealing with the uncertainty of the renewable energy sources to make an optimal price decision in order to maintain the operational cost at the minimum level. In [64], Cherikad *et al.* proposed a distributed dynamic pricing model for PEVs charging and discharging scheduling and building energy management in a microgrid. Their model was based on a decentralized communication architecture and they used a linear optimisation approach to achieve the efficient price decision to maximizes PEVs utility, and maintains the microgrid stability.

The authors in [62] using a dynamic linear program for PEVs charging process, proposed a real-time price strategy for the CSs to minimize the cost of electricity purchased from the grid. However, temporal PEV load shifting was not the focus of this research.

As discussed above, although researchers have made important contributions in the areas of charging strategy, dynamic pricing, and load management, none of the existing solutions presents a coordinated pricing model to control PEVs demand at CSs and mitigate the extra stress on the power grid at peak hours, which is the main focus of Chapter 4.

### 2.3.3 Portable charging stations

As discussed in the previous sections, the anticipated challenges associated with increasing PEV numbers, are the long waiting times at fixed charging stations (FCSs) with impacts on actual road traffic patterns and electricity demand from utility networks. To resolve these challenges, several planning methods have been proposed.

Some of the proposed strategies for managing charging demand in FCSs are based on the estimation of traffic flow [60, 65, 66]. However, considering different driving patterns of PEVs and conventional vehicles, estimated data may not reflect the real charging demand of PEVs. Consequently, existing charging strategies based on PEV demand estimations may not be accurate and result in longer queueing times for charging at peak hours.

In recent studies [5, 78, 79, 59], different methods have been proposed to control charging demands in order to manage electricity balance of PEVs in FCSs and improve the stability of the power grid. However, these strategies have proposed solutions that manage uncoordinated PEV charging requests without considering their impacts on the power grid at peak hours.

In practical implementations, public charging stations would need to established to decrease concerns of range anxiety among PEV owners [17, 80, 81]. To establish a charging station effectively, a reliable interface to the distribution grid is required based on cooperation between provider and operator [82]. According to the flexible mobility of PEVs, charging stations can be categorized into two types: FCSs and portable charging stations (PCSs). FCSs usually feature fixed facilities built in specified parking lots while PCSs can move and they are not limited to an established fixed point [82]. PCSs have emerged as a way to deliver extra capacities for EV networks and also to give emergency charging to PEVs when they are out of charge.

The PCS power source comes in the form of battery storage installed on the back of a truck type vehicle and utilizing the back compartment, side panel and the dashboard [82]. Capacity and charging rate are two main factors for selecting suitable batteries for PCSs in order to effectively charge PEVs. One of the most promising batteries in this context are lithium batteries which are light weight, have high energy density, high specific energy and high specific power. In ultra capacitor consideration, the most appropriate is electric double-layer capacitor because of its high power density. The combination of these two energy storage can conduct all ac and dc charging levels [83, 52].

The distinct advantages of PCSs over FCSs are [84]: a) Establishing FCS are limited by construction cost, maintenance cost, site size, power grid capacity, etc [84]. While, there are fewer requirements for the sizing and allocating/dispatching of PCSs due to their portability and flexible capacities; b) PCSs do not rely on the power grid and can effectively reduce the overall PEV load demands particularly during peak hours; c) Considering the portability of PCSs, service providers can optimize their placements near hotspot areas based on the PEV charging demands to minimize cost of energy while also reducing the stress on the power grid; and d) Unlike FCSs, the whole charging process of a PCS is supervised by a trained technical staff that will help to reduce possible failure rates and improve the user's experience.

#### 2.3.3.1 Related research

The scope of research in adopting PEVs in the EV network is growing rapidly. There is a lot of research which proposes smart charging strategies based on real-time information of users and charging stations, to control charging loads. Some of these propose optimum routing strategies to to manage PEV traffic in an smart way in order to decrease cost and increase the stability of the grid by the coordinate charging loads [5, 85, 86, 6]. Another effective method in controlling charging demand of PEVs is dynamic pricing strategy which depends on the user's response to the pricing strategy in order to control PEVs loads on the grid, specifically during peak hours [77, 87, 62]. Although most of these research aimed to solve the non-stability of power grid by controlling the PEV charging load, there still exists queues at charging stations in hotspot areas during peak hours. This is a major challenge as it can overlap with residential peak loads and cause serious issues of instability in the power grid.

In addition to proposed charging strategies for better management of PEV loads in the EV network, in this thesis, a new architecture of EV networks is proposed that include the portable charging stations to the existing EV network to reduce the increase on peak demand.

There are a few studies that have investigated using PCSs as an alternative for charging PEVs. Yang *et al.* in [88] have proposed mobile charging stations in order to minimize waiting times. However, whilst mobile charging stations may provides users with better waiting times than fixed charging stations, but they have not considered the specific temporal load shifting of PEVs demand during peak hours. In [17], the authors propose a portable charging service in urban areas that considers queueing-based analysis to assign the PCS to the nearest PEV request in their coverage area. Although they evaluated their proposed model based on real traffic data, but they failed to consider controlling charging demand in hotspot areas during peak hours as a main objective. Qi Liu *et al.* in [84] investigated the portable charging facility to recharge PEVs and proposed their scheduling strategies based on user charging behaviour to increase the charging efficiency in both waiting times of PEVs and load rats of stations, however they only considered PCSs without including fixed CSs and also they did not account for the peak load shaving in hotspot areas.

Relevant industries have also considered portable charging stations as an emergency option to charge PEVs in city areas. Based on the information in [89, 90, 91], the investment of charging station providers on the portable charging facility has been already begun. These providers are going to develop this idea, with the aim of decreasing the cost of energy by using portable instead of fixed charging infrastructures.

Based on the above literature review, using portable charging stations is still a relatively new concept. As none of the literature specifically considers influencing PEVs demand at CSs to mitigate the extra stress on the power grid during peak hours, that is the main goal of Chapter 5.

## 2.4 Research questions

As discussed in Section 2.3 several smart charging research projects have already been conducted; however there has been insufficient depth of analysis on controlling charging of PEVs to prevent extra power grid peak load. Smart Grids with measuring devices and a communication infrastructure, among other devices, should help to solve the problem of uncoordinated charging and irregular load on distribution grids. This thesis targets the different smart charging strategies to prevent the peak load period for PEV charging from overlapping with the residential peak. After reviewing the existing literature which have been investigated in the previous section, this thesis asserts that there are still unanswered research gaps in the area of smart charging for electric vehicles charging stations. Therefore, the following research questions are addressed in this thesis:

- What is the best approach to adopt a charging strategy that identifies the most suitable charging station for a PEV user, so that the users can recharge at the minimum cost and reach their destination without a significant delay? In Chapter 3 of this thesis, the research challenge is modeled as a multiobjective optimisation problem where the goal is to reduce charging time, travel time, and charging cost. A queuing model has been applied to estimate the delay at various charging stations.

- How PEVs demand can be controlled in response to charging prices at various charging stations in order to reduce overlaps with the residential peak load periods? In Chapter 4 of this thesis, a new coordinated dynamic pricing model is introduced, implemented and evaluated for vehicle charging in EV networks. Additionally, a rule based heuristic solution is presented to address the dynamic pricing challenge in real-time. The proposed solution is included in a charging strategy, which is then implemented using an ACO model for bench-marking.

- How can an alternative option for the fixed charging stations can be implemented to alleviate power grid stress from extra peak loads? In the Chapter 5 of this thesis, the research question is modeled as an assignment problem of PCS problem in the specified locations in the proposed EV network in terms of a constrained optimisation problem. Then a heuristic solution to solve the NP-hard optimisation problem has been proposed which can significantly reduce the average PEV waiting times and decrease the overlap between PEV and residential loads during peak hours in the EV network.

## 2.5 Concluding remarks

This chapter has provided an outline of the relevant research undertaken to develop the smart charging strategies that take into account minimizing the overlap between PEVs and residential loads during peak hours. In this context, this chapter has presented an overview of the impacts of PEVs charging integrated into the power grid, charging infrastructures, smart charging solutions for small PEVs. Several challenges related to increasing PEVs loads during peak hours have also been discussed. Finally, this chapter has identified several gaps in the existing literature and set out the key research questions of the study. Chapter 3 will present the smart charging strategy considering the optimum routing strategy for PEVs to charging station.

# Chapter 3

# SMART CHARGING STRATEGY FOR ELECTRIC VEHICLE CHARGING STATIONS

In this chapter, a smart charging strategy for a PEV network is presented that supports multiple charging options at its charging stations. Multiple charging options as a multi-server queuing system is modeled in order to estimate the waiting time for each charging option at a charging station. The queuing system is presented in detail in Section III. The optimal charging station-finding problem also is presented as a multi-objective optimisation problem where the objective is to minimize the travel time, waiting time and charging cost. The optimisation problem and related constraints are presented in the last part of this Section. Considering the industry demand for a robust solution, the problem is extended as a meta-heuristic optimisation problem. A detailed description of the meta-heuristic solution is presented in Section IV. The main objectives of this chapter, can be summarized as follows:[1]

- Introducing a smart charging strategy that considers multiple charging options and relevant price information at each charging station in a PEV network. The research question is modeled as a multi-objective optimisation problem, and reflecting the need for a real-time solution, als a meta-heuristic solution is presented.

- Presenting that dynamic price variation at charging stations can be a useful mechanism to control the average charging time, which ultimately can prove pivotal in reducing the overlap extension between the PEV and residential peak load periods.

[1]The presented chapter has been published as: Moghaddam, Z., Ahmad, I., Habibi, D., Phung, V., (2018), Smart Charging Strategy for Electric Vehicle Charging Stations. IEEE Transactions on Transportation Electrification, 4(1), 76-88, IEEE, DOI: 10.1109/TTE.2017.2753403.

- Verifying the significance of the proposed solution by using a computer simulation on a Washington City PEV network.

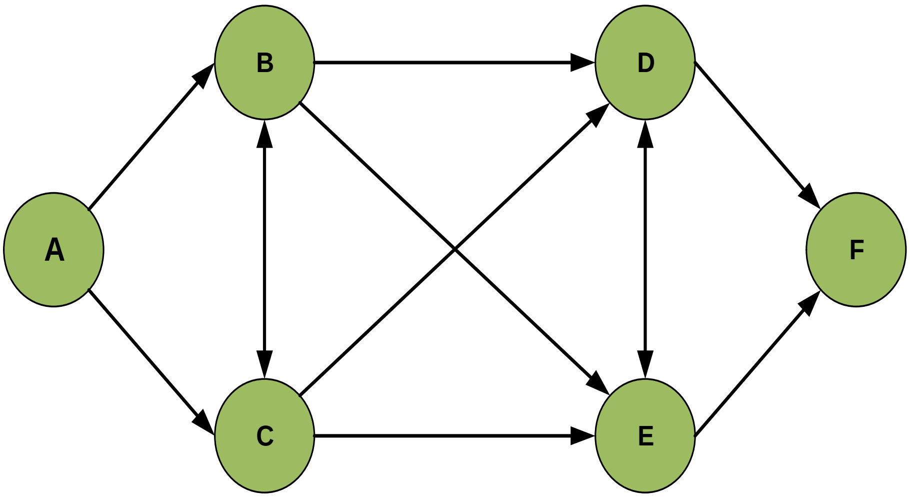



Figure 3.1: A graph representation of a PEV network

## 3.1 System Model

A PEV network can be considered as a weighted directed graph $G = (V,\ E)$, where $V$ is the set of charging stations which is denoted as $j:\ (j = 1...N)$ and $E$ is the set of connecting paths between the nodes as shown in Figure 3.1. Each charging station provides three charging options: i) DC fast charging, ii) AC level 2 charging and iii) battery swapping facilities [92]. Each charging option has a queue, and each queue has a specific service rate, waiting time and price. The queue length is influenced by factors such as PEV arrival rates, and service times (i.e., time to fully recharge). The queue length is an important parameter as it determines the waiting time before the actual service is offered. The PEV arrival rate is also partially influenced by price information. In our system model, each PEV indexed by $i$ at a time instant $t$ can be attributed by its current state of charge $SoC_i(t)$, current location $S_i$ and intended destination $dst_i$. All charging stations and PEVs are connected to the smart grid and can exchange information in real-time. If a PEV plans to go from a source to a destination node and its current $SoC$ suggests that it will not have enough stored energy, it will have to recharge at a charging station. A PEV driver may also prefer to charge at a faster rate from a fast charging station instead of using the slow charging facility at his/her accommodation. The research question then translates into finding the optimum charging station that does not significantly increase the travel time to the destination and offers the best price for recharging.

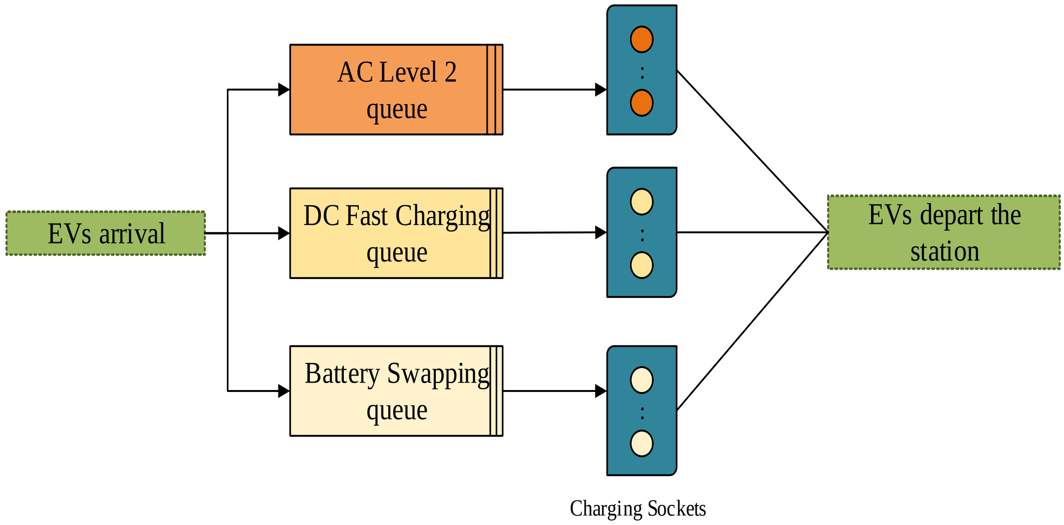



Figure 3.2: The $M/M/s/C$ queuing model for a charging station

For a PEV, the total travel time depends on the time required to reach the charging station, the time spent waiting in the queue for the preferred charging option, service/charging time and time required to reach the destination. As such, following sub-sections show how to model and calculate the total travel time taking the queuing delay and charging cost for each charging option into account.

*1) Driving Time from Source to Destination*

For a PEV at a time instant $t$, if $T^{drive}(s,\ dst)$ indicates the driving time from its current location $s$ to the destination $dst$ and $j$ indicates the charging station along the way, then $T^{drive}(s,\ dst)$ can be obtained by:

$$T^{drive}(s,\ dst) = \frac{D(s,\ j)}{v(s,\ j)} + \frac{D(j,\ dst)}{v(j,\ dst)} \tag{3.1}$$

where the first term of the above equation is the time required for the PEV to travel from its current location to the charging station and the second term states the travel time from the charging station to the specific destination. Here, $D(s,\ j)$ and $D(j,\ dst)$ indicate the route distance from the source to the charging station and the charging station to the destination, respectively. $v(s,\ j)$ and $v(j,\ dst)$ indicate the average moving speed of the PEV from its source to the charging station and the charging station to the destination, respectively. To make sure that the PEV does not run out of charge before reaching the charging station, $D(s,\ j)$ must be less than $D^{max}$, the maximum distance that the PEV can travel based on its current $SoC$. The maximum distance that the PEV can travel based on its $SoC$ at a current time $t$, can be given by:

$$D^{max}(t) = \frac{E^{ca} SoC(t)}{E^{Travel}} \tag{3.2}$$

where $E^{ca}$ is the total capacity of batteries in PEV, and $E^{Travel}$ represents its energy consumption per unit of traveling distance. In addition to the net driving time as indicated by Eq. (3.1), the PEV would have to wait in the queue at a charging station before it obtains access to the desired facility. The waiting time in the queue at a charging station can be estimated using a queuing system which is presented in the next section.

*2 ) Queuing Model for a Charging Station*

Figure 3.2 shows the queuing system used for charging stations with multiple charging options in our model. To estimate the waiting time for each charging option at a station, the $M/M/s/C$ model is used [93, 19], where the letters have the following meaning:

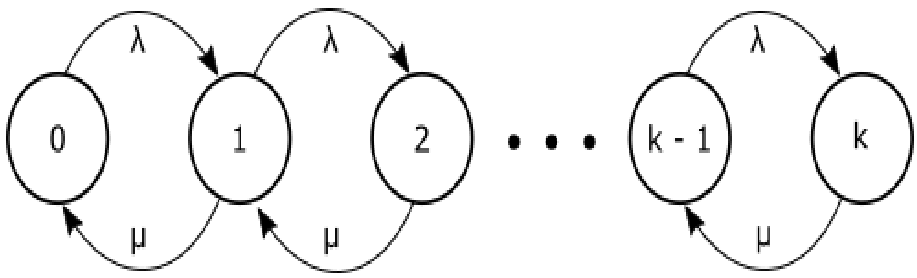



Figure 3.3: The state transition diagram of the $M/M/s/C$ queuing system

- the first $M$ (Markov): Markovian (exponential) PEVs arrival time distribution
- the second $M$ (Markov): Markovian (exponential) charging time distribution
- $s$: the number of servers
- $C$: the system capacity ( the number of PEVs that can be parked at the station).

Every PEV that arrives at a station can immediately recharge if there is an available socket in the charging station. If all the sockets are busy, the PEV needs to wait in a queue until a socket becomes available. In this study it is assumed that each charging station has three queues, one for each charging option. PEVs in each queue are served by $s$ servers. Each server operates with an exponential service rate $\mu_j^k$ facilitated by a socket. The PEV arrival process at a charging station follows a Poisson distribution with a mean arrival rate $\lambda_j$. The service rates are constrained by the infrastructure (i.e., sockets and charging rates) whereas the mean PEV arrival rate during various hours of the day can be derived from historical data. A smart charging strategy that influences the route selection decision can have an impact on arrival rates at a charging station. However, the traffic/load analysis based on the data collected over a period of time is expected to capture this impact. Based on the principle of Markov chains [94], the state transition diagram for the $M/M/s/C$ queueing process can be derived and depicted as shown in Figure 3.3, where each state of the chain corresponds to the number of PEVs in the queue. When new PEVs arrive or a PEV recharges and departs the station, the queing process moves to a different state. This state transition is essentially a stochastic process with $X_r$ being the random variable that represents the value of the chain at step $r$. This stochastic process with state space $\xi = \{1,\ 2,\ 3,\ ...\}$ exhibits the property of a Markov chain because of the $P(X_{r+1} = j|X_r = i, X_{r-1} = x_{r-1}, ..., X_0 = x_0) = P(X_{r+1} = j|X_r = i)$ attribute.

