NATIONAL UNIVERSITY OF SCIENCE AND TECHNOLOGY POLITEHNICA BUCHAREST

Doctoral School of Electronics, Telecommunications and Information Technology

Decision No. 81 from 19.07.2024

Ph.D. THESIS SUMMARY

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CONTRIBUȚII LA COMUNICATIILE IN INTERNETUL VEHICULELOR

CONTRIBUTIONS TO THE COMMUNICATIONS IN INTERNET OF VEHICLES

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BUCHAREST 2024

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Chapter 1

Introduction

This chapter begins with a brief background about the internet of vehicles (IoV). IoV is a unique and customised aspect of the internet of things (IoT) that allows enables integrated management of intelligent transportation and additional applications within smart cities [1] (e.g., Figure 1.1). Moreover, this chapter presents the field of the doctoral thesis; enabling of electric vehicles (EVs) within the smart cities through the IoV communication. It explains the benefits of integrating EVs within cities, highlighting that EVs can significantly reduce air pollution and gas emissions as they are a sustainable transportation strategy, producing zero carbon emissions. Additionally, the IoV facilitates the monitoring and management of EV charging infrastructure, enabling real-time data exchange between EVs, charging stations, and other power grid operators like aggregators.

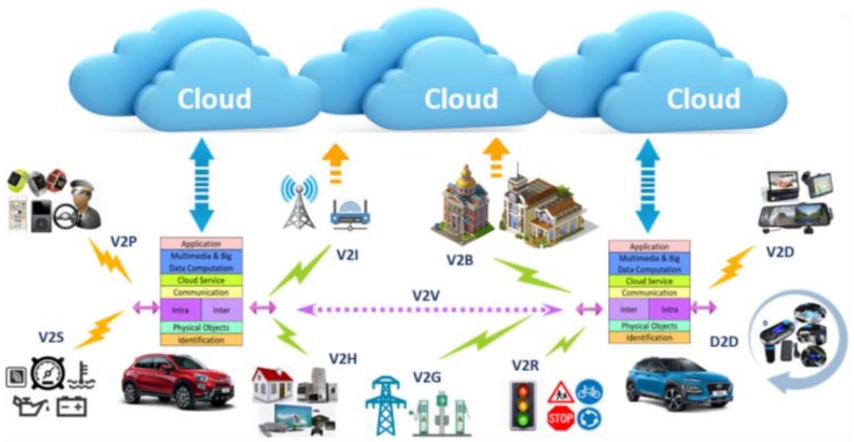


***Figure 1.1** Communication types of vehicles in smart cities through the IoV* [2].

1.1 Scope of the Ph.D. thesis

This thesis focuses on the EV charging problem and coordination requirements. Here are some research challenging issues that are addressed in this thesis with the focus on the EV charging problems:

1. What is the concept of G2V/V2G technology, and how does it facilitate bidirectional energy flow between EVs and the grid?

2 What are the diverse applications of G2V/V2G technologies, and how can it contribute to the overall energy system?
3 What are the different charging patterns observed in EV charging?
4 Why is charging coordination necessary, and how can both EV users and service providers benefit from implementing it?
5 How can a charging scheme be designed to effectively coordinate EV charging, taking into account various constraints and factors?
6 What optimisation techniques can be employed to obtain an optimal charging scheme for EVs, considering multiple factors such as grid capacity and current status, user preferences, and energy costs?

1.2 Content of the Ph.D. thesis

The work ahead is organised as follows.

Chapter 2 explores the crucial aspects of charging and discharging EVs within G2V/V2G networks and surveyed integration of software-defined networking (SDN) in vehicular networks for improved communication and coordination EVs among, charging stations, and the power grid. The chapter identifies open research issues highlighting the need for further exploration.

Chapter 3 provides a review of EV technology and addresses the problems of optimising charging scheme. The charging systems are introduced and addressed their advantages and disadvantages, they are classified into: centralised, decentralised and hierarchal. The chapter covers recent research in optimisation techniques aiming to optimise EV charging and also identifies the limitations and gaps in the current solutions. Also, several challenges with their potential solutions are proposed.

Chapter 4 explores the benefits of SDN and Cloud computing, to introduce a new flexible charging system model. A novel optimised charging method is proposed for solving the EVs charging scheduling and routing aims to minimise the time cost.

Chapter 5 focuses on the multi-objectives optimisation problem. The study utilised the “bi-non-dominated genetic algorithm (NSGA-II)” to jointly optimise two factors, including charging cost and time. The work compared NSGA-II with genetic algorithms (GA) in minimising the total costs in terms of time and price. Additionally, the work has been extended, by comparing the ant colony optimisation (ACO) and simulated annealing (SA) to optimise the EVs charging in terms of time and costs.

Chapter 6 proposes an adaptable charging strategy to mitigate the surges of peak load on the power grid, while considering the situation of urgent EVs charging demand. The work uses the algorithm of particle swarm optimisation (PSO) to adaptively select the charging mode for the EVs users.

Finaly the contributions of this thesis are concluded in *Chapter 7,* and future works are proposed for further exploration.

Chapter 2

Intelligent Control Approaches: Enabling Efficient Charging and Discharging

This chapter address various intelligent control strategies that facilitate efficient charging and discharging of EVs. It is discuss energy dispatch mechanisms in terms of G2V and V2G from the perspectives of benefits of both the power grid and EV users. Whereas a successful implementation of G2V/V2G requires the installation of three critical elements:

- A wireline or wireless connection that allows bi-directional charging interface to transfer the electrical energy between the power grid and EV.
- A communication sub-system with the grid operator through control and data connections to send and receive information from the grid, e.g., indicating and in which direction the power should be sent (i.e., charging or discharging demand) and others.
- Controls and monitoring logic onboard vehicles.

2.1 SDN integration in smart grid

This section discusses the integration of software-defined networking (SDN) in smart grids, highlighting its potential to enhance system stability and management. For instance, in a SDN-based smart grid one may have load balancing and shifting, dynamically altering the routing paths for smart grid control commands, fast failure detection, security, self-healing, and monitoring and scheduling of crucial smart grid traffic flows [3]. This chapter presents numerous contributions that have addressed the integration of SDN into grid. For instance, the study in [4] proposed a two-tier SDN-based framework used for the plug-in electric vehicles (PEVs)" to be integrated with smart grid. The study in [5] proposed a software defined vehicle to grid (SD-V2G) system, which integrate the SDN technology. The work [6] introduced a hybrid electric vehicle (HEV) charging system, namely, green-software-defined-charging-network, that incorporates both wireless and wire methods for charging. Finaly, the study in [7] proposed a battery status sensing software-defined multicast (BSS-SDM) system, enabling the smart grid to control and monitor distributed EVs energy.

2.2 Open research issues

This section identifies several open research issues in the EVs charging/discharging domains for further exploration:

1. *Intelligent EV charging/discharging management*: The management of EV charging and discharging is a complex issue that involves balancing several factors such as optimise the experience for EV users, the electricity grid, and charging costs. So, the main focus is here on how to coordinate the charging/discharging behaviour of EVs and develop an optimal scheme that maximises the benefits for EV users with respect to the power grid conditions.
2. *Communication and notifications:* EV users can receive notifications or use mobile applications that provide real-time information on electricity pricing and peak demand periods. This allows them to adjust their charging schedule accordingly and optimise their electricity consumption. Establishing a communication network between EVs, stations, and the grid enables real-time monitoring and control.
3. *Smart charging algorithms:* Intelligent algorithms can optimise the charging schedules of EVs based on factors such as grid conditions, electricity prices, and user preferences. These algorithms can coordinate the charging of EVs to maximise the utilisation of renewable energy, minimise grid stress, and reduced costs.
4. *Wired and wireless charging:* Various charging standards have been implemented in practise (in either a wireless or wired charging technology). To be researched and defined would be a single charging standard. Static and dynamic charging may both play an important role in wireless EV charging.
5. *Synchronising between tiers:* The aggregators in primary-feeders receive and implement the instructions from the upper-tier. On the other hand, they receive requests from the lower-tier physical devices and respond appropriately. It is necessary to conduct more research on the issue of balancing and analysing the process between requests in the lower tier and directions in the top tier [4].

The work in the next chapters focuses on addressing the challenges of how to coordinate the EVs charging (i.e., issues 1 and 3), and the development of optimise charging schemes.

Chapter 3

Optimisation Schedule Schemes for Charging Electric Vehicles: Overview, Challenges, and Solutions

It is important to implement smart charging schemes that manage and regulate the charging processes of EVs. However, various scientific survey papers on the optimisation of charging strategies have been published such in [8] [9] [10] [11]. However, the existing research primarily explored general EV charging methods and focused on standard EV charging scheduling under dynamic prices strategies, and energy flow management. Complementarily, this chapter provides a comprehensive overview of various optimisation scheduling schemes for EV charging. It categorizes EVs and their charging modes, including home, public, and mobile charging. The chapter reviews different charging strategies, such as uncoordinated and coordinated charging, and contrasts centralised and decentralised systems. Various optimisation techniques, including linear programming, dynamic programming, heuristic algorithms, and machine learning approaches, are analysed for their applicability in EV charging. The chapter contribute with a discussion on the limitations and gaps in current research and suggests potential directions for future studies.

3.1 Types of electric vehicles

There are four main types of EVs are categorised in the literature [12] (refer to Table 3.1): battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), hybrid electric vehicles (HEVs), and fuel cell electric vehicles (FCEVs).

