OPTIMAL PLACEMENT AND SIZING OF ELECTRIC VEHICLE CHARGING STATION IN POWER DISTRIBUTION SYSTEM

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2024

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A report submitted
in partial fulfilment of the requirements for the degree of
Bachelor of Electrical Engineering with Honours

Faculty of Electrical Technology and Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2024

DECLARATION

I declare that this project entitled "OPTIMAL PLACEMENT AND SIZING OF ELECTRIC VEHICLE CHARGING STATION IN POWER DISTRIBUTION SYSTEM" is the result of my own research except as cited in the references. The project report has not been accepted for any degree and is not concurrently submitted in the candidature of any other degree.

Signature	:	najmi zin
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APPROVAL

I hereby declare that I have checked this report entitled "OPTIMAL PLACEMENT AND SIZING OF ELECTRIC VEHICLE CHARGING STATION IN POWER DISTRIBUTION SYSTEM" and in my opinion, this report fulfils the partial requirement to be awarded the degree of Bachelor of Electrical Engineering with Honours.

Signature	:	
Supervisor Name	:	PM IR. DR. AIDA FAZLIANA BINTI ABD KADIR
Date	:	24th JANUARY 2024

DEDICATIONS

I dedicate this project to my beloved mother and father, family members and friends for the moral support they gave me during this period. Last but not least, to my lovely supervisor and all the UTeM lecturers who guided me throughout this process.

ACKNOWLEDGEMENTS

Alhamdulillah, praise to Allah S.W.T The Most Gracious, The Most Merciful, there is no power, no strength saves in Allah, The Highest and The Greatest, whose blessing and guidance have helped me through the process of completing this Final Year Project. Peace and blessing of Allah be upon our prophet Muhammad S.A.W who has given light to mankind.

First and foremost, I would like to take this opportunity to express my sincere acknowledgement and my deepest gratitude to my supervisor, Associate Professor Ir. Dr. Aida Fazliana Binti Abdul Kadir, an associate professor from the Faculty of Electrical Technology and Engineering at Universiti Teknikal Malaysia Melaka (UTeM) for all the knowledge, motivation, support and encouragement towards the completion of my final year project and this report.

I would also like to extend my thanks to the panel members for their valuable feedback and suggestions during the presentation on my project. Their critical evaluation helped me to improve the quality of my work and present it in more comprehensive ways.

Lots of love from the deepest of my heart goes to my parents, Mohd Zin Bin Ismail and Rahimah Binti Dollah and my whole family for their unlimited love and support. I sincerely thank almost all my lecturers and all my friends for helping me directly or indirectly. May Allah bless all of you.

ABSTRACT

Increased demand for electric vehicle charging stations (EVCSs) in power distribution systems has resulted from the growing popularity of electric vehicles (EVs). By integrating optimal EVCS placement and sizing, numerous benefits can be obtained such as a reduction in power losses and minimize average voltage deviation of the system. If the EVCS in the power distribution system is placed and sized optimally, these benefits can be achieved and enhanced. Inappropriate placement and sizing of EVCS would result in negative impacts including increased power losses of the system. Therefore, the aim of this project was to identifying the best locations for EVCS installation and determine the appropriate sizes in order to achieve the minimum system losses and average voltage deviation. This objectives ensures the efficient utilization of power distribution infrastructure while providing realible and sustainable charging services for EVs. In this project, the cost of charging different types of EVs in Malaysia is evaluated in order to determine the most optimum charging power for EV chargers and a method for determining the optimal placement and sizing of EVCS in the power distribution system is presented. A multi-objective function is developed in order to reduce total real power losses and average voltage deviation. In order to find the optimal compromise solution, a Gravitational Search Algorithm (GSA) based heuristic algorithm is proposed as an optimisation technique. The objective functions have been solved by integrating the load flows algorithm from MATPOWER into the MATLAB environment. The performance of the optimal EVCS placement and sizing in the power distribution system by using GSA and PSO technique will be evaluated in two test system which are IEEE 33-bus and IEEE 69-bus radial distribution systems. Then, the outcome of this project shows that the power losses and average voltage deviation can be reduced and minimized and the performance between GSA and PSO were compared. The overall results show that GSA performs up to 3.72% than PSO in obtaining the best fitness value for optimal placement and sizing of EVCS in power distribution system.

ABSTRAK

Peningkatan permintaan untuk stesen pengecas kenderaan elektrik (SPKE) dalam sistem pengagihan kuasa telah terhasil daripada peningkatan populariti kenderaan elektrik (KE). Dengan menyepadukan peletakan dan saiz SPKE yang optimum, banyak faedah boleh diperolehi seperti pengurangan kehilangan kuasa dan meminimumkan sisihan voltan purata sistem. Jika SPKE dalam sistem pengagihan kuasa diletakkan dan bersaiz optimum, faedah ini boleh dicapai dan dipertingkatkan. Peletakan dan saiz SPKE yang tidak sesuai akan mengakibatkan kesan negatif termasuk peningkatan kehilangan kuasa sistem. Oleh itu, matlamat projek ini adalah untuk mengenal pasti lokasi terbaik untuk pemasangan SKPE dan menentukan saiz yang sesuai untuk mencapai kerugian sistem minimum dan sisihan voltan purata. Objektif ini memastikan penggunaan infrastruktur pengagihan kuasa yang cekap sambil menyediakan perkhidmatan pengecasan yang nyata dan mampan untuk KE. Dalam projek ini, kos mengecas pelbagai jenis KE di Malaysia dinilai untuk menentukan kuasa pengecasan yang paling optimum untuk pengecas KE dan kaedah untuk menentukan penempatan dan saiz optimum SPKE dalam sistem pengagihan kuasa dibentangkan. Fungsi berbilang objektif dibangunkan untuk mengurangkan jumlah kehilangan kuasa sebenar dan sisihan voltan purata. Untuk mencari penyelesaian kompromi yang optimum, algoritma heuristik berasaskan Algoritma Carian Graviti (ACG) dicadangkan sebagai teknik pengoptimuman. Fungsi objektif telah diselesaikan dengan menyepadukan algoritma aliran beban daripada MATPOWER ke dalam persekitaran MATLAB. Prestasi penempatan dan saiz SPKE yang optimum dalam sistem pengagihan kuasa dengan menggunakan teknik ACG dan Prestasi Kuruman Zarah (PKZ) akan dinilai dalam dua sistem ujian iaitu sistem pengagihan jejari IEEE 33-bas dan IEEE 69-bas. Kemudian, hasil projek ini menunjukkan bahawa kehilangan kuasa dan sisihan voltan purata boleh dikurangkan dan diminimumkan dan prestasi antara ACG dan PKZ telah dibandingkan. Keputusan keseluruhan menunjukkan bahawa ACG berprestasi sehingga 3.72% berbanding PKZ dalam mendapatkan nilai kecergasan terbaik untuk penempatan dan saiz EVCS yang optimum dalam sistem pengagihan kuasa.

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LIST OF SYMBOLS AND ABBREVIATIONS

EV	-	Electric Vehicle
EVCS	-	Electric Vehicle Charging Station
PSO	-	Particle Swarm Optimization
GSA	-	Gravitational Search Algorithm
GTFS	-	Green Technology Financing Scheme
IEA	-	International Energy Agency
HEV	-	Hybrid Electric Vehicle
FCEV	-	Fuel Cell Electric Vehicle
PHEV	-	Plug-in Hybrid Electric Vehicle
BEV	-	Battery Electric Vehicle
ICE	-	Internal Combustion Engine
kW	-	Kilowatt
kWh	-	Kilowatt-hours
km	-	Kilometre
kg	-	Kilogram
AC	-	Alternating Current
DC	-	Direct Current
CCS	-	Combined Charging System
MAA	-	Malaysian Automobile Association
EC	-	Energy Commission of Malaysia
NETR	-	National Energy Transition Roadmap
LP	-	Linear Programming
GA	-	Genetic Algorithm
GWO	-	Grey Wolf Optimization
TLBO	-	Teaching Learning Based Optimization
DNO	-	Distribution Network Operator Approach
CSO	-	Charging Station Owner Approach
SOC	-	State of Charge
IEC	-	International Electrotechnical Commission

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LIST OF PUBLICATIONS

Conference

1) Abdul Kadir, A. F., Sulaima, M. F., Ab Aziz, N. H., Zin, A. N. M., Shareef, H., & Rahman, Z. A. (2023). Evaluation of Charging Costs for Various Types of EVs in Malaysia. *2023 10th International Conference on Power and Energy Systems Engineering, CPESE 2023*, 317–322. https://doi.org/10.1109/CPESE59653.2023.10303243

CHAPTER 1

INTRODUCTION

1.1 Background

Globally, electric vehicles (EVs) are gaining popularity due to their environmental benefits and cost savings. Demand for electric vehicle charging stations (EVCS) increases as the number of EVs on the road increases. This rapid adoption of EVs has drastically reshaped the landscape of transportation motivated by the increasing global concern for lowering greenhouse gas emissions and dependence on fossil fuels [1]. Thus, EVCS plays an important role in supporting the widespread use of EVs by providing convenient and accessible charging infrastructure. EVCS serves as key connectors between the electric grid and EVs by allowing owners of EVs to charge their vehicles in a manner that is both efficient and reliable. In a simple term, EVCS are in charge of supplying the necessary electricity to charge the batteries of EVs in order to increase the driving range of EVs and promote their sustainability as an attractive alternative to conventional automobiles powered by internal combustion engines [2].

Therefore, the optimal placement and sizing of EVCS within a power distribution system is essential for assuring reliable and efficient operation while preventing overloading and preserving power system stability. In Malaysia, the government is committed to promoting the use of electric vehicles and has set a target of 125,000 EVs on the road by 2030 as part of its efforts to reduce carbon emissions and meet its national energy policy target. Research indicates that by 2030, EVs could reduce CO2 emissions by 28% [3]. The government has implemented a number of policies and initiatives to promote the adoption of electric vehicles and the development of EVCS infrastructure in order to achieve this objective.

The Green Technology Financing Scheme (GTFS) is one of the policies introduced by the government of Malaysia. This policy wants to encourage the adoption of sustainable transportation by providing financial incentives and assistance for the establishment and expansion of EVCS infrastructure. These policies typically consist of grants, loans, tax incentives and subsidies that can encourage the deployment of EVCS and speed up the transition to green transportation [4]. The government has also released the Low Carbon Mobility Blueprint 2021-2030 which outlines the strategies and initiatives to support the development of electric vehicle. The policy prioritizes the construction of EV charging infrastructure, financial incentives and regulatory support to stimulate the adoption of electric vehicles. It also aims to reduce carbon emissions, improve energy efficiency and promote sustainable mobility in Malaysia [5].

Besides, National Energy Policy 2022-2040 was introduced to strike a balance between economic development and environmental sustainability [6]. To attain Malaysia's goal of Net Zero Carbon Emissions by 2050, the government has set a target of generating 31% of the country's electricity from renewable sources by 2025, with that percentage increasing to 40% by 2035. The policy of Net Zero Carbon Emissions by 2050 establishes a long-term goal for Malaysia to accomplish carbon neutrality which describes strategies and measures to reduce greenhouse gas emissions across multiple sectors including transportation. To facilitate the transition to a low carbon economy, the policy prioritizes sustainable practices, the incorporation of renewable energy and technological advances [7]. The optimal placement and sizing of EVCS in the power distribution system can play a crucial role in attaining this objective by reducing the carbon footprint of transportation and facilitating the incorporation of renewable energy sources into the power system.

1.2 Motivation

In Malaysia, the optimal placement and sizing of EVCS in the power distribution system has become crucial due to a number of important factors and policies promoting sustainable transportation and the transition to a greener future. The Green Technology Financing Scheme, the Low Carbon Mobility Blueprint 2021-2030, the National Energy Policy 2020-2040, National Energy Transition Roadmap (NETR) and the commitment to achieve Net Zero Carbon Emissions by 2050 are five significant drivers of this motivation. Firstly, the purpose of the Green Technology

Financing Scheme in Malaysia is to promote the adoption of green technologies and practices [4]. This scheme is aligned with optimal placement and sizing of EVCS that can maximize the environmental benefits of electric mobility and help reduce carbon emissions.

The Low Carbon Mobility Blueprint 2021-2030 then establishes ambitious goals for reducing carbon emissions from the transportation industry [5]. Strategic placement and sizing of EVCS are crucial to attaining these objectives. By identifying appropriate locations for EVCS and assuring their optimal capacity, it can provide a charging infrastructure that is convenient, dependable and conducive to the widespread adoption of electric vehicles. This transition to electric mobility reduces carbon emissions, improves air quality and reduces dependence on fossil fuels. Additionally, the National Energy Policy 2022-2040 for Malaysia emphasizes the development of a sustainable and diverse energy composition. By contemplating the integration of EV charging infrastructure with the power distribution system, the optimal placement and sizing of EVCS align to this policy. By strategically placing EVCS in areas with grid infrastructure capacity and considering load management strategies, it can reduce strain on the power grid, optimize energy distribution and assure reliable and sustainable charging for electric vehicles [6].

Latest, the National Energy Transition Roadmap (NETR) was introduced as catalyst and dynamic shift towards a sustainable and efficient energy landscape [8]. The roadmap recognizes the role electric vehicles play in the future of transportation and the subsequent surge in demand for charging infrastructure. The NETR aims to accelerate electrification of vehicles by reducing the regulatory challenges in ramping up EV adoption including for setting up of charging infrastructure. Lastly, the optimal placement and sizing of EVCS in the power distribution system is motivated by the need to comply with policies aimed at attaining Net Zero Carbon Emissions by 2050 [7]. The optimal placement and sizing of EVCS contribute to achieving this objective by facilitating the transition to electric mobility and reducing the carbon emissions associated with conventional vehicles. By integrating EVCS effectively, it can accommodate the growing demand for electric vehicle charging while mitigating environmental impact and supporting the long-term goal of achieving net zero carbon emissions.

1.3 Problem Statements

1. Due to their impact on affordability and attractiveness to buyers, the cost of charging is a critical factor in the adoption of EVs. There is no study has been conducted to determine the optimal charging power for EV chargers through a comprehensive evaluation of charging costs across different types of EVs. A research article by [9] emphasizes the importance of examining the cost of charging in order to plan electric vehicle charging systems effectively. The International Energy Agency (IEA) has also recommended that policymakers analyze the charging costs for different types of electric vehicles as essential data for developing effective policies and regulations [10]. By comprehending the charging expenses associated with various types of electric vehicles (EVs), it helps in assessing the financial viability for potential purchasers and guarantees that EVs continue to be an appealing choice for consumers. Hence, there is a need to assess the charging costs associated with different types of EVs and identify the most optimal charging power for EV chargers in Malaysia.

2. Due to the high penetration of electric vehicles, the demand for charging infrastructure increases proportionally to the growth of EV adoption [11]. This high penetration of EVs can burden the EVCS which resulting in challenges that can impact the power distribution system. The deployment of a high number of EVCS without sufficient planning and inappropriate placement and sizing of EVCS would inject negative impact that result in increasing the power losses. These power losses not only waste energy but also raise operational expenses for both the distribution system operator and end users [12]. Thus, there is a need to identify the optimal placement and sizing of EVCS in power distribution system by using a problem formulation for effective optimization technique.

3. To optimize the EVCS, several studies have focused on the determining the optimal placement and sizing only. However, there is a need to explore a more effective optimization technique for solving the problem in determining the optimal placement and sizing of EVCS in power distribution system [13].

Hence, a comparative study must be carried out to identify the performance of both by comparing the performance between the proposed technique with the efficacy of the Particle Swarm Optimization (PSO) which will contribute to better understanding on the impact of optimized EVCS placement and sizing and for future EVCS infrastructure planning.

1.4 Objectives

Regarding the problem statement as mentioned before, this project deals with the following objectives. The mapping for problem statements and objectives is shown in Table 1.1.

1. To evaluate the cost of charging for various types of EVs in Malaysia in order to determine the most optimum charging power for EV chargers.

2. To identify the optimal placement and sizing of EVCS in power distribution system by considering power losses reduction and minimization of average voltage deviation by using Gravitational Search Algorithm (GSA) technique.

3. To compare the performance between the proposed technique with the Particle Swarm Optimization (PSO) technique.

Table 1.1 Mapping for Problem Statements and Objectives

	Problem Statement 1	Problem Statement 2	Problem Statement 3
Objective 1	X		
Objective 2		X	
Objective 3			X

1.5 Project Scope

The main scope of the project is to study and understand the EVCS while applying a simple optimization algorithm in order to determine the optimal placement and sizing. The study was conducted on two test system, which were IEEE 33-bus and IEEE 69-bus radial distribution systems, using MATLAB simulation software in order to find the proper placement and the most suitable sizing for EVCS to be installed in the distribution system. The load flow analysis will be simulated using MATPOWER, which is a power system analysis tool. Gravitational Search Algorithm (GSA) has been used to determine the best solution for EVCS placement and sizing. The results obtained were then compared with the commonly used technique such as Particle Swarm Optimization (PSO) to validate the performance and effectiveness of GSA. This study concentrated on the impact of EVCS based on two objectives which are total real power loss and average voltage deviation.