The state transition probability matrix $P$ for the above mentioned stochastic process can be given as Eq. 3.3 [95, 96] :

$$P = \begin{bmatrix} -\lambda & \lambda & \cdots & & & \\ \mu & -(\lambda+\mu) & 0 & \cdots & & \\ 0 & 2\mu & 0 & 0 & \cdots & \\ 0 & 0 & \lambda & 0 & 0 & 0 \\ \vdots & & & & & \\ & & \ddots & & & \\ & & & (c-1)\mu & -(\lambda+(c-1)\mu) & \\ & & & & c\mu & \lambda \\ & & & & & \ddots \end{bmatrix} \tag{3.3}$$

**Definition 3.1.** In the probability matrix $P$, $P^T.\pi^T = 0^T$, where $\pi$ is the row vector that contains the stationary distributions. Assuming the occupancy rate with $\rho = \lambda/c\mu$, the $r^{th}$ stationary distribution can obtain by:

$$\pi_r = \pi_0 \frac{\lambda^r}{n!\mu^r} = \frac{(c\rho)^r}{r!}\pi_0 \tag{3.4}$$

and reaching the system capacity $C$, the capacity for each station which is shown by $c$:

$$\underset{r=0,1,2,\ ...,\ c+r=C}{\pi_{c+r} = \rho^r \pi_c = \rho^r \frac{(c\rho)^c}{c!}\pi_0,} \tag{3.5}$$

Now if $\sum_{p=0}^{\infty} \pi_p = 1$, the $\pi_0$ stationary distribution is:

$$\pi_0 = \frac{1}{\sum_{i-0}^{c}(\frac{1}{i!}\left(\frac{\lambda}{\mu}\right)^i + \sum_{j=c+1}^{R}\frac{1}{C^{j-c}})(\frac{1}{c!})\left(\frac{\lambda}{\mu}\right)^i} \tag{3.6}$$

Using this formula, also the mean queue lengths for each queue is obtained by:

$$E(L_q) = \sum_{k=c}^{R}(p-c).\pi_p \tag{3.7}$$

where $\pi_p$ is the $p^{th}$ stationary distribution. After substituting the proper values and simplification of the equation, queue length can be given as:

$$E(L_q) = \pi_0.\frac{\rho(c\rho)^c}{c!(1-\rho)^2}\left[1-\rho^{R-c}-(R-c)\rho^{R-c}(1-\rho)\right] \tag{3.8}$$

Using the Little law at each charging station for three types of charging options, the mean waiting time at each queue can be given as[97, 98, 99] :

$$\overset{\forall o:(o=1,\ 2,\ 3)}{E(W_j^k) = \frac{E(L_j^o)}{\lambda_j(1-\pi_j^R)}} \tag{3.9}$$

Therefore, for the queue corresponding to the battery swapping facility at a charging station $j$, the mean waiting time is calculated as follows:

$$E(W_j^1) = \frac{\mu_j^1}{\lambda_j(\mu_j^1-\lambda_j)(1-\pi_j^R)} \tag{3.10}$$

for the DC-fast charging queue, the mean waiting time is calculated by:

$$E(W_j^2) = \frac{\mu_j^2}{\lambda_j(\mu_j^2-\lambda_j)(1-\pi_j^R)} \tag{3.11}$$

and for the AC-normal charging queue, the mean waiting time is calculated by:

$$E(W_j^3) = \frac{\mu_j^3}{\lambda_j(\mu_j^3 - \lambda_j)(1 - \pi_j^R)} \tag{3.12}$$

*3) Charging Cost for a PEV with a Specific Charging Option at the Charging Station*

The charging cost of each PEV depends on its associated charging option and the associated charging rate at the station $j$. For a PEV, the charging cost is calculated through the formula below:

$$C_j^{recharge}(o) = ((d_{charging} Pr_k)\ j \in J \tag{3.13}$$

where $d_{charging}$ is the charging demand of each PEV, which depends on the remaining and target $SoC$ for each PEV:

$$d_{charging} = \sigma E - SoC \tag{3.14}$$

Here, $\sigma$ is the coefficient for partial charging, which can vary from the current $SoC$ to the maximum $SoC$ (e.g., 90% battery capacity). Under normal circumstances, most users would prefer full charging (i.e.,$\sigma = 0.9$). However, during peak-hours a preference for full charging would lead to longer waiting times. Longer waiting times can stretch the PEV peak period and make it overlap with the residential peak period. Partial charging (i.e., $\sigma < 0.9$) can encourage users to postpone their full charging process and depart the queue early. Partial charging can be influenced by a suitable dynamic pricing model, and together, these measures can provide an effective solution to the problem of longer waiting times during peak hours.

## 3.2 Proposed Model

The objective of the proposed charging strategy is to find a charging station along the path such that the total travel time - including driving time from current location to destination, waiting and charging time at a charging station - and the charging cost are minimized. Mathematically, considering equations (3.1), (3.9) and (3.13), the objective of our charging strategy can be modeled as: for $\forall i \in I$ find a charging station $j$ that minimizes total travel time and recharging cost, as below:

$$min[x(T^{drive}(s,\ d)) + yT_j^{wait}(o) + zC_j^{recharge}(o)] \tag{3.15}$$

where $x$, $y$ and $z$ are the positive coefficients of the objective function.

s.t.

$$T^{drive}(s,\ d) \leq ((E^{ca}SoC(t))/E^{Travel})/v(s,j) \tag{3.16}$$

$$T_j^{wait}(o) <= T_j^{max\_wait}(o) \tag{3.17}$$

$$SoC_{min} \leq SoC(t) \tag{3.18}$$

$$\forall j \in J \sum_{i=1}^{M} E^{ca} \leq E_j^{ca}, \tag{3.19}$$

$$E_j^{ca} < E_{ca,\ grid}^{max} \tag{3.20}$$

In the optimisation problem, the summation of driving time from source to destination, waiting time at the station for a specific queue, and charging cost for each $PEV_i$ at a charging station $j$ should be minimized. Constraint (3.16) shows the constraint for the driving time from the current source to a charging station, which is explained in Eq. (3.2). In constraint (3.17) the maximum waiting time for each queue at charging stations is presented. This should be less than the maximum waiting time at each charging station for different charging options. Constraint (3.18) indicates that initial amount of $SoC$ for a PEV at charging station $j$ should be greater than $SoC_{min}$. An additional constraint is defined in Eq. (3.19), which states that the summation of the charging power capacity for all PEVs at a charging station should be less than the maximum capacity of that charging station, and constraint (3.20) considers the maximum grid capacity for each charging station.

## 3.3 Smart Charging Strategy Using Metaheuristic Algorithm

In the previous section, the proposed smart charging strategy formulated as a classical optimisation problem. However, the optimisation solution is NP-hard due to the path discovery mechanisms [97]. This motivated us to further investigate the research problem and find a heuristic solution.

### 3.3.1 Ant Colony Optimisation (ACO)

ACO is a category of swarm intelligence that analyzes the survival behavior pattern of the insects in solving complex optimisation problems [98]. ACO is a widely recognized meta-heuristic approach and has been successfully used across diverse domains, including vehicle routing and scheduling [100, 101, 99, 102]. The main characteristic of ACO is that every single ant in a colony can construct a possible solution by considering both heuristic and stochastic information and exchanging that information with the ants and the environment [98]. The collective intelligence gathered from a group of ants traveling along alternate routes leads to the identification of an optimal route [54, 103]. As a description of the ACO algorithm, consider a colony with $m$ ants that iteratively exploits the graph and searches for feasible solutions to the problem. At each iteration $u$, an ant $k$ moves stochastically, based on a constructive decision policy which uses the information of pheromone trails and attractiveness to obtain the probability for choosing the next node, as below:

$$P_{ij}^{k}(u) = \frac{\tau_{ij}(u)^{\alpha}\eta}{\sum_{l \in N_i^k} \tau_{il}(u)^{\alpha}\eta} \, \text{if} j \in N_i^k \tag{3.21}$$

Here $N_i^k$ is the set of feasible neighborhood nodes in the graph. For a node $i$, a set of feasible neighborhood nodes indicates that the list of nodes that are directly accessible from node $i$ and candidates for searching based on the heuristic information. Nodes that are in the feasible neighborhood set offers a better chance of finding the optimum solution [101, 104], $\tau_{ij}(u)$ is the sum of pheromones deposited between nodes $i$ and $j$ which denotes the desirability of the move between the nodes; $\eta_{ij}$ is heuristic information which specifies the attractiveness of that move, and $\alpha$, $\beta$ are parameters which control the relative weight of pheromone and heuristic information. During the completion of a tour, each ant deposits the pheromone information on the respective edges of its path. There is a rule for updating pheromone information, as below:

$$\tau_{ij}(u+1) = \rho\tau_{ij}(u) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(u) \quad \forall(i,\ j) \tag{3.22}$$

where $0 \leq \rho \leq 1$ is the pheromone evaporation rate, which causes the pheromone value to decrease over time to prevent a local optimum, and $\Delta\tau_{ij}^{k}(u)$ refers to the inputs of ants between nodes $i$, $j$. Consequently, each ant moves through those nodes similar to its partial solution. Although the convergence properties of the ACO algorithm have been proven, the probabilistic decisions depend on the problem-definition and user preferences [98]. For the proposed objective function, the routing algorithm should consider the lowest travel time, the lowest recharge cost and the lowest waiting time at each station, as the heuristic information.

ACO is not only sensitive to the number of variables but also runs faster, which is an important ability in relation to solve dynamic vehicle routing and refuelling problems. ACO is a probabilistic search algorithm which has specific characteristics, considering the problems in terms of the heuristic information in the probabilistic decision, and the strategy of updating the pheromone trail in the path is based on the search objectives [99], [103].

### 3.3.2 Proposed Smart Charging Strategy using Ant Colony Optimisation

The main reason for choosing ACO in our proposed scenario is that using the heuristic information in the ACO algorithm our model can estimates the minimum travel time and charging cost at every node of the graph to accelerate the computation. With the arrival of a new PEV every neighbor exploration allows us to test for the defined constraints and exclude non-feasible alternatives at the first stage. However, the conventional ACO algorithm keeps track of the variable it aims to minimize along the entire search. In the proposed model, the smart-strategy in Algorithm. 3.1 is iteratively called up to provide up-to-date information to the PEV driver. As information is shared between the smart grid and a PEV driver, the following processes occur:

**Algorithm 3.1** ACO algorithm for the smart charging strategy

**Require:** Graph Of Charging Stations, Charging Station Specifications, PEVs Specifications, $SoC$ , Destination Coordination;
**Ensure:** optimum path, $P$
SetAdjustableParameters ($G$, $PEV$, $t$, $\alpha$, $\rho$, $\tau$, $\beta$, $SoC$, $\eta$, $CS$);
Initialize ($t$,$counter$,$iteration$);
t: time slot;
Set $t \leftarrow 0$;
**while** maximum iteration is not met **do**
$t \leftarrow t + 1$;
Initialize $\tau_{global}$;
**for** each node j of graph $G$ **do**
**if** $j$ is in graph $G$'s selected path **then**
Call function of driving time;
Call function of waiting time;
Call function of charging cost;
$P_g \leftarrow 0$;
**else**
**for** each ant $n$ **do**
Initialize $\tau_{local}$ ;
**for** $P \leftarrow 1$ to $G$ **do**
**while** constraints are not met **do**
$g \leftarrow \eta_{Pg}$(t);
$x^n_{Pg} \leftarrow link(Pg)$;
**end while**
Update $\tau_{local}$;
**end for**
**end for**
Sort (RouteSolution($N$)) ascendingly;
$I^p_{best}(t)$= RouteSolution(1);
Update $\tau_{global}$;
**end if**
**end for**
**end while**
Update Information ($PathInfo, \mathcal{P}$);

- Loading initial information: the modified ACO algorithm receives as input a graph describing all possible paths, the current $SoC$ of the PEVs battery, the maximum energy consumption of the PEV, the coordination of the source and destination, the colony number, the number of ants in each colony, the initial pheromone level and the coefficient of the creation and evaporation of the pheromone.

- Selecting specific heuristic information to obtain the probability distribution function: In a conventional ACO algorithm, for calculating the probability distribution in Eq. 3.21 only the pheromone and one heuristic value (distance) are considered. In the smart charging strategy, since PEVs look for an optimum path in terms of minimum travel time and charging cost, a modification is used to maintain the driving time, waiting time and charging cost as a set of heuristic information. Considering the three objectives in the aforementioned objective function, the ACO algorithm for each $j \in N_i^k$ can be implemented with the Eq. 3.23:

$$P_{ij}^k(u) = \frac{\tau_{ij}(u)^{\alpha}[(T^{drive}(s,d))T_j^{wait}(o)C_j^{recharge}(o)]^{\beta}}{\sum_{l \in N_i^k} \tau_{ij}(u)^{\alpha}[(T^{drive}(s,d))T_j^{wait}(o)C_j^{recharge}(o)]^{\beta}} \tag{3.23}$$

where the variables $\tau_{ij}(u)$, $T^{drive}(s,\ dst))$, $T_j^{wait}(o)$ and $C_j^{recharge}(o)$ are the pheromone intensity, driving time, waiting time and charging cost of a path. The parameters $\alpha$ and $\beta$ are constants, which determine the relative influences of the pheromone and heuristic parameters on the PEV's decision. For the probability distribution, there is a trade-off between the three objectives. The process of finding an optimum path is described in the following:

- Pheromone initialization: Collect the possible solution at each iteration and update the pheromone values using the general Eq. (3.22), $\tau_{ij}(u+1)$ symbolizes the pheromones of a vehicle moving from the current location $s$ to a destination $d$ or stopping at node $j$ for charging during time period $(u+1)$ with the objective of minimizing travel time. Here, the updated value of the pheromone is a function of time and is controled by the number of PEVs on each route.

- Generate the best possible path: This step uses the modified ACO algorithm which is described in algorithm 3.1 for the PEV network which receives as input a graph describing all possible paths including charging stations, the source and destination nodes, and the *SoC* of the PEVs. Each time a neighbouring node is explored, the function Feasible_nodes is responsible for selecting feasible nodes from the graph with a calculation of the distance from each current location to all charging stations, then using the output of this function (which is a set of feasible nodes, with function get_nodes and using sub functions w-time and cost-to-charge) the heuristic values can be obtained for calculating the probability function of the modified ACO. As illustrated in Figure 3.4, the first step is exchanging information between PEVs and charging stations using the smart grid panel in real-time. For planning and managing the charging strategy, the smart grid needs PEV components and the charging station's specifications. The next step uses our proposed algorithm to implement a charging strategy for PEVs along their trip. During this process, the algorithm needs to consider the capacity of each charging station and the lengths of the queues which are updated for all the iterations in the simulation. The analytical and numerical results are explained in Section V.

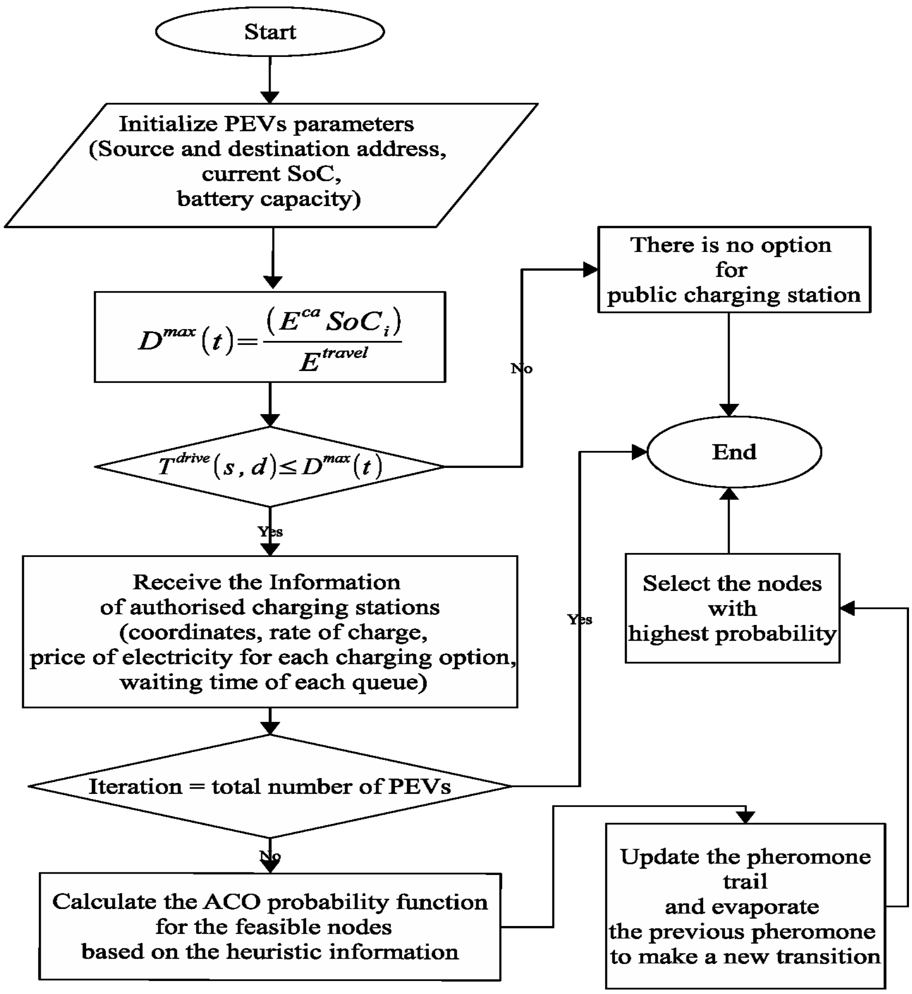



Figure 3.4: Flowchart of the proposed smart charging strategy

- Local pheromone update: While constructing the path decision solution, a local pheromone update is executed so that the visited path becomes less attractive, allowing the next PEV to explore other paths. This local update can be defined as:

$$\tau_{ij}(u+1) = (1-\rho)\tau(u) + \tau_{ij}^{l} \quad \forall(i,\ j) \in iter^{l} \tag{3.24}$$

where based on the ACO algorithm, for the local best solution at each local iteration, only the PEV which constructed the best solution is allowed to deposit the pheromone information. $\tau_{ij}^{l}$ is the incremental amount of the local updating phase for the local iteration.

- Evaluation of the tour: When the PEV arrives at the destination, for each PEV tour the optimisation function value (total travel time), denoted as drive-time in Algorithm 3.1 is calculated. The PEV tour that utilized the optimum path with the minimum travel time and charging cost among all the PEV tours that are found in the previous iterations is selected as the best tour.

- Global pheromone update: After a few iterations, each node is then able to estimate the potential path, regardless of the varying conditions of the model topology and the PEV traffic. In fact, the global pheromone update rule is only employed by a PEV that has constructed the best global solution so far and this update gives the PEVs more opportunities to explore the search space, thus balancing the need for exploration and PEV exploitation. The global pheromone update at each global best solution can be defined as:

$$\tau_{ij}(u+1) = (1-\rho)\tau(u) + \tau_{ij}^{g} \quad \forall(i,\ j) \in iter^{g} \tag{3.25}$$

where $\tau_{ij}^{g}$ is the incremental amount of global updating phase for the global iteration.


Figure 3.5: The Washington green highway PEV network [4]

## 3.4 Simulation and Results

### 3.4.1 Simulation Model

In the simulation, EV network of the Washington City road network along the driving route from Oregon to Vancouver, Canada is considered (Figure 3.5). The PEV network consisted of 28 charging stations, each equipped with two charging options (CHAdeMO Fast charger and AC level 2 charger) and a battery swap facility. For the simulation, 1000 PEVs comprising Nissan Leaf (30kWh), BMW i3 (22kWh) and Smart Ed (16 kWh) are used, with their $SoC$ modeled as a uniform distribution in the 10%~90% range. The PEV arrival at each charging station was modeled as a Poisson distribution. The number of sockets for a charging option at a station was distributed uniformly in the 1~10 range. For the fast DC charging option, each socket was assumed to supply 20 kW power [105, 106, 107]. For the AC level II option, each socket supplied 7 kW power [108] and the average time to swap a battery was considered as 3 minutes [109]). PEVs were assumed to travel at a maximum speed of 60 miles/hour, consuming 0.12kWh/mile [110]. The time of use (i.e., dynamic) tariff was modeled using an exponential function [111] with the minimum and maximum rate set as \$0.24 and \$0.46 [112, 113, 114], respectively. Price variation at different charging stations was implemented using a uniform distribution within the $-10$ to $+10$ range of the standard time of use tariff rate. The MATLAB platform is used to perform the simulation.