Table 3.1 *The types of EVs*

Type	Cost	Driving Design	Charging Accessibility	Models	Ref.
HEVs	Low to	All driving habits	Not	Toyota Prius, Honda	[13]

	moderate		applicable; self-charging	Accord Hybrid, Ford Fusion Hybrid	[14] [15]
PHEVs	Moderate to high	Short daily travels, occasional longer travels	Public or home stations	Ford Fusion Energy, Toyota Prius Prime, Chevrolet Volt,	[12] [13] [14]
BEVs	High	Short to medium daily travels, occasional longer travels	Public or home stations	BMW i3, Tesla Model S, Nissan Leaf,	[12] [16] [17]
FCEVs	High	All driving habits	Hydrogen stations	Honda Clarity, Toyota Mirai, Hyundai Nexo	[14] [18]

3.2 Charging Patterns and modes for EVs

There are four main modes of charging based on the Deltrix Chargers classification [19]. Mode 1 is the slowest form of charging for an EV located at home stations. Mode 2 is also uses a home plug for charging EVs. It provides shock prevention against both AC and DC currents. Mode 3 is the most popular charging method among EV users. It can be implemented both at home and at public charging stations and the necessary connecting cables are provided at the stations. Mode 4, often referred to as fast charging mode, it involves the use of charging stations that convert AC power to DC, allowing direct charging for EVs.

There are three primary charging patterns for EVs: home charging, public charging, and mobile charging. Home charging, also referred to as electric vehicle supply equipment (EVSE), can be installed in a garage or outdoors, offering a reliable and secure charging solution. Public charging are typically located in public areas such as parking lots, shopping centers, or along major roads [20]. Mobile charging, also referred to as on-the-go charging, emerges as a trend for EV transport, by offering a portable charging solution for EV owners at remote locations where the availability of home and public charging stations are limited.

3.3 EV Charging strategies

EV battery charging is typically performed through two charging strategies: uncoordinated and coordinated. Uncoordinated charging strategy refers to a random charging behaviour, where EV owners can charge their vehicles at any type of charging stations and at any time as they prefer. The problem with uncoordinated charging is that it can lead to overloaded transformers, power outages, and increased electricity costs. In contrary, coordinated charging strategy involves planned and managed charging schemes that are applicable to optimise and manage EV charging operations, such as mitigating grid stress, enhancing energy efficiency, and minimising costs. Generally, coordinated schemes can be implemented using two types of charging systems: centralised, decentralised, or hieratical charging.

3.4 Centralised, decentralised, and hieratical systems

Following centralised schemes, a central entity coordinates the charging of EVs within a specific geographic area, such as a neighbourhood in a city [21]. The central entity in this charging system, known as an aggregator, communicate with both EV users and grid operators. It obtains and transmits demands as well as performs system configuration and coordinates other operations. To achieve this, the aggregator first collects charging information from EV owners, such as the identity (ID) number of an EV, battery capacity, SOC, etc. Then it executes an algorithm to optimise charging schedules based on the collected data, by taking into account the overall power demand and electricity prices in the market. Figure 3.1 presents a simplified high-level architecture of a centralised charging system, showing the primary functional units responsible for implementing system management and control.

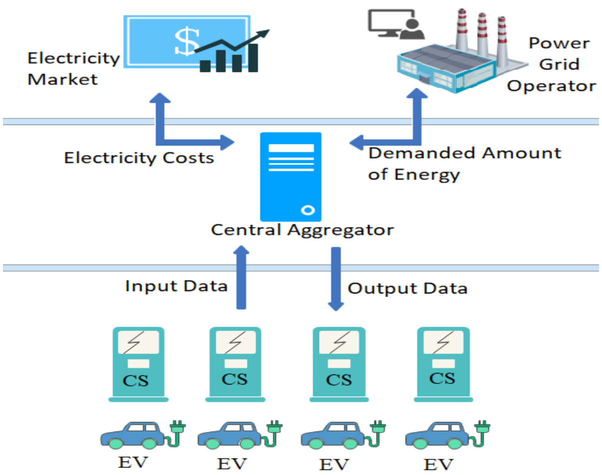


Figure 3.1 *Architecture of the centralised charging system for EVs.*

In the decentralised charging approach, an incentive-based strategy is introduced where the charging schedules of EVs are affected indirectly by electricity prices [22]. The EV owners play an active role in making their charging decisions, utilising information provided by the aggregator, such as current electricity prices and the availability of charging stations in the area managed by that aggregator. The primary objective of adjusting electricity prices is to motivate EV users to charge their vehicles during off-peak hours, thereby reducing the load on the grid during periods of high demand. Similar to a centralised approach, each aggregator collects user information or even predicts the charging demand of EVs for the next period of time. This information is used to find an optimal charging scheme. Figure 3.2 presents a simplified high-level architecture of a decentralised charging system.

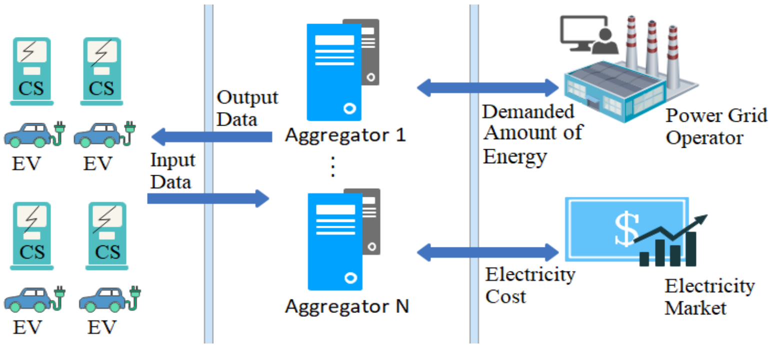


Figure 3.2 *Architecture of the decentralised charging system for EVs.*

Both centralised and decentralised charging systems discussed above have their advantages and disadvantages as summarised in Table 3.2.

Table 3.2 *The centralised and decentralised charging systems.*

System nature	Centralised	Decentralised
Control	More control over EV charging, aligned with grid needs (the schedule decisions are fully taken by the system)	Less control from the system part (users are involved in the decisions), but more flexibility, and better scalability
Information	The aggregator access to global information, potential for better schedules	Incomplete vehicle data and user preferences can lead to suboptimal schedules (possible disparity between users' and the system view on optimal schedule)
Data Sharing	Requires sharing private user data with an aggregator	Less need for user data sharing with an aggregator
Computational Complexity	Increased as the number of EVs increased	Distributed computational complexity
Failure Impact	Prone to failure problem affecting the entire system (centralisation - native drawback)	Distributed nature offers more resiliency
Infrastructure Investment required	Significant investment (needed to build a large network interconnected charging station, managed from a central aggregator)	Lower investment (The cost is often distributed locally among different stakeholders)

Hierarchical charging systems combines features of both centralised and decentralised systems. The architecture of these systems are multi-layer, typically involving central, regional, or local aggregators. This feature divides the responsibilities of management across several levels to optimise charging operations for EVs - the decision-making is distributed across different layers, reducing the load on a single aggregator and improving response times. These layers can be categorised as follows.

Top layer: this layer includes a central controller that makes broad, strategic decisions based on grid conditions, energy prices, and overall demand forecasts.

Middle layer: this layer composes multiple regional aggregators that gather local data from the charging stations and/or EVs in their region and make localised decisions to optimise charging schedules and manage resources effectively.

Bottom layer: this layer includes the charging stations and EVs. In this level, specific operational decisions can be made, such as adjusting charging power rates (select the charging mode).

3.5 Optimisation techniques for EV charging

This section presents various optimisation techniques, including linear programming (LP), dynamic programming (DP), heuristic optimisation algorithms, and machine learning (ML), which can be utilised or develop (individually or in combination) for optimising EV charging. Table 3.3 provides a comprehensive analysis that summarises various algorithms for EV charging, and present their applications, advantages, limitations, as well as computational complexity.

Table 3.3 *Summary comparison of algorithms.*

Algorithm	Advantages	Limitations	Computational Complexity
LP	Effective in multi-scenario optimisation, suitable for peak shaving and valley filling strategies	Can be complex in scenarios with a large number of variables	Variable; can be high in large-scale scenarios
DP	Effective for multi-stage decision problems, adaptable to changing conditions	Computationally expensive (curse of dimensionality), requires substantial computational resources	High due to recursive computations
Heuristic Algorithms (e.g., PSO, GA, ACO)	Good at finding near-optimal solutions for large or complex problems, adaptable to different scenarios	Parameter tuning can be complex, may not always find the global optimum	Variable: lower than exact methods but can increase with problem size
Machine Learning Techniques	Adaptive to new data, can improve accuracy over time, suitable for dynamic systems	Requires large datasets for training, some models may be “black box” with low interpretability	Depends on the model; deep learning models can be computationally intensive

Moreover, the current solutions in the sate-of-the-art that have been introduced to solve the EVs charging problems are critically analysed in this section and identifies their limitation and gaps (the details can be found in the thesis). For instance, LP has been utilised in many studies such in [23] [24], proved to be effective in optimising charging schedules that encompass multiple EVs, charging stations, and power grids. The studies in [25][26] utilised MILP to formulate the scheduling of EV charging and discharging. The study in [27] formulated the problem of online charging scheduling as a finite-horizon DP problem. While in [28] proposed an optimal scheduling method integrated with DP to minimise the costs of battery replacement during the entire service life of electric bus fleets (EBFs).