1.6 Thesis Outline

This report consists of five chapters. Each chapter represents a different part of the project. Chapter 1 presents the overall view of the project including the background, motivations, problem statements, objectives and scopes of the project. Chapter 2 reviews the overview of electric vehicles, infrastructure of EVCS, their impact to modern power grid, review and discussion on previous research works that related with this project. Chapter 3 describes the methodology and techniques were used in this project to determine the optimal placement and sizing of EVCS in power distribution system. All the software algorithms that are used are discussed and presented. Chapter 4 presents the results and discussion of the project by stressing the significance and implications of the finding of the project. Finally, Chapter 5 concludes the overall project and gives recommendations for future improvement. This chapter contains a summary of the entire work, including the methods, results and major conclusions or recommendations arising from the work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In this chapter, the related topic from the various papers is reviewed and summarized. This chapter will focus primarily on the types of electric vehicle, infrastructure of EVCS, impacts of EVCS to modern power grid and average voltage deviation are being discussed and presented. On the other hand, optimal placement and sizing of EVCS conducted by the previous studies or researchers and significant findings are also reviewed and discussed.

2.2 Electric Vehicles

An electric car is a vehicle that uses electric motors to fully or partially power their movement, relying on rechargeable batteries to store the energy. Electric cars have undergone various changes and continuous development, providing users with a wide range of options. Presently, terms such as BEV, HEV, PHEV, and FCEV are becoming increasingly familiar worldwide. The functioning of an electric car is dependent on its specific type, and understanding how it works requires knowledge of its particular classification [14].

The four main categories of electric vehicles are Hybrid Electric Vehicles (HEVs), Fuel Cell Electric Vehicles (FCEVs), Plug-in Hybrid Electric Vehicles (PHEVs), and Battery Electric Vehicles (BEVs) [15]. PHEVs and HEVs utilize both an internal combustion engine and an electric motor as sources of energy, while FCEVs are powered by hydrogen, which is converted into electricity through a highly efficient electrochemical process to power an electric motor. On the other hand, BEVs is a vehicle powered by electric motors and rechargeable batteries instead of traditional internal combustion engines that rely on fossil fuels like gasoline and diesel, meaning that their driving range is dependent on the capacity of the battery [16].

In contrast to alternative electric vehicle configurations like PHEV and BEV, HEV exclusively rely on regenerative deceleration, the internal combustion engine (ICE) or a combination of the two to charge their batteries. HEVs in contrast to other electric vehicles which lack a charging port, which means their batteries cannot be recharged via an external power source such as the EVCS infrastructure [17]. PHEVs are a subset of hybrid vehicles. Drivers are given the option to select their power source and utilize a blend of conventional fuels such as petrol and rechargeable battery packs. Petrol fuels the internal combustion engine, while the rechargeable battery pack energizes the electric motor. The car can be charged by connecting it to an EVCS or by harnessing electricity through regenerative braking, resulting in a complete charge of the battery [18].

The two modes of operation that are available for a standard PHEV are the Hybrid Mode and the All-Electric Mode. In the All-Electric Mode, the vehicle is powered exclusively by the battery and the motor. Conversely, when the Hybrid Mode is engaged, the vehicle simultaneously employs electrical and combustible power. Certain PHEVs can travel over 70 kilometers on electricity alone [19]. The electric vehicle that depends on a rechargeable battery pack solely for its power is called a BEV. BEVs are zero-emission cars, because they do not rely on petrol or any other form of combustion for power, and therefore do not emit emissions from the tailpipes [20]. The main source of power for a Battery Electric Vehicle (BEV) is its battery pack, which can be recharged by connecting the car to either an electrical outlet or a dedicated charging station. The electric motor utilizes the energy stored in the battery to power the vehicle, resulting in a quiet and smooth driving experience [21]. Thus, EVs offer several benefits including environmental friendliness, lower operating costs, and reduced dependence on fossil fuels and carbon footprint. Additionally, the growth of the EV market is seen as a catalyst for job creation in industries related to electric vehicle manufacturing, charging infrastructure development and the renewable energy sector.

2.3 Insfrastructure of EVCS

The global electric vehicle charging infrastructure has been growing rapidly in recent years as the demand for EVs continues to rise. According to a report by the International Energy Agency (IEA), there were over 16.5 million electric vehicles on the roads worldwide in 2022, and the number is expected to reach 250 million by 2030 [22]. The key facts about the global EV charging infrastructure because of the number of charging stations. As of 2021, there are over 1.4 million EV charging stations worldwide. Europe has the largest number of charging stations, followed by China and the United States. According to Globe Newswire, there will be 2.3 million charging stations around the globe by November of 2022. By the end of 2028, the population is projected to exceed 16.83 million. This rapid expansion is primarily attributable to two factors which are the growing popularity of electric vehicles and the increasing use of DC fast charging technology. There are currently over 600,000 DC rapid chargers in operation around the world.

For infrastructure of EVCS in Malaysia, a total of 2093 units of EVs were registered according to the Malaysian Automobile Association (MAA). In 2023, the MAA expects that the demand for electric vehicles will increase by 45.6%, or 4,449 units. Government tax incentives for EV owners and EV market participants will make these adjustments possible [23]. About 600 electric vehicle (EV) charging stations existed in Malaysia as of August 2022, which was insufficient to meet the requirements of the substantial EV market. The government has pledged to build approximately 10,000 electric vehicle (EV) charging stations by 2025 after recognizing infrastructure development gaps and requirements. To achieve this target, the government has implemented several initiatives including the installation of charging stations in public areas such as shopping malls, commercial buildings and residential areas. Additionally, several private companies have also entered the EV charging market in Malaysia such as Shell Recharge, TNB Electron, Go To-U Charging Hub, Gentari, chargEV by Green Tech, CarputZAP and others with some offering innovative solutions such as mobile charging stations that can be deployed to remote areas. With government targets and private sector investments, EVCS infrastructure in Malaysia is predicted to grow rapidly in the coming years [24].

2.3.1 Levels of EVCS

The demand for charging stations has increased due to the rising popularity of electric vehicle (EVs). Factors such as power capacity, location, charging time, equipment specs, pricing, and impacts on the electrical grid all play a role in determining the levels of EV charging [25]. Charging stations are classified into three levels namely Level 1, Level 2 and Level 3 based on their charging rate and voltage. This categorization is illustrated in Figure 2.5 [26].

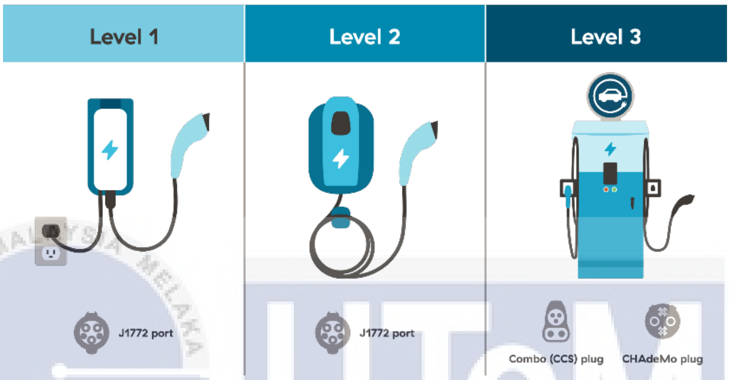

Figure 2.1 Levels of EVCS

An easy and fundamental way to charge electric vehicles is using a Level 1 charging station. It connects to standard wall outlets that are rated for 16 Amps and can withstand 230 V in single phase and 400 V in three phase AC power. This type of outlet is similar to the ones used for common home appliances [27]. The Level 1 charging station is often included as standard equipment with the electric vehicle (EV) and is capable of fully charging the battery overnight starting from zero capacity. Level 1 charging offers a comparatively low charging output rate of 1.4kW - 2.0kW. Consequently, the charging time for an electric car might range from 8 to 21 hours depending on the capacity of the battery. [26].

In comparison to Level 1 charging stations, Level 2 stations are more powerful and can charge electric cars (EVs) more quickly. Equipped with a higher charging power rate ranging from 3kW to 22kW, it would take 4 to 8 hours to completely charge an electric vehicle's battery, depending on its size. This is approximately four times faster than a Level 1 charger [28]. A licensed electrician must install a Level 2 charging station's electrical components, which use a 230 V AC single phase or 400 V AC three phase power source [27].

Next, a Level 3 charging station, often called a DC fast charger or DCFC, is where electric vehicles (EVs) are charged most efficiently. It takes 30 minutes to 2 hours to completely charge an electric vehicle's battery, depending on its size, and it has a very high charging output rate ranging from 20 kW to 350 kW [28]. When compared to Level 1 and Level 2 chargers, this one is ten times faster and six times faster, respectively. Because level 3 charging stations use a direct current (DC) electrical supply, a certified electrician and specialized electrical infrastructure are required to set them up [27].

In general, level 3 charging stations are the fastest and most powerful chargers currently available for electric vehicles (EVs), making them well-suited for long-distance travel as they enable drivers to rapidly and effortlessly recharge their batteries. These charging stations may be used with a diverse range of electric vehicles and have the capacity to help businesses and public establishments attract a larger number of electric vehicle drivers. Despite requiring a higher initial investment, Level 3 chargers are more economically advantageous and efficient in the long run, making them an essential element of the growing electric vehicle charging infrastructure [29].

2.3.2 Different between AC and DC EV Charging

The electricity from the grid is alternating current. However, energy of the electric vehicle is stored in its battery and a battery stores its power in DC. AC EVCS differs from DC EVCS in that the former converts AC power into DC power and charges the battery. It takes a considerable amount of time for the vehicle's onboard converter to convert DC to AC. In DC, the conversion occurs at the charging station prior to the power being delivered directly to the EV battery. As a result, it is able to circumvent the limitations of the electric vehicle's on-board charger and provide more electricity [30], [31].

2.3.3 Charging Prices

Multiple firms in Malaysia have entered the electric vehicle charging industry. The charging rates supplied by these companies vary due to factors such as pricing structure, charging speed, technology offered and market rivalry. This project specifically examines two firms which are Gentari and TNB Electron among the existing EV charging service providers. These companies are chosen as baseline references to determine and analyze the prices for charging different types of EVs in Malaysia. Therefore, Table 2.1 presents the charging rates offered by Gentari while Table 2.2 shows the charging rates provided by TNB Electron.

Table 2.1 Charging Price Rates Offered by Gentari

<table>
<tr><th colspan="2">Level 2 AC Charger</th><th colspan="2">Level 3 DC Fast Charger</th></tr>
<tr><td rowspan="4">All Charger
(7kW, 11kW,
22kW)
RM 0.50 / kWh</td><td rowspan="4">All Charger
(7kW, 11kW,
22kW)
RM 0.10 / min</td><td rowspan="2">180kW
RM 1.00 / kWh</td><td>30kW
RM 0.60 / min</td></tr>
<tr><td>50kW
RM 1.20 / min</td></tr>
<tr><td rowspan="2">350kW
RM 1.20 / kWh</td><td>60kW
RM 1.40 / min</td></tr>
<tr><td>180kW
RM 3.60 / min</td></tr>
</table>

Table 2.2 Charging Price Rates Offered by TNB Electron

Level 3 DC Fast Charger
80kW RM 2.05 / min
90kW RM 2.20 / min
100kW RM 2.35 / min

2.4 Impacts of EVCS to Modern Power Grid

Electric Vehicle Charging Stations (EVCS) can have negative impacts on modern power grids especially the impact due to increase in peak demand [32]. As the number of electric vehicles increases and EVCS become more prevalent, the demand for electricity will rise which can put a strain on the power grid during peak demand periods. This can result in increased costs for energy consumers, power outages or blackouts and environmental impacts.

Then, EVCS can also lead to negative impacts such as voltage instability and phase unbalance [32]. During charging periods, there is a significant demand for electricity which can result in voltage drops and phase imbalances in the power grid. Voltage instability can happen when the amount of voltage in the electric grid falls below what is considered acceptable which can result in equipment failure and power outages. While phase unbalance happens when the voltage and current in the power grid are distributed unevenly which can harm electrical equipment and lead to power quality problems [33].

Power quality problems may arise due to EVs charging. High EV integration can have an impact on the quality of the power network because EV chargers require power electronic equipment. Electric power system components that are intended to be supplied by pure sinusoidal waveforms will suffer detrimental impacts from harmonics introduced into the power grid by EV chargers which will also result in higher system losses [32]. For several EV models, the effect of slow and quick charging on total harmonic distortion (THD) was evaluated. Fast charging was seen to have a significant total harmonic distortion of current (THDi) ranging from 12% to 24%. However, the charger harmonics can be greatly reduced by using an effective EV charger circuit design, control method and filters integrated into the charger circuit. Lastly, EVCS can also increase power losses due to the additional energy required to charge the EVs. This might lead to decreased system performance, increased running expenses and more carbon emissions. To mitigate these impacts, it is important to implement charging systems that can optimize the location and sizing in order to minimize the impact on the power grid [32].

2.5 Impacts of Average Voltage Deviation on EVCS

The installation of electric vehicle charging stations (EVCS) is crucial for the widespread adoption of electric vehicles (EVs), thereby making a significant contribution to the development of a more sustainable and ecologically sound transportation system. Voltage deviation is a critical aspect that necessitates careful consideration during the operation of EVCS. In order to ensure that charging processes at EVCS are effective, voltage deviation must be minimized [34]. The charging cycle is optimized when voltage levels remain constant, which decreases the time needed for electric vehicles to reach their intended state of charge. Moreover, the maintenance of consistent voltage minimization facilitates acceleration and predictability in charging rates, thereby satisfying the demands of electric vehicle proprietors and encouraging wider acceptance of electric vehicles [35].

Then, consistent and minimal voltage fluctuations are essential for preserving the health and longevity of electric vehicle batteries [36]. Sharp voltage spikes or drops can have adverse effects on battery performance and lifespan. Minimization on voltage deviation also contributes to better power quality during the charging process. Stable voltage levels prevent issues such as overheating, ensuring a reliable and consistent power supply to electric vehicles. By operating within specified voltage limits, the risk of damage to charging station components is reduced. Thus, ensuring the overall safety and reliability of the charging infrastructure. Voltage deviation must be kept to a minimum for EVCS to function seamlessly with the power grid [37]. The enhancement of charging infrastructure reliability and the contribution to the overall stability of the power grid are both outcomes of minimizing voltage fluctuations. Constraints regarding the sustainability and resilience of the energy ecosystem become ever more critical as the demand for electric vehicles continues to rise.

2.6 Previous Research Works on EVCS Planning

There are two types of techniques were being practiced by former researchers to find the optimal placements as well as sizes of EVCS which are classical and heuristic optimization techniques.

2.6.1 Optimization Techniques on EVCS Planning

The objectives of applying optimization techniques are to find the optimal solution to the optimization problem by minimizing or maximizing the objective function. To maximize the objective function, one could utilize one of many optimization methods [38]. Specifically, formulations of optimization problems for the placement and sizing of EVCS can have a single or multiple objectives and be linear or nonlinear. Depending on the variables employed, the formulated problem can be continuous, discrete, integer or a combination of the three [39]. The proper selection of optimization techniques for a given problem is therefore a crucial choice. This report provides a concise overview of some optimization techniques for determining the optimal location and sizing of EVCS and distinguishes between classical and advanced optimization techniques as the two primary categories which are classical optimization techniques and advance optimization technique [39].

Techniques of classical optimization can be helpful in locating and sizing the optimal solution as well as the unconstrained maxima or minima of continuous and differentiable functions. In addition, several of the classical approaches utilize objective functions that are neither continuous nor differentiable which means that their applicability in real-world settings is restricted to a certain extent [39]. While advanced optimization approaches or meta-heuristic optimization are utilized in the process of resolving large-scale problems that incorporate multi-modality, high dimensionality and differentiability. These types of challenges cannot be efficiently managed by classical optimization techniques. In contrast to classical methods which are founded on knowledge on gradients, more recent methods are able to deal with non-differentiable functions. When it comes to solving optimization problems, classical strategies frequently have difficulty overcoming the influence of local optima [40]. Therefore, advanced optimization techniques are designed to overcome these limitations and effectively solve optimization problems. The optimization techniques consist of the classical and meta-heuristic optimization as illustrated in Figure 2.2.