### 3.4.2 Results and Discussion

In this section, the average waiting time, travel time, charging cost and charging station queue occupancy are presented. The waiting time results from the time spent waiting in the queues plus charging time, whereas the travel time is made up of driving time plus waiting time. The queue occupancy parameter indicates the current occupied queue length expressed as a fraction of the maximum queue length at a charging station. The proposed solution is compared with the active scheduling, known as the AS model in the literature. In the AS model [6], the smart charging strategy is modeled as a meta-heuristic optimisation problem ($A^*$ search algorithm) where the goal was to find charging stations that reduced the travel time. The AS model, however, does not consider multiple charging options (i.e., does not include a queuing model) and the costs associated with recharging at a charging station. To the best of our knowledge, for a PEV network, the AS model is the most relevant and best performing smart charging solution available in the literature.

The discussion of the results begins with Figure 3.6, which shows the normalized average waiting time for PEVs at charging stations. The average waiting time over the travel time is normalized, i.e., the period of time a PEV has to wait at a charging station on average expressed as a fraction of the travel time. As the figure suggests, the average waiting time increases with the increasing volume of traffic. This is because for a bigger fleet of PEVs, more PEVs are required to share the limited charging facilities. The result, however, shows that the waiting time is significantly lower in the proposed solution compared to the AS model. This is because in our model, multiple charging options as a queuing model are implemented and considered the queuing delay for each charging option while selecting the best charging station for a PEV, which was missing in the AS model. In our model, information in relation to the queuing delay for each charging option at every charging station was communicated to a PEV, which allowed the PEV to make an informed decision while choosing the best charging station.

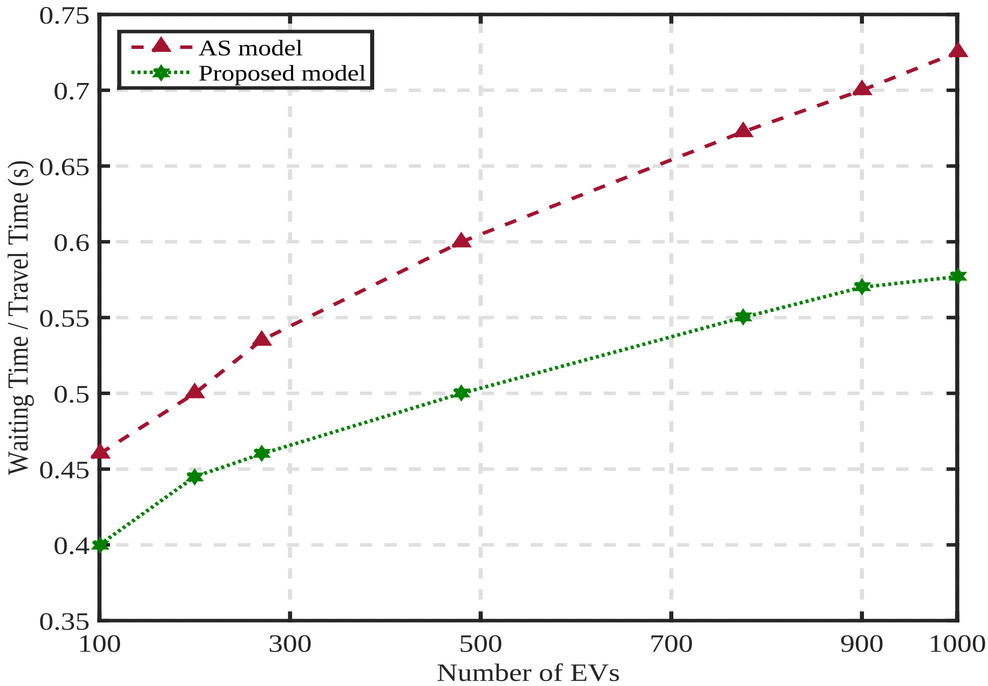



Figure 3.6: Normalized waiting time for different number of PEVs

Figure 3.7 presents a comparison of the average travel time in the proposed and AS models. It is evident that compared to the AS model, the proposed model reduces the average travel time. This is because in the AS model, many PEVs show up at charging stations (e.g., hotspot areas) where the queue lengths corresponding to their preferred charging options are too long, and PEVs are required to wait for a longer period before they can be served. In our proposed model, the waiting time corresponding to each charging option at a charging station is calculated based on the queuing model, which when communicated to the PEV users, can help them to make a better decision.

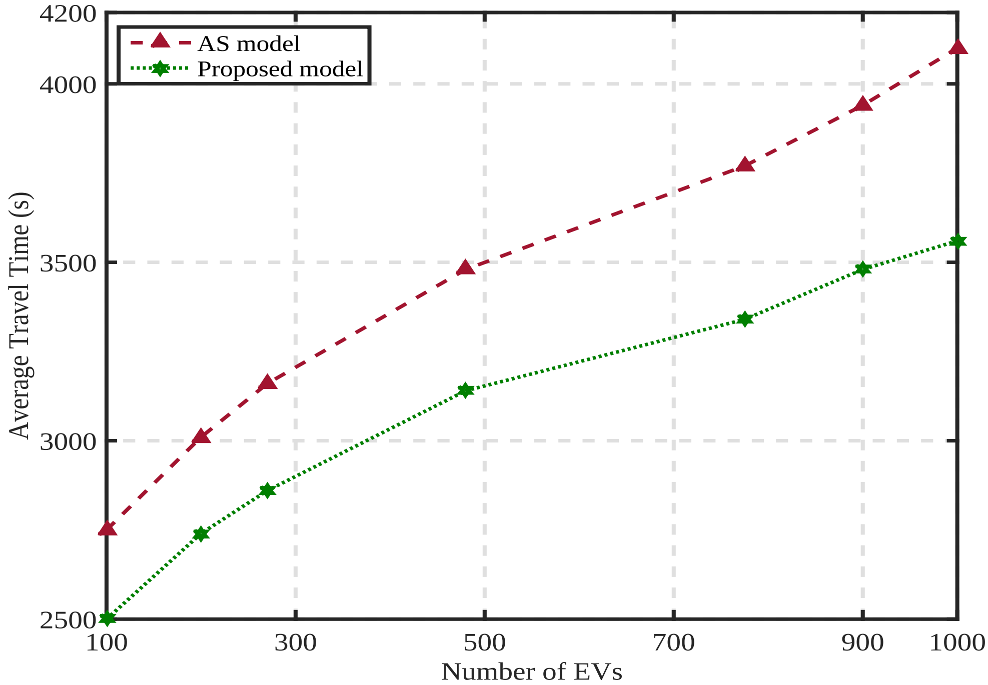



Figure 3.7: Average travel time for different number of PEVs

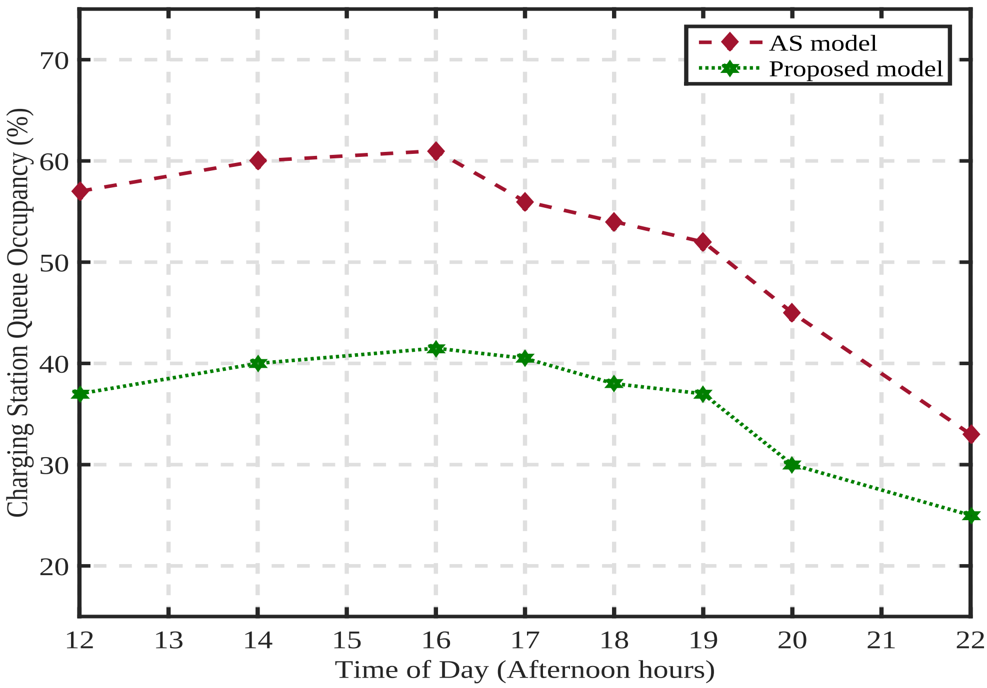



Figure 3.8: Charging station queue occupancy in hotspot areas

In Figure 3.8, the comparison of average queue occupancy at charging stations is demonstrated in hotspot areas (i.e., nodes with greater number of edges) for both models. It is apparent that the AS model results in higher average queue occupancy because the model does not use queue information specific to an individual charging type. In our proposed model, PEVs tend to distribute themselves more uniformly among the available charging stations, thereby reducing the pressure on charging stations in hotspot areas.

Just as gas/petrol prices vary from place to place, prices per charging option can vary between charging stations. In the proposed model, therefore considered the price per charging option at various charging stations, which ultimately generated a lower average charging cost. In Figure 3.9, the average charging cost during various hours of the day is shown. It is evident that because the price information is not taken into account while calculating the route in the AS model, the average charging cost in the proposed model is significantly lower than the average cost in the AS model.

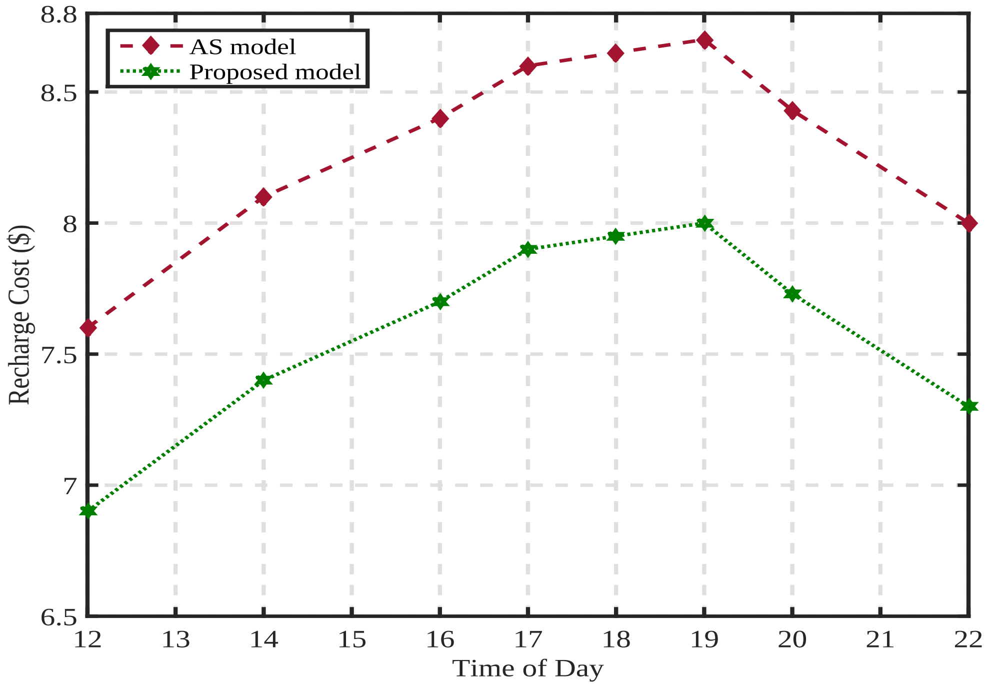



Figure 3.9: Average charging cost in AS and proposed model

Figure 3.10 illustrates the average waiting time during the peak PEV load period in response to dynamic charging prices. As shown in the figure, the higher price option encourages many PEV users to go for either partial charging or to avoid charging during the peak load period, making the average waiting time shorter. Since the ultimate decision in relation to the choice of time to recharge PEVs belongs to owners, a service provider cannot enforce a policy to not to serve/charge a PEV, even when it creates a problem for the grid. But the behaviour of PEV users can be significantly influenced by setting a suitable price so that both the users and grid can benefit.

As evident in Figure 3.11, in the proposed model, the average PEV load per charging station is higher during the busiest hour compared to the AS model. This is because the proposed model efficiently uses the available PEV charging facilities by providing information in relation to the queue length and price for the preferred charging options to PEV users. The reduced average waiting time achieved by the proposed model also causes the PEV load curve to decline at a faster rate, making energy management for the residential load less challenging for the grid.

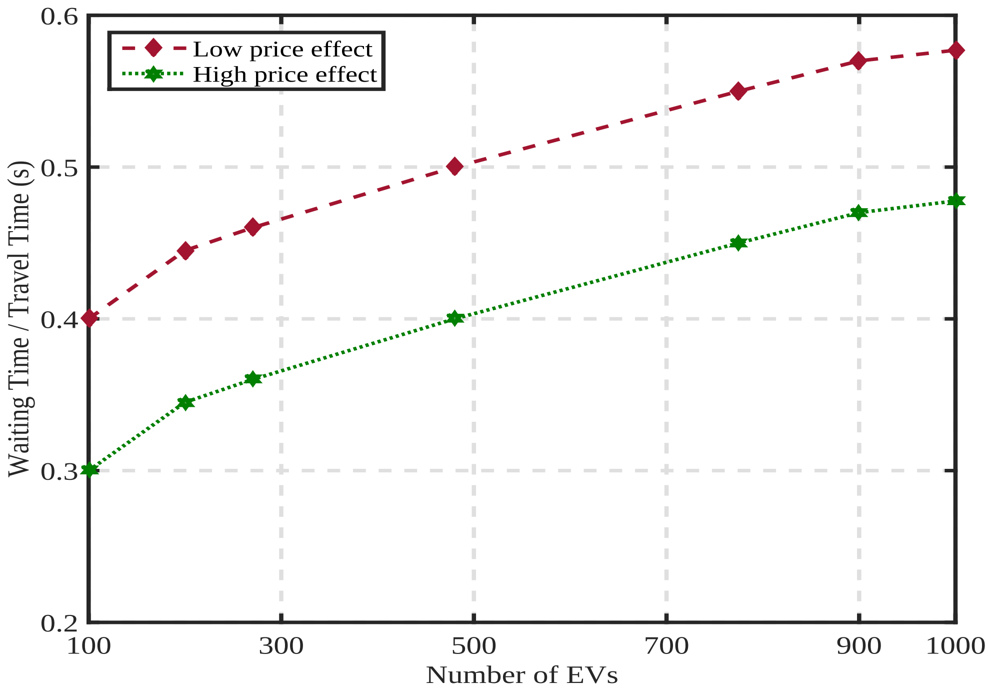



Figure 3.10: Improvement in waiting time with price variation

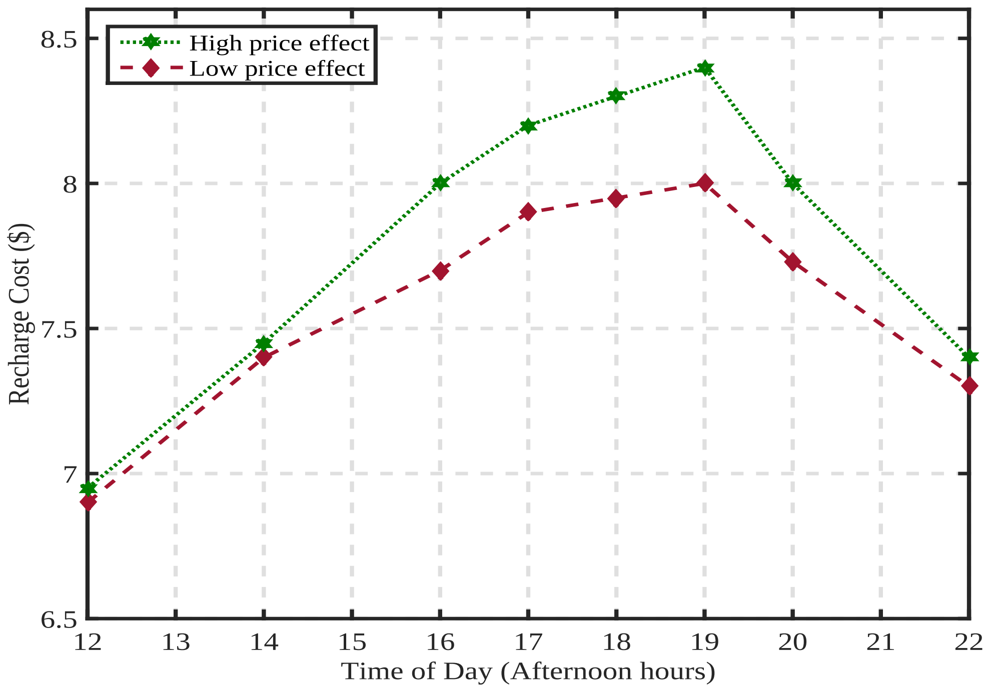



Figure 3.11: Average charging cost for the proposed model with price variation.

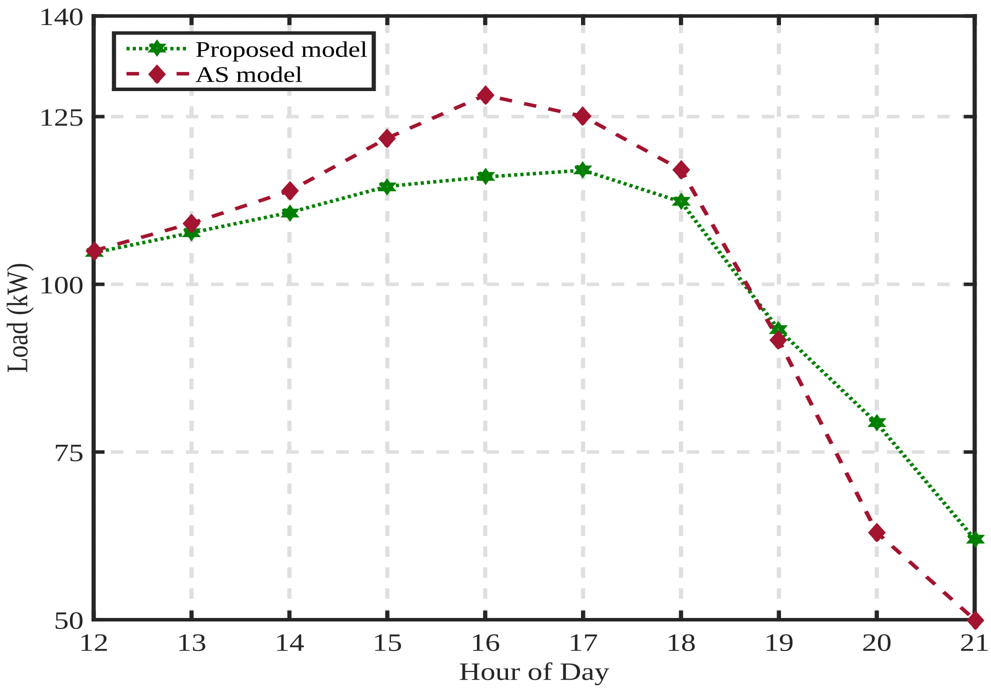



Figure 3.12: PEV load with AS model and proposed model.