Heuristic optimisation algorithms such as genetic algorithm (GA), ant colony optimisation (ACO), and particle swarm optimisation (PSO), have been proven beneficial in addressing charging scheduling problems such in [29][30][31][32][33][34].

Machine learning (ML) algorithms can analyse and interpret large datasets, identify patterns, and make predictions or decisions based on the patterns discovered. For instance, the study in [35] developed four DL techniques to forecast EVs charging demand: gated recurrent units (GRUs), long short-term memory (LSTM), recurrent neural networks (RNNs), and artificial neural networks (ANNs). The study in [36] has been introduced an optimal charging scheme utilising deep reinforcement learning (DRL) to address the challenges of rapid charging station selection and route planning for EVs in the smart grid.

Table 3.4 summarises multiple popular charging optimisation solutions highlighting their findings and contributions, address their integration feasibility, and point out their limitations and gaps.

***Table 3.4** Examples of charging optimisation solutions*

Ref.	Key Findings/Contribution	Alg.	Charging System	Integration	Limitations and Gaps
[23]	Developed an LP model to optimise power consumption at parking lots, demonstrating effective peak shaving and valley filling strategies (optimise the grid side)	LP	Decentralised	None	▪ The study is conducted in a small-scale area (a university) with a limited number of EVs and parking spots. ▪ Lack of considering of EV user preferences such as required SOC and charging mode, or a specific time for charging.
[24]	Utilised LP to enhance self-consumption of PV in a microgrid, showing significant reduction in peak demand and increased efficiency (optimise the grid operators)	LP	Decentralised	V2G and Renewable energy	▪ The study is limited to small-scale areas, so it may need to for improvement to apply large-scale scales. ▪ Uncertainty in various factors, such as PV power and load demand predictions, EV trip times, and energy use. ▪ Lack of considering of the EV constraints (e.g., SOC, charging mode, EV location)

[25]	Demonstrated cost-effective EV charging management with PV and minimising charging costs of EVs and power load on the grid to enhance the grid stability (optimise both the grid and user sides)	MILP	Decentralised	V2G, Renewable energy (PV), and TOU	▪ The study is limited to a small area and may face challenges in real-world implementation at a larger scale. ▪ The model relies on prediction data of solar generation and energy prices. ▪ Lack of considering of the EV constraints (e.g., SOC, charging mode, battery capacity)
[26]	Presented a novel approach for optimising EV charging, significantly maximising aggregator revenue and energy storage usage (optimise the grid operator)	MILP + LP-based heuristic algorithm	Centralised	None	▪ The model is based on simulations and its effectiveness needs validation in the real-world application
[27]	Proposed effective algorithms for managing dynamic EV arrivals and charging, focused on minimising EV charging cost, power load, and computation time (optimise the grid side), suitable for fluctuating EV numbers and demands.	DP + MPC	Centralised	None	▪ The study is based on simulations and may need further validation with real-world data. For instance, information such as arrival EVs is not known. This makes the potential to apply real-time scenarios integrated into a V2G system.
[28]	Suggested a DP-based method for reducing battery replacement costs in EBFs, enhancing sustainability and economic efficiency (optimise the user operator)	DP	Centralised	None	▪ The study was conducted in a public transit system for five EBFs with five routes a day. The applicability to different or larger-scale transit systems is not discussed.
[30]	Developed a PSO-based method to minimise charging costs and time in parking-lots (optimise both the grid and user sides)	PSO	Centralised	Renewable energy (wind turbine and five PV)	▪ The study considered a small number of EVs and did not account for varying user behaviour and preferences in charging.
[31]	Implemented PSO for efficient EV charging management to minimising charging costs of parking lots (optimise the grid operator)	PSO	Centralised	V2G	▪ The study did not use the aggregation technique
[32]	Introduced a GA-based scheme for load profile optimisation, by flattening the load	GA	Centralised	None	▪ Lack of consideration of the EV preferences or constraints (e.g., SOC, charging mode, battery capacity).

	prevent aging of power system elements (optimise the grid operator)				
[33]	Proposed a GA-based scheme to minimise waiting time and distance for emergency EV charging during peak times (optimise the user side)	GA + NJF and EDF	Centralised	None	▪ The study was conducted for urgent EV charging in high-density regions and did not consider the charging costs aspect.
[34]	Optimise charging operation efficiency for the grid side by minimising the total delay in EV charging at stations with high traffic	ACO	Centralised	None	▪ The study did not address the variability in individual EV charging needs or preferences.
[35]	Developed DL models to accurately predict EV charging demand, particularly effective in the context of Morocco (optimise the grid operators)	GRU	Centralised or decentralised	None	▪ The study is specific to Morocco electricity market, and the applicability of the findings of the study to other regions or market structures may vary. ▪ The study did not consider the variability of EV user behaviour and its impact on charging demand predictions.
[36]	Utilised DRL for efficient station selection and route planning, reducing EV charging costs and time for EV (optimise the user side)	DRL	Centralised	SDN, VEC, and TOU	▪ Inflexible to select the charging mode of the EV user, its adaptability to different urban environments with varying traffic needs to be further explored.

3.6 Open research and future directions

This section discusses the open research areas and future directions in optimizing EV charging schedules:

1. *Limited availability of public charging datasets*: developing machine learning models for optimising EV charging is hindered by a lack of comprehensive public datasets. Effective training and validation of these models require extensive data. To address this challenge, it is essential to promote collaboration among industry, government, and academia to create standardised, anonymised datasets and develop business models that encourage data sharing.
2. *Maximising the utilisation of RESs*: integrating RESs into the EV charging schedule is crucial for maximising green energy use, minimising

environmental impact, and reducing costs [37]. However, the limited variability in solar and wind output can be challenging, suggesting the need for more research into incorporating EVs as mobile storage units that can store and later supply this energy, helping to stabilize the grid during peak times.

3. *Time efficiency and user convenience*: the development of an optimal EV charging method that adapts to real-time changes and manages large-scale demands efficiently is crucial. Such a system needs to minimise waiting times and ensure reliable access to charging stations, thereby enhancing user convenience. In scenarios like a large city event or peak workday hours, the demand for charging can spike unexpectedly, varying greatly due to factors like battery capacity and SOC. To address this, real-time data monitoring is essential to dynamically adjust charging plans based on current conditions.
4. *Grid stability and user accessibility*: load balancing is a critical problem in EV charging, especially considering the grid's capacity and the fluctuating demand at charging stations. The challenge for grid operators is to manage the overload charging stations while accommodating high charging demands during peak hours. Future research would propose more dynamic and adaptive approach. Such approach should sets limitations, such as set a maximum SOC threshold for EVs during peak hours.
5. *User convenience*: Focusing on the specific requirements of EV users, the service can ensure a convenient, efficient, and cost-effective charging experience. The service providers should allow EV owners to specify their charging preferences, such as preferred charging infrastructure (e.g., home, public, or mobile station), charging modes, desired price rate, and charging at specific time.
6. *Cost optimisation*: the challenge with fast charging lies in its higher power rate, which has the potential to strain the grid and, in extreme cases, lead to power outages if the overall demand exceeds the grid capacity. To overcome this challenge, optimise charging schedules based on user needs and grid capacity using TOU pricing strategy to manage the charging demand during peak hours.

Chapter 4

Routing and Scheduling Charging Scheme for Electric Vehicles in SDN-based Vehicular Network:

This chapter tickles the problem of random EVs charging and introduces a novel routing and scheduling charging scheme for EVs within an SDN-based vehicular network. The methodology involves a system model and a mathematical framework that considered for optimising the charging process. The chapter utilised two algorithms, including fuzzy logic control and Dijkstra, to develop an advanced algorithm. The develop algorithm designed to achieve load balancing across multiple charging stations while ensuring efficient routing and scheduling for EVs. Several factors are considered in this study, including the SOC, EV battery capacity, charging mode (fast or slow), availability of charging stations. Additionally, this chapter proposes a new optimised scheme that prioritizes the fast charging demands of EVs over slow charging demands. The main objective of this propose is to minimise both service time (in terms of travel time, waiting time, and charging time) and charging costs. The TOU mechanism is applied to calculate the charging costs. This work evaluated in MATLAB tools. The develop algorithm applied in two schemes: first come first served (FCFS) and the proposed scheme (fast charging priority-base), both are compared with the random charging scheme. The simulation results demonstrate the effectiveness of the developed algorithm with the proposed scheme in reducing service time.

4.1 Methodology

This study proposed the architecture of SDN-based cloud computing for EVs charging (refer figure 4.1), this allows to have a real-time interaction between the EVs users and the grid operators. This architecture composes three layers: application layer, control layer, and physical layer. The mathematical model of the proposed schemes is summarised in this subsection. Firstly, the service time for each EV user is formulated.