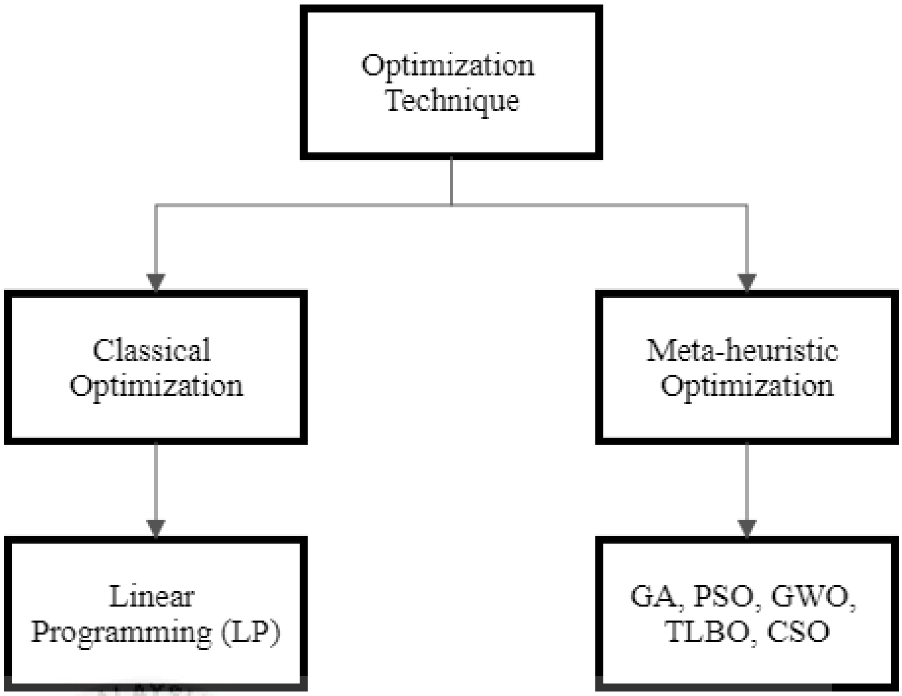

Figure 2.2 Classification for Optimization Technique

Besides, there are three different approaches for determining the optimal placement and sizing of EVCSs. These approaches include the Distribution Network Operator (DNO) approach, the Charging Stations Owner (CSO) approach, and the Electric Vehicle Users (EV User) approach [41]. The DNO strategy entails the need to supply electrical power to diverse interconnected electric loads in residential, commercial, and industrial zones. It should be emphasized that the characteristics of the DNO can be influenced by the location and size of additional loads. Hence, in order to identify the positioning and dimensions of EVCSs through the DNO method, various criteria are taken into account. These elements encompass the optimization of costs related to active power loss, reactive power loss, voltage variation, reliability, and stability of the distribution system. [12].

For the CSO approach, the complete cost of EVCS installation is then paid by the charging station owner in order to maximize revenue from the EVCS through EV charging. As a result, the CSO is looking for CS locations and sizing with the most revenue and the lowest investment. Thus, the CSO strategy considers the investment cost, installation cost, operating cost, maintenance cost, road construction cost and land cost while determining the best EVCS location and sizing [42].

Lastly, the placement and sizing of EVCS has a direct impact on the charging behavior of EV users. In previous research [43], various factors such as access cost, travel cost from the demand point to the EVCS, waiting time cost and charging time cost have been considered as objective functions when determining the optimal placement and sizing of EVCS from the perspective of EV drivers. These considerations are crucial in understanding and optimizing the placement and sizing of charging stations to cater to the needs and preferences of EV users. Thus, ensuring convenient access, minimizing travel and waiting times and optimizing the overall charging experience for EV drivers. Figure 2.3 illustrates the approaches of problem formulation for optimal placement and sizing of EVCS while Table 2.3 summarizes the problem formulations for EVCS optimization in existing research studies.

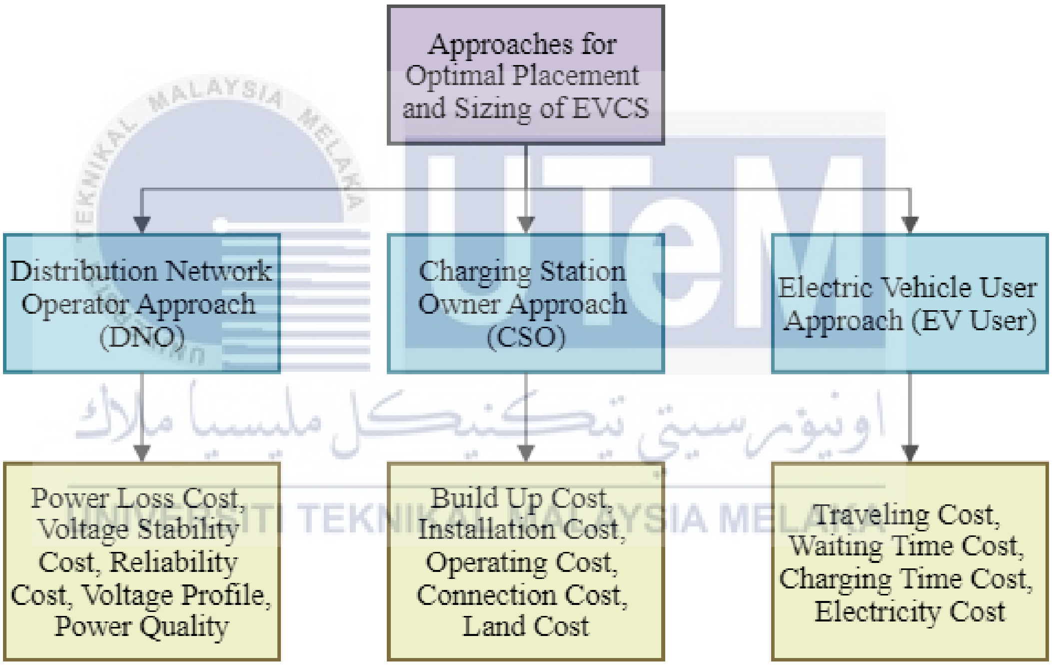

Figure 2.3 Approaches of Problem Formulation for EVCS

Table 2.3 Optimization Problem Formulations in Existing Research Studies

Reference Number	Method Applied	Objective Function	Remarks
[44]	GA	Construction cost and CS cost	For the purpose of reducing the overall cost, the optimal site for the EVCS is determined.

[45]	PSO	Cost of Investment, connection, power losses and demand respond	Cost-based optimal placement and sizing of EVCS are conducted to optimize the objective functions problem by taking into consideration the impact of DRPs.
[46]	GA-PSO	Power loss, voltage variation and cost	On the IEEE 33 test system, optimal placement and sizing of RESs and EVCSs are conducted to reduce power losses, voltage variations, and EV storage cost.
[47]	GA	Cost and power loss	Optimal sitting and sizing of EVCS are performed to reduce power loss and total cost.
[48]	TLBO	Voltage stability, reability,power loss and cost	To simultaneously minimize costs and VRP index on IEEE 33-bus and IEEE 123-bus, optimal placement and sizing of RESs and EVCSs are performed.
[49]	CSO-TLBO	Voltage profile, power loss and wait time	EVCS are strategically placed to minimise voltage fluctuations, power loss, and wait times at charging stations.
[50]	PSO	Cost , wait time and power loss	Optimal sitting and sizing of FCSs are performed reduce cost, waiting time and power loss.
[51]	GA	Cost and VRP index	The distribution system's VRP index has been optimised with the implementation of EVCS placement on IEEE 33-bus systems.
[52]	GA	Installation cost, power losses and waiting time	The problem of EVCS placement is resolved by reducing installation costs, power losses, and charging time.
[53]	GWO-PSO	Installation cost, power losses and waiting time	The installation of EVCSs and DGs on IEEE 33-bus and IEEE 69-bus systems is carried out in order to perform a reliability evaluation on the distribution network.

[54]	GA-PSO	Cost and power loss	The cost of upgrading protective devices is considered when installing EVCSs in the Allahabad distribution unit.
[55]	GWO	Voltage profile and power loss	The impact of electric car placement on the 69-bus test system has been analysed in order to optimise voltage profile and significantly reduce power losses.

2.6.2 Heuristic Methods

Heuristic methods represent a computation-oriented approach focused on creating computer programs capable of searching for problem solutions and enhancing search strategies. The algorithms are presented in a straightforward, informal manner, steering clear of excessive notation while upholding clarity and rigor as highlighted by Pearl in 1984. These methods are popular and widely being used in the optimal placement and sizing of EVCS in power distribution system.

2.6.2.1 Genetic Algorithm (GA)

The Genetic Algorithm is a form of evolutionary algorithm that employs methods that are inspired by natural evolution in order to find solutions for optimization problems. These methods include inheritance, selection, mutation and crossover. During the process of optimization, GA is able to investigate and locate the optimal solution on a global scale which is one of the many benefits of utilizing this method [56]. [57] introduced a technique for addressing EVCS siting and sizing issues using GA, which entails locating EVCS within established urban traffic networks. The strategy entails employing GA to optimize the positioning of charging stations using a grid partitioning technique that minimizes transportation costs. In [44], the utilization of the GA technique is employed to address the suggested optimal placement model for EVCS. This model encompasses two objective functions namely the construction cost of EVCS and the cost associated with accessing the charging stations. In [58], have specifically focused on determining the optimal charging station locations to promote sustainable cities. They have also introduced multi-objective functions to tackle the optimization problem.

Additionally, [59] proposed a cost model that forecasts the overall number and distribution of EVs in a specific area. This method required applying conversation theory which takes into consideration the fixed load point of charging stations in each district depending on the local traffic flows. Finally, GA was used to improve the model. In order to find the optimal distribution and number of charging stations, the [60] proposed a multi-objective optimization model with stringent time frame restrictions. A two-stage heuristic technique was used to solve the model. The research showed that the charging station needs different places and the time limits for charging might determine the best placement of EVCS. However, it was observed that GA required a significant amount of computational time when determining the optimal location and size of EVCS. Another drawback of GA is that it can result in premature convergence [61].

2.6.2.2 Particle Swarm Optimization (PSO)

Eberhart and Kennedy were the ones who first presented the concept of Particle Swarm Optimization (PSO), which was influenced by the general aspects of artificial life, such as the behavior of fish schools, bird swarming, and the social interaction behavior of humans. The PSO algorithm makes use of the idea of simulating social behavior in a problem space where each particle represents a potential solution to the issue that is being addressed. The PSO has an advantage over other optimization approaches since it can find the global optimal solution with a higher degree of efficiency and probability than those other techniques. PSO, in contrast to GA, does not involve any of the evolution operators like crossover or mutation thus making it easier to build and leading to a quicker convergence [62].

As an example, [63] used PSO to establish the most optimal location for a CS by considering the expenses of building and operation, in addition to geographical data and traffic flow, which served as limitations in the process. In order to evaluate the current CS and then compare the results, they made use of an improved PSO algorithm that had a range of different inertia factors. In a similar manner, [64] created an optimal planning model for EVCS by combining the global search capacity of PSO with a weighted Voronoi diagram. PSO was used to determine the ideal positions after the intended region had first been partitioned using a weighted Voronoi diagram. After this, PSO was used to determine the optimal locations. PSO is prone to low accuracy and divergence, which means that the proposed EVCS solutions could be considered potentially suboptimal. The use of a power loss in an imbalanced radial distribution system has been proposed as an objective function for the purpose of determining the ideal placement of EVCSs which can be found in [65]. The PSO technique was ultimately successful in providing a solution to the previously described optimization problem. In [66], an approach was taken toward determining the ideal placement of EVCSs by selecting the objective functions of the yearly average construction cost of EVCS, the annual running cost of EVCS and the cost of charging. The PSO algorithm was also utilized in order to find solutions for these objective functions.

The PSO optimization method is made up of three essential components which are particles, the social and cognitive features of particles and the velocity of the particles. The term "cognitive learning" refers to the experience that an individual particle has and "social learning" refers to the information that is gathered through the interactions of the entire swarm. Within the framework of the algorithm, the term "personal best" or P_{best} refers to cognitive learning, whereas "global best" or G_{best} stands for social learning. To put it another way, P_{best} is shorthand for the best answer that an individual particle has arrived at on its own, whereas G_{best} directs the particle based on the consensus of the swarm. P_{best} and G_{best} are both used in the calculation of the velocity of the particles in order to determine their subsequent position. In most cases, the PSO method kicks out with the initialization of a number of parameters, one of which is the number of particles in the swarm, which is determined by the degree of difficulty of the problem. After that, the particles will start moving around from one location to another as they look for the greatest possible answer based on the information provided by P_{best} and G_{best} [67].

Figure 2.4 illustrates the general flowchart of PSO algorithm. By referring to the flowchart below, the PSO method requires the specification of the parameters, which were previously explained, as well as the required total number of iterations.

After that, the initial population which is also known as the number of particles is distributed evenly across the search space and put in motion. The iteration count is set to 1 at the beginning of the loop. Each particle assesses its own fitness and looks around it to investigate its surroundings. The values for cognitive learning (P_{best}) and social learning (G_{best}) are figured out during this step. After locating the particle that most accurately represents the optimal solution, the new velocity at which it must travel in order to arrive at the new optimal position is computed. This method will carry on until the desired end criterion is reached, while simultaneously performing repeated searches for the optimal outcome.

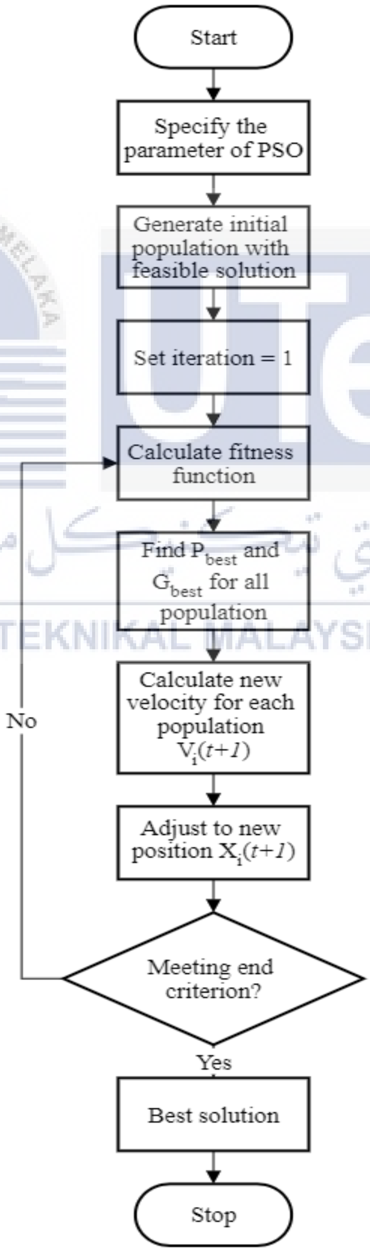

Figure 2.4 General Flowchart for PSO Algorithm

2.6.2.3 Grey Wolf Optimization (GWO)

GWO was first presented to the public by [68] in the year 2014. The natural behavior and hunting strategies of grey wolves, which are known for maintaining a strict hierarchical structure among their packs, serve as the basis for this hunting method. The individuals who take charge of the pack are known as the alpha wolves (α), while the rest of the members of the pack fall into the second group and are there to provide support for the alphas. Beta (β) wolves are the name given to the supportive members of the pack. In addition, there is another type of wolf known as a delta (δ) wolf, which occupies a lower rung on the evolutionary ladder when compared to the first two groups. Their primary goal is to show respect for the authority of the alpha and beta wolves while maintaining some degree of control over the omega wolves. The omegas (ω) are the least important of all the wolves, and they are required to pay respect to the dominating grey wolves [53].

2.6.2.4 Teaching Learning Based Optimization (TLBO)

The Teaching Learning Based Optimization (TLBO) algorithm was presented by [69], which takes its inspiration from the influence that teachers have on their students. TLBO stands out from other nature-inspired algorithms such as Artificial Bee Colony (ABC) and Particle Swarm Optimization (PSO) due to its reduced computational effort and constant ability to find global solutions for continuous nonlinear optimization issues. In its most basic form, TLBO is an imitation of the traditional teaching and learning process that takes place in a classroom setting. TLBO is based on the presumption that the process of learning can be broken down into two different phases which are the teacher phase and the learner phase. During the teacher phase, learning takes place under the direction of a teacher and during the learner phase, contact with other students helps further learning. TLBO is an algorithm that, like population-based algorithms, considers a group of students to be the population, the design factors of the optimization problem to be subjects, the best solution among the entire population to be the teacher and the fitness function to be the outcomes produced by the learners [70].

2.6.3 MATPOWER Power Flow

MATPOWER is an open-source software package developed by the Power System Engineering Research Centre (PSERC) for power flow analysis and optimal power flow (OPF) [71]. In the first of its three stages, MATPOWER analyses the input file that contains information about the power system including specifics on buses and branches as well as generator. Step two involves determining power flow using the standard Newton-Raphson method. The last step is to display all of the results. Optimizations of power systems are becoming more important as they allow operators to control systems at reduced costs [72]. However, as more limitations are applied, the complexity and diversity of these optimization challenges increase. Therefore, optimizing heuristic algorithms is important for successfully tackling these complex problems.

Several author studies pertaining to the optimal discovering process using applied MATPOWER have been published. The optimal sizing and location of RESs and EVCSs are conducted in [48]. The application of MATPOWER for power flow calculation is encountered during the objective function evaluation procedure. The impact of EVCS deployment on the 69-bus test system is resolved in [55]. The objective function of multi-objective optimization for power system loss calculation incorporates applied MATPOWER. For loss reduction, [73] describes the installation of EVCS and DG on IEEE 33-bus and IEEE 69-bus systems. Utilizing power flow analysis with MATPOWER, the objective function of power loss in the system is determined. By integrating MATPOWER with optimization techniques including GSA and PSO, this project determines the optimal placement and sizing of EVCS in a power distribution system by considering the minimization of power losses and the average voltage deviation.