As in the proposed model, the introduction of the recharge cost in the objective function is capitalized, an extended overlap period between the PEV and residential peak periods can be avoided by setting a higher recharge price in our model, which would then encourage PEV users to perform partial charging at charging stations during busy hours and/or complete the charging process at home/charging stations during off-peak hours. It should be noted that an optimum dynamic pricing model, which would have the greatest benefit for both the grid and PEV users, can be modeled as an optimisation problem. This, however, is not within the scope of this work. In this work, in order to show the impact of pricing on partial charging and the average waiting time during the peak load period, two indicative maximum price levels, (i.e., US$ 0.46 vs 0.56 per kWh as the maximum price) are used. In response to the higher charging price during the peak load period, the partial charging coefficient value for a PEV was assigned a value in the range of its current $SoC$ to the maximum $SoC$ using a normal distribution. The mean value of this distribution was assumed to decrease exponentially with increasing charging price. For partial charging, there is a trade-off between the recharge price and the delay at charging stations. As shown in Figure 3.12, the average peak hour recharging cost with dynamic pricing is relatively higher.

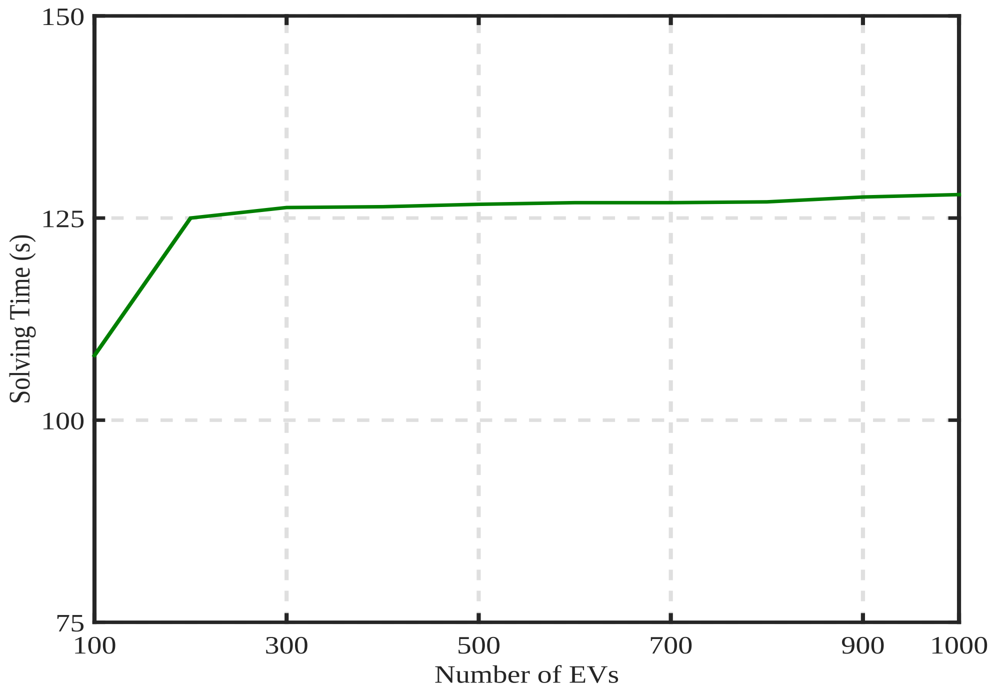



Figure 3.13: Convergence graph with ACO for the optimal paths

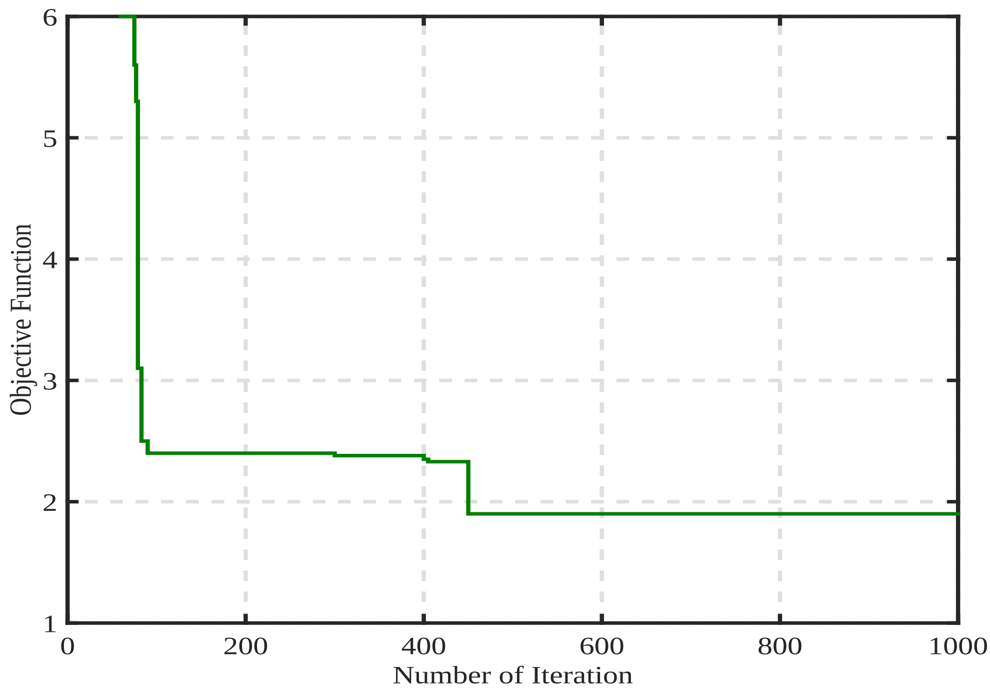



Figure 3.14: Average computation time for PEVs

Since the smart charging strategy is intended largely for PEV users, it is important to have a solution that can be solved in real-time. This motivated us to investigate the time complexity of the proposed ACO-based smart charging solution. Figure. 3.13 presents the convergence test result for the proposed solution. This suggests that the ACO-based approach converges to the optimal solution after 440 iterations for a fleet of 500 PEVs. In real-time, ACO-based approach requires around 127s to find the best route for a PEV (Figure 3.14). The computation time for each PEV remains relatively constant, even for a large fleet of PEVs.

Table 3.1 summarizes the performance improvements of the proposed model over the AS model for a fleet size of 1000 PEVs. The Table clarifies the reduction in the average waiting time and the average travel time as well as the recharging cost.

Table 3.1: Summarized Simulation Results

| Evaluation parameters | With AS model | With the proposed model | Improvement |
|---|---|---|---|
| Average waiting time (min) | 48.5 | 36.2 | 25.3% |
| Average travel time (min) | 68.3 | 58.2 | 15% |
| Charging cost (US$) | 8.9 | 7.5 | 16% |

## 3.5 Concluding remarks

In this chapter, a smart charging strategy proposed for a PEV network that offers multiple charging options at charging stations. Just as traditional gas stations have different capacities and pricing options, charging stations can have different capacities and pricing options, and the recharge price for each option can vary from one station to another. In a scenario like this, it is important to adopt a charging strategy that identifies the most suitable charging station for a PEV user, so that the user can recharge at the minimum cost and reach his/her destination without a significant delay. Research challenge has modeled as a multi-objective optimisation problem where the goal was to reduce the charging time, travel time and charging cost. A queuing model is used to estimate the delay at various charging stations. To mitigate the challenge of longer waiting times and the potential overlap between the peak PEV and residential load periods, the concept of partial charging also has introduced, which showed that pricing could be used as a useful tool to encourage PEV drivers to choose the partial charging option during peak load hours. In light of the significant time complexity of the optimisation solution, research problem has been solved by introducing an ACO-based meta-heuristic solution. The simulation results confirm that the proposed solution significantly reduces the average charging delay (up to 25%) and cost (up to 15%).

# Chapter 4

# A COORDINATED DYNAMIC PRICING MODEL FOR ELECTRIC VEHICLE CHARGING STATIONS

In this chapter, a new coordinated dynamic pricing model is introduced to reduce the overlap between the PEV and residential loads during the evening hours. The coordinated pricing policy provides a price vector, that encourages a uniform distribution of PEV loads across all charging stations so that the EV network can be utilized to its maximum capacity. This leads to a reduction in PEV load during the evening hours. This however, is not a trivial approach since charging cost is not the only influencing factor. EV owners are influenced by other factors as well including driving distance and waiting time, which is also considered in the proposed approach.

In summary, the major contributions are:[1]

- Introducing a new coordinated dynamic pricing model for temporal PEV load shifting to reduce the overlap between loads associated with CS and residential networks.
- Formulating the research challenge as a constrained optimisation problem. Estimation of demand in response to charging price variation is presented for each station during various time slots. Considering the time complexity of the optimum solution, a rule-based model to derive the appropriate price information is proposed.
- The proposed model significantly reduces the overlap between the PEV peak load period and the residential peak load period, which ultimately leads to a lower evening peak demand. In order to quantify and benchmark the benefits, the proposed coordi-

[1]The presented chapter has been published as: Moghaddam, Z., Ahmad, I., Habibi, D., Masoum, M.A.S, A Coordinated Dynamic Pricing Model for Electric Vehicle Charging Stations. IEEE Transactions on Transportation Electrification,2019.

nated dynamic pricing model is tested on the Washington green highway EV network [4] and compare the results with the smart charging strategy of reference [5] which uses an ant colony optimisation.

It should be noted that a pricing model has an impact on multiple parties including the electricity utilities, PEV and CS owners. In this chapter, the potential grid stability issue is considered which caused by an increase in peak demand during the evening peak hours as the major challenge. As such, direct profit maximization of CS owners is not within the scope of this work.

Assuming the utilities will enjoy the maximum benefit from the reduction of the peak load, they will need to provide necessary incentives (e.g., adjustment of selling price to CSs, reward for contribution to the reduction of peak load etc. [115, 116]) to the CSs to promote a dynamic pricing model. One can argue that increasing the capacity of the utility during the evening peak hours can solve the problem, but this would require capital investment and the high evening peak demand (i.e., the duck curve problem) would not help with the economics of this decision (i.e., a low return on investment caused by the high peak-to-average demand ratio).

## 4.1 Formulation of Proposed Dynamic Pricing Model

This section presents the proposed coordinated dynamic pricing model for EV charging stations in terms of Eqs. 4.1- 4.20 that is used in Section IV to present a new EV charging strategy to reduce the overlaps between residential and CS loads by inspiring temporal PEV load shifting during evening peak load hours.

In EV smart charging, two entities, namely the PEVs and the electricity utility are directly involved. The optimisation model included in Eqs. 4.1- 4.5 is intended for PEVs. This model finds the optimum CS for an electric vehicle so that the travel time, waiting time and charging cost can be minimised. In the proposed model, charging price is highlighted as an influential factor in the decision-making process of PEV owners, and the utility can influence their behaviours (e.g., which CS to choose and when, and thereby time-shift the load) by controlling the charging price at various charging stations.

Equations 4.6 - 4.9 constitute the main problem formulation in this chapter. This formulation is intended for the utility where the goal is to find the price vector for various time slots, which will ultimately reduce the amount of overlap between the PEV and residential loads during evening hours. As a result, while the waiting time parameter is a key concern from PEV owners perspective, this parameter is not a direct concern for the utility. Instead, the PEV load, which is a direct concern for the utility is estimated based on a recursive least square approach (Eqs. 4.10 - 4.15 and Figure 4.2) and included in the problem formulation.

### 4.1.1 Charging Station System Model

Assume a city with a set of CSs under different ownership structures which buy the electricity from the power grid as shown in Figure 4.1. At each CS, there are multiple charging options including AC level 2 charging, DC fast charging and battery swapping facilities.

In smart charging, both PEVs and the electricity utility are directly involved. In the existing works [5, 6], smart charging strategies that have been designed for PEV owners attempt to find the optimum charging station for a PEV by considering multiple factors including driving time, waiting time and the price to charge at a CS. Mathematically, the objective of such smart charging strategies can be given as [5]:

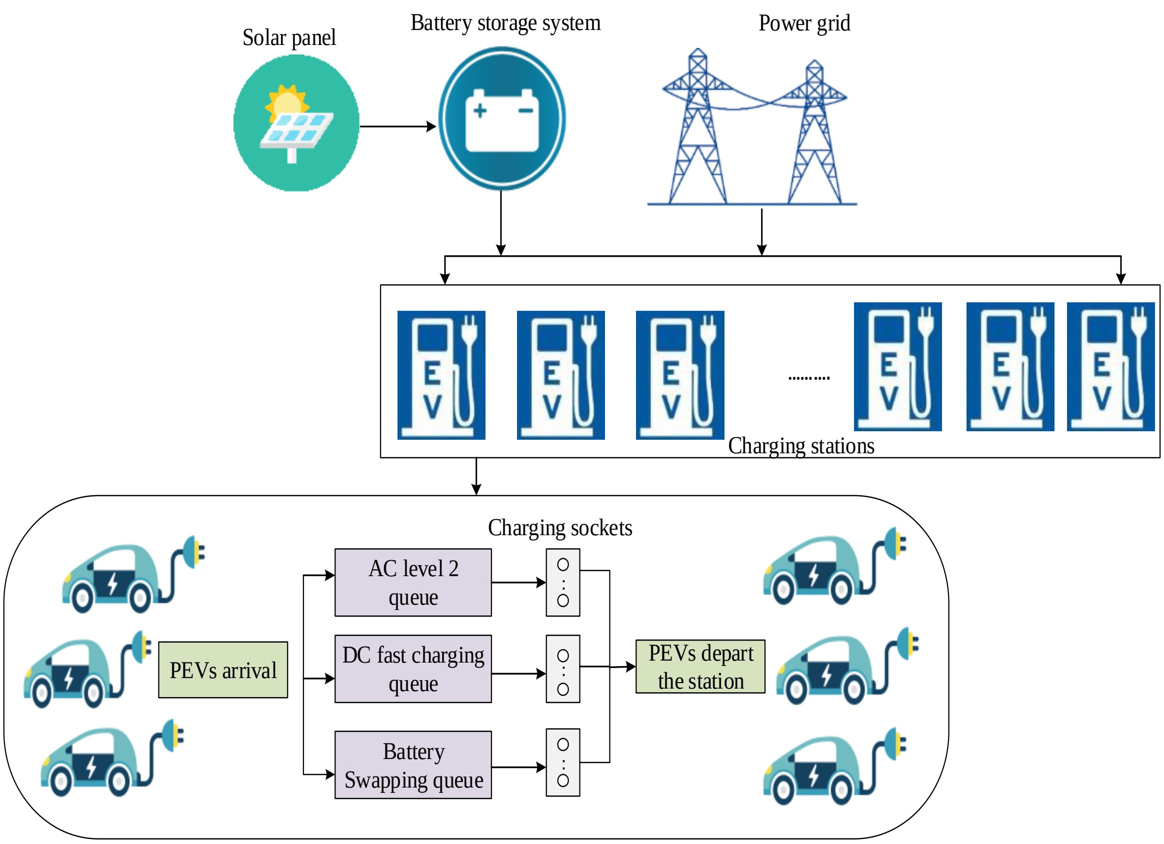



Figure 4.1: Architecture of the PEV charging station.

$$min[x(T^{drive}(src,\ dst)) + yT_j^{wait}(o) + zC_j^{recharge}(o)] \tag{4.1}$$

where $x$, $y$ and $z$ are the positive coefficients of the objective function. For a PEV, $T^{drive}(src,\ dst)$ shows the total driving time from its current location $src$ to the final destination $dst$, while $j$ shows the charging station along the way and $C_j^{recharge}(o)$ indicates the charging cost. In addition to the driving time, a PEV needs to stay in the queue at a CS to access an available charging socket. As a result, the total waiting time ($T_j^{wait}(o)$) at a charging station $j$ depends on the waiting time in the queue ($E(W_j^o)$) and the time to recharge. Average waiting times for the three types of charging options at time $t$ can be estimated using the $M/M/s/C$ and the Little law models [94]:

$$E(W_j^o) = \frac{E(L_j^o)}{\lambda_j(1-\pi_j^R)} \qquad \forall o : (o = 1,\ 2,\ 3) \tag{4.2}$$

Therefore, for the queue of the battery swapping facility at $CS_j$, the mean waiting time can be obtained[5]:

$$E(W_j^1) = \frac{\mu_j^1}{\lambda_j(\mu_j^1 - \lambda_j)(1-\pi_j^R)} \tag{4.3}$$

Similarly, the mean waiting times for DC-fast and AC charging queues are:

$$E(W_j^2) = \frac{\mu_j^2}{\lambda_j(\mu_j^2 - \lambda_j)(1-\pi_j^R)} \tag{4.4}$$

$$E(W_j^3) = \frac{\mu_j^3}{\lambda_j(\mu_j^3 - \lambda_j)(1-\pi_j^R)} \tag{4.5}$$

In addition to the parameters such as driving time and waiting time, the other parameter that influences the decision of a PEV owner is the charging cost. Charging cost depends on the charging prices at CSs. Existing works [5, 6] assume that all charging stations use their own pricing models, which offer no price coordination among CSs and no price incentive to PEVs for selecting lightly loaded CSs during various hours of the day. While this assumption causes no major problem for PEV owners, such an approach introduces a major concern for the electricity utility.

One risk associated with such charging strategies is that even when there are several other lightly loaded CSs available nearby while a PEV waits at a heavily loaded CS located at a hotspot area, the additional driving time and energy consumption would discourage many PEV owners to use the lightly loaded CSs. The other risk associated with such charging strategies is that many PEV owners may prefer partial charging at heavily loaded CSs [5], [117], meaning these owners are likely to plug into the grid straightaway after they reach home, which will increase the peak residential load.

The overall risk is that due to the non-uniform distribution of charging load, the maximum capacity of the charging network will not be fully utilized during the peak PEV load period, meaning a fraction of this PEV load will shift and overlap with the residential peak load. This is a major concern for the utility and a coordinated dynamic pricing model can be useful here to influence PEV owners to select lightly loaded CSs. Next section, shows how a coordinated time-varying pricing model can be represented as an optimisation problem.