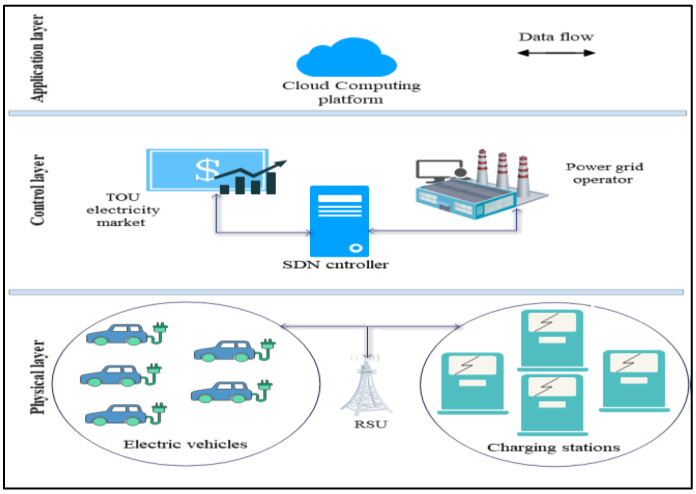


Figure 4.1 *SDN-based cloud computing architecture.*

The service time ($T_{v,c}^{service}$) represents the total time for an EV need to be fully charged, including travel time, wating time, and charging time. It can be calculated as:

$$T_{v,c}^{service} = T_{v,c}^{travel} + T_{v,c}^{waiting} + T_{v,c}^{charging}, \tag{4.1}$$

The $T_{v,c}^{traveling}$ represents the travel time, which is amount of time needed for the EV to move between nods, which can be obtained by:

$$T_{v,c}^{traveling} = \frac{D_{v,c}}{V_v}, \tag{4.2}$$

Where $D_{v,c}$ is the distance between two nodes (e.g., from current EV location v to the charging station c). V_v is the average driving speed of an EV. Hence, an EV may has very low of energy and cannot reach to all the charging stations in the city. Therefore, this study considered from [38] the maximum distance for the EV to travel, represented by D_{max} and can be calculated as:

$$D_{max,v} = \frac{B^{size} B^{soc}}{e}, \tag{4.3}$$

Where the e indicates how much energy an EV battery uses for a certain distance (0.15 kwh/km). B^{size} donates the battery capacity size, and the B^{SOC} represents the battery state of charge. However, an EV should wait at the queue if all the charging units at the station are busy. So this study uses the M/M/S model as in [39] to estimate the waiting time each EV. The wating time for an EV is represented by $T_{v,c}^{waiting}$:

$$T_{v,c}^{waiting} = \frac{L_{q,c}}{\gamma_{c,\tau}}, \tag{4.4}$$

Where, $\gamma_{c,t}$ represents the arrival rate of EVs at time slot τ. $L_{q,c}$ represents the queue length at a charging station. However, as mentioned earlier, this study assumed that each EV user should select one of two charging modes i.e. slow or fast charging. The selection one of these modes is dependent on the user desire, where each mode has a specific power rate that effect the EV charging time. The charging time is represented by $T_{v,c}^{charging}$, it can be obtained by:

$$T_{v,c}^{charging} = \frac{B^{size}(\sigma - B^{soc})}{\vartheta_c^o}, \tag{4.8}$$

Where, ϑ_c^o denotes the charging rate of an EV mode. The charging mode indexed by o, (e.g., if $o = 1$, is fast, else $o = 0$, is slow). The percentage of an EV battery expected to be charged denoted by σ (i.e., $\sigma = 95\%$). Moreover, this study utilised TOU charging price mechanism to calculate the charging cost for each EV. So the day can be divided into three periods including peak (P^{peak}), regular ($P^{regular}$), and valley (P^{valley}). The charging cost, represented by $C_{v,c}^o$, can be calculated by:

$$C_{v,c}^o = \begin{cases} P^{regular} \\ P^{valley} \\ P^{peak} \end{cases} * E_{v,c}^{amount}, \tag{4.9}$$

Where, $E_{v,c}^{amount}$ represents the amount of energy demanded by an EV. Noting that, in random charging pattern particularly considers the classical electricity price $P^{clasical}$, which is fixed. Furthermore, the proposed objective function is modelled to represent the total cost for EV charging. This total cost is denoted as $T_{v,c}^{total}$ and is defined as follows:

$$T_{v,c}^{total} = min[w_1 T_{v,c}^{traveling} + w_2 T_{v,c}^{waiting} + w_3 T_{v,c}^{charging}] + C_{v,c}^o \tag{4.11}$$

Where $w_1, w_2, and\, w_3$ represent the weight coefficients of three metrics, respectively, traveling time, waiting time, and charging time. This is subject to the following conditions:

$$D_{v,c} \leq D_{max} \tag{4.12}$$

$$B^{size} B^{soc} + E_{v,c}^{amount} - D_{v,c}\, e = B^{size} \tag{4.13}$$

$$E_{total} < E_{supply} \tag{4.14}$$

The constraint in (4.12) is the travelling distance of an EV to a charging station is equal or less to the maximum distance. The constraint in (4.13) guaranties the EV is fully charged. The constraint in (4.14) maintains the grid stability.

The proposed **Algorithm** for solving this problem and managing EVs charging is divided into two parts. The first part utilises the Dijkstra algorithm, which is widely utilised for solving the shortest distance routing problem. In the second part of the **Algorithm** utilises the fuzzy logic control to manage and distribute load of EVs over charging stations.

Algorithm: *Pseudocode of routing and scheduling EVs charging* [Annex A.1.1]

Input: information of EVs profile, graph of charging network, and information of charging stations.

Initial: SDN controller receive charging demands from certain number of EVs at t = certain moment, the availability of charging stations, the queue length at each charging units at each available station

1: Set $EV^{profile}[User^{id}$, B^{size}, B^{SOC}, charging mode o, current location].

2: ***For*** each *EV* ***do***

3: Determine the $T_{v,c}^{charging}$.

4: Determine the D_{max}.

5: Search for available charging stations within EV range using *Dijkstra* and considering D_{max} .

6: Determine the $T_{v,c}^{travelling}$ for EV at each available charging station.
7: Evaluate the *wating time* ($T_{v,c}^{waiting}$) at each available charging station.
8: ***if*** the available charging stations satisfied the constraints of (4.12) (4.13) and (4.14) ***then***
  9: Make Fuzzy input as a MATRIX of *travelling time* and *waiting time*.
  10: Determines the *Max. Weight* value from the Fuzzy output.
  11: Scheduling the EV at a charging station with minimum time cost.
12: *else*
  13: The EV cannot reach any charging station.
14: ***end if***
15: Determine the objective function $T_{v,c}^{total}$ using (4.11).
16: Update the queue length at the selected charging station.
17: ***end do***
18: Repeat steps 2-16 for all EVs
19: *end*

4.2 Results and discussion

This study used the MATLAB tools to evaluate the performances of the proposed **Algorithm**, considering the graph of Bucharest city to mimic the real simulation [40]. Table II illustrates the parameters which are used as benchmarks in this study.

Table 4.1 *The simulation parameters.*

<table>
<tr><th colspan="2">Rate of Charging Mode</th><th colspan="5">Slow = 22 kw</th><th colspan="5">Fast = 50 kw</th></tr>
<tr><td rowspan="3">Charging Prices (TOU)</td><td>Regular periods:
12 - 6 a.m., and
10 p.m. - 12 a.m.</td><td colspan="5">1.53 lei/kwh</td><td colspan="5">2.29 lei/kwh</td></tr>
<tr><td>Valley periods:
6 - 8 a.m., 11 a.m. - 5 p.m.,
and 8 - 10 p.m.</td><td colspan="5">2.88 lei/kwh</td><td colspan="5">4.30 lei/kwh</td></tr>
<tr><td>Peak periods:
8 -11 a.m., and 5 - 8 p.m.</td><td colspan="5">3.92 lei/kwh</td><td colspan="5">5.86 lei/kwh</td></tr>
<tr><td colspan="2">Classical Charging Price</td><td colspan="5">1.45 lei/kwh</td><td colspan="5">1.95 lei/kw</td></tr>
<tr><td colspan="2">Charging Station</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td></tr>
<tr><td colspan="2">Number of Charging Units</td><td>4</td><td>3</td><td>3</td><td>4</td><td>3</td><td>3</td><td>3</td><td>5</td><td>4</td><td>5</td></tr>
</table>

Figure 4.6 illustrates the EVs wating time at the charging station and figure 4.7 illustrates EVs service time, compared between three charging schemes: random, FCFS with proposed algorithm, and fast charging priority-based with proposed algorithm. The results show that the proposed algorithm with proposed scheme outperform other schemes as many EVs are distributed equally at the stations. Where lowest wating and service time is achieved.

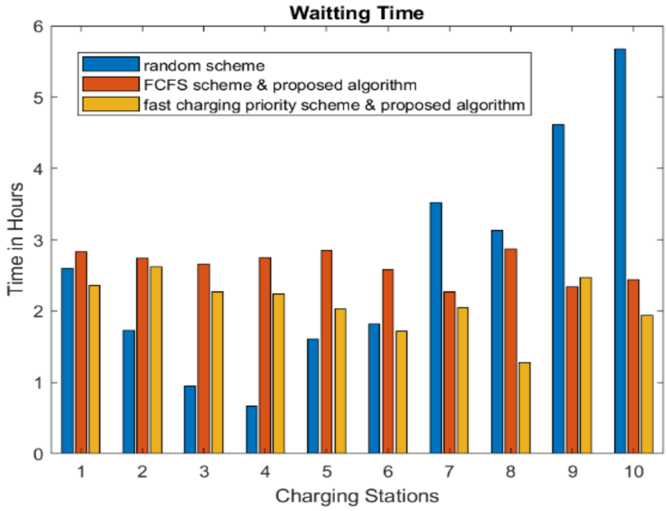


Figure 4.6 *Total waiting time for EVs at charging stations.*

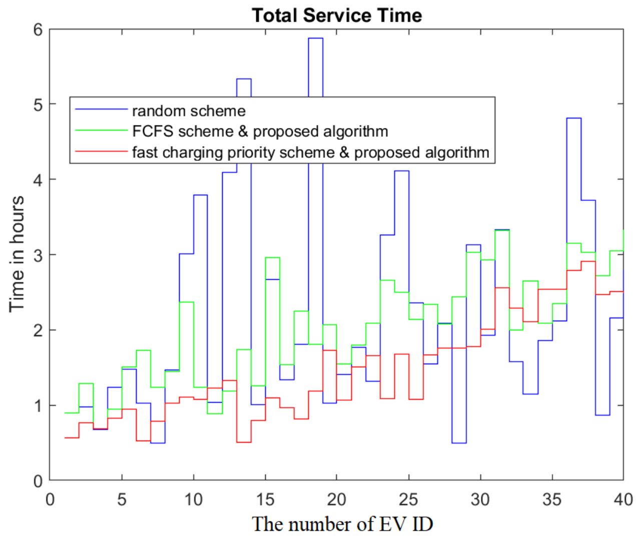


Figure 4.7 *Total service time for EVs at charging stations.*

Finally, in Figure 4.9 shows the charging cost for each EV with the proposed algorithm in the comparison between TOU and classical prices. The results show that applying the TOU can increase the total incomes for the service providers compared with the classical charging prices.