A mathematical formulation of the power flow equations in an electrical power system is the fundamental tool for solving the MATPOWER power flow problem. The power flow equations show how much power is flowing across each bus. Here are some common power system equations that describe how power flows across a bus and the power balance equations for bus i are as follows [71]:

$$P_i = \sum_{j=1}^{N} V_i \cdot V_j \cdot \left(G_{ij} \cdot \cos\theta_{ij} + B_{ij} \cdot \sin\theta_{ij}\right) \tag{2.1}$$

$$Q_i = \sum_{j=1}^{N} V_i \cdot V_j \cdot \left(G_{ij} \cdot \sin\theta_{ij} + B_{ij} \cdot \cos\theta_{ij}\right) \tag{2.2}$$

Where P_i and Q_i are the active and reactive power injections at bus i, V_i is the voltage magnitude at bus i, θ_{ij} is the phase angle difference between buses i and j, G_{ij} and B_{ij} are the conductance and susceptance of the transmission line connecting bus i and i and N is the total number of buses in the system.

2.7 Summary

This chapter describes the overview of electric vehicle along with a brief discussion on the types of EV which are hybrid, fuel cell, plug-in hybrid and all electric vehicle. This was followed by a review on the infrastructure of EVCS and levels of EVCS which are slow AC charger, moderate AC charger and DC fast charger. Then, the charging prices of EV charging, its impacts to modern power grid and benefits in minimizing average voltage deviation are also discussed and presented. A review of the heuristic methods used for previous research works on optimal placement and sizing of EVCS is also presented in this chapter. As the previous research did not employ any GSA method, so the GSA method is proposed in this project. In this report, the heuristic technique based on GSA and PSO are used for solving the optimal placement and sizing of EVCS in power distribution systems. The next chapter elaborated on the methods used in achieving the objectives function which are to minimize the real power losses and average voltage deviation. The optimization technique which are GSA and PSO are also being discussed throughout the chapter and this study focussed on two radial distribution system that are IEEE 33-bus and IEEE 69-bus radial distribution system.

CHAPTER 3

METHODOLOGY

3.1 Introduction

In this chapter, the work plan of the project, Gantt chart and project milestone are being tabulated and presented to make sure that the project is within the given timeline. To achieve the first objective of the project, the evaluation and comparison the cost of charging for various types of EVs in Malaysia were performed and discussed in order to determine the most optimum charging power for EV chargers. For the next objectives, the problem formulations, constraints condition, algorithms and network systems are discussed and presented in order to locate EVCS with optimal sizes. This project was conducted by using simulation via MATLAB in order to identify the optimal placement and sizing of EVCS in power distribution system by considering power loss reduction and minimization of average voltage deviation. The total power losses and average voltage deviation were obtained from MATPOWER Newton Raphson load flow. Gravitational Search Algorithm (GSA) was implemented as the proposed optimization technique in order to identify for the best solution in placement and sizing of EVCS. Lastly, the results obtained from the proposed optimization was being compared with the commonly used technique namely Particle Swarm Optimization (PSO) in order to analyze the different in term of system performances.

3.2 Evaluation on Charging Prices

It is essential to evaluate the charging prices of various EVs on the market in order to have a complete understanding of the financial feasibility and accessibility of EV ownership and use in Malaysia. To conduct this analysis, not only the precise charging needs of each EV model, but also a number of factors that affect the charging rates for various EV models. To evaluate the time and cost needed to charge different kinds of electric vehicles within the context of the Battery Management System (BMS), this study presupposes the use of a constant charging rate in relation to the battery capacity.

First, the charging capacity and rate of power of the battery severely impact the time and cost needed to charge an electric vehicle. Typically, the cost to charge an electric vehicle with a large battery is greater than that of a smaller battery because charging a large battery requires more power. There are a number of companies in Malaysia that offer services related to charging electric vehicles. Factors such as cost structure, charging speed, technology offered and market competitiveness cause these charging rates to vary. In order to determine and compare the costs of charging different kinds of electric vehicles in Malaysia, this study employs Gentari and TNB Electron as reference points among the many accessible EV charging service providers.

The cost of recharging an electric vehicle is also impacted by the charging infrastructure as well as the pricing structure of that infrastructure. At public charging stations, there is the potential for a number of different pricing structures to be implemented, such as hourly charges, flat prices, and payments based on the length of time spent getting charged. There is also the possibility that private charging stations, such as those that are put in houses or companies may have varying electricity prices, which can further alter the overall expenses of charging. Hence, the calculation of the charging cost and charge time can be readily determined by employing the following formula [74]:

$$Charging\ cost = Battery\ capacity \times Electricity\ cost \tag{3.1}$$

$$Charge\ time = \frac{Battery\ capacity}{Charging\ power} \times 60 \tag{3.2}$$

Where kWh is the unit of battery capacity, RM/kWh is the unit of electricity cost, and kW is the unit of charging power. Finding the best charging power for electric vehicles requires looking at a number of factors, including the charging price rates offered by Gentari and TNB Electron, as well as the specifications of various EV models. These factors include battery capacity, charging time, and the relevant electricity costs.

3.3 Gravitational Search Algorithm (GSA) Implementation

The Gravitational Search Algorithm (GSA) was first proposed in 2009 as a solution for optimization challenges. This algorithm is derived from Newton's law of gravity and the law of motion. The gravitational force employed in GSA is directly related to the multiplication of mass and inversely proportional to the square of the distance. The gravitational force between two objects can be mathematically represented as follows [75]:

$$F = G \times \frac{M_1 \times M_2}{R^2} \tag{3.3}$$

Where G is the gravitational constant that approximately equal to $6.67 \times 10^{-11} N.m^2/kg^2$, M_1 and M_2 are the masses in the unit of kilogram (kg) of the objects 1 and 2 respectively while R is the distance between two objects in unit of meter (m) and F is the gravitational force between two objects in the unit of newton (N). The acceleration of the particle, a is related to its mass, M and the gravitational force, F and can be computed by using the following formula [75]:

$$a = \frac{F}{M} \tag{3.4}$$

Equations (3.3) and (3.4) demonstrate the gravitational influence on all particles. The distance separating two particles plays a crucial role in determining the gravitational force between them which a shorter distance results in a stronger gravitational force. Figure 3.1 visually depicts the foundational physics of the GSA. This illustration features four objects, with the size of each object representing its mass. Object M_1 experiences gravitational effects from the other three objects which are M_2, M_3 and M_4. Thus, leading to the generation of the resultant force, denoted as F. The algorithm converges towards the optimal solution and the gravitational force remains unaffected by the environment, showcasing a robust local value for gravity.

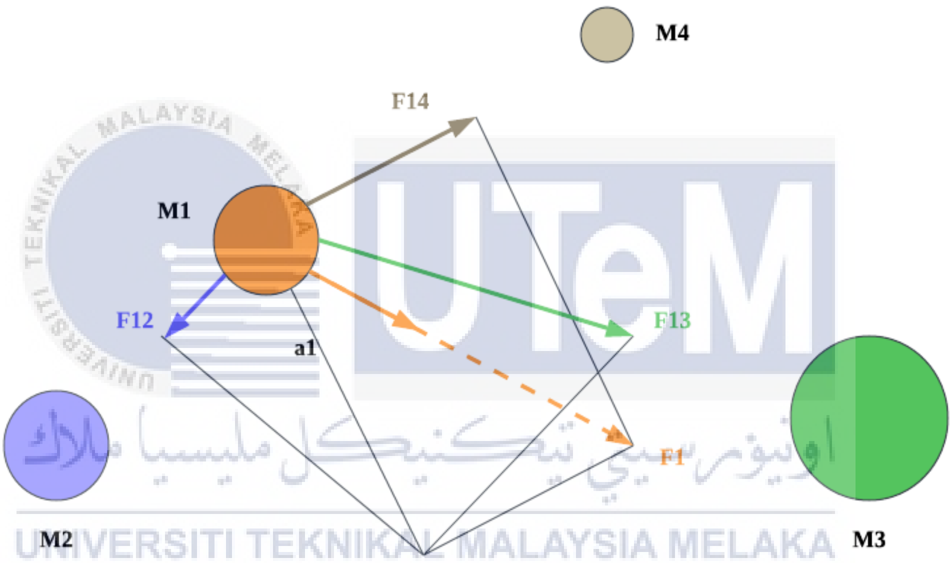

Figure 3.1 Gravitational Force Phenomena

Each particle in motion through space undergoes a transformation into an object possessing a distinct mass in GSA. These objects interact gravitationally, attracting one another. The mutual attraction among particles generates accelerations that causing them to connect and move in the direction of the resultant force. The effectiveness of these objects is gauged by their masses, with smaller mass objects gravitating towards those with greater mass. Consequently, the optimal solution emerges from the larger objects. The utilization phase of the algorithm is ensured by the slow motion of heavier masses which is indicative of an effective solution. Four parameters comprise the GSA which are position, inertial mass, active and passive gravitational masses. The solution is denoted by the position, whereas the fitness function is employed to ascertain the gravitational and inertial masses. The computations performed by GSA take into consideration the following equations. Initially, the positions of N objects are randomly generated and introduced into a function in which defining the position of the i^{th} object as [76]:

$$X_i = (x_i{}^1, \dots, x_i{}^d, \dots, x_i{}^n) \quad \text{for } i = 1, 2, \dots, N \tag{3.5}$$

Where $x_i{}^d$ is the position of i^{th} agent in the d^{th} dimension. Therefore, the detailed position of each i^{th} agent can be expressed as follows:

$$X_i{}^n = [(Size, VC, Placement)_1, (Size, VC, Placement)_N] \tag{3.6}$$

Where $X_i{}^n$ is the position of each i^{th} agent, $Size$ is the capacity of the EVCS, VC is the voltage control and $Placement$ is the location of the EVCS. Then, the update of gravitational constant is stated as below :

$$G(t) = G_0 \times \frac{T - t}{T} \tag{3.7}$$

Where $G(t)$ is the value of the gravitational constant at time t, G_0 is the gravitational constant value at the first quantum interval of time t_0 and T is the total number of iterations. The initial value for G_0 is established at 100. Every particle or object, characterized by a specific mass, possesses inertia. In this context, the inertia is directly proportional to the mass which means larger masses exhibit greater inertia. The inertial mass of each object is intricately linked to its self-adaptation degree based on its position, allowing for calculation. A higher inertial mass signifies a stronger attraction, facilitating the attainment of an optimal solution. The following fitness values correspond to the update of mass when a weighting range of 0 to 1 is evaluated [76]:

$$m_i(t) = \frac{fitness_i(t) - worst(t)}{best(t) - worst(t)} \tag{3.8}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{n} m_j(t)} \tag{3.9}$$

Where the fitness value of the agent i at time t denoted as $fitness_i(t)$, $worst(t)$ is the maximum fitness value and $best(t)$ is the minimum fitness value. The update of K_{best} is determined by the following equation [76]:

$$K_{best} = K_{best\_final} + \left[\frac{T-t}{T}(100 - K_{best\_final})\right] \tag{3.10}$$

In equation (3.10), the optimal applying force, K_{best} is steadily decreases from 100% of $K_{best^{max}}$ to 2.0% of $K_{best^{min}}$. At time t, the gravitational force calculation between object j and object i is expressed by the following formula [76]:

$$F_{ij}{}^{d} = G\frac{M_{ij}}{R_{ij} + \varepsilon}(x_j{}^{d} - x_i{}^{d}) \tag{3.11}$$

$$R_{ij} = \left\|X_i, X_j\right\|_2 = \sqrt{\sum_{d}^{D}(x_j{}^{d} - x_i{}^{d})^2} \tag{3.12}$$

R_{ij} represents the Euclidean distance between object j and object i, and ε is a small coefficient specifically 2^{-52}. Adopting a stochastic approach, the overall force acting on agent, i across the dimension, d is subject to random weighting which determined by the sum of the d^{th} components of forces exerted by other agents. Consequently, the total force can be expressed as follows [75]:

$$F_i{}^{d}(t) = \sum_{j \in K_{best}, j \neq i}^{N} rand_i F_{ij}{}^{d}(t) \tag{3.13}$$

Where $rand_i$ is a random number in the interval 0 and 1. Therefore, the updating acceleration, velocity and position towards the best solution are formulated as follows [75]:

$$\alpha_i{}^d = \frac{F_i{}^d}{M_i} \tag{3.14}$$

$$v_i{}^d(t+1) = rand_i v_i{}^d(t) + \alpha_i{}^d(t) \tag{3.15}$$

$$x_i{}^d(t+1) = x_i{}^d(t) + v_i{}^d(t+1) \tag{3.16}$$

The operation of GSA is guided by two contrasting objectives namely exploration and exploitation. Exploration pertains to the capacity to broaden the global investigation of the search space, while exploitation is concerned with the capability to identify optimal locations in the surrounding area of a particular solution. Prioritizing exploration is important for the algorithm in order to prevent it from becoming limited to a local optimum. The priority of exploitation to improve the quality of the obtained solution gradually replaces exploration as the search process advances. The optimal equilibrium between exploration and exploitation, on the other hand, presents difficulties for the Gravitational Search Algorithm (GSA). The convergence rate can be influenced by the level of exploitation, whereas an excessive amount of exploration may lead to premature convergence. The optimum agent within GSA further investigates the global space, even when it is in an optimal position.

Additionally, GSA offers a variety of benefits such as an adaptable learning rate, an algorithm that does not require memory and rapid convergence. However, it is important to mention that the convergence rate might decelerate as the search phase advances.

Figure 3.2 represents the flowchart of the GSA algorithm which is designed to determine the optimal placement and sizing of EVCS in power distribution system. Firstly, the optimization process starts by specifying the parameters of GSA. The initial population is generated where best, worst and fitness values are set to their initial values. Then, the GSA iteration loop begins where the algorithm repeatedly performs the following steps until a termination condition is met. During the first iteration, the objective function is calculated and the fitness of each agent is evaluated. This involves evaluating the power losses and voltage deviation minimization. After that, the position of each agent is updated and the criterion condition is checked. If the conditions are met, the algorithm proceeds to print the best solution and the optimization is concluded. Otherwise, the GSA iteration loop is repeated until the conditions are satisfied before the GSA algorithm ends.