### 4.1.2 Proposed Optimisation Model for Temporal PEV Load Shifting

Assume a set of $N$ CSs in an EV network. The price vector $\overrightarrow{P(t)} \in \mathbb{R}^N$ indicates the charging prices offered by the CSs in the network where $p_j(t)$ stands for the charging price offered by the charging station $j$ at $t$. The main objective of the proposed model is to obtain an appropriate price vector $\overrightarrow{P(t)}$ (i.e., decision variable) for the time slots during the busy hours to minimise the overlap between the PEV load ($d_j(t)$) and residential load ($r(t)$). Mathematically, the objective function of the proposed optimisation model can be given as (4.6):

$$minimise\ Z = r(t) + \sum_{j=1}^{N} d_j(t) \tag{4.6}$$

subject to:

$$p_j^{min} \leq p_j(t) \leq p_j^{max} \qquad \forall j = 1, ..., N,\ \forall t \tag{4.7}$$

$$\sum_{j=1}^{N} d_j(t) \leq E^{ca} \qquad \forall t \tag{4.8}$$

$$d_j(t)[p_j(t) + I_j(t) - c_j(t)] \geq \phi_j^{min}(t) \quad \forall j = 1, ..., N, \ \forall t \tag{4.9}$$

Constraint 4.7 defines the upper ($p_j^{max}$) and lower bounds ($p_j^{min}$) for the charging price at a CS. Constraint 4.8 indicates that the aggregate PEV loads across all CSs ($\sum_{j=1}^{N} d_j(t)$) should be less than the maximum capacity of the EV network ($E^{ca}$). Constraint 4.9 ensures that the price vector does not lead to revenue loss for charging stations. $I_j(t)$ represents the incentive [118], [119] provided to $CS_j$ by the utility for the time slot $t$ in appreciation of the contribution of the charging stations in reducing the peak load. $c_j(t)$ indicates the electricity cost for the time slot $t$ at the charging station $j$.

The PEV and residential load profiles can vary from day to day (e.g., weekdays vs weekends). The optimisation model however, can still find the optimum price vector, which would lead to a reduction of overlap and peak load during the evening hours. In cases when the overlap is not a significant concern for the utility (e.g., low PEV load in the afternoon hours during a public holiday), the period of interest can be adjusted to reflect this in the optimisation model.

The model is independent of the number of charging stations and distances between the stations. The optimisation problem can be solved given that the impact of price vector on PEV loads (i.e., $f_j(p_j(t))$ at various CSs (Eq. 4.10) can be quantified. This is not a trivial task since the demand is influenced by multiple factors including the locations of CSs, their distances from PEVs, and the relative price differences in their offered charging price.

$$\begin{bmatrix} d_1(t) \\ d_2(t) \\ \vdots \\ d_N(t) \end{bmatrix} = \begin{bmatrix} f_1(p(t)) \\ f_2(p(t)) \\ \vdots \\ f_N(p(t)) \end{bmatrix} \tag{4.10}$$

Following section presents how a demand vector can be estimated in response to a change in the price vector in an EV network.

### 4.1.3 Temporal Demand Estimation at Charging Stations in response to a Price Vector

Using the general demand function [120], PEVs demand is characterized based on the price fluctuations. Therefore, charging demand function can be characterized by price variations during different time slots in a day, which can be given as:

$$\begin{bmatrix} d_1(t) \\ \vdots \\ d_N(t) \end{bmatrix} = \begin{cases} d_1(t) = \alpha_1(t) - \beta_{1,1}p_{1,k}(t) + \cdots + \beta_{N,1}p_{N,k}(t) \\ d_2(t) = \alpha_2(t) - \beta_{2,1}p_{2,k}(t) + \cdots + \beta_{N,1}p_{N,k}(t) \\ \vdots \\ d_N(t) = \alpha_N(t) + \beta_{1,N}p_{1,k}(t) + \cdots - \beta_{N,N}p_{N,k}(t) \end{cases} \tag{4.11}$$

where $[\alpha_{1,} \dots \alpha_N]$ are factors other than price (e.g., distance, location, hourly aggregate load) that affect charging demand, and $[\beta_1, \dots \beta_N]$ are the price coefficients that influence the demand. For demand estimation, the price coefficients during various hours of the day are needed.

Equation 4.11 defines a linear system of PEVs demand function, which is affected by the price coefficients of all the CSs in the EV network. The price elasticity coefficients of such a linear system can be estimated by the Recursive Least Square (RLS) algorithm (Figure 4.2) [121]. RLS is an adaptive filter algorithm that recursively finds the price coefficients at different time slots relating to the input parameters. For applying the RLS algorithm, the following equations are required:

$$e_j(t) = d_j(t) - \overrightarrow{\beta_j(t)}\overrightarrow{p_j(t)} \tag{4.12}$$

$$\overrightarrow{g_j(t)} = \frac{\overrightarrow{p_j(t)}\overrightarrow{Q_j(t-1)}}{\epsilon + \overrightarrow{Q_j(t-1)}\overrightarrow{p_j(t)}} \tag{4.13}$$

$$\overrightarrow{\beta_j(t)} = \overrightarrow{\beta_j(t)} + e_j(t)\overrightarrow{g_j(t)} \tag{4.14}$$

$$\overrightarrow{Q_j(t)} = \frac{1}{\epsilon}\overrightarrow{Q_j(t-1)} - \frac{1}{\epsilon}\overrightarrow{g_j(t)}\overrightarrow{p_j(t)} \tag{4.15}$$

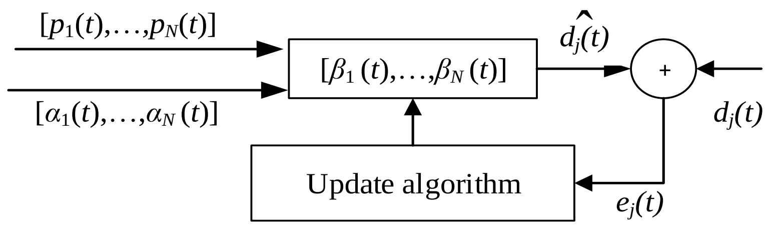



Figure 4.2: Dynamic state presentation of the price vector.

where $e_j(t)$ is the prediction error while $0 < \epsilon \leq 1$ is the forgetting factor that helps us to capture the last charging demands and ignore the old information and track charging demand variation over time. $\overrightarrow{g_j(t)}$ is the gain vector and $Q(t)$ is the inverse correlation matrix of the input vector. In the RLS algorithm, for a given time slot, the price coefficients are derived, and the demand at a CS can be estimated for a given price vector. This demand information is required to find the optimum solution of the optimisation problem.

The model described in the previous section is a non-convex NP-hard constrained optimisation problem. Since the optimal solution is untraceable and computationally expensive, a sub-optimal solution is needed. Considering the need for a robust solution, the problem is solved by introducing an iterative rule-based pricing model, which is described in the following section.

### 4.1.4 Proposed Rule-Based Pricing Model

The rule-based instructions is introduced as shown in Table. 4.1 to obtain the spatial price vector for all CSs at different time slots. The rule-based model attempts to find a price vector which encourages a uniform distribution of PEV loads across all CSs so that the EV network can be utilized to its maximum capacity during the peak PEV load period.

The rule-based model starts with input parameters, which include the current time slot $t$, current demand $\kappa_j(t)$ at each $CS_j$ and the target demand vector $\overrightarrow{\gamma(t)}$ in the EV network obtained under the uniform distribution condition. $\overrightarrow{\gamma(t)}$ at the time slot $t$ can be derived from a charging strategy by uniformly allocating the PEVs among all CSs according to their capacities (i.e., sockets). It should be noted that the demand parameters in the rule-based solution are expressed in terms of queue occupancy in contrast to the demand parameter in the optimisation model, which is expressed in terms of energy demand.

Table 4.1: Operation Rules of the Proposed Dynamic Pricing Model

| Rule-Based Instructions |
|---|
| ***Rule* 1:** Input parameters: current price vector, estimated demand at each CS in response to the current price vector during the next time slot, current time $t$ and the demand vector $\gamma(t)$ under uniform load distribution condition during the next time slot. |
| ***Rule* 2:** At each iteration, $\forall j = 1, ..., N$ update the price vector according to the following conditions: $$if \quad \kappa_j(t) \geq \gamma_j(t) \tag{4.16}$$ $x_j(t) = \|\kappa_j(t) - \gamma_j(t)\|,$ $\sigma = \frac{p_j^{max} - p_j^{min}}{\kappa_j^{max}(t) - \kappa_j^{min}(t)}$ $p_j(t) = p_j(t) + \sigma x_j(t);$ *else* $$x_j(t) = \|\kappa_j(t) - \gamma_j(t)\|, \tag{4.17}$$ $\sigma = \frac{p_j^{max} - p_j^{min}}{\kappa_j^{max}(t) - \kappa_j^{min}(t)}$ $p_j(t) = p_j(t) - \sigma x_j(t);$ |
| ***Rule* 3:** a) Use the updated price vector derived from Rule 2 and apply the RLS algorithm to estimate the demand vector $\overrightarrow{\kappa(t)}$ for the current time slot. b) $\forall j = 1, ..., N, \forall t$ $$if \quad d_j(t)[p_j(t) + I_j(t) - c_j(t)] \geq \phi_j^{min} \tag{4.18}$$ |
| *Apply Rule 2 to update the price vector;* *else* *Keep the current price vector.* |
| ***Rule* 4:** Test the goodness of the updated price vector using the following equations: $$\chi^2 = \frac{\sum[\kappa_j(t) - \gamma_j(t)]^2}{\sum \gamma_j(t)} \tag{4.19}$$ $$if \quad \chi_m^2(t) < \chi_{m-1}^2(t) \tag{4.20}$$ *update* $\kappa_j(t)$ *with the new* $p_j(t)$ $m = m + 1;$ *Repeat Rules 2 to 4* *else* $\overrightarrow{P(t)}$ *is the solution.* |

The rule-based model adjusts the price vector at the start of each time slot so that the corresponding demand vector, which is derived from the RLS algorithm moves closer to the solution under the uniform distribution condition. In order to benchmark the proposed dynamic pricing model, the proposed solution in a smart charging strategy modeled as an ant colony optimisation, which is presented in the following section. The flowchart of the charging strategy incorporating the proposed dynamic pricing model is illustrated in Figure 4.3.

## 4.2 Charging Strategy Using the Proposed Dynamic Pricing Model

As discussed in Section III, in order to find an optimum charging station for a PEV, a charging strategy considers multiple factors including the total driving time, total waiting time (queue and charging time) and the price to charge. In this section, the implementation of a charging strategy is described using ant colony optimisation (ACO) [5] considering the impact of the proposed pricing model on the grid and PEV owners. ACO is selected as a meta-heuristic solution to provide a robust solution in real-time. Using this approach, real-time information about the distance to a CS, waiting times at the CS and updated pricing information for each time slot is included. This enables us to estimate the optimum path in the CS network, using the proposed pricing model based on the following steps:

- Initialize the parameters including the CSs number and their attributes, number of PEVs and their attributes and pheromone level as well as the evaporation rate of the pheromone for the ACO approach in the EV network.

- Calculate $P_{ij}^k(u)$ in each iteration with respect to the heuristic values such as travel time, waiting time and updated price at each charging station.

$$P_{ij}^k(u) = \frac{\tau_{ij}(u)^\alpha[(T^{drive}(src, dst))T_j^{wait}(k)p_j(t)]^\theta}{\sum_{l \in N_i^k} \tau_{ij}(u)^\alpha[(T^{drive}(src, dst))T_j^{wait}(k)p_j(t)]^\theta} \tag{4.21}$$

  In Eq. 4.21 at each iteration u, using the updated information of pheromones and attractiveness of the heuristic information in the model, a PEV k moves stochastically to obtain the probability function of choosing the next node in a graph of charging station.

- For the path constructions, the local and global pheromone are updated using the new price coefficient vector (Eqs. 4.16, 4.17) as follows [103]:

$$\tau_{ij}(u+1) = (\sigma[(1-\rho)\tau(u) + \tau_{ij}^{l}]) \ \ \forall(i,\ j)] \in iter^{l} \tag{4.22}$$

$$\tau_{ij}(u+1) = (\sigma[(1-\rho)\tau(u) + \tau_{ij}^{g}]) \ \ \forall(i,\ j) \in iter^{g} \tag{4.23}$$

where $\tau_{ij}^{l}$ and $\tau_{ij}^{g}$ are the incremental amounts of the local and global update at each iteration, respectively.

Figure 4.3 shows the flowchart of the proposed dynamic pricing approach to minimise the overlap between PEVs and residential loads.

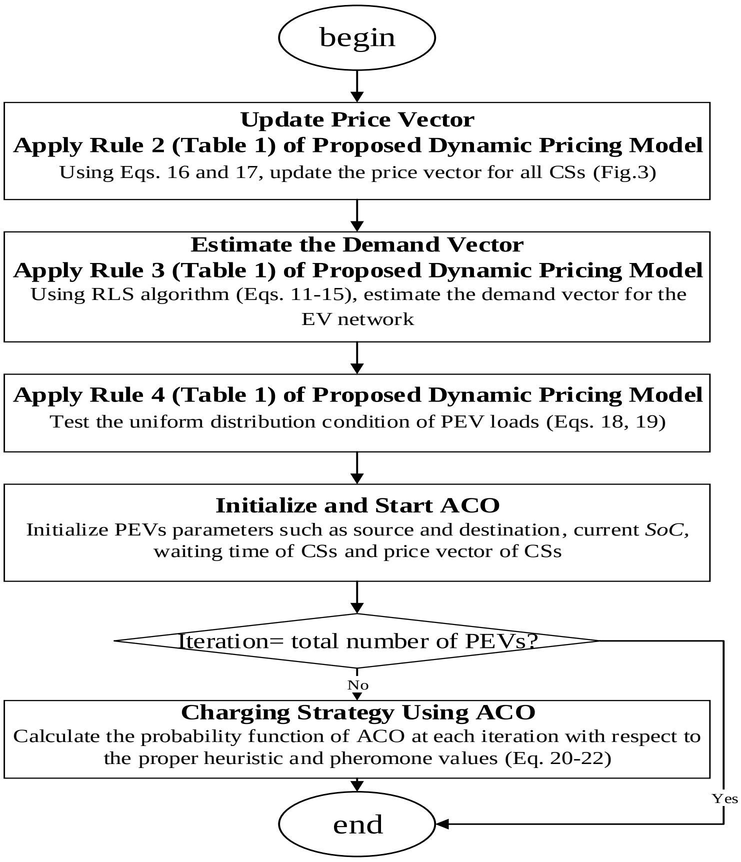



Figure 4.3: Smart charging strategy using the proposed dynamic pricing model.

## 4.3 Simulation Results and Discussions

### 4.3.1 Simulation Model

The proposed solution is tested using a simulation based on the Washington City road EV network, as shown in Figure 3.5. Each CS is equipped with two charging options (DC fast charger and AC level 2 charger) and a battery swap facility. In the simulation a mix

Table 4.2: Simulation Parameters

| Description | Value |
|---|---|
| Number of charging stations ($N$) | 15 |
| Number of PEVs ($M$) | 500 |
| Arrival rate at charging station $j$ ($\lambda_j$) | 5 to 10 PEVs/hour |
| Service time of DC fast charging socket to full-charge ($\mu_j^2$) | 30 min |
| Service time of AC level II charging socket to full-charge ($\mu_j^3$) | 60 min |
| Service time of swap battery ($\mu_j^1$ ) | 3-5 min |
| State of charge for PEV ($SoC_{PEV}$) | $10\% \leq SoC \leq 90\%$ |
| Charging price at peak hours in the UP model, decided by $CS_j$ using a uniform distribution ($p_j$) | 22 ~ 46 cents/kWh ([112, 114]) |
| Pheromone evaporation in ACO ($\rho$ ) | $0 \leq \rho \leq 1$ |
| Weight of pheromones in ACO ($\alpha, \theta$) | $\alpha = \theta = 1$ |
| Pheromone intensity in ACO ($\tau$) | 0.97 |

of up to 500 PEVs comprising of Nissan Leafs (30 kWh), BMWs i3 (22 kWh) and Smart Eds (16 kWh) is considered with uniform state of charge ($SoC$) distribution in the range of 10%~90%. The PEV arrival at each CS is modeled as a Poisson distribution with the arrival rate $\lambda_j$ . The number of sockets for a charging option at a station is also distributed uniformly in the range of 1~10. The fast DC is 50 kW [107] and the AC level II charging is 22 kW [108], while the average time to swap a battery is considered to be 3 minutes [122]. Simulation parameters are presented in Table 4.2. The charging prices for all CSs at each time slot are generated based on the proposed pricing model of Section III. It should be noted that the peak charging price at CSs is maintained below the peak residential price (i.e., 55 cents/kWh). This is to encourage PEV owners to use CSs instead of charging sockets at homes during evening hours since the load from too many PEVs charging at the same time is likely to cause stress on local substations. Simulation results using the MATLAB software package are presented in Figures 4.4 - 4.13, and summarized in Table 4.3. The price vector in the EV network (Eq. 4.14) is updated hourly using the proposed pricing model as discussed in Section 4.2.

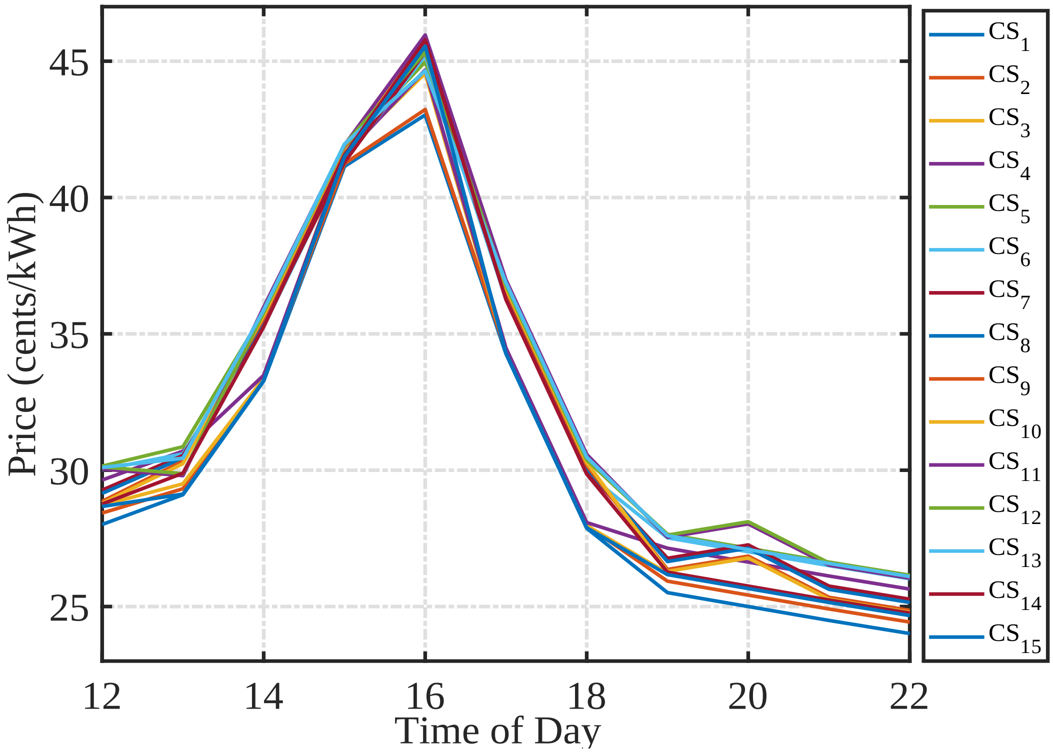


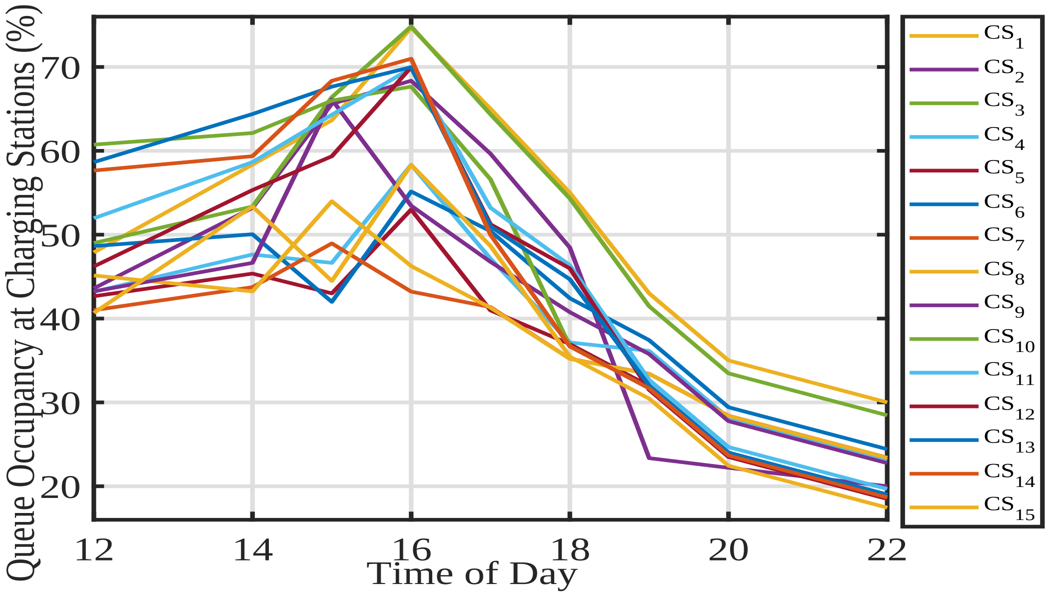

Figure 4.4: Hourly electricity price of the charging stations.