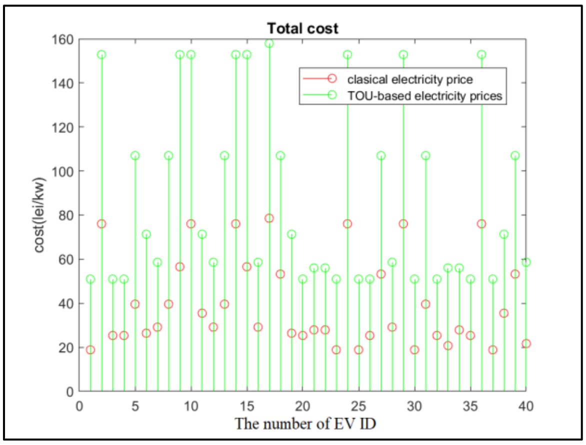


Figure 4.9 *The charging cost for EVs.*

Chapter 5

Non-Dominated Sorting Genetic Optimisation for Charging Scheduling of Electrical Vehicles with Time and Cost Awareness

The exploration and exploitation balancing for EV charging is still an open issue and needs to be studied further. Therefore, this chapter formulate the problem of EVs charging schedule into multi-objectives in terms of time and cost. It introduces a bi-objective optimisation model using the bi-non-dominated sorting genetic algorithm (NSGA-II) to address trade-off between charging time and costs by providing a diverse set of non-dominated solutions. The means of non-dominated solutions are set of solutions that no one is superior in all objectives, but each one is superior to some and inferior in others. The empirical evaluations demonstrate the superiority of NSGA-II over traditional genetic algorithms (GA). The results show that NSGA-II offers a balanced solution in terms of charging time and costs compared to the GA. Additionally, the work in this chapter extended by comparing the performance of ant colony optimisation (ACO) and simulated annealing (SA) algorithms. The best solutions obtained by ACO and SA represent scheduling a number of EVs over charging stations with the aim of minimising total cost in terms of service time and charging cost. The result show that ACO has superior capabilities in charging optimisation compared to SA.

5.1 Methodology

In this study assumes the implementation of the proposed optimisation algorithm (e.g., NSGA-II, ACO, and SA) in a centralised charging system. The charging schedule procedures begins by EVs send information such as SOC, battery capacity, charging mode, and location to the aggregator. Meantime, the charging stations share with the aggregator their locations, capacities, availability status, and pricing rates, continuously updating any changes. The information of travel time and distances between EVs and stations assumed to be available for simplification. The central aggregator analyses and processes information from EVs and charging stations and runs the NSGA-II algorithm. The optimisation objective in this system is to minimises the total cost for EVs charging (in terms of time and price). This work utilises similar mathematical model used in chapter four, whereas the problem of EVs charging has two major objectives: *service time* and *charging cost.* Following to the equation (4.1), the first objective is the *service time* indexed by $T_{v,c}^{service}$. It composes three parameters: *traveling time* (indexed by. $T_{v,c}^{traveling}$), *waiting time* (indexed by $T_{v,c}^{waiting}$), and *charging time* (indexed by $T_{v,c}^{charging}$), respectively, follow the equations (4.2), (4.4), and (4.8).

The second objective is the *charging cost*, which is vary based on factors such as the energy prices, charging mode, and the total amount of energy required to charge the battery. In order to reduce the *charging cost*, this work uses the TOU tariffs. The charging cost with applying TOU can be expressed as follows:

$$\mathrm{C}_{v,c} = \begin{cases} p_{off-peak,class(i)}\ E_{v,c}^{amount} \\ p_{peak,class(i)}\ E_{v,c}^{amount} \end{cases} \tag{5.1}$$

Here, $\mathrm{C}_{v,c}$ denotes the *charging cost* and $E_{v,c}^{amount}$ is the amount of energy of the EV requires to be charged. $p_{class(i),off-peak}$ and $p_{peak,class(i)}$, respectively, denote the pricing rates of charging in off-peak period and peak period at a charging statin. Where $class(i)$ is the charging mode (i.e., fast, slow, regular).

5.1.2 Optimise EVs charging using NSGA-II

This study proposes the usages of NSGA-II to solve the problem of multi-objective EV charging. The NSGA-II begins by initialising a population of random solutions *P(0)* to find a solution for the problem of EV charging. The pseudocode below illustrates the process of NSGA-II algorithm.

Algorithm – Pseudocode of optimisation EV charging using NSGA-II [Annex A.1.2]

Input: population size (*N*), number of generations *(G), crossover probability* P_c*, and mutation probability (*P_m*)*
Output: *Pareto-optimal solutions*
1: *Initialise population P(0) of size N with random solutions (initial random schedule of EVs at stations*
2: *Evaluate the objective values (service time (4.1) and charging cost eq. (5.1)) of each solution in P(0)*
3: *t ← 0*
4: *While t < G do*
    5: *Perform non-dominated sorting on P(t) to rank solutions based on dominance*
    6: *Calculate the crowding distance for each solution in P(t)*
    7: *Create an empty offspring population Q(t)*
    8: *Apply crossover with probability* P_c *to generate two offspring solutions*
    9: *Apply mutation with probability* P_m*to each offspring solution*
    10: *Evaluate the objective values of the offspring solutions*
    11: *Add offspring solutions to Q(t)*

12: *P(t+1) ← Q(t)*
13: *t ← t + 1*
14: *End while*
15: *Return Pareto-optimal solutions from the final population P(G)*

5.1.2 Ant colony optimisation

In this work, the proposed ACO method initializes by setting a uniform pheromone matrix; representing the probability of assigning each EV to a charging station (see the annex A.1.2 part 2). For each iteration, each ant construct solutions by probabilistically assigning EVs to stations based on the pheromone levels. The objective function in this work is the total cost in terms of time and price, respectively, using the eq. (4.1) and eq. (5.1). It can be written by:

$$cost_{v,c}^{total} = w_1 T_{v,c}^{service\ time} + w_2 C_{v,c}^{o} \tag{5.4}$$

Each solution is evaluated using the objective function (5.4), and the best solution of the iteration is identified. If this solution improves upon the overall best solution, it is saved as the current best. After all ants have completed their assignments, the pheromone matrix is updated. The pheromone levels are partially decayed and additional pheromone is deposited on successful assignments based on solution quality. This iterative process continues until a specified number of iterations is completed, resulting in an optimised assignment of EVs to charging stations; in terms of minimal *time and cost,* as it is the ACO output.

5.1.3 Simulated Annealing

In this work, the proposed SA algorithm begins by generating a random initial solution that assign each EV to the charging stations (see annexes A.1.2 part 2). Similar to the work of ACO, the objective function in eq. (5.4) is used to evaluate the initial solution, aiming to minimises the total cost in terms of *time and price*. The initial solution serves as both the current and best-solution. The algorithm iteratively generates neighbouring solutions by modifying the charging stations assignment for a randomly selected EVs. The objective value eq. (5.4) is computed in each neighbouring solution, and a decision is made on whether to accept it as the current solution or not. If the neighbour solution has a lower cost, it is accepted; if not, it may still be accepted with a probability influenced by the current temperature and the objective difference, encouraging exploration in early stages. The temperature is gradually reduced by a cooling rate, allowing the algorithm to refine solutions around. This process continues until the predefined iteration limit is reached, at which point the best solution found is saved as the SA result.

5.2 Results and discussion

The experimental evaluation was conducted using MATLAB 2020b. Table 5.1 outlines the parameters used for the experimental evaluation.

Table 5.1 *Parameters used for experimental evaluation.*

Parameter Name	Value	Parameter Name	Value
EVs	100	crossover fraction	0.7, 0.9
EV battery sizes	[40,100]	EVs in the queue	10
prices of off-peak period	[0.10, 0.15, 0.20]	ACO iterations no.	1000
prices of peak period	[0.20, 0.25, 0.30]	ACO ants no	100
population size	[50, 100, 200]	pheromone decay rate	0.5
stations no.	20	SA iterations no.	1000
generations	200	SA initial temperature	100
mutation probability	0.08, 0.1	SA cooling rate	0.8
crossover fraction	0.7, 0.9		

Firstly, generated six distinct Pareto fronts corresponding to sixth individual experiments. The findings showed NSGA-II provides diverse non-dominated solutions regarding the two optimisation goals: charging cost and service time. Conversely, the conventional GA typically produced a singular solution with reduced service time and charging cost (refer to Figure 5.2). The NSGA-II consistently offered more optimised solutions than GA, a limitation in the latter stemming from its predisposed objective weighting. The findings of the study revealed that increasing the population size from 50 to 200, with other parameters constant, yielded no significant alterations in average charging cost or service time.