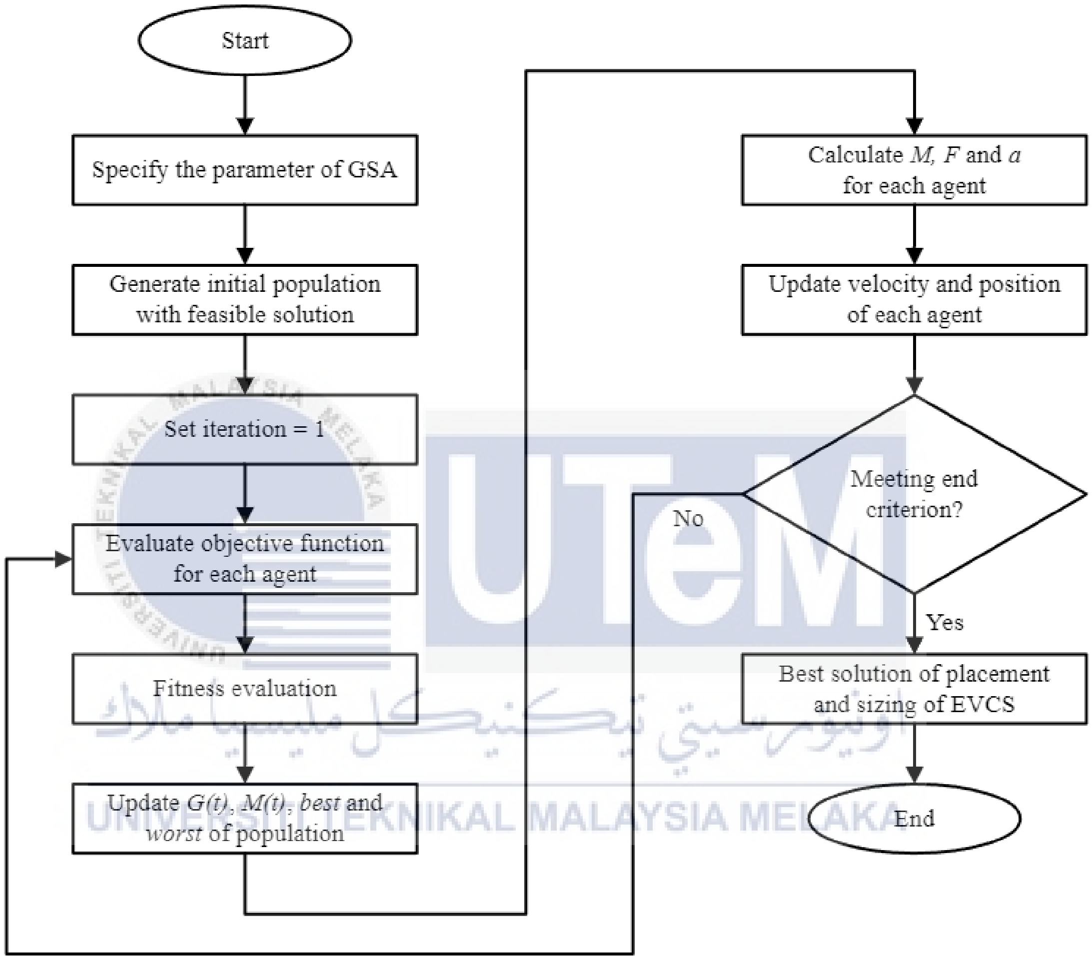

Figure 3.2 Flowchart of the GSA Algorithm

3.4 Particle Swarm Optimization (PSO) Implementation

Particle Swarm Optimization is a computational optimization algorithm inspired by the flocking or schooling behavior of birds and fish. It is a population-based stochastic optimization method used to determine the optimal solution for a given problem. In PSO, a population of particles each of which represents a potential solution travel over a multidimensional search space in order to locate the best possible answer. The motion of each particle is affected both by personal best (P_{best}) as cognitive component and by global best (G_{best}) as social learning. Particles traverse and utilize the search space by continuously modifying their locations and velocities. This results in the particles gradually converging towards the optimal solution. The cognitive component can be readily computed using the equation provided below [77]:

$$P_{best_i}(t+1) = \begin{cases} P_{best_i}(t) & if\ f(X_i(t+1) \geq f\left(P_{best_i}(t)\right)) \\ X_i(t+1) & if\ f(X_i(t+1) < f\left(P_{best_i}(t)\right)) \end{cases} \tag{3.17}$$

Where i is the index of each particle, t is the current iteration number, $X_i(t+1)$ is the new position of particle, $P_{best_i}(t)$ is the current personal best and $P_{best_i}(t+1)$ is the new personal best position. Then, the formulation for the social learning value of the swarm which represents the best fitness achieved by any particle can be expressed as follows [77]:

$$G_{best_i}(t) = arg_{i=1}^{n} Min\{f(P_{best_i}(t))\} \tag{3.18}$$

Where n is the total number of particles. Therefore, the updating velocity of the particle towards the best solution can be expressed as follows [77]:

$$V_i(t+1) = \omega V_i(t) + c_1 r_1 \left(P_{best_i} - X_i\right) + c_2 r_2 (G_{best_i} - X_i) \tag{3.19}$$

Where $V_i(t+1)$ is the new velocity of the particle for i-th iteration, ω is the inertia weight of the particle, $V_i(t)$ is the current velocity of the particle for i-th iteration, c_1 and c_2 are the constants that defined weightage factor of random acceleration terms while r_1 and r_2 are uniformly distributed random numbers in the interval of 0 and 1. Thus, the new position of the particle is stated as below [77]:

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{3.20}$$

Where $X_i(t+1)$ is the new position of particle, $X_i(t)$ is the particle position for i-th iteration and $V_i(t+1)$ is the new velocity of the particle for i-th iteration. In order to commence the PSO algorithm, a preliminary population is created as a binary string. The length of this string is dictated by the number of EVCS. Furthermore, the quantity and capability of each installed station are developed. Two categories of variables are encountered in this project which are binary and discrete variables. The discrete variables refer to the sizes of the designated EVCSs while the binary variables determine the locations of EVCSs. As a consequence, the algorithm of the particles contains both discrete and binary decision variables which represent the location and size of EVCSs respectively. Figure 3.3 illustrates the state of swarm and the details of the components of PSO have been tabulated in Table 3.1.

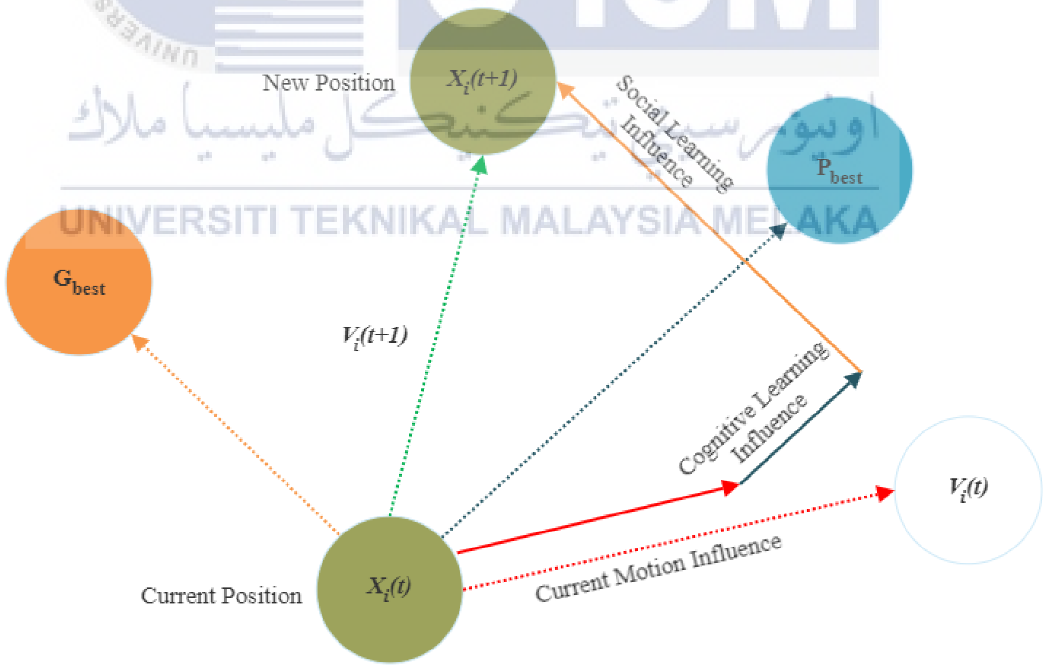

Figure 3.3 Generation Scheme of the Particles

Table 3.1 Details of the Components of PSO

Notation	Name of Component	Contribution of the Component in Updating the Velocity
$V_i(t)$	Velocity	Using the previous velocity, it functions as a record of the most recent voyage. Additionally, it is considered an inertia component that balances the exploration and exploitation of each particle in search space.
$c_1 r_1 (P_{best_i} - X_i)$	Cognitive	This cognitive component drives particles to their optimal position and is proportional to the distance between the particle's optimal position and its current position.
$c_2 r_2 (G_{best_i} - X_i)$	Social	This is the social component of the velocity equation that propels the particle to the optimal position determined by the swarm.

The flowchart in Figure 3.4 illustrates the PSO algorithm, which is specifically developed to identify the best location and size for EVCS in a power distribution system. This approach focuses on lowering power losses and minimizing the average voltage deviation. Firstly, the optimization process starts by specifying the parameters of PSO include the swarm size which determines the number of particles in the algorithm. Each particle is associated with a position and velocity in the search space. After the initialization, the initial population is generated where the personal best, global best and fitness values are set to their initial values. Then, the PSO iteration loop begins where the algorithm repeatedly performs the following steps until a termination condition is met. The objective function is computed and the fitness of every particle is assessed during the initial iteration. This process entails the computation of power losses experienced by the system as well as the assessment of average voltage deviation minimizations.

Next, the personal best position, global best position and fitness are updated if the current fitness is better than the previous best. The new velocity is calculated and adjusted based on the cognitive, social components and inertia weight. Additionally, the velocity is limited to stay within the specified maximum velocity bounds. After that, the position of the particles is updated by adding the velocity to the current position. Then, the criterion condition is checked which includes reaching the maximum number of iterations or achieving a desired fitness level. If these conditions are met, the algorithm proceeds to print the best solution of optimal placement and sizing of EVCS and the optimization is concluded. Otherwise, the PSO iteration loop is repeated until the conditions are satisfied before the PSO algorithm ends. Figure 3.4 illustrates the flowchart of the PSO algorithm for optimal placement and sizing of EVCS in power distribution system.

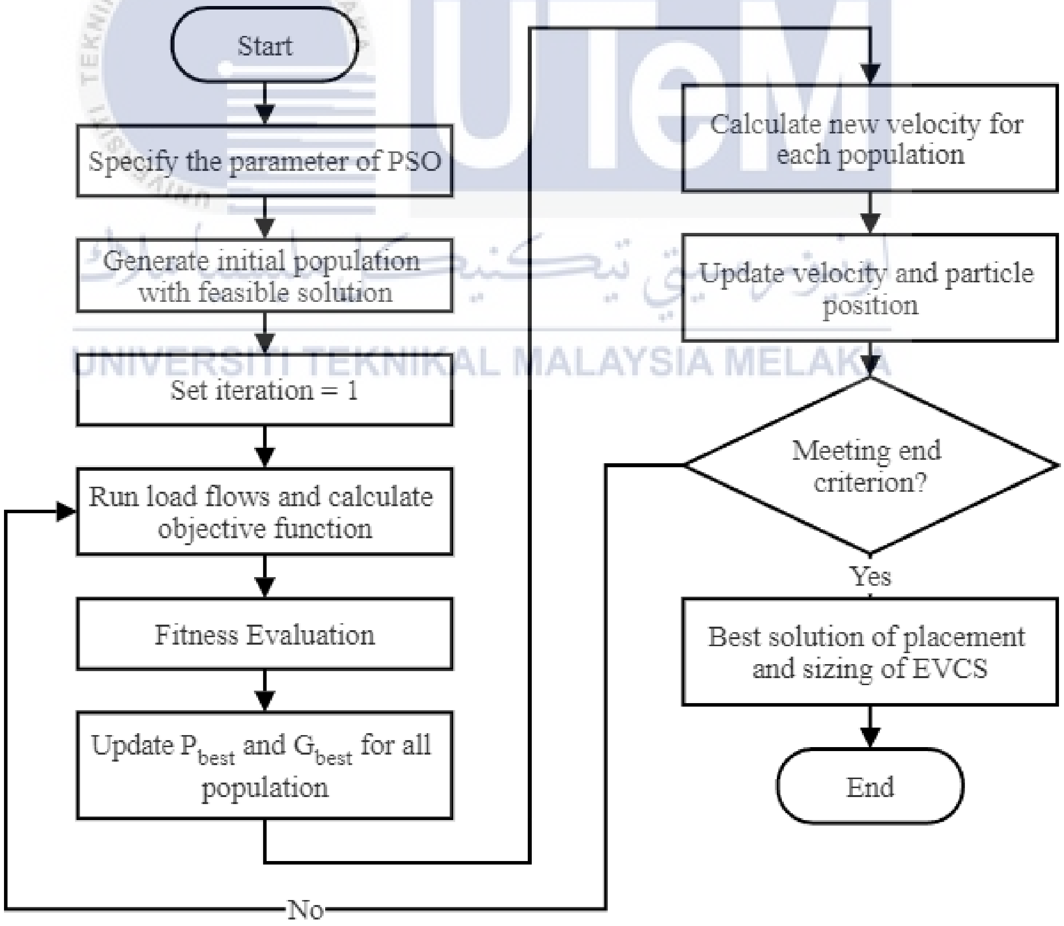

Figure 3.4 Flowchart of the PSO Algorithm

3.5 Problem Formulations

An optimization refers to the process of maximizing an objective function while adhering to various equality and inequality constraints. In the context of optimal placement and sizing of EVCS, a multi-objective optimization is employed to reduce the total power loss and minimize the average voltage deviation. Therefore, the representation of the general optimization problem can be expressed as:

$$F_{min} = (\gamma P_{loss}) + (\beta V_{dev}) \tag{3.21}$$

Where F_{min} is the minimum fitness function, P_{loss} is the total power losses and γ is the coefficient of P_{loss} while V_{dev} is the average voltage deviation of the system buses and β is the coefficient of V_{dev}. To find the best optimum solution, a method that sums up the coefficient factor is used in order to determine the relative importance of the objectives. In this optimization, all objectives which are reducing the power losses and minimizing average voltage deviation are considered equally significant with assigned a coefficient factor of 0.5 each. Therefore, the total real power losses and average voltage deviation are determined as follows:

$$P_{loss} = \sum_{i=1}^{n} P_{loss_i} \tag{3.22}$$

$$V_{dev} = \frac{V_{i_{ref}} - V_i}{V_i} \tag{3.23}$$

$$V_{min} \leq |V_i| \leq V_{max} \tag{3.24}$$

Where n is the numbers of lines, V_{dev} is the voltage deviation, $V_{i_{ref}}$ is the reference voltage at bus i and V_i is the actual voltage at bus i while V_{min} is the lower limit and V_{max} is the upper limit of the bus voltage because bus voltage must be maintained within the permissible operating range throughout the optimization process.

3.6 Constraints Condition

The objective function or problem formulation described previously is governed by the constraints of bus voltage limit [78], [79]. An abnormal condition, also known as a fault working state, will be entered by the distribution network whenever the voltage at any node in the network deviates from the predefined fluctuation range. The bus voltage limit range can be expressed as follows:

$$V_{k,min} \leq V_k \leq V_{k,max} \tag{3.25}$$

Where V_k represents the bus voltage at k^{th} node, $V_{k,min}$ is the minimum allowable bus voltage at k^{th} node which is 0.95 per unit and $V_{k,max}$ is the maximum allowable bus voltage at k^{th} node which is 1.05 per unit. There are certain boundary limits that apply to the study dedication. These constraints include the sizes and locations of voltage control and EVCS. Within the range of 0.99 to 1.01 is where the boundary of the voltage control parameter is defined. Due to the fact that the installation of EVCS is only permitted on load buses, the slack bus cannot be considered a viable place for EVCS installation. The assumption is also made that there is only one EVCS on each load bus.

3.7 Test System Description

In evaluating the efficacy of GSA and PSO, two test systems are utilised which are the IEEE 33-bus and IEEE 69-bus radial distribution systems. This section contains information regarding both systems. The primary objective of the project is to depict the base case conditions of each system prior to the installation of Electric Vehicle Charging Stations (EVCS). By employing this methodology, the effect of EVCS installation on the actual power losses and voltage deviation of the system can be demonstrated.

3.7.1 IEEE 33-Bus Radial Distribution System

The IEEE 33-bus radial distribution system network is a balanced three-phase system comprising 33 buses and 32 branches. It operates at a voltage level of 11 kV and all loads are assumed to be supplied from the substation at bus 1 which referred to as the slack bus. The system encompasses 32 loads with a total demand of 3.72 MW and 2.30 MVAr for real and reactive power loads respectively. The system details are sourced from [80] and Figure 3.5 illustrates the IEEE 33-bus distribution system as described by [81]. The configuration of branches is presented in Table 3.2.

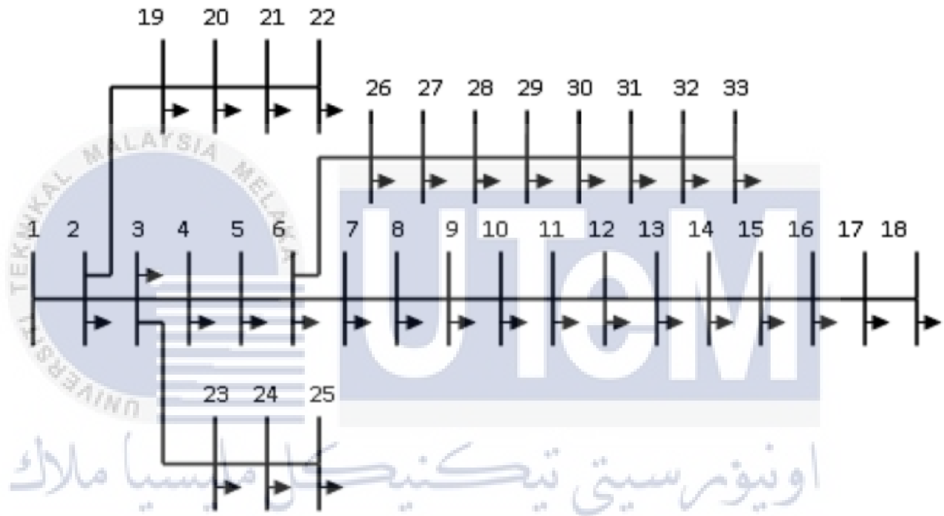

Figure 3.5 The IEEE 33-Bus Radial Distribution System

Table 3.2 Branches for IEEE 33-Bus

Feeder	**Buses**
Substation	1
1	2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18
2	19,20,21,22
3	23,24,25
4	26,27,28,29,30,31,32,33

3.7.2 IEEE 69-Bus Radial Distribution System

The IEEE 69-bus radial distribution network is a balanced three-phase system comprising 69 buses and eight feeders. Operating at a voltage level of 12.66 kV, the system assumes that all loads are supplied from the substation located at the slack bus [81]. It encompasses 48 loads with a combined demand of 3.8 MW and 2.69 MVAr for real and reactive power loads respectively. Figure 3.6 provides a visual representation of the IEEE 69-bus distribution network and the configuration of branches is detailed in Table 3.3.