### 4.3.2 Results and Discussion

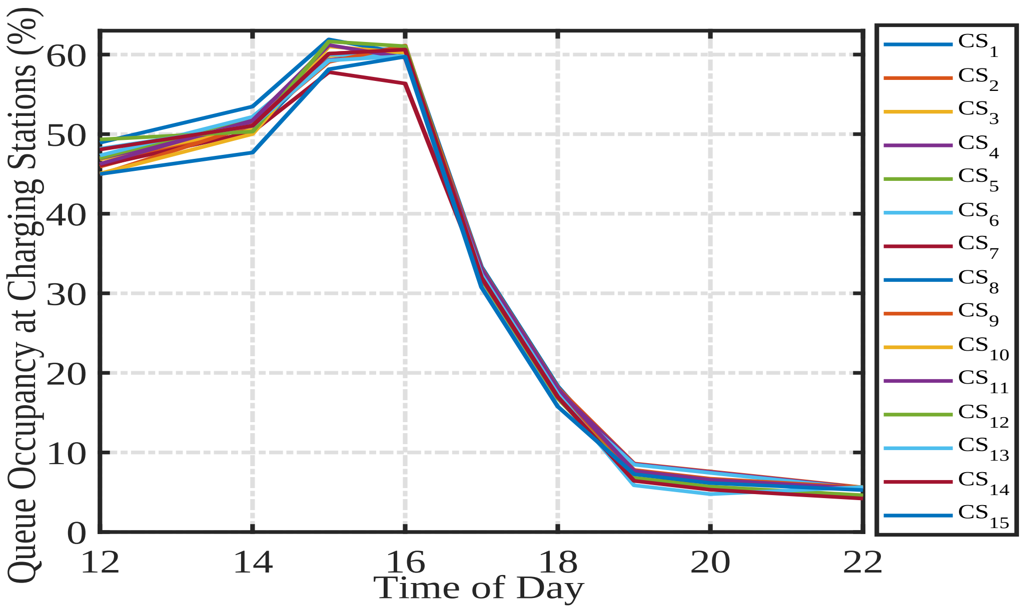
In this section, the hourly electricity price, queue occupancy and the average waiting times at CSs as well as the probability of overlap between PEV and residential loads are analyzed with the proposed dynamic pricing model described in Section III. The proposed solution is compared with existing studies that use an uncoordinated pricing (UP) model for all CSs [5, 6]. In the UP model, charging stations independently choose their own charging price.

The discussion of the results begins with Figure 4.4 which shows the hourly electricity prices provided by the proposed model for the 15 CSs in the EV network of Figure 3.5. As the figure suggests, charging prices at CSs are: i) moderate before 3 p.m. (to motivate early PEV charging that could be supplied from BSSs and/or renewable energy resources, ii) high from 3 p.m. to 4 p.m. due to the increase in demand, iii) low during the late evening hours due to a drop in demand at CSs. The price trend corresponds to the PEV load profile where the PEV peak load is observed at 4pm. If there is a change in the PEV load profile (e.g., PEV peak load shifts left or right depending on days or there is an increase in demand at CSs during the evening hours), the proposed dynamic pricing model would follow the load trend and adjust the price at various hours accordingly.

The average queue occupancy at all CSs is investigated during different times of the day in Figure 4.5. Figure 4.5a presents the queue occupancy of the UP model. This shows that when there is no price coordination among charging stations, PEV demands remain divergent during different time of a day, while Figure 4.5b shows that changing the prices at CSs using the proposed model influences the queue occupancy (i.e., load at a CS). As shown in the figure, the proposed model distributes the load among CSs more uniformly so that the EV network can be utilized to its maximum capacity during the peak traffic period.




(a)




(b)

Figure 4.5: Hourly queue occupancy of the charging stations in Figure , with; (a) the UP model, (b) the proposed model

Figure 4.6 shows the impact of the proposed coordinated price strategy on the PEVs load during different time slots. As it indicates, the PEV charging load during the peak period decreases, resulting in uniform distribution of PEV loads across all CSs. As evident in Figure 4.7 the net PEV load per CS is significantly lower during the peak residential load period (e.g., 6 P.M. to 8 P.M.) in the proposed model compared to the PEV load in the existing UP model. This is because, the proposed model makes the best use of the

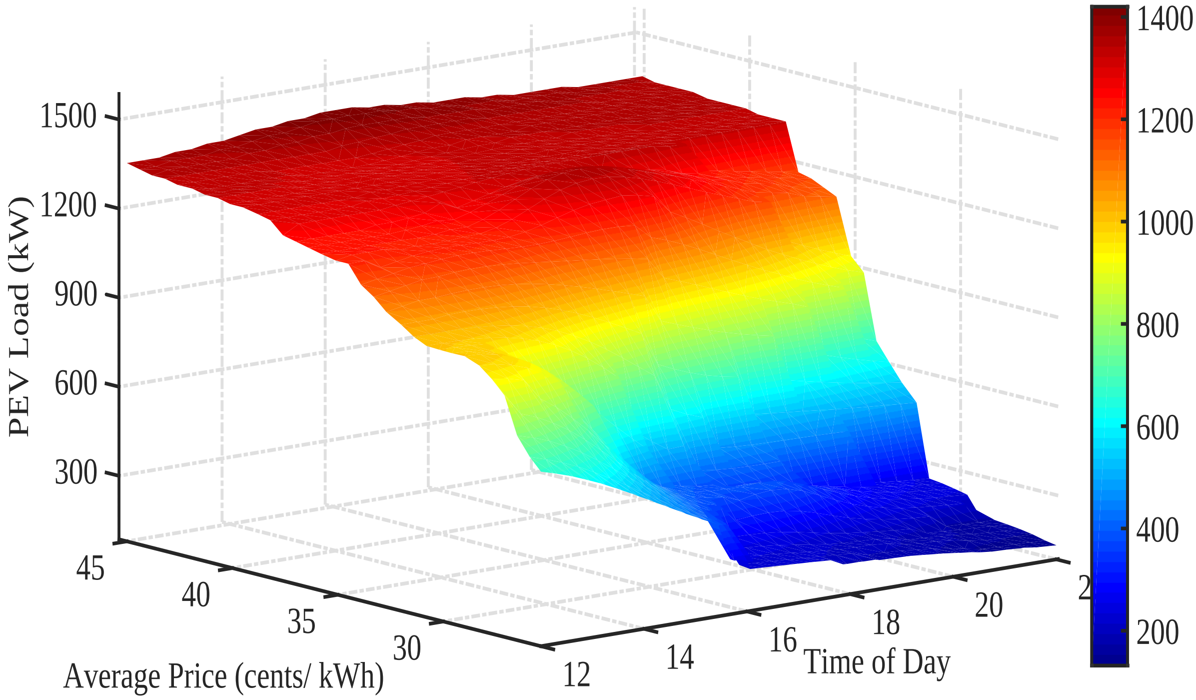



Figure 4.6: Impact of the proposed coordinated price model on the PEVs load.

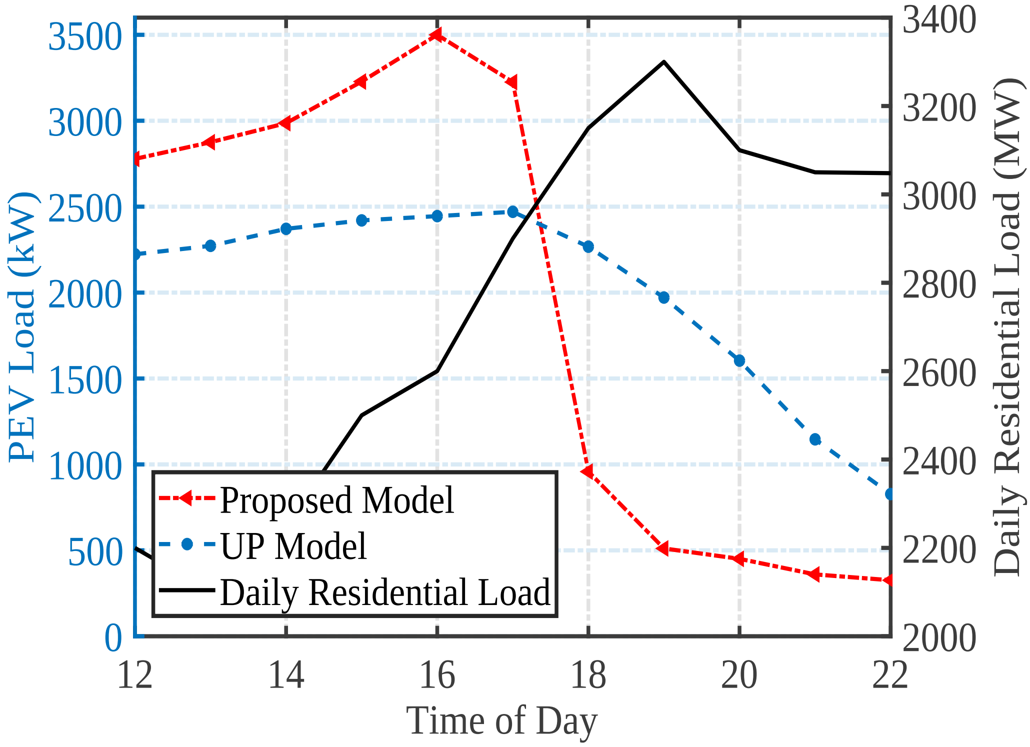



Figure 4.7: PEV charging loads comparing UP model and the proposed model( [5, 6])

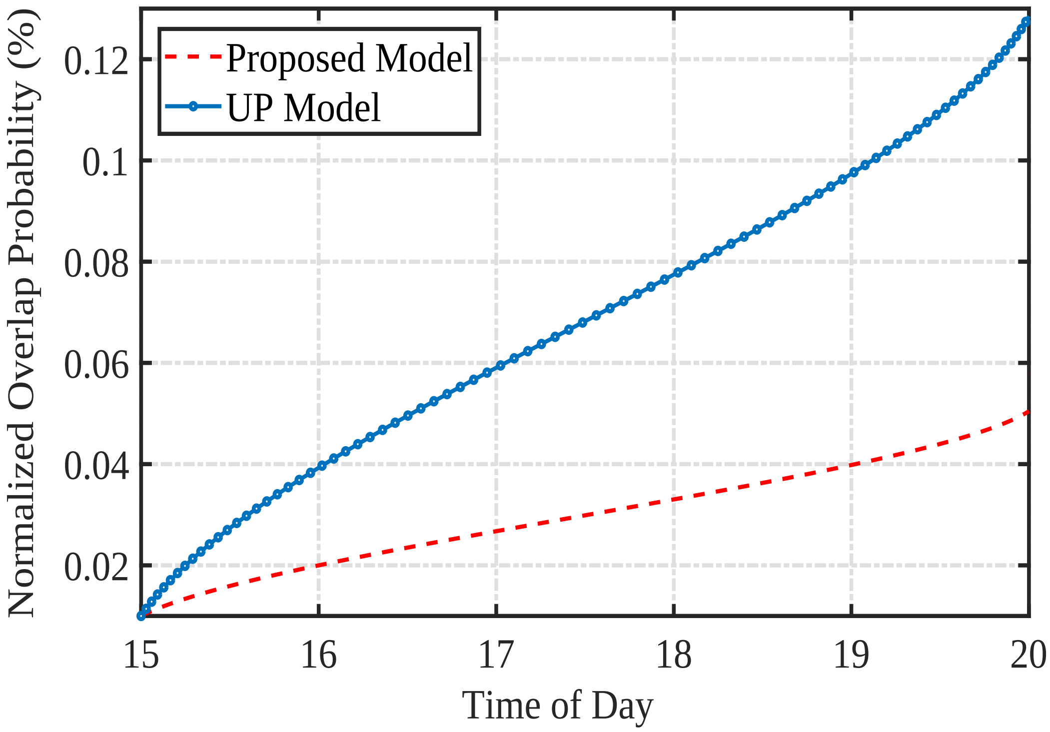



Figure 4.8: Probability of overlap between PEV and residential loads while comparing UP model and the proposed model( [5, 6]).

As evident in Figure 3.11, the net PEV load per CS is significantly lower during the peak residential load period (e.g., 6 p.m. to 8 p.m.) in the proposed model compared to the PEV load in the existing UP model. This is because the proposed model makes the best use of the maximum capacity of the EV network during the peak PEV load period by encouraging uniform load distribution through the implementation of a coordinated pricing model. Figure 4.8 shows that the average price at charging stations with the UP model is higher than the proposed model during the day time and lower than the proposed model during the afternoon hours. This is because in the proposed model, considering the PEV demands at each time slot, price will change to encourage a uniform distribution of PEV loads across all CSs.

Figure 4.9 presents the probability of an overlap between PEVs and residential loads during different time slots. As the PEVs loads decrease during the peak hours with the proposed model, it is obvious that the probability of an overlap between PEVs and residential loads will decrease significantly.

In Figure 4.10, the average waiting time over the travel time for both models is nor-

ma ... l is

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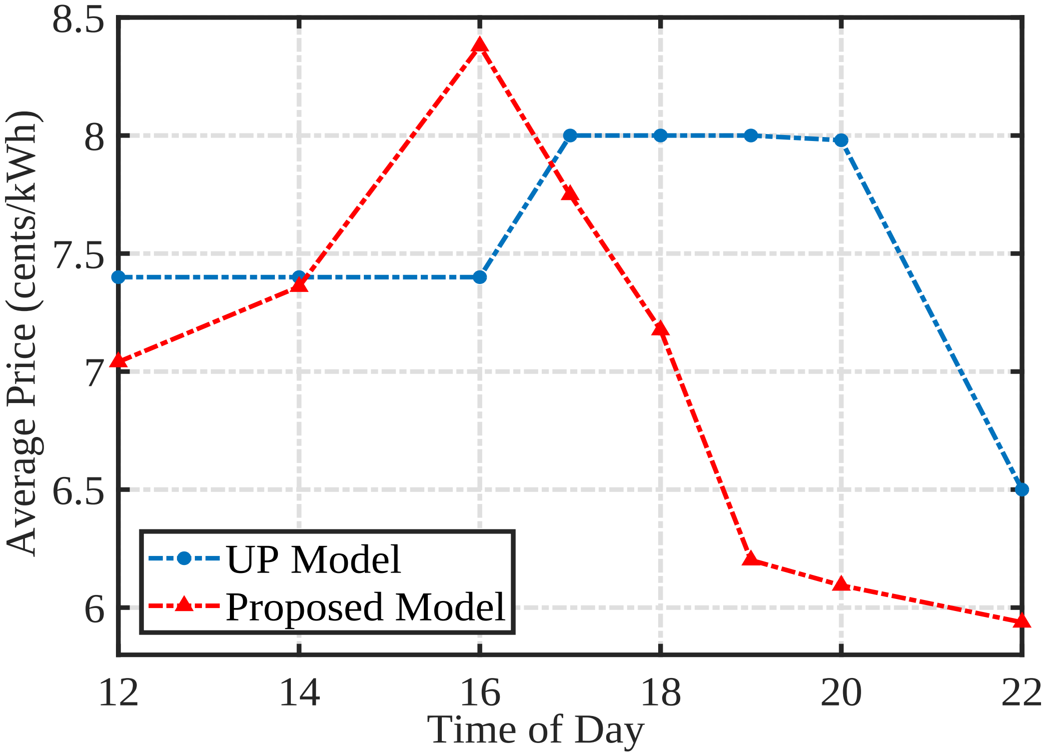



Figure 4.9: Performance comparison of the UP model ([5, 6]) and the proposed model for average PEV charging price