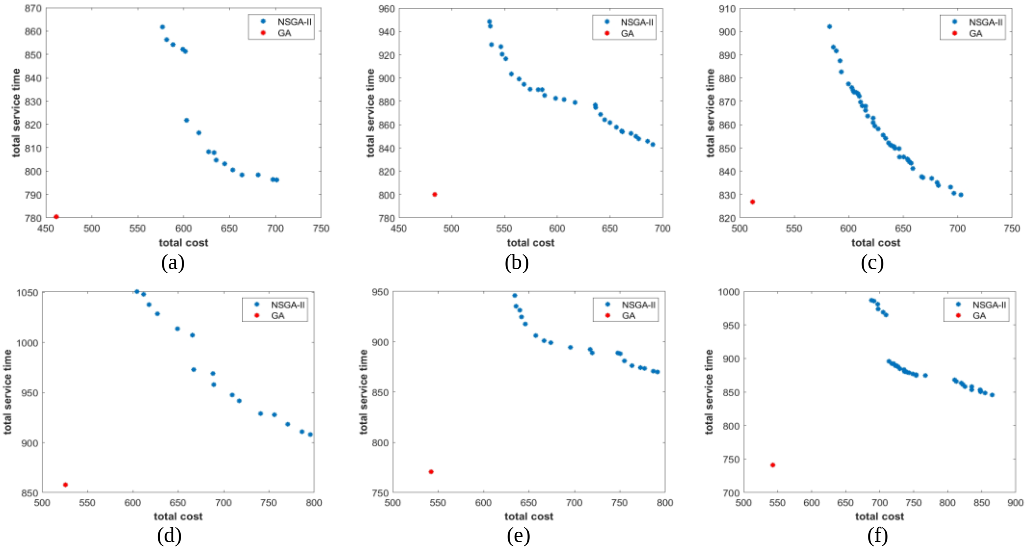


Figure 5.2 *The Pareto front for the six experiments generated from NSGA-II and traditional GA with crossover fraction 0.7 and 0.9, mutation probability 0.08 and 0.1, and population size (a,d) 50 (b,e) 100 (c,f) 200.*

Figure 5.3 showcases solution from the conventional GA show uneven distribution is symptomatic of GA inherent restrictions, revealing its inadequacy in optimising assignments evenly. In contrary, the solution generated from NSGA-II terms of service time (Figure 5.4 (a)) and charging cost (Figure 5.4 (b)), show a more balanced EV distribution across several charging stations.

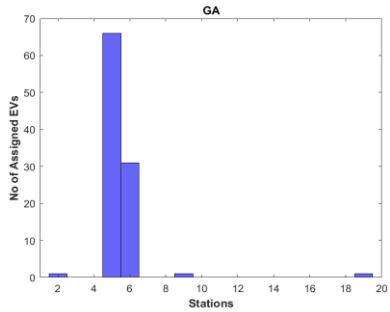
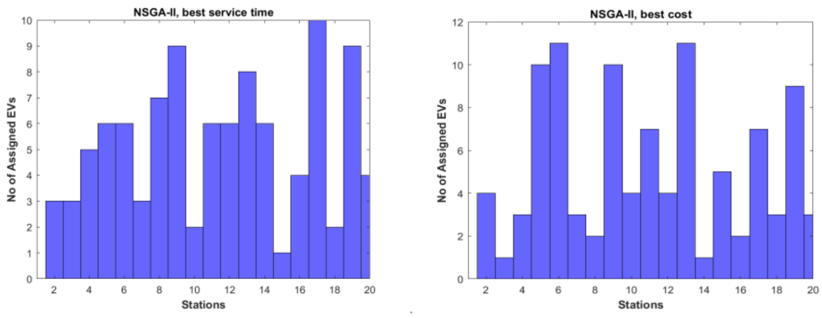
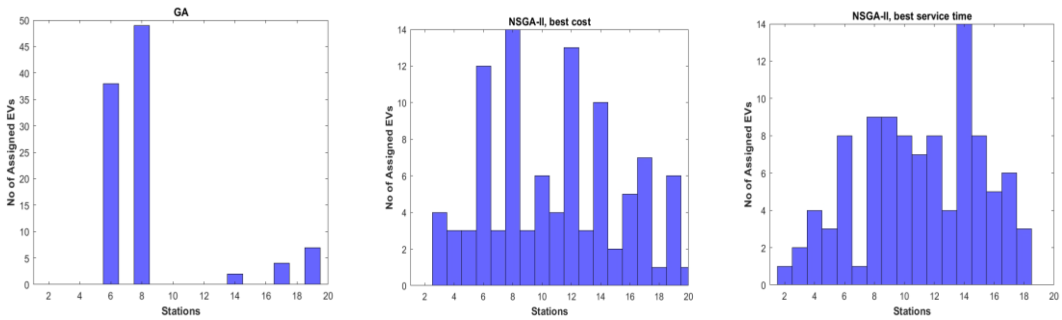


Figure 5.3 *The assignment of 100 EVs over 20 stations generated by GA with crossover fraction 0.7, mutation probability 0.08, and population size 50 in terms of service time and cost*



(a) (b)

Figure 5.4 *The assignment of 100 EVs over 20 stations generated by NSGA-II with crossover fraction 0.7, mutation probability 0.08, and population size 50 in terms of (a) service time and (b) charging cost*

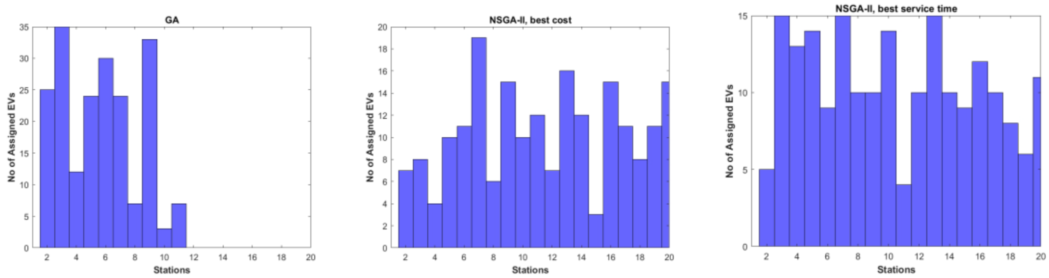


(a) (b) (c)

Figure 5.5 *The assignment of 100 EVs over 20 stations with crossover fraction 0.9, mutation probability 0.1, and population size 200 in terms of (a) GA and (b) NSGA-II; charging cost (c) NSGA-II; service time*

For more analyses, the experiment repeated, and the number of crossover fraction changed up to 0.9, the number of mutation probability up to 0.1, population size up to 200. The result in Figure 5.5 is almost the same as the previous one. This emphasises that changing the parameters values of the GA or NSGA-II almost have no side effects.

The number of EVs expanded to 200 to assess the efficacy of our proposed solution with a larger vehicle count. Figure 5.6 (a) showcases the solution produced by GA, indicating noticeable improvements with the increased EV assignments. In contrast, the NSGA-II solutions in (b) service time and (c) charging cost demonstrate more assigning of EVs than GA.



(a) (b) (c)

Figure 5.6 *The assignment of 100 EVs distributed over 20 stations during the off-peak period generated from GA and NSGA-II.*

In this evaluation, the best solutions obtained from the ACO and SA algorithms are compared in term of total cost: *service time* and *charging cost* (see Figure 5.7).

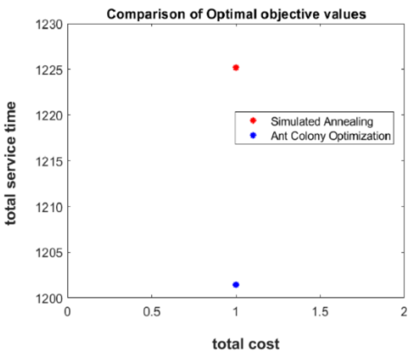
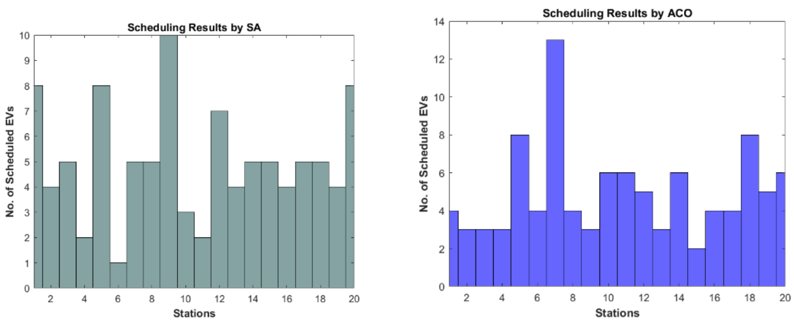


Figure 5.7 *The best objective values obtained by ACO and SA.*

Figure 5.8 shows the best solutions obtained from (a) SA and (b) ACO . The results demonstrate that ACO an improvement by assigning more EVs to each CS than SA.