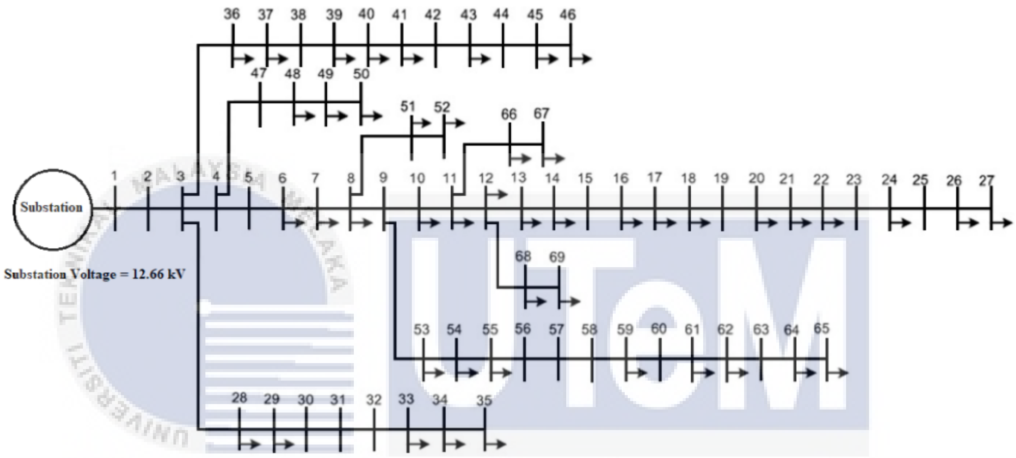

Figure 3.6 The IEEE 69-Bus Radial Distribution System

Table 3.3 Branches for IEEE 69-Bus

Feeder	Buses
Substation	1
1	2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18, 19,20,21,22, 23,24,25,26,27
2	28,29,30,31,32,33,34,35
3	36,37,38,39,40,41,42,43,44,45,46
4	47,48,49,50
5	51,52
6	53,54,55,56,57,58,59,60,61,62,63,64,65
7	66,67
8	68,69

3.8 Optimal Placement and Sizing of EVCS

This section delves into the discussion of the optimal placement and sizing methodology for Electric Vehicle Charging Station (EVCS) in the IEEE 33-bus and IEEE 69-bus systems. Various assumptions have been considered concerning the effects of EVCS installation on factors such as real losses and voltage deviation in both test systems:

1. The simulation is implemented based on a snapshot during peak load conditions as they exert a more substantial influence on power losses compared to average load conditions.

2. Cost considerations are not factored into the simulation.

3. The maximum permissible number of EVCS installations in the system is limited to two.

4. Population sizes for GSA and PSO are standardized at 50.

5. Thirty independent runs are conducted to assess the frequency of reaching optimal solutions.

6. The maximum iteration for GSA and PSO is capped at 300.

The procedure of the simulation is shown in Figure 3.7. The simulation process begins with the collection of all distribution system information. Data pertaining to the basic case is recorded. On the system, heuristic algorithms including GSA and PSO are implemented. Computing the load flow analysis with MATPOWER load flow. For the calculation of the objective function, equation (3.21) is used. It is imperative that the bus voltage remains within the specified range of 0.9 per unit to 1.05 per unit. Finally, the minimum value of the criterion is utilized in determining the optimal solution.

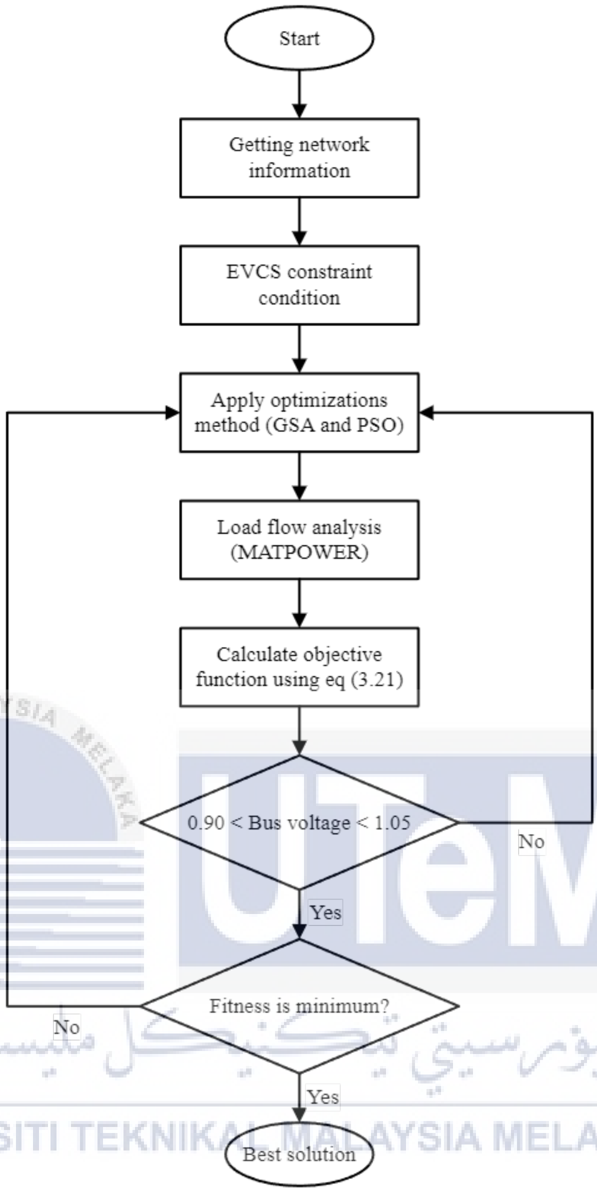

Figure 3.7 The Simulation Process of EVCS Placement and Sizing

3.8.1 IEEE 33-Bus Radial Distribution System

There are three cases being examined in this test system:

i. **Case I:** Base Case before the Installation of EVCS.

ii. **Case II:** 1-EVCS Installed at Optimum Placement and Sizing.

iii. **Case III:** 2-EVCS Installed at Optimum Placement and Sizing.

3.8.2 IEEE 69-Bus Radial Distribution System

There are three cases being examined in this test system:

i. **Case I:** Base Case before the Installation of EVCS.

ii. **Case II:** 1-EVCS Installed at Optimum Placement and Sizing.

iii. **Case III:** 2-EVCS Installed at Optimum Placement and Sizing.

3.9 Summary

In this chapter, the evaluation on the costs associated with charging each of the various types of EVs were described and presented. Then, an optimization technique to find the optimal placement and sizing of EVCS in power distribution system was proposed where the total real power losses and the average voltage deviation were employed as the objective functions to be reduced and minimized. The proposed optimization technique was formulated as Gravitational Search Algorithm (GSA) and was applied to two radial distribution systems that are the IEEE 33-bus and IEEE 69-bus radial distribution systems. The proposed optimization then will be compared with other optimization method namely Particle Swarm Optimization (PSO). The problem formulation or objective functions such as total power losses and voltage deviation were discussed and the problem formulation presented are subject to some constraints condition mentioned such as bus voltage limits are also presented in this chapter. Therefore, the findings will be used as input for determining the optimal placement and sizing of EVCSs and the results of all cases were recorded and discussed in the next following chapter.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Introduction

In this chapter, the results of the study are presented and discussed. The results are organized following to the sequence of cases that have been discussed in the last chapter. First, the cost of charging for various types of EVs have been calculated and discussed by comparing the charging prices for each EVs from Gentari and TNB Electron charging station in order to identify the most efficient and cost-effective charging power to charge an EV. Next, the optimal EVCS placement and sizing problem were investigated using multi-objective function and were analyzed by considering power loss reduction and minimization of voltage deviation. Then, the performance between the proposed optimization with other commonly used technique were also being compared in order to assess the performance and efficiency of different approaches in achieving desired outcomes.

4.2 Evaluation of Charging Prices for Various Types of EVs in Malaysia

The assessment of the charging costs for different electric car models in Malaysia necessitates considering several factors, such as the battery capacity, predicted range, maximum charging power, and vehicle weight. This study solely focuses on the battery capacity of electric vehicles. The study aims to determine the optimal and efficient charging power for each electric car model, while also assessing the financial implications of charging. Table 4.1 displays the specifications of several types of electric vehicles.

Table 4.1 Specification of Various EV Types

EV Model	Battery Capacity (kWh)	Estimated Range (km)	Max. Charge Power (kW)	Weight (kg)
Hyundai Ioniq 5	72.6	430	350	2100
Kia EV6 GT	77.4	506	350	2105
Audi RS e-tron GT	85.0	501	270	2420
Porsche Taycan Turbo S	93.4	416	270	2295
BMW i4 M50 EV	83.9	510	200	2290
Volvo C40 Recharge	78.0	438	150	2045
Tesla Model Y	75.0	514	250	2003

A detailed summary of the charging prices that TNB Electron provides may be seen in Table 4.2. The charging powers that are available through TNB Electron range from 80kW to 100kW. In this analysis, the charging prices of a number of popular electric vehicle models are evaluated by taking into consideration the different battery capacity and charging times of each model. As demonstrated in Table 4.2, the cost per minute rises in proportion to the amount of power that is being charged. As a result, the amount of time and cost required to charge each electric vehicle type will decrease. There are only three charging powers that TNB Electron provides which are 80kW, 90kW and 100kW. Because of this, utilizing a charger that has a greater power rating can result in more cost-effective services.

Table 4.2 Comparison Between CT and CP for Charging Power Offered by TNB Electron

Charging Power	80kW (RM2.05/min)		100kW (RM2.35/min)	
EVs Model (Battery Capacity)	CT (min)	CP (RM)	CT (min)	CP (RM)
Hyundai Ioniq 5 (72.6kWh)	55	112.75	44	103.40
Kia EV6 GT (77.4kWh)	58	118.90	46	108.10

Audi RS e-tron GT (85kWh)	64	131.20	51	119.85
Porsche Taycan Turbo S (93.4kWh)	70	143.50	56	131.60
BMW i4 M50 EV (83.9kWh)	63	129.15	50	117.50
Volvo C40 Recharge (78kWh)	59	120.95	47	110.45
Tesla Model Y (75kWh)	56	114.80	45	105.75

Table 4.3 Comparison between CT and CP for Charging Power Offered by Gentari

Charging Power	60kW (RM1.40/min)		180kW (RM3.60/min)	
EVs Model (Battery Capacity)	CT (min)	CP (RM)	CT (min)	CP (RM)
Hyundai Ioniq 5 (72.6kWh)	73	102.20	24	86.40
Kia EV6 GT (77.4kWh)	77	107.80	26	93.60
Audi RS e-tron GT (85kWh)	85	119.00	28	100.80
Porsche Taycan Turbo S (93.4kWh)	93	130.20	31	111.60
BMW i4 M50 EV (83.9kWh)	84	117.60	28	100.80
Volvo C40 Recharge (78kWh)	78	109.20	31	111.60
Tesla Model Y (75kWh)	75	105.00	25	90.00

Table 4.3 presents a comparison of the charging rates and charge times offered by Gentari for different charging powers. The charge rate was denoted in RM/min. Higher charging power leads to a corresponding rise in the charging rate. The study findings suggest that charging an electric vehicle with a capacity of 180 kW results in a decrease in both the required charging time and the associated cost. Charging an

electric car with a power rating of 180 kW enhances the convenience and satisfaction of users due to the efficient operation of the charging services.

The assessment of charging costs for various EV models in Malaysia provides valuable insights for determining the most efficient charging capacity and forecasting the charging needs of individual EVs. The 180kW charging capacity should be taken into account when calculating the cost of the charge in RM/min. This suggests that when choosing charging capacity, consideration should also be given to the pricing structures offered by different charging providers. Owners of electric vehicles have the ability to choose the most economical power source for charging purposes.

Charging time and cost are substantially reduced when the charging power specification is set at 180kW. Electric vehicle (EV) owners can recharge their vehicles at a reduced rate due to the expedited charging rates facilitated by higher charging power ratings. This feature proves particularly advantageous for mobile drivers who require sudden battery recharges. By offering efficient charging services, electric vehicles (EVs) boasting a power rating of 180kW enhance user convenience and satisfaction.

Additionally, charging stations that possess greater power classifications such as 180kW may offer charging services at a lower cost. This results in reduced costs per unit of energy consumed by EV consumers, thereby enhancing the cost-effectiveness of the charging process. The assessment is crucial in order to ascertain the most efficient charging capacity for different electric vehicle models and approximate their charging demands. With knowledge of the optimal charging capacity, the government involved in the planning of EV infrastructure can make informed decisions regarding the installation of charging stations. This guarantees that the charge infrastructure adequately caters to the requirements of electric vehicle (EV) users. As a result, it facilitates the growth and acceptance of electric vehicles in Malaysia by promoting expedient charging services.

4.3 Optimal Placement and Sizing of EVCS

In this section, the results obtained from determining the optimal placement and sizing for Electric Vehicle Charging Stations in two test systems which are the IEEE 33-bus and IEEE 69-bus radial distribution system were presented and discussed. The optimal placement and sizing of EVCS is executed through a comparative study of two heuristic optimization techniques which are GSA and PSO by performing 30 simulation runs. The optimization objective function considers reducing real power loss and minimizing average voltage deviation of the system.

4.3.1 IEEE 33-Bus Radial Distribution System

The optimal placement and sizing of EVCS in the IEEE 33-bus radial distribution system were explored across three case scenarios. Initially, a base case was conducted without any EVCS in the system. Then, load flow analyses were performed for the case scenarios involving the installation of one and two EVCS in the system.

4.3.1.1 Case I: Base Case

The test system undergoes simulation in the absence of an EVCS by employing the MATPOWER software program to assess the power loss and voltage deviation within the system. The total loss for the IEEE 33-bus radial distribution system is 0.2027 MW and the total load of the system is 3.72 MW. The results for the base case were recorded in Table 4.4. The original voltage profile of each bus in the system is tabulated in Table 4.5 and the voltage plot is illustrated in Figure 4.1.

Table 4.4 Base Case Results for IEEE 33-Bus

System Performances	Base Case Value
Losses (MW)	0.2027
Voltage Deviation (p.u.)	0.0515

Table 4.5 Original Voltage Profile in IEEE 33-Bus

Bus	Voltage (p.u.)	Bus	Voltage (p.u.)	Bus	Voltage (p.u.)
1	1.0000	12	0.9269	23	0.9794
2	0.9970	13	0.9208	24	0.9727
3	0.9829	14	0.9185	25	0.9693
4	0.9755	15	0.9171	26	0.9477
5	0.9681	16	0.9157	27	0.9452
6	0.9497	17	0.9137	28	0.9337
7	0.9462	18	0.9131	29	0.9255
8	0.9413	19	0.9965	30	0.9219
9	0.9351	20	0.9929	31	0.9178
10	0.9292	21	0.9922	32	0.9169
11	0.9284	22	0.9916	33	0.9166

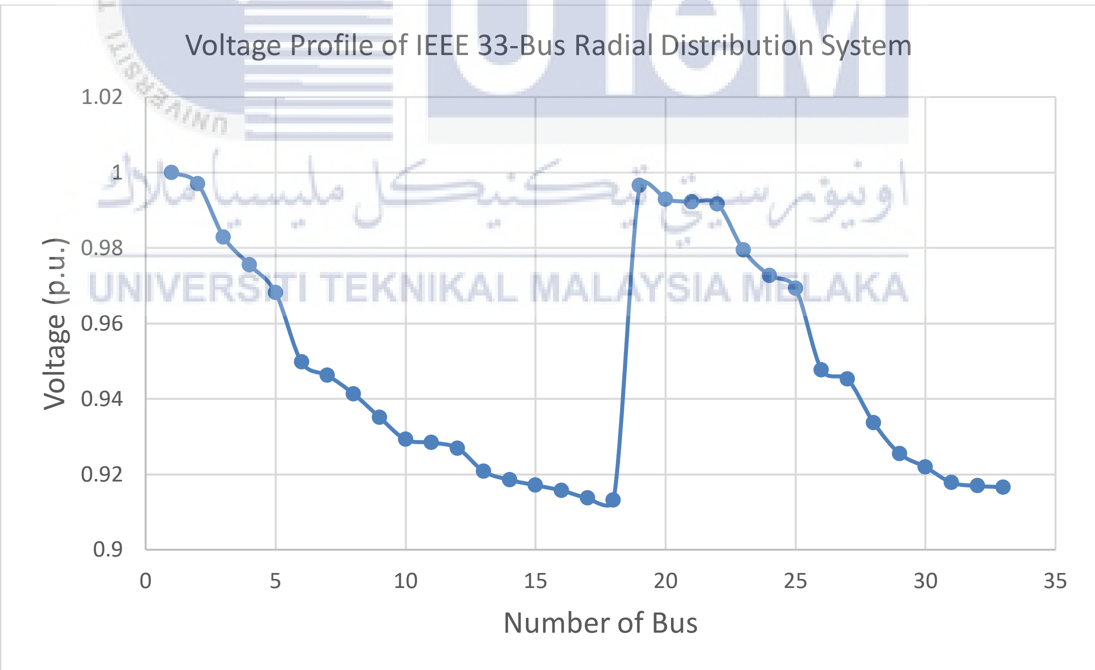

Figure 4.1 Original Plot for Voltage Profile in IEEE 33-Bus

4.3.1.2 Case II: 1-EVCS Installed at Optimum Planning

The results of two optimization algorithms, PSO and GSA were compared to determine the optimal placement and sizing for EVCS. The PSO algorithm suggested that the optimal placement for EVCS is at bus 23 with a size of 2.4922 MW and a 0.9940 p.u. voltage. On the other hand, the GSA algorithm suggested that the optimal placement for EVCS is at bus 25 with a size of 3.1335 MW and a voltage of 0.9962 p.u. Although both algorithms had the same minimum fitness value of 0.1322, the GSA algorithm performed better in terms of average fitness value with 0.1338 compared to PSO with 0.1385. However, the average computational time for PSO was the shortest. In terms of accuracy, GSA had a lower standard deviation of 0.0012 compared to PSO with 0.0132. The overall optimization results for this case are tabulated in Table 4.6 and the Figure 4.2 shows the convergence characteristics of GSA and PSO for one EVCS placement in IEEE 33-bus system.