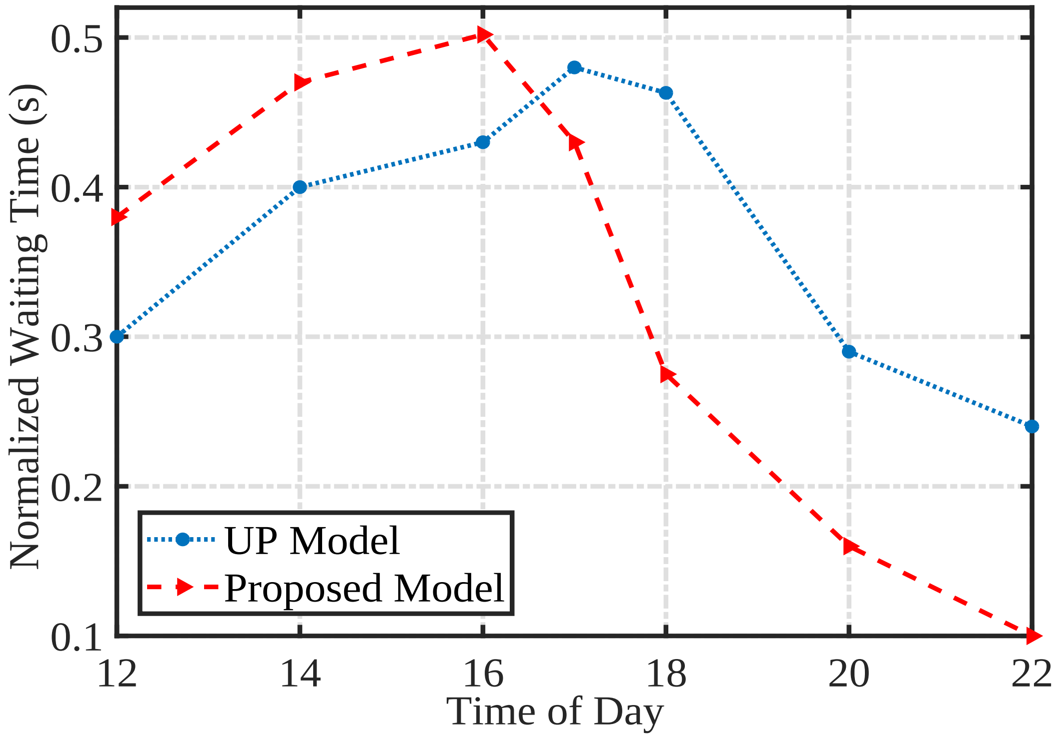
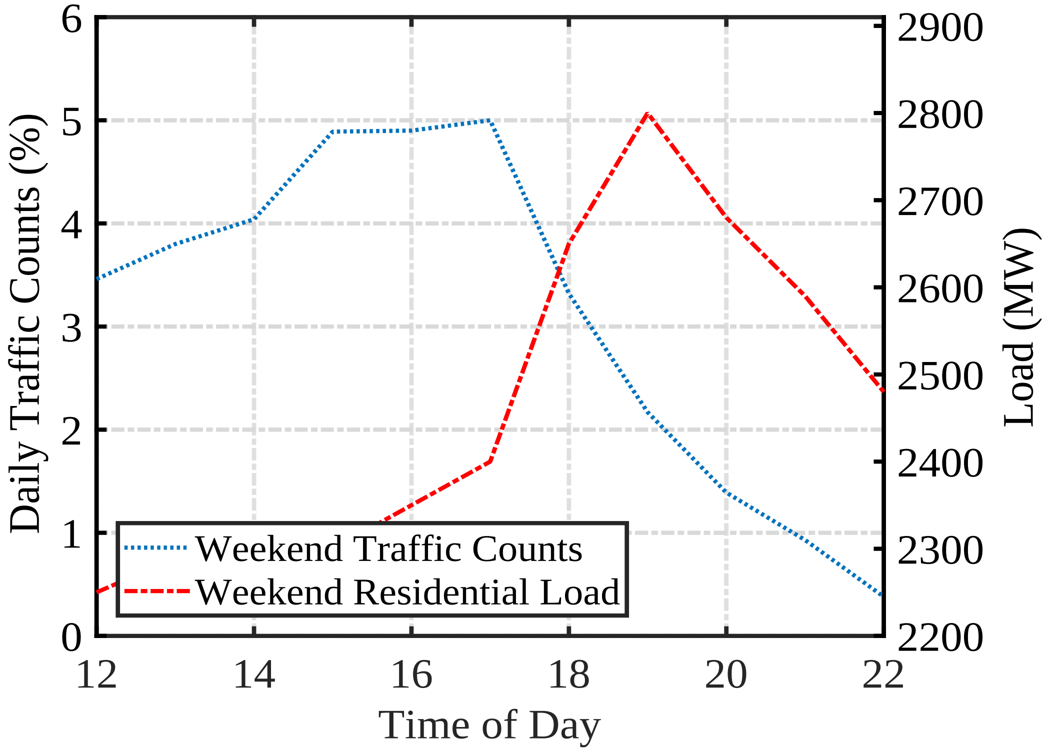
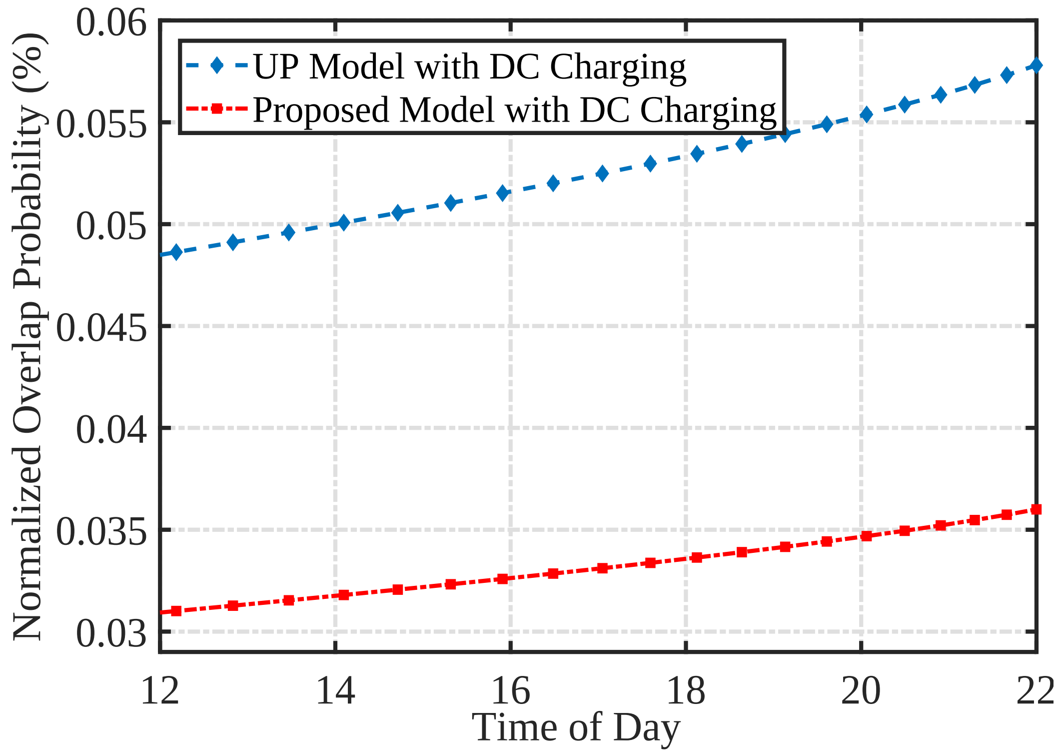



Figure 4.10: Performance comparison of the UP model ([5, 6]) and the proposed model for normalized waiting time in the queues.




(a)




(b)

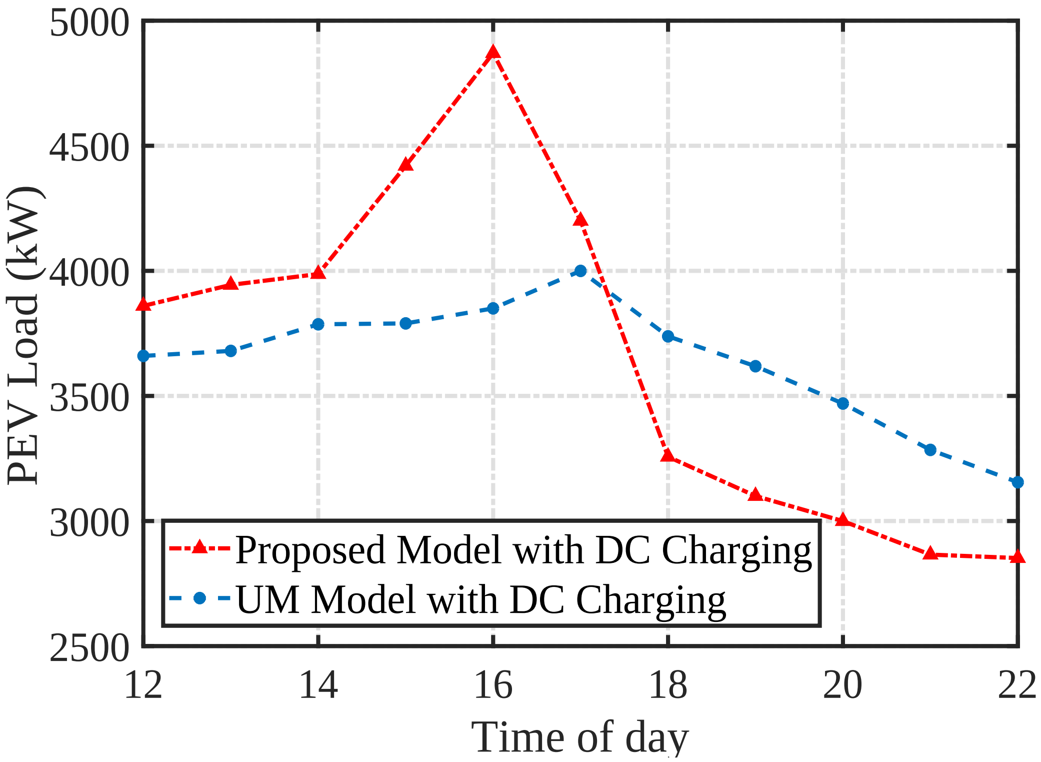
Figure 4.11: Performance comparison of the UP model [5, 6] and the proposed model for a typical weekend in NSW [7], [8]; (a) Weekend traffic counts and residential load, (b) PEV charging load of weekend.

Figure 4.11a shows the PEV and residential loads during a typical weekend in NSW [7], [8]. Note that the overlap between the PEV and residential loads during peak hours (Figure 2.2) is lower in the weekend compared to weekdays. Figure 4.11b illustrates that the proposed model maintains its superior performance in terms of the reduced load overlapping during the weekend as well.

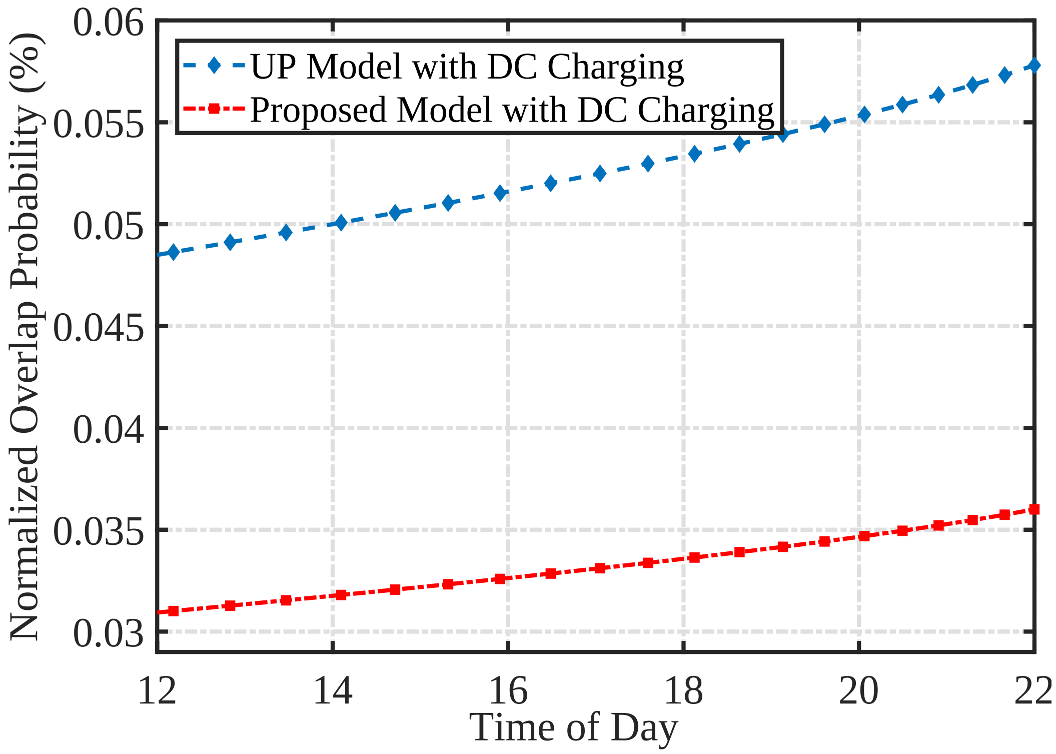
Considering the popularity of Tesla's PEVs, and DC fast charging stations, the proposed coordinated dynamic pricing model is implemented in a scenario where PEVs were considered to have the capacity equivalent to Tesla Model 3 PEVs (80.5 kWh battery capacity [38]) , and the AC charging sockets were replaced with DC fast charging sockets in all CSs. Relevant results as shown in Figure 4.12, which indicates a similar trend observed in Figures 4.7 and 4.8 where the proposed model was found to outperform the existing model in terms of peak demand during the evening peak hours and the overlap period.

Since a smart charging strategy needs to be robust, a solution is desired in real time. The real-time computation time (in sec) required by the proposed dynamic pricing model is applied to provide a solution. As evident in Figure 4.13a , the computation time of the rule-based model increases at a moderate rate with the number of CSs. Figure 4.13b demonstrates the computation time for PEVs to find a charging station. As it shows, the average computation time, remains relatively constant as the number of PEVs increases.

Although the proposed solution relies on the estimated PEV and residential loads, the uncertainty in loads will have impacts on the outcomes. This uncertainty, however, is captured in our simulation results where the PEV arrival process at source nodes is implemented using Poisson distributions with arrival rate $\lambda$ (Eqs. 4.2 - 4.5 and Table 4.2); hence the actual PEV load at various stations varies from the estimated load during various time slots. As such, the results presented in Section V captured this uncertainty in PEV load (Figures 4.4 - 4.12). For the residential load, data supplied by the utility and assumed that their estimation error is not significantly high.

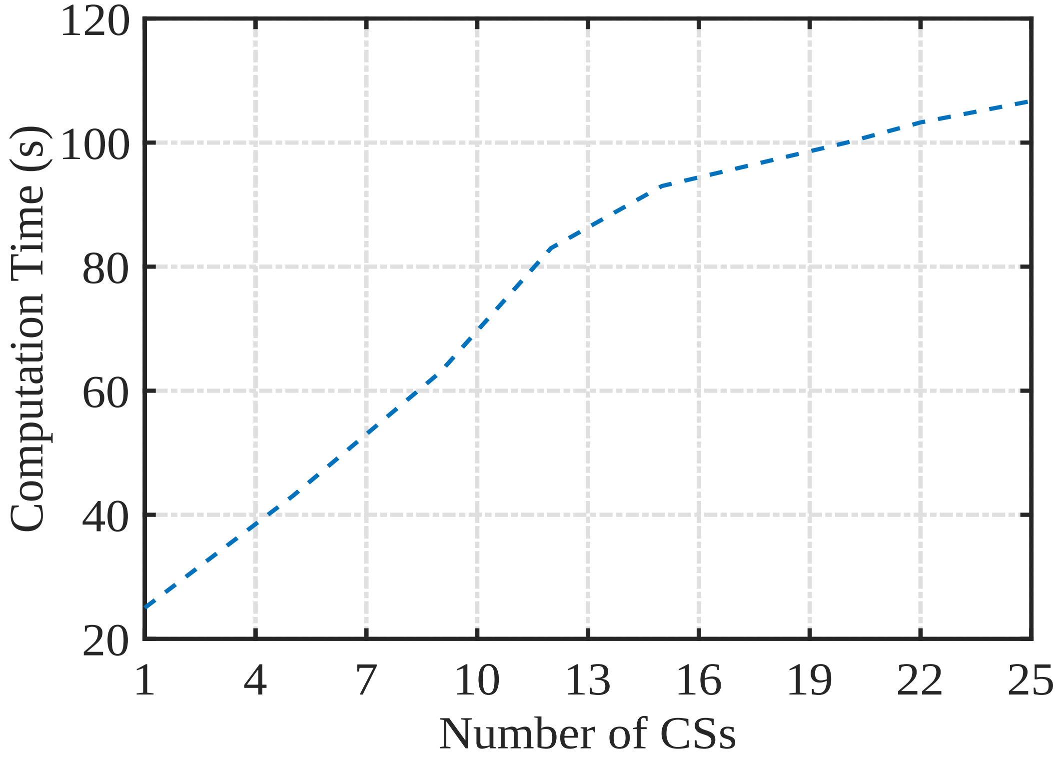



(a)

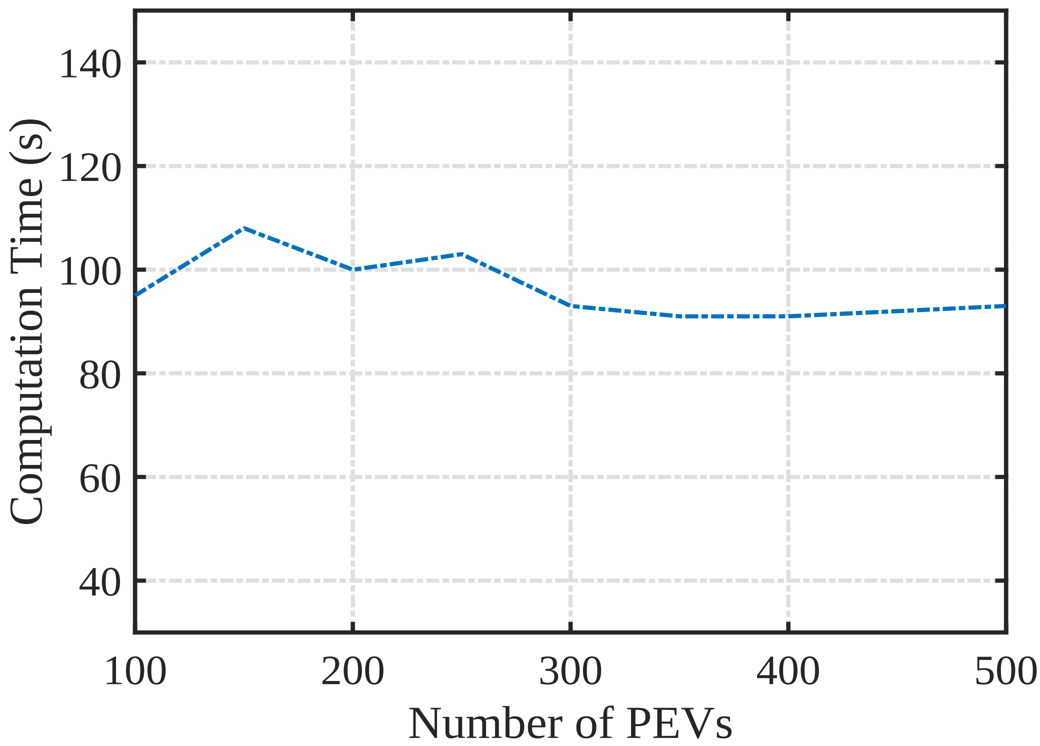



(b)

Figure 4.12: Performance comparison of the UP model ([5, 6]) and the proposed model with high capacity batteries for PEVs and DC charging in CSs; (a) PEV charging loads, (b) probability of overlap between PEV and residential loads.




(a)




(b)

Figure 4.13: Computation time for the proposed charging strategy; (a) computation time for the proposed rule-based model, (b) average computation time of ACO. (Computer specifications include Intel i5 2.4 GHz CPU, 8 GB RAM.)

Table 4.3 summarizes the performances improvements of the proposed dynamic pricing strategy over the existing UP model, given a fleet size of 500 PEVs. This table clarifies that the proposed model provides a significant reduction of the overlap and the peak load during the evening hours. It should be noted that the duck curve challenge motivated us to investigate the overlap between the PEV and residential loads in this work. However, the proposed model can be applied to reduce the overlap in other scenarios as well, for example, PEV and commercial loads by changing the period of interest and load profile in the optimisation and the rule-based model. Similarly, the proposed model would work for different PEV and residential load profiles (e.g., weekend vs weekdays). However, the period of interest can be different depending on the load profiles, and the utility would have the option to adjust this period of interest. The proposed model works by providing price incentives to EV owners to use less popular/underutilized CSs. As such, the impact of the proposed solution would be more significant for a large EV network since the disparity in terms of load distribution is expected to be high in a large network. The proposed solution would work well for a scenario where the price consideration enjoys the same level of attention compared to other factors such as driving time, energy consumption. In cases where the less popular/underutilized stations are located far from other stations, the price incentive may not significantly influence EV owners' behaviour because of the additional driving time and energy consumption. As such, the impact of the proposed solution can be limited in such networks.

Table 4.3: Summarized Simulation Results

| Evaluation Parameters | UP Model [5, 6] | Proposed Model | Improvement of Proposed Strategy |
|---|---|---|---|
| Average waiting time | 38.87 min | 31.82 min | 22.15%* |
| Probability of overlap | 0.044% | 0.030% | 46.7%* |
| Average PEV load during evening hours (6 p.m. to 8 p.m.) | 1947 kW | 639 kW | 67.2% ** |

*) Percentage improvement of proposed coordination strategy compared with UP model of[5, 6].