(a) (b)

Figure 5.8 *Number of EVs scheduled at charging stations using (a) SA and (b) ACO.*

Chapter 6

Smart and Adaptable Charging Method for Electric Vehicles, Considering Urgent Charging

This chapter proposes a smart and adaptable charging scheme for EVs that considers urgent charging demands. The scheme dynamically adjusts charging rates based on the urgency of the demand, using the particle swarm optimization (PSO) method to prevent grid overload. The system's performance is evaluated under different numbers of EVs and two charging patterns (home and public). The proposed scheme is compared with two normal schemes: one that satisfies the minimum SOC and another that satisfies the maximum SOC. The results demonstrate that the proposed scheme effectively reduces EV load and shifts power demand from peak to off-peak hours, enhancing grid stability and efficiency.

6.1 Methodology

Similar to previous works, the proposes of smart and adaptable charging method is assumed to be performed in centralised system. However, each EV driver has a specific charging demand and should share the information of its charging demand with an aggregator. In this work, the EV information considered are SOC, size of battery capacity, and arriving time and leaving time (e.g., at home or public stations). This study adopted the formula as in [41], to generate the data of arriving time (t_{1a}) and leaving time (t_{1l}) of EVs, according to the probability distribution function (PDF) and Monte Carlo Simulation:

$$f(t_{1a}) = \begin{cases} \frac{1}{\sqrt{2\pi}\sigma_{1t_a}} exp\left(\frac{-(t_{1a}+24-\mu_{1t_a})^2}{2{\sigma_{1t_a}}^2}\right) & 0 < t_{1a} \leq \mu_{1t_a} - 12 \\ \frac{1}{\sqrt{2\pi}\sigma_{1t_a}} exp\left(\frac{-(t_{1a}-\mu_{1t_a})^2}{2{\sigma_{1t_a}}^2}\right) & \mu_{1t_a} - 12 < t_{1a} \leq 24 \end{cases} \tag{6.1}$$

$$f(t_{1l}) = \begin{cases} \frac{1}{\sqrt{2\pi}\sigma_{1t_l}} exp\left(\frac{-(t_{1l}-\mu_{1t_l})^2}{2{\sigma_{1t_a}}^2}\right) & 0 < t_{1l} \leq \mu_{1t_l} + 12 \\ \frac{1}{\sqrt{2\pi}\sigma_{1t_l}} exp\left(\frac{-(t_{1l}-24-\mu_{1t_l})^2}{2{\sigma_{1t_a}}^2}\right) & \mu_{1t_l} + 12 < t_{1l} \leq 24 \end{cases} \tag{6.2}$$

In public charging, the arriving time (t_{2a}) and leaving time (t_{2l}) of EVs follow the normal distribution and also are calculated similar to eq. (6.1 and 6.2). Moreover, this study considered the time period for EV charging scheduling in one day is allocated into time 96 slots, this allows a discrete treatment of the charging process control. Each slot represented by j and conveniently equal to 15 minutes. Furthermore, in this scheme, the total load of the power grid consists of the basic load (p_j^{basic}) and EVs charging load ($\sum_{v=1}^{N} k_{v,j}\, p_v$), which is calculated by:

$$\mathcal{P}_j^{total} = \mathcal{P}_j^{basic} + \sum_{v=1}^{N} k_{v,j}\, \mathcal{P}_v \tag{6.7}$$

Where, $k_{v,j}$ represent a binary variable for indicating the EV charging state (i.e., if $k_{v,j} = 0$, the EV is not charging, if the $k_{v,j} = 1$, the EV is charging). As mentioned above, there are two charging modes (charging rates) are applied in this proposed method, including slow charging ($\mathcal{P}^{slow}$) and fast charging ($\mathcal{P}^{fast}$). The selection of the charging rate for each EV user considered to be applied by the aggregator (adaptably between $\mathcal{P}^{slow}$ and $\mathcal{P}^{fast}$) taking into account the urgency of EV charging demand (i.e., a higher charging rate assign for the EV that is an urgent and a lower charging rate assign for the EV that is non-urgent. This can be simplified by:

$$\mathcal{P}^{slow} \leq \mathcal{P}_v \geq \mathcal{P}^{fast} \tag{6.8}$$

The main objective of this study is to minimise the power load variation on the grid. This can be achieved by shifting the EVs power demand from the peak to valley times, which can be expressed by:

$$min\left[\mathcal{P}_{max}^{total} - \mathcal{P}_{min}^{total}\right], \tag{6.9}$$

Where, $\mathrm{p}_{\mathrm{max}}^{\mathrm{total}}$ and p_{min}^{total}, respectively, are the maximum and minimum total power load demand from the grid. A power threshold constraint is considered in this proposed scheme to maintain the SOC of all EVs within a specified range when they are disconnecting from the grid. So, the SOC of an EV should be between minimum and the maximum value, it can be expressed by:

$$B_{v,min}^{SOC} \geq B_{v,discon}^{SOC} \geq B_{v,max}^{SOC}, \tag{6.10}$$

Where, $B_{v,max}^{SOC}$ and $B_{v,min}^{SOC}$ are the minimum and the maximum value of SOC of an EV, respectively. The $\mathrm{B}_{\mathrm{v,discon}}^{\mathrm{SOC}}$ represents the SOC of an EV when it is disconnected from the power grid. $B_{v,con}^{SOC}$ represents the SOC of an EV when is connected to the power grid. Moreover, to ensure that a new charging peak load of the power grid in the proposed method do not appear compared to the random charging scheme, so another constraint for the power grid is given as:

$$\mathcal{P}_{max}^{total} \leq \mathcal{P}_{max,B_{N,max}^{SOC}}^{total-random}, \tag{6.13}$$

Where, the $\mathcal{P}_{max,B_{N,max}^{SOC}}^{total-random}$ represents the maximum value of the total power load of the grid in the random charging scheme, while considering that all EVs should meets the maximum value of SOC.

To solve the addressed problem of EVs charging, the PSO algorithm is utilised in this study. The fitness function represents the objective function, in this study, the peak power load of EVs that need to be shifted from peak-to-valley period. Additionally, the simple additive weighting (SAW) method is applied to formulate the fitness function. The SAW is responsible to set a priority weight for all EVs according to their urgency state. The fitness function can be formulated mathematically as:

$$max_i \sum_{b=1}^{B} w_b \; f_b\,(i) = \; w_1\, B^{SOC}(i) + w_2\, j^{con}\,(i) + w_3\, j^{discon}(i) \qquad (6.14)$$

Where, $f_b\,(i)$ denotes the fitness function value for i particle in the search space of PSO. The w_b represents the corresponding weight value for each criterion. Since the three criteria are different and have varying units and scales, normalisation is essential in multicriteria decision-making. So, the fitness function can be written as.

$$max_i \sum_{b=1}^{B} w_b \; f_b\,(i) = \; w_1\, NB^{SOC}(i) + w_2\, Nj^{con}\,(i) + w_3\, Nj^{discon}(i) \qquad (6.19)$$

Furthermore, the search space involves all the feasible solutions, which can be chosen between upper-bound and lower-bound values. In this proposed, the solution represents scheduling EVs for charging consider the urgent EVs demands. So, the search space for optimal solution between $\mathcal{P}^{slow}$ and $\mathcal{P}^{slow}$ values. The search space can be represented as:

$$S(i) = (\mathcal{P}^{slow}\,, \mathcal{P}^{fast}\,) \qquad (6.20)$$

6.2 Results and discussion

This section provides the simulation model and the evaluation of the proposed charging method using the MATLAB tool. In this study, different number of EVs are considered (e.g., 100 and 500) in both home charging and public charging patterns. According to the [42], value of $B_{v,discon}^{SOC}$ generated uniformly between (0.1-0.3), $B_{v,min}^{SOC}$ between (0.4-0.6), and $\mathrm{B}_{\mathrm{v,max}}^{\mathrm{SOC}}$ between (0.8-1.0). The parameters of charging rates are given as p^{slow} = 3.5 kW, and p^{fast} =10 kW. Figure 6.6 and figure 6.7 shows a plot of daily load as a function of time in one day comparing the proposed smart adaptable charging method with two methods of normal charging in the home charging. The results demonstrate that the power load required from EV is significantly reduced in the proposed method compared to other two normal charging methods, particularly when the number of EVs increases. The first normal method (blue line) satisfy the minimum SOC for EVs, while the second method satisfy the maximum SOC for EVs (red line).

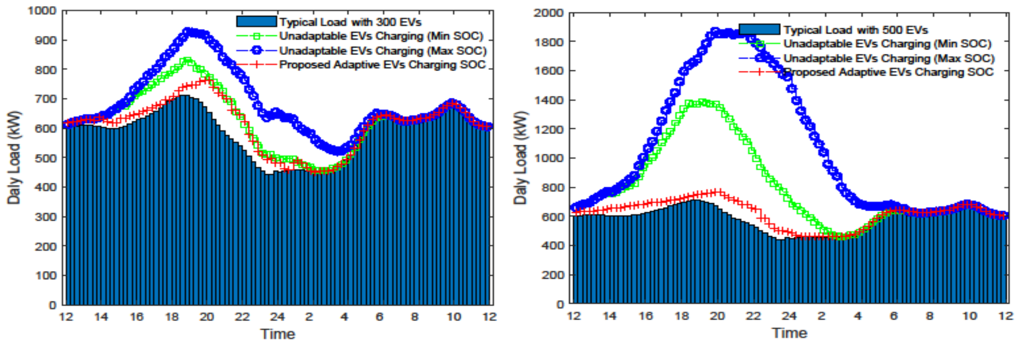


Figure 6.6 *and* ***Figure 6.7*** *Plots of daily load compared between the proposed adaptive and two normal methods in home public charging for 100 and 500 EVs.*

Figure 6.8 and Figure 6.9 shows plots of daily load as a function of time comparing the proposed smart adaptable charging method with two normal charging methods in the public charging. The result shows that the EVs demand increased the peak load, where the basic load in public charging can only be filled by a few EVs.