Table 4.6 Optimization Results for IEEE 33-Bus with One EVCS Installed

Technique	PSO	GSA
Optimization Results		
EVCS1 Location	23	25
EVCS1 Size (MW)	2.4922	3.1335
EVCS1 Voltage (p.u.)	0.9940	0.9962
Algorithms Performances		
Worst Fitness	0.1987	0.1358
Best Fitness	0.1322	0.1322
Average Fitness	0.1385	0.1338
Standard Deviation	0.0132	0.0012
Average Computational Time (s)	105.6683	107.3669
EVCS Overall Impacts		
Losses (MW)	0.2128	0.2119
Voltage Deviation (p.u.)	0.0526	0.0524
Number of Charger Nozzles for 1 EVCS		
EVCS 1	13	17

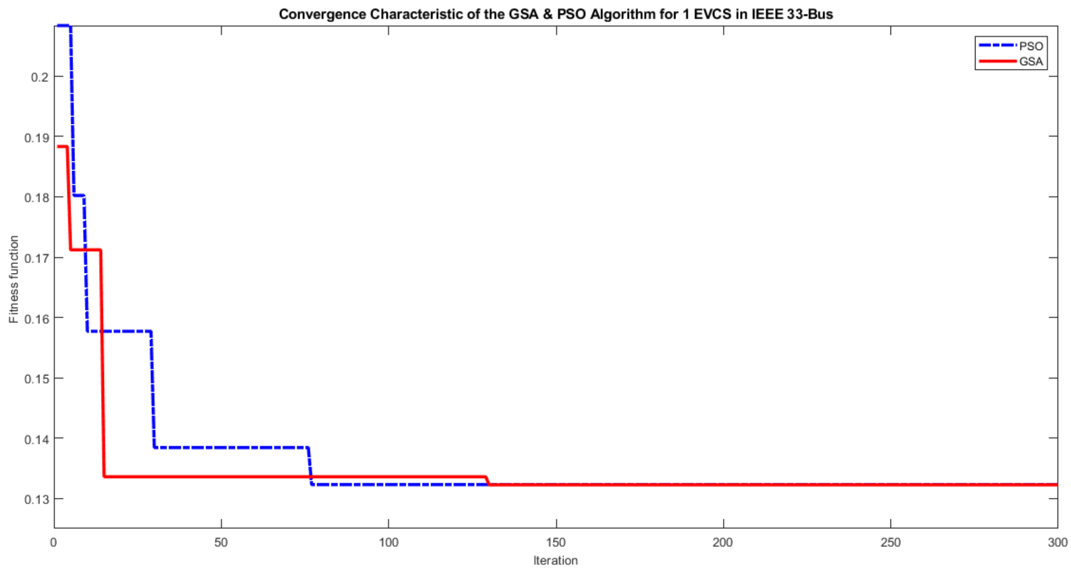

Figure 4.2 Convergence Characteristic of GSA and PSO for One EVCS

From the Figure 4.2, the fitness function value improves as the number of iterations increases until it reaches a constant after certain number of iterations. Additionally, by using the most optimum charging power for various EV models obtained from the evaluation before which is 180 kW per charger nozzle, the maximum number of charging nozzles in one EVCS for PSO is up to 13 nozzles while for GSA is up to 17 nozzles. Then, with the introduction of EVCS as an additional load, the losses and average voltage deviation for the base case with EVCS installed exhibit a slightly increase compared to the base case without any EVCS installation. However, GSA and PSO optimization demonstrate enhanced improvements in the losses and average voltage deviation of the system compared to the base case with EVCS installed. The comparison between GSA and PSO optimization focuses on losses and average voltage deviation within the bus system by highlighting the efficacy of GSA in reducing and minimizing these objective functions. The comparison is summarized in Table 4.7 and the voltage plot for GSA and PSO after one EVCS installed are illustrated in Figure 4.3.

Table 4.7 Comparison in Losses and Voltage Deviation in IEEE 33-Bus System

Method	Base Case	Base Case with EVCS Installed	PSO	GSA
Losses (MW)	0.2027	0.2414	0.2128	0.2119
Voltage Deviation	0.0515	0.0558	0.0526	0.0524

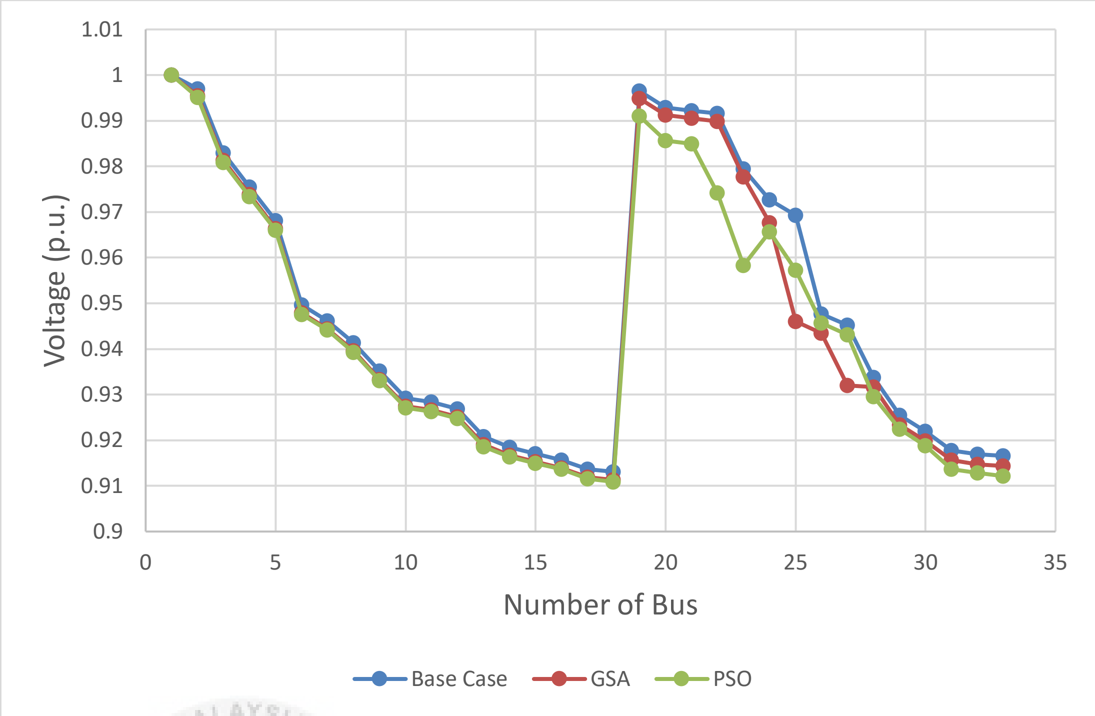

Figure 4.3 Voltage Profile of the GSA and PSO for One EVCS Installed

4.3.1.3 Case III: 2-EVCS Installed at Optimum Planning

In this case, according to the results obtained from the PSO algorithm, the optimal placement and sizing for EVCS are at bus 20 and 22 with sizes of 2.2098 MW and 3.1113 MW respectively. However, the GSA algorithm suggests that the best placement for EVCS is at bus 19 and 22 with optimal sizes of 2.3999 MW and 2.7638 MW. When two EVCS are installed in the system, GSA performs better than PSO. It gives the lowest best fitness and average fitness value of 0.1331 and 0.1491 respectively compared to PSO with 0.1347 and 0.1598. GSA also executed results faster than PSO with an average computational time of 113.5124 seconds. In terms of accuracy, GSA outperforms PSO with the lowest value of standard deviation which is 0.0138 compared to 0.0207 for PSO. The overall optimization results for this case are summarized in Table 4.8 and the convergence characteristics of GSA and PSO are shown in Figure 4.4.

Table 4.8 Optimization Results for IEEE 33-Bus with Two EVCS Installed

Technique	PSO	GSA
Optimization Results		
EVCS1 Location	20	19
EVCS2 Location	22	22
EVCS1 Size (MW)	2.2098	2.3999
EVCS2 Size (MW)	3.1113	2.7638
EVCS1 Voltage (p.u.)	1.0044	0.9911
EVCS2 Voltage (p.u.)	1.0050	1.0077
Algorithms Performances		
Worst Fitness	0.1966	0.1825
Best Fitness	0.1347	0.1331
Average Fitness	0.1598	0.1491
Standard Deviation	0.0207	0.0138
Average Computational Time (s)	153.8196	113.5124
EVCS Overall Impacts		
Losses (MW)	0.2164	0.2133
Voltage Deviation (p.u.)	0.0529	0.0528
Number of Charger Nozzles for 1 EVCS		
EVCS 1	12	13
EVCS 2	17	15

From the Figure 4.4 below, the fitness function value improves as the number of iterations increases until it reaches a constant after certain number of iterations. In this case, GSA gives the lowest best fitness function compared to PSO. Additionally, by using the most optimum charging power for various EV models obtained from the evaluation before which is 180 kW per charger nozzle, the maximum number of charging nozzles in two EVCS for PSO is up to 12 nozzles for EVCS 1 and up to 17 nozzles for EVCS 2. While for GSA is up to 13 nozzles for EVCS 1 and up to 15 nozzles for EVCS 2. With a total nozzle count of 28 for GSA and 29 for PSO, but GSA exhibits lower losses and voltage deviation in comparison to PSO.

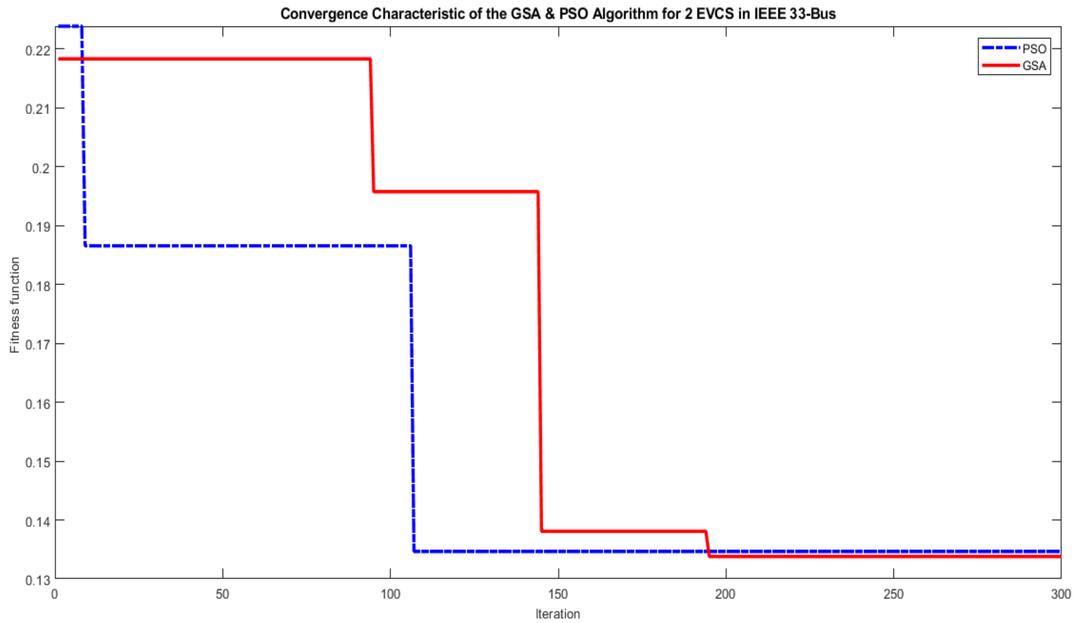

Figure 4.4 Convergence Characteristic of GSA and PSO for Two EVCS

With the introduction of two EVCS as an additional load, the losses and average voltage deviation for the base case with EVCS installation exhibit a slightly increases compared to the base case without any installation of EVCS. However, GSA and PSO optimization also demonstrate enhanced improvements in the losses and average voltage deviation of the system compared to the base case with EVCS installed when evaluating the overall impacts after two EVCS installed in the IEEE 33-bus system. The losses and average voltage deviation improves from 0.2492 MW and 0.00545 p.u. to 0.2164 MW and 0.0529 p.u. by using PSO while 0.2133 MW and 0.0528 p.u. when using GSA optimization. The comparison between GSA and PSO optimization focuses on losses and average voltage deviation within the bus system by highlighting the efficacy of GSA in reducing and minimizing these objective functions. The comparison in losses and voltage deviation in the IEEE 33-bus system is tabulated in Table 4.9 and the voltage plot for GSA and PSO after two EVCS installed is illustrated in Figure 4.5.

Table 4.9 Comparison in Losses and Voltage Deviation in IEEE 33-Bus System

Method	Base Case	Base Case with EVCS Installed	PSO	GSA
Losses (MW)	0.2027	0.2492	0.2164	0.2133
Voltage Deviation	0.0515	0.0545	0.0529	0.0528

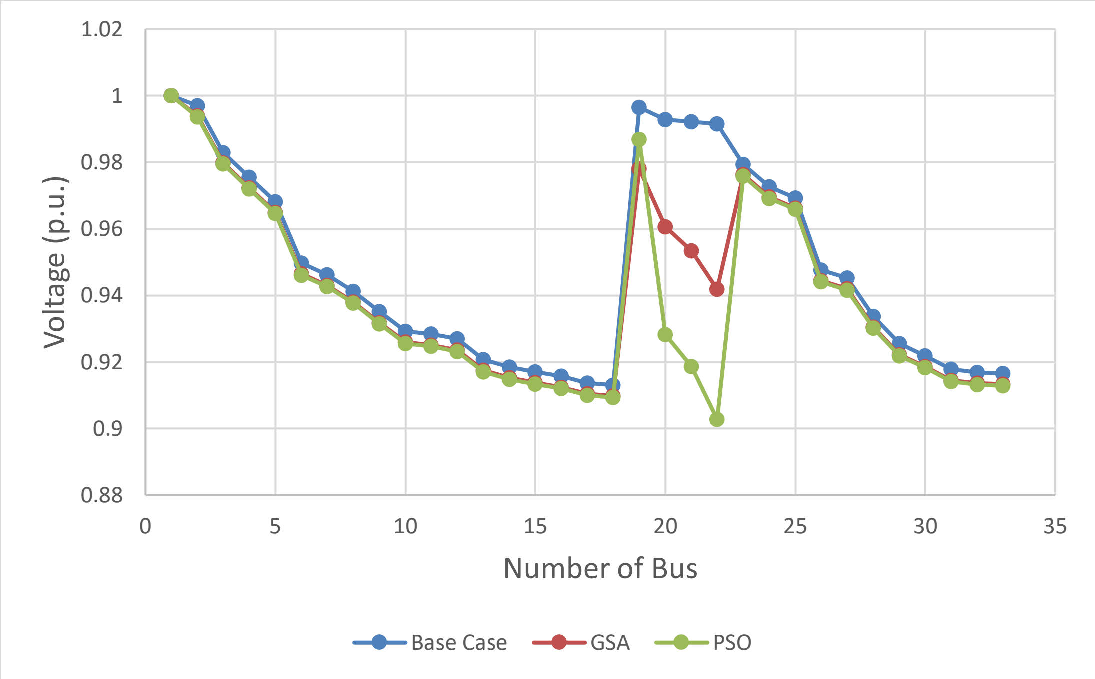

Figure 4.5 Voltage Profile of the GSA and PSO for Two EVCS Installed

4.3.2 IEEE 69-Bus Radial Distribution System

Similar to the IEEE 33-bus, the optimal placement and sizing of EVCS in the IEEE 69-bus radial distribution system were tested across three case scenarios. Before implementing EVCS in the system, a base case was conducted to obtain the initial values for system losses and voltage deviation. Subsequently, the results were compared for scenarios involving the installation of one and two EVCS in the system.