**) Percentage improvement of proposed coordination strategy compared with daily residential load of[38].

The work presented in this chapter is intended for the electricity utility. However, since smart charging involves both the utility and the PEV owners, a real-time communication platform, such as mobile applications would be useful in maintaining real-time communication between the two entities. The mobile application can capture any change in the dynamic price information, which would influence the PEV owners' decisions. It can also analyze historical data and provide useful information to the PEV owners such as the period of a day or the day of a week when the charging price is low.

## 4.4 Concluding remarks

In this chapter, a new coordinated dynamic pricing model for vehicle charging in CS networks introduced, implemented and evaluated that will encourage temporal PEV load shifting to reduce their overlaps with the residential peak load periods. The dynamic pricing model was formulated as a constrained optimisation problem. The PEVs demand can be estimated in response to charging prices at various CSs. a rule based heuristic solution also presented to address the dynamic pricing challenge in real-time. The proposed solution was included in a charging strategy, which was then implemented using an ACO model for bench-marking. The findings of this study revealed significant benefits to both the consumers by minimising the waiting times at the CSs (by up to 22.15%) and the utilities by shifting the charging demands to reduce their overlaps (by up to 46.7%) and average PEV loads (by up to 67.2%) with peak residential loads and mitigate grid congestion.

In this work, all CSs is considered to cooperate with the utility, which would have a direct influence in changing/controlling the charging prices at various CSs in the network. In many cases, charging stations can be owned by independent entities, and the utility may not have a direct control over how these independent entities choose/change their prices. In such cases, a reward based model will be required where the utility will provide rewards to CSs for their contributions in temporal PEV load shifting so that a potential grid stability problem can be avoided.

At the request of the author chapter 5 is not included in this version of the thesis

# Chapter 6

# CONCLUSION AND FUTURE WORK

Transportation electrification has a remarkable role in reducing $CO_2$ emissions, fossil-fuel dependency and also they are capable of being independent of power grid in terms of using renewable energy sources. Due to the PEVs use-patterns in urban areas, they can potentially operate as flexible electric loads, or even as storage, to support the operation of power systems and the integration of renewable energies [6]. When the PEV penetration level goes high, the charging demand will have greater impacts on the power grid [128], [129]. The majority of the PEVs charging demands is synchronized with the daily driving patterns and occur at the peak hours of the residential demand [39]. The PEV load combined with the increasing residential load during the evening hours, commonly known as the "duck curve" problem, offers a major challenge (i.e., high peak-to-average demand ratio) for the energy industry.

This thesis presented new approaches of smart charging strategies in EV networks to prevent the negative impacts of PEVs load on the power grid. The proposed charging strategies alleviates the extra load stress from power grids during peak hours. The focus of this thesis was mainly on issues as follows: (i) better management of PEVs charging loads at hot-spot areas during peak hours; (ii) minimizing the overlap between the PEVs and residential loads during peak hours; (iii) coordinating the charging prices of CSs to have a uniform distribution of PEVs load during peak hours, (iv) an alternative option for charging PEVs in the EV network to minimize the total waiting times at hot-spot areas during peak hours, and (v) investigating of using BSS in charging stations, considering their different capacities to support the extra PEV loads during peak hours. These issues were investigated, and different solution approaches were proposed. This concluding chapter summarizes the main findings and the contributions of this thesis. In addition, several research directions for future works are suggested.

## 6.1 Contribution of this thesis

The main contributions of this thesis are summarized as follows:

- Chapter 3 presented a smart charging strategy for EV networks that first suggests multiple charging options, such as ac level 2 charging, dc fast charging and battery swapping facilities at charging stations. Then, for a PEV requiring facilities, the issue of finding the optimal charging station is modeled as a multiobjective optimisation problem, where the goal is to find a station that ensures the minimum charging time, travel time, and charging cost. Then the model is extended to a methahuristic solution in the form of an ant colony optimisation. Presented simulation results in the last section of chapter 3, indicate that the proposed solution significantly reduces the average waiting time (up to 25%) during peak hours.
- Chapter 4 of this thesis, introduced a new coordinated dynamic pricing model for electric charging stations in order to reduce the overlaps between residential and CS loads by inspiring temporal PEV load shifting during evening peak hours. The purpose of the proposed model is to dynamically adjust price incentives to drift PEVs towards less popular/underutilized CSs. Then the challenge is formulated as a constrained optimisation problem which have been solved by a heuristic solution. Considering the obtained results in this chapter, it is recommended that using a coordinated dynamic pricing model, there are significant benefits to both users, by minimizing waiting times of CSs and utilities, by shifting the charging demands during peak hours.
- The network and coverage of FCSs are currently constrained by infrastructure costs. As a result, FCSs are not as ubiquitous as traditional gas stations. In addition, as PEVs require a reasonably long time to recharge, waiting times at public charging stations can easily become overwhelming during busy traffic hours. In chapter 5 through the smart management of portable charging stations (PCS), the above mentioned challenge has been addressed to a great extent. In particular, smart strategy is proposed for dispatching/allocating PCS during various hours of the day to reduce waiting times at public charging stations. This also helps to decrease overlap between total PEV demand and peak residential load. First the research challenge of smart management of PCS problem is formulated as a constrained optimisation problem. Then a heuristic solution is introduced to solve the NP-hard problem. The corresponding detailed simulation results show that this proposed model can significantly

reduce average PEV waiting times and decrease the PEV charging loads in FCSs at peak hours by up 64% and 67% , respectively.

## 6.2 Future Work

The integration of the PEVs to the grid have connected the grid issues and transportation sector. In this thesis some of the important challenges of a high penetration of PEVs for the power grid are presented. Then, three different smart charging strategies have proposed to prevent the negative impact of PEVs charging for the utility. As the future work, proposed charging strategies can be developed in the following directions:

- Implementing a reward -based model for the profit management of CSs in EV network: this model explores price and non-price rewards for the required changes in PEVs charging process under the smart charging strategy. Extending the smart charging strategy into temporal, spatial and economic management in the EV network can be a central point for the analyses of integrated transportation electrification and power systems at the operational level.

- Developing a model for the best placement/sizing of FCSs in the EV network, considering the determination of minimum required number of PCSs: a novel method for a real EV network can be proposed to answer the PEVs drivers' concerns in finding the best CSs at hot-spot areas. Then using the real-time information and considering different effective parameters for estimating PEVs demand (such as PEVs travel pattern, rate of charging price at each time slot a day, ... ) the optimum size/number of PCSs can be determined.

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# Appendix A

# Ant Colony Optimisation as a Heuristic Optimisation Technique

Heuristic optimisation techniques facilitate solving problems that were previously difficult or impossible to solve [130]. To avoid the high time complexity of solving difficult problems, alternative methods have been proposed, which are able to determine not perfectly accurate, but with a good quality approximations to exact solutions [130]. These methods, are known as heuristics solutions which explore the search space in a particularly convenient way.

The main existing heuristic solutions are genetic algorithm (GA), particle swarm optimisation (PSO) algorithm, ant colony optimisation (ACO), stochastic diffusion Search (SDS), Differential Evolution (DE), etc. The main aspect of these techniques is their flexibility for solving the optimisation problems which have different mathematical constraints.

There are two types of search strategies; uninformed and informed. Uninformed search or blind search, also called unguided search, is a class of general purpose search algorithms. The term 'uninformed' means that they have no additional information about states beyond that provides in the problem definition. Since they do not take into account the target problem, they can be applied to a variety of search problems. Some of the uninformed search algorithms (non-heuristic) are Depth First Search (DeFS), Breadth First Search (BrFS), or Uniform Cost Search (UnCS) [131, 132, 133].

Informed search strategies use problem-specific knowledge. Usually, this knowledge is represented using an evaluation function that assesses either the quality of each state in the search space, or the cost of moving from the current state to a goal-state, using various possible paths. The famous informed search algorithms are Best First Search (BeFS), Beam Search (BeS) , the A* Search (A*S) and Ant Colony Optimisation (ACO ) [130, 131].

## Ant colony optimisation

The classic ACO algorithm, proposed by Marco Dorigo in 1992 [101], is inspired from the natural behaviour of ants, which are able to find their way using pheromone trails.

ACO has raised a lot of interest in the scientific community. There are now hundreds of successful implementations of the ACO metaheuristic applied to a wide range of different combinatorial optimization problems. The vast majority of these applications concern NP-hard combinatorial optimization problems [101]. In many applications to NP-hard combinatorial optimization problems, ACO algorithms perform best when coupled with local search algorithms. Local search algorithms locally optimise the ants' solutions and these locally optimized solutions are used in the pheromone update. The use of local search in ACO algorithms can be very interesting as the two approaches are complementary. In fact, ACO algorithms perform a rather coarse-grained search, and the solutions they produce can then be locally fine-tuned by an adequate local search algorithm. On the other side, generating appropriate initial solutions for local search algorithms is not an easy task. In practice, ants probabilistically combine solution components which are part of the best locally optimal solutions found so far and generate new, promising initial solutions for the local search. Experimentally, it has been found that such a combination of a probabilistic, adaptive construction heuristic with local search can yield excellent results [134, 135, 136]. Despite the fact that the use of local search algorithms has been shown to be crucial for achieving state-of-the-art performance in many ACO applications, it should be noted that ACO algorithms also show very good performance when local search algorithms cannot be applied easily [137, 138].

## Heuristic Information

The possibility of using heuristic information to direct the ants' probabilistic solution construction is important because it gives the possibility of exploiting problem specific knowledge. This knowledge can be available a *priori* (this is the most frequent situation in NP-hard problems) or at run-time (this is the typical situation in dynamic problems). For most NP-hard problems, the heuristic information $\eta$ can be computed at initialization time and then it remains the same throughout the whole algorithm's run. An example is the use, in the TSP applications, of the length $d_{ij}$ of the edge connecting cities $i$ and $j$ to define the heuristic information $\eta_{ij} = 1/d_{ij}$ . However, the heuristic information may also depend on the partial solution constructed so far and therefore be computed at each step of an ant's solution construction. This determines a higher computational cost that may be compensated by the higher accuracy of the computed heuristic values. It should be noted that while the use of heuristic information is rather important for a generic ACO algorithm, its importance is strongly reduced if local search is used to improve solutions. This is due to the fact that local search takes into account information about the cost to improve solutions in a more direct way.

Probability function of ACO and the required equations for pheromone update in a path are have explained in Chapter 3.

# Appendix B

# Queueing System Concepts

It is often necessary to make projections of performance on the basis of existing load information or on the basis of estimated load for a new environment. In following section two important types of queueing system is presented.

Before introducing the queue system structure, there are the following notations:

- $\lambda$ =arrival rate; mean number of arrivals per second
- $T_s$ =mean service time for each arrival; amount of time being served, not counting time waiting in the queue
- $\rho$ =utilization; fraction of time facility (server or servers) is busy
- $w$ =mean number of items waiting to be served
- $T_w$ =mean waiting time (including items that have to wait and items with waiting time = 0)
- $r$ =mean number of items resident in system (waiting and being served)
- $T_r$ =mean residence time; time an item spends in system (waiting and being served)

The simplest queueing system is depicted in Figure B.1 The central element of the system is a server, which provides services to items. Items from some population of items arrive at the system to be served. If the server is idle, an item is served immediately. Otherwise, an arriving item joins a waiting queue. When the server has completed serving an item, the item departs. If there are items waiting in the queue, one is immediately dispatched to the server. The server in this model can represent anything that performs some function or service for a collection of items. Examples: a processor provides service to processes; a transmission line provides a transmission service to packets or frames of data; an I/O device provides a read or write service for I/O requests [9].

Items arrive at the facility at some average rate (items arriving per second) $\lambda$. At any given time, a certain number of items will be waiting in the queue (zero or more); the average number waiting is w, and the mean time that an item must wait is $T_w$. $T_w$

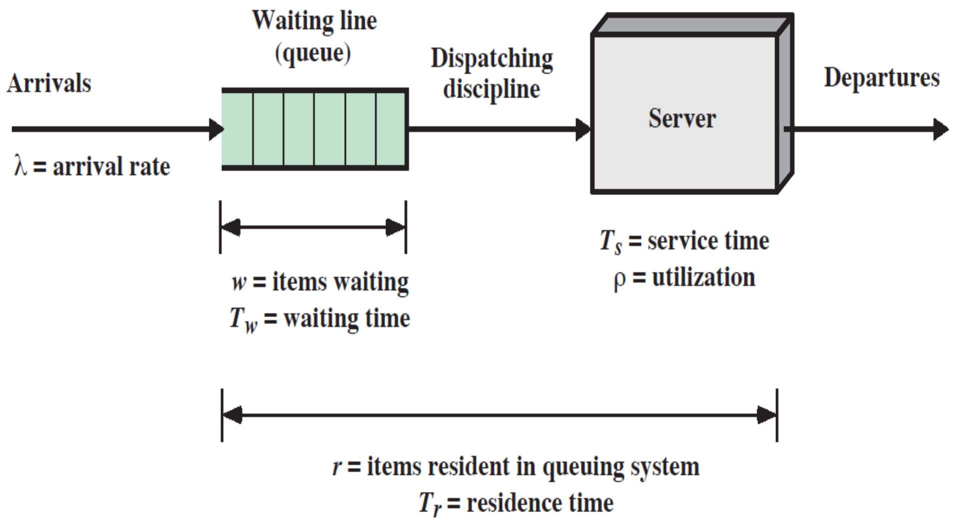


Figure B.1: Single-server queue structure [9]

is averaged over all incoming items, including those that do not wait at all. The server handles incoming items with an average service time $T_s$; this is the time interval between the dispatching of an item to the server and the departure of that item from the server. Utilization, $\rho$, is the fraction of time that the server is busy, measured over some interval of time. Finally, two parameters apply to the system as a whole. The average number of items resident in the system, including the item being served (if any) and the items waiting (if any), is $r$; and the average time that an item spends in the system, waiting and being served, is $T_r$; we refer to this as the mean residence time. If we assume that the capacity of the queue is infinite, then no items are ever lost from the system; they are just delayed until they can be served. Under these circumstances, the departure rate equals the arrival rate. As the arrival rate increases, the utilization increases and with it, congestion [9]. The queue becomes longer, increasing waiting time. At $\rho = 1$, the server becomes saturated, working 100% of the time. Thus, the theoretical maximum input rate that can be handled by the system is:

$$\lambda_{max} = \frac{1}{T_s}$$

However, queues become very large near system saturation, growing without bound when $\rho$= 1. Practical considerations, such as response time requirements or buffer sizes, usually limit the input rate for a single server to between 70 and 90% of the theoretical maximum.

Figure B.2 shows a generalization of the simple model which can be considered for multiple servers, all sharing a common queue. If an item arrives and at least one server is available, then the item is immediately dispatched to that server. It is assumed that all servers are identical; thus, if more than one server is available, it makes no difference which server is chosen for the item. If all servers are busy, a queue begins to form. As soon

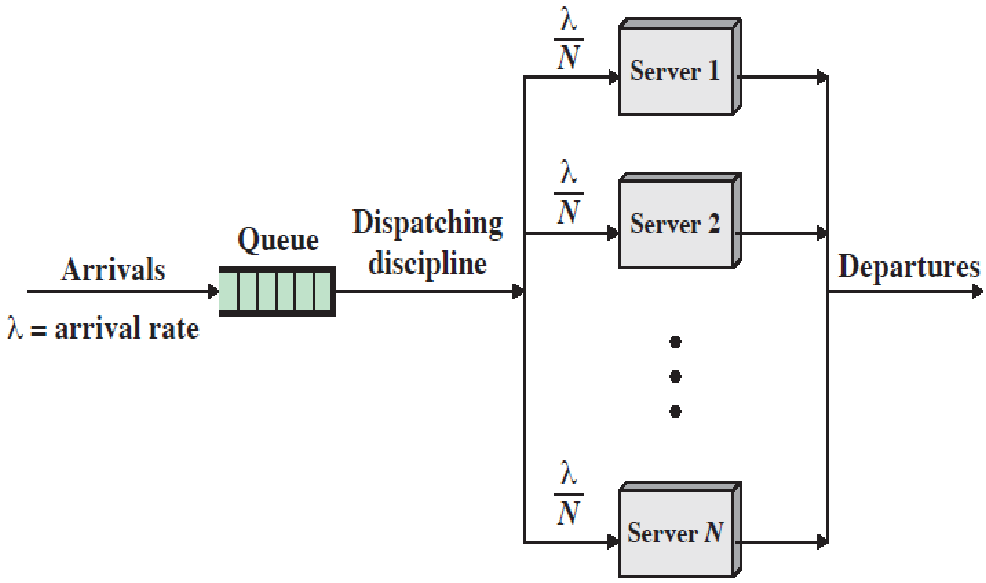


Figure B.2: Multi-server queue [9]

as one server becomes free, an item is dispatched from the queue using the dispatching discipline in force.

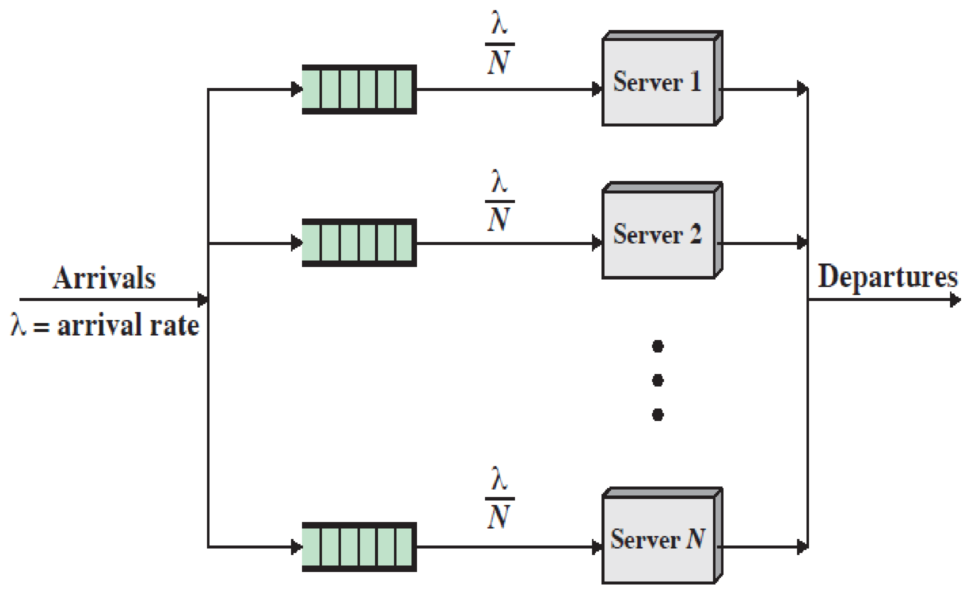


Figure B.3: Multiple Single-Server Queues [9]

With the exception of utilization, all of the parameters illustrated in Figures B.2, B.3 carry over to the multi-server case with the same interpretation. If we have $N$ identical servers, then $u$ is the utilization of each server, and we can consider $N_\rho$ to be the utilization of the entire system; this latter term is often referred to as the traffic intensity, $u$. Thus, the theoretical maximum utilization is $N * 100$, and the theoretical maximum input rate is:

$$\lambda_{max} = \frac{N}{T_s}$$

The key characteristics typically chosen for the multi-server queue correspond to those for the single-server queue. That is, we assume an infinite population and an infinite queue size, with a single infinite queue shared among all servers. Unless otherwise stated, the dispatching discipline is FIFO. For the multi-server case, if all servers are assumed identical, the selection of a particular server for a waiting item has no effect on service time [9].