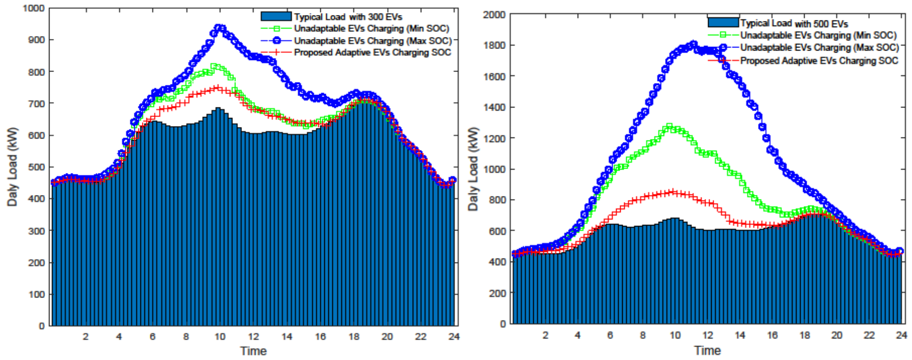


Figure 6.8 *and* ***Figure 6.9*** *Plots of daily load compared between the proposed adaptive and two normal methods in home and public charging for 100 and 500 EVs.*

Figure 6.11 shows the distribution of a large number of EVs over charging stations comparing the proposed charging method and normal. The results shows the effectiveness of the proposed charging method that prioritise the urgent charging demand in the load distribution, unlike the normal charging that distribute the EVs randomly over stations.

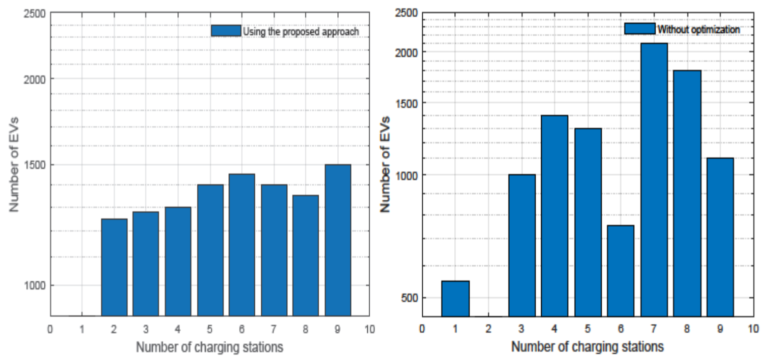


Figure 6.11 *Comparison of distribution the EVs at charging stations between normal charging and a proposed method.*

Chapter 7

Conclusions and Future Work

EV is a critical component in the smart cities and IoV network. This thesis explored and addressed the challenges associated with the optimisation of charging schedules for EVs. The scope of this thesis included examining charging systems approaches (e.g., centralised and decentralised), optimising schedule schemes, and several optimisation methods for EVs charging. The study also invested the integrating of SDN within smart grid environments to enable efficient energy management and communication between vehicles, charging infrastructure, and the power grid. However, there are several charging schemes have been proposed in the research to solve the problem of random charging patterns and also many optimisation techniques are invested or developed for this purpose. The complexity arises from the need to balance various factors such as charging speed, cost, energy source sustainability, grid stability, and user convenience. This nature of multi-criteria EV charging problem, where each of these criteria can have different levels of importance depending on the user side, grid side, or stakeholder priorities. Therefore, there is no such an optimal charging scheme that fits all requirements, and dynamic and adaptable scheme would be more efficient solution for EV charging problem.

7.1 Original contributions

This section presents the main contributions of this thesis, specifying the original work that has been published. Each contribution is identified in the format of (m,p), where ‘m’ represents the mentioned contribution and ‘p’ denotes the corresponding published paper (as numbered in section 7.3).

(1,1) provided a survey of V2G/G2V technologies. It identifies several challenges facing V2G technology from the communication perspective, including managing wired and wireless charging standards, synchronizing data transmission between different tiers of network architecture, and integrating V2G with emerging concepts like Energy Internet and Fog and Cloud computing for 5G-enabled networks.

(2,1) introduced the concept of using SDN as a control solution for managing the interaction between EVs and the smart grid. It discusses the potential advantages of SDN-based smart grids, such as increased system stability, efficiency, and reliability, by providing a centralised management system. The document includes case studies that illustrate the application of the recent proposed SDN-based frameworks in real-world scenarios, highlighting the practical implications and benefits of integrating EVs into the smart grid.

(3,1) proposed some solutions to some of the identified challenges, including a general SDN-based V2G framework aimed at improving the efficiency, reliability, and stability of the system. It also discusses specific solutions like the use of multicast communication for battery status sensing and coordination among EVs for charging/discharging operations.

(4.6) provided a comprehensive overview related to the optimised charging schemes for EVs within existing charging infrastructure, focusing on user demands. The study highlighted the impact of random charging behaviours on the power grid and pointed out the need of an optimal charging scheme.

(4,6) discussed several aspects associated with EV charging demands, such as EV types, charging modes, charging patterns (e.g., home, public, and mobile), and centralised and decentralised systems.

(5,6) presented a critical review on the optimisation techniques then analysed the recent solution in the state-of-the-art, and also identified their limitations and gaps. proposed several potential solutions for the problem of optimal charging scheme based on the identified limitations and gaps.

(6,6) proposed some potential research directions relevant to EV charging scheduling, aimed to help other engineers and researchers to develop such sustainable, efficient, and user friendly schemes for EV charging.

(7,2) developed a novel SDN-based charging system model, which optimises the energy dispatch from both the power grid and EVs perspective, enhancing grid reliability and EV user convenience.

(8,2) proposed an advanced scheduling and routing algorithm to the problem of EV charging. The study conducted a simulation for three schemes, considering in Bucharest city map, demonstrate the effectiveness of the proposed algorithm with proposed scheme in minimising the service time for EVs while achieving load balancing across charging stations.

(9,4) Proposed a smart and adaptable charging scheme that dynamically adjusts the charging rates for EVs users considering the state of urgent demands. This scheme can transfer the EV charging demand from rush hours to off-peak hours. The PSO algorithms have been used to find the optimum solution in this scheme.

(10,5) proposed the usages NSGA-II to simultaneously optimise charging cost and service time for EVs charging. This approach provides a novel method to handle the conflicts of two objectives (e.g., charging cost and service time) that faced in EV charging. The NSGA-II was compared with the GA and the results showed its superiority in achieving a diverse set of non-dominated solution.

(11,7) extended the work in (10,5) and investigated the ACO and SA algorithms to evaluate their performances in minimising the total charging cost for EVs in terms of time and price for EVs.

7.2 List of original publications

All the mentioned works in this thesis, such in chapter two, chapter three, chapter four, chapter five, and chapter six have been published. They are listed as follows:

1- **H.M. Al-alwash**, M.K. Hamadani, *Vehicular to Grid Technologies – A Survey on Architectures and Solutions*, The Eighteenth International Conference on Networks Vehicular - ICN 2019, pp. 25–30, March 24-28, Valencia, Spain, 2019.
2- **H. Al-Alwash**, E. Borcoci, *Optimal Charging Scheme for Electric Vehicles (EVs) in SDN-based Vehicular Network, Scheduling, and Routing*, The 14th International Conference on Communications - COMM 2022, pp. 1–8, June 16-18, Bucharest, Romania, 2022.
3- M.K. Hamadani, **H.M. Al-alwash**, *Centralised Multi-hop Routing for Device-to-Device communication: simulation and results*, The 11th International Conference on Electronics, Computers and Artificial Intelligence - ECAI, pp. 1–6, June 27-29, Pitesti, romania, 2019.
4- **H.M. Al-Alwash**, E. Borcoci, *a Smart Adaptable Charging Method for Electric Vehicles, Considering Urgent Charging Demand*, UPB Scientific Bulletin, Series C: Electrical Engineering and Computer Science, 85(3), pp. 307–318, 2023.
5- **H.M. Al-alwash**, E. Borcoci, I. The, *Non-Dominated Sorting Genetic Optimisation For Charging Scheduling Of Electrical*, UPB Scientific Bulletin, Series C: Electrical Engineering and Computer Science, 86(1), pp. 117–128, 2024.
6- **H.M. Al-Alwash**, E. Borcoci, M.C. Vochin, I.A.M. Balapuwaduge, F.Y. Li, *Optimization Schedule Schemes for Charging Electric Vehicles: Overview, Challenges, and Solutions*, IEEE Access, 12(March), pp. 32801–32818, 2024.
7- **H.M. Al-alwash**, E. Borcoci, *Optimising Charging Scheduling for Electrical Vehicles*, SD–ETTI 2023: 1st Doctoral Symposium on Electronics, Telecommunications, and Information Technology, pp. 2–5, June 27-29, Bucharest, Romania, 2023.

7.3 Future work

A suggestion for future work can be made as follows:

1. Future studies could focus on investigate the methods of machine learning or artificial intelligence in predicting EV charging patterns, optimising energy consumption, or optimise EV charging scheme.
2. The integration of RESs such as solar, wind, and other with EV charging stations still an open research issue. Future research could focus on optimising the use these resources in charging stations to reduce reliance on fossil fuels and reduce carbon emissions.
3. Investigating the broader implications of V2X technologies and their integration with smart grids and IoV for enhanced vehicle communication, energy management, and urban mobility.

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