4.3.2.1 Case I: Base Case

The test system is simulated without the installation of EVCS by using MATPOWER software program to determine the power losses and voltage deviation in the system. The total loss for the IEEE 69-bus is 0.2298 MW and the load of the system is 3.8 MW. The results for base case were recorded in Table 4.10. The original voltage profile of each bus in the system is tabulated in Table 4.11 and the voltage plot is illustrated in Figure 4.6.

Table 4.10 Base Case Results for IEEE 69-Bus

System Performances	Base Case Value
Losses (MW)	0.2298
Voltage Deviation (p.u.)	0.0272

Table 4.11 Original Bus Voltage for IEEE 69-Bus

Bus	Voltage (p.u.)	Bus	Voltage (p.u.)	Bus	Voltage (p.u.)
1	1.0000	24	0.9555	47	0.9998
2	1.0000	25	0.9553	48	0.9985
3	0.9999	26	0.9553	49	0.9947
4	0.9998	27	0.9553	50	0.9942
5	0.9990	28	0.9999	51	0.9775
6	0.9901	29	0.9999	52	0.9775
7	0.9808	30	0.9997	53	0.9736
8	0.9775	31	0.9997	54	0.9704
9	0.9764	32	0.9996	55	0.9659
10	0.9714	33	0.9993	56	0.9615
11	0.9703	34	0.9990	57	0.9390
12	0.9671	35	0.9989	58	0.9279
13	0.9642	36	0.9999	59	0.9236
14	0.9613	37	0.9997	60	0.9186
15	0.9584	38	0.9996	61	0.9112
16	0.9579	39	0.9995	62	0.9109
17	0.9570	40	0.9995	63	0.9105
18	0.9570	41	0.9988	64	0.9086
19	0.9565	42	0.9986	65	0.9080
20	0.9562	43	0.9985	66	0.9702
21	0.9558	44	0.9985	67	0.9702
22	0.9557	45	0.9984	68	0.9668
23	0.9557	46	0.9984	69	0.9668

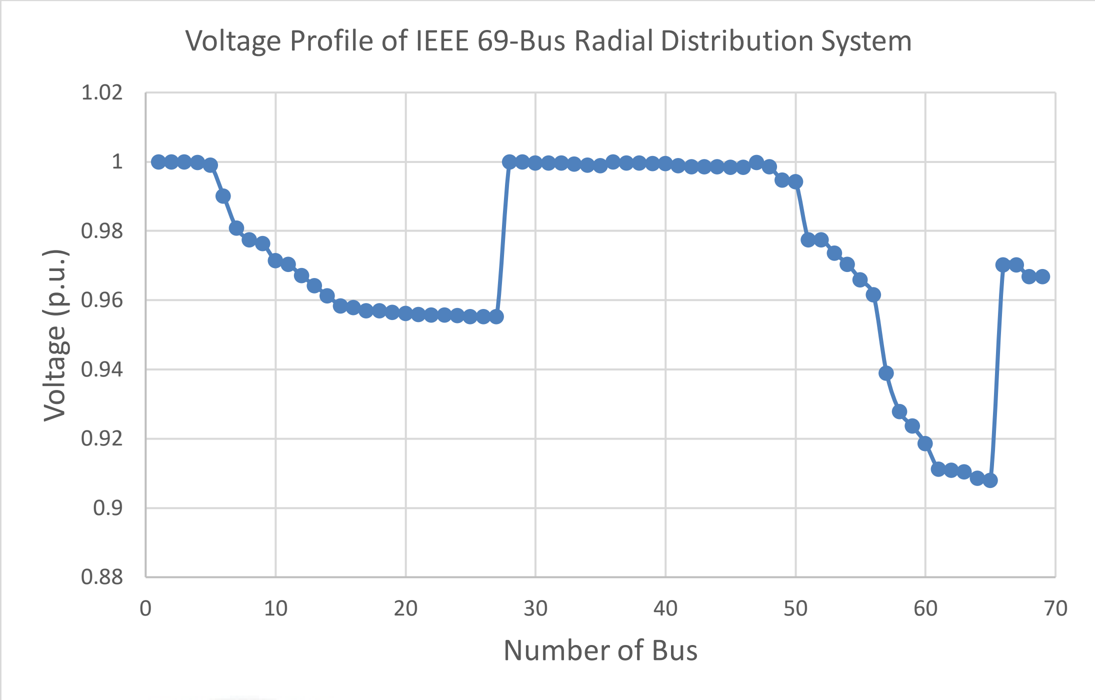

Figure 4.6 Voltage Profile for IEEE 69-Bus

4.3.2.2 Case II: 1-EVCS Installed at Optimum Planning

The optimal placement and sizing for EVCS by using PSO algorithm is at bus 5 with size of 1.2335 MW and 0.9955 p.u of voltage. However, the optimal placement for EVCS by using GSA algorithm is at bus 45 with optimal size of 2.0083 MW and 0.9938 p.u of voltage. In this case, the minimum best fitness value for GSA and PSO techniques are the same which is 0.1285 but for average fitness value, the GSA outperformed PSO with the average fitness value of 0.1285 compared to 0.1286 for PSO. The average computational time taken for the two optimization techniques shows that GSA is the faster than PSO with average of 121.9977 seconds. In term of accuracy, GSA gives the lowest value of standard deviation which is 0.000018 compared to PSO with 0.000168. The overall optimization results for this case are recorded in Table 4.12 and the convergence characteristic of GSA and PSO for one EVCS placement in IEEE 69-bus system are shown in Figure 4.7.

Table 4.12 Optimization Results for IEEE 69-Bus with One EVCS Installed

Technique	PSO	GSA
Optimization Results		
EVCS1 Location	5	45
EVCS1 Size (MW)	1.2335	2.0083
EVCS1 Voltage (p.u.)	0.9955	0.9938
Algorithms Performances		
Worst Fitness	0.1294	0.1286
Best Fitness	0.1285	0.1285
Average Fitness	0.1286	0.1285
Standard Deviation	0.000168	0.000018
Average Computational Time (s)	132.4114	121.9977
EVCS Overall Impacts		
Losses (MW)	0.2371	0.2339
Voltage Deviation (p.u.)	0.0287	0.0279
Number of Charger Nozzles for 1 EVCS		
EVCS 1	6	11

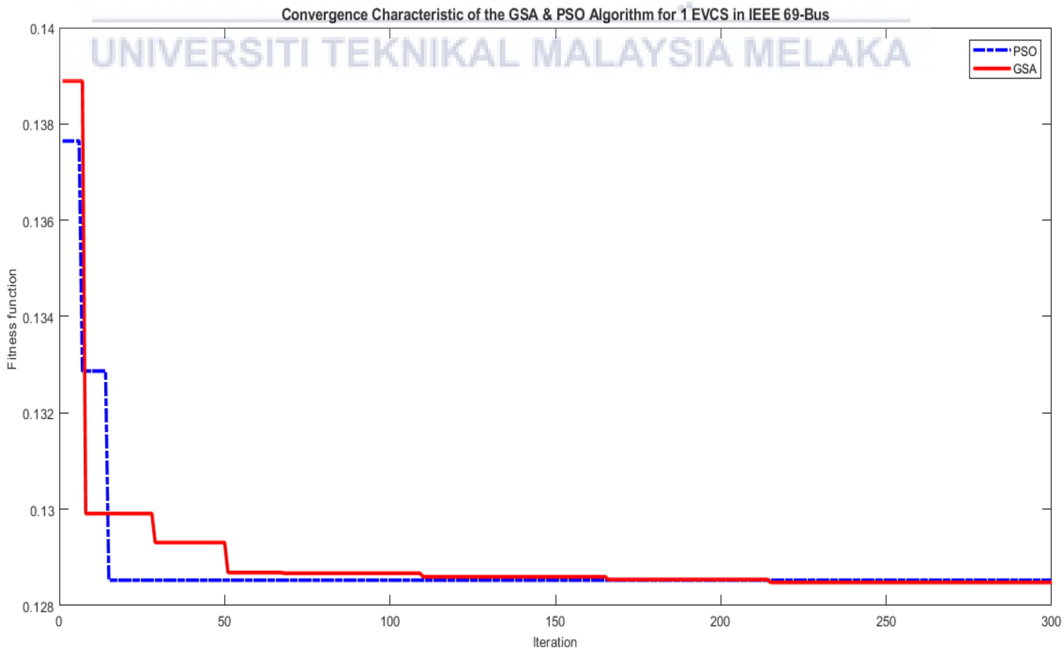

Figure 4.7 Convergence Characteristic of the GSA and PSO for One EVCS

From the Figure 4.7, the fitness function value also improves as the number of iterations increases until it reaches a constant after certain number of iterations. In this case, GSA gives the lowest best fitness function compared to PSO. Moreover, by using the most optimum charging power for various EV models obtained from the evaluation before which is 180 kW per charger nozzle, the maximum number of charging nozzles in one EVCS for PSO is up to 6 nozzles while for GSA is up to 11 nozzles. Then, with the introduction of EVCS as an additional load, the losses and average voltage deviation for the base case with EVCS installed exhibit a slightly increases compared to the base case without any EVCS installation. GSA and PSO optimization demonstrate enhanced improvements in the losses and average voltage deviation of the system compared to the base case with EVCS installed when evaluating the overall impacts after one EVCS installed in the IEEE 69-bus system. The losses and average voltage deviation in this bus system are compared between GSA and PSO in order to indicate the reduction and minimization of the objective functions. The comparison in losses and voltage deviation in the IEEE 69-bus system is tabulated in Table 4.13 and the voltage plot for GSA and PSO after one EVCS installed is illustrated in Figure 4.8.

Table 4.13 Comparison in Losses and Voltage Deviation in IEEE 69-Bus System

Method	Base Case	Base Case with EVCS Installed	PSO	GSA
Losses (MW)	0.2298	0.2398	0.2371	0.2339
Voltage Deviation	0.0272	0.0294	0.0287	0.0279

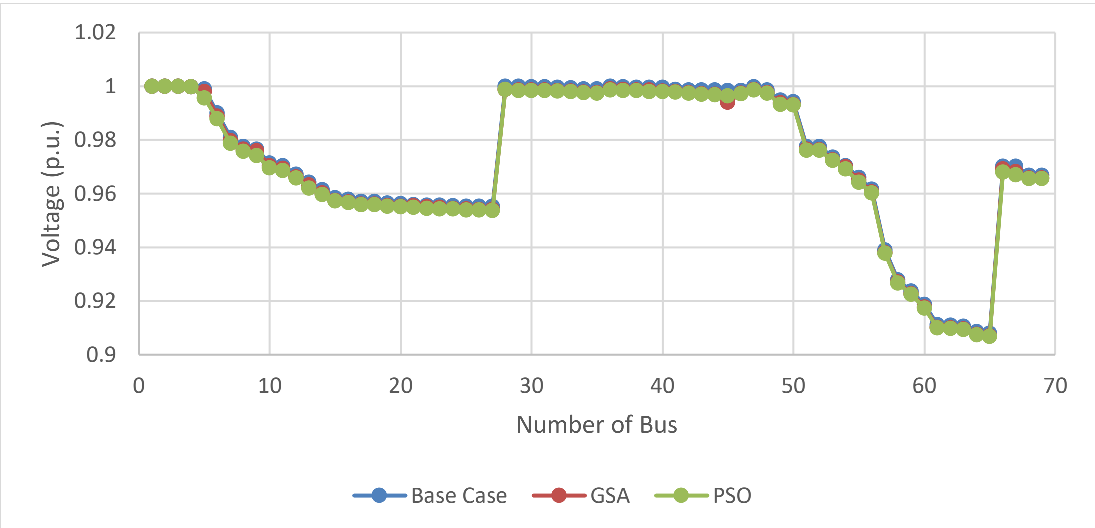

Figure 4.8 Voltage Profile of the GSA and PSO for One EVCS Installed

4.3.2.3 Case III: 2-EVCS Installed at Optimum Planning

In this case, the optimal placement and sizing for EVCS by using PSO algorithm are at bus 8 and 33 with sizes of 1.2858 MW and 1.9622 MW respectively. However, the optimal placement for EVCS by using GSA algorithm are at bus 29 and 30 with optimal sizes of 1.7383 MW and 1.8180 MW. When two EVCS are installed in the system, GSA performs better than PSO and it gives the lowest best fitness value of 0.1211 compared to 0.1256 for PSO. The average of fitness value for GSA also better than PSO which is 0.1286 compared to 0.1297 for PSO. GSA also executed results faster than PSO with the average computational time of 106.9026 seconds. In term of accuracy, GSA also gives the lowest value of standard deviation which is 0.001434 compared to PSO with 0.004292. The convergence characteristic of GSA and PSO are shown in Figure 4.9 and the overall optimization results for this case are tabulated in Table 4.14.

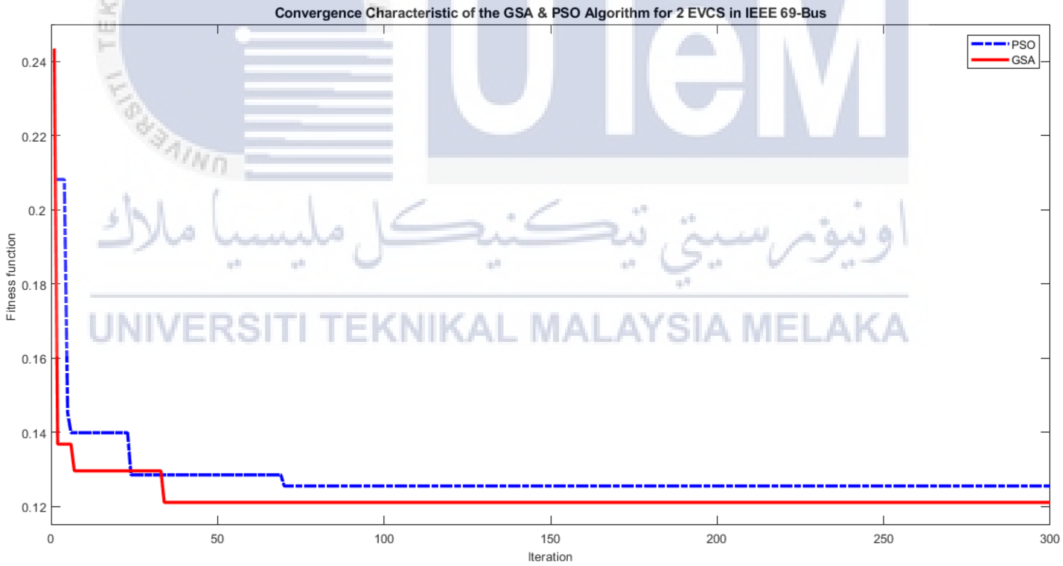

Figure 4.9 Convergence Characteristic of the GSA and PSO for Two EVCS

From the Figure 4.9, the fitness function value also improves as the number of iterations increases until it reaches a constant after certain number of iterations. In this case, GSA gives the lowest best fitness function compared to PSO. Moreover, by using the most optimum charging power for various EV models obtained from the evaluation before which is 180 kW per charger nozzle, the maximum number of charging nozzles in two EVCS for PSO is up to 7 nozzles for EVCS 1 and up to 10 nozzles for EVCS 2. While for GSA is up to 9 nozzles for EVCS 1 and up to 10 nozzles for EVCS 2.

Table 4.14 Optimization Results for IEEE 69-Bus with Two EVCS Installed

Technique	PSO	GSA
Optimization Results		
EVCS1 Location	8	29
EVCS2 Location	33	30
EVCS1 Size (MW)	1.2858	1.7383
EVCS2 Size (MW)	1.9622	1.8180
EVCS1 Voltage (p.u.)	0.9974	0.9960
EVCS2 Voltage (p.u.)	0.9997	0.9927
Algorithms Performances		
Worst Fitness	0.1501	0.1296
Best Fitness	0.1256	0.1211
Average Fitness	0.1297	0.1286
Standard Deviation	0.004292	0.001434
Average Computational Time (s)	129.6782	106.9026
EVCS Overall Impacts		
Losses (MW)	0.2365	0.2341
Voltage Deviation (p.u.)	0.0284	0.0278
Number of Charger Nozzles for 1 EVCS		
EVCS 1	7	9
EVCS 2	10	10

GSA optimization outperforms PSO optimization when it comes to reducing losses and average voltage deviation in the IEEE 69-bus system especially after installing two EVCS. This comparison between GSA and PSO optimization focuses on minimizing these objective functions and the results show that GSA is more effective in achieving this goal. Although introducing two EVCS as an additional load slightly increases the losses and average voltage deviation for the base case with EVCS installed compared to the base case without any EVCS installation, the overall performance of GSA is still superior. The comparison in losses and voltage deviation in the IEEE 69-bus system is summarized in Table 4.15 and Figure 4.10 illustrates the voltage plot for GSA and PSO after installing two EVCS.

Table 4.15 Comparison in Losses and Voltage Deviation in IEEE 69-Bus System

Method	Base Case	Base Case with EVCS Installed	PSO	GSA
Losses (MW)	0.2298	0.2443	0.2365	0.2341
Voltage Deviation	0.0272	0.0297	0.0284	0.0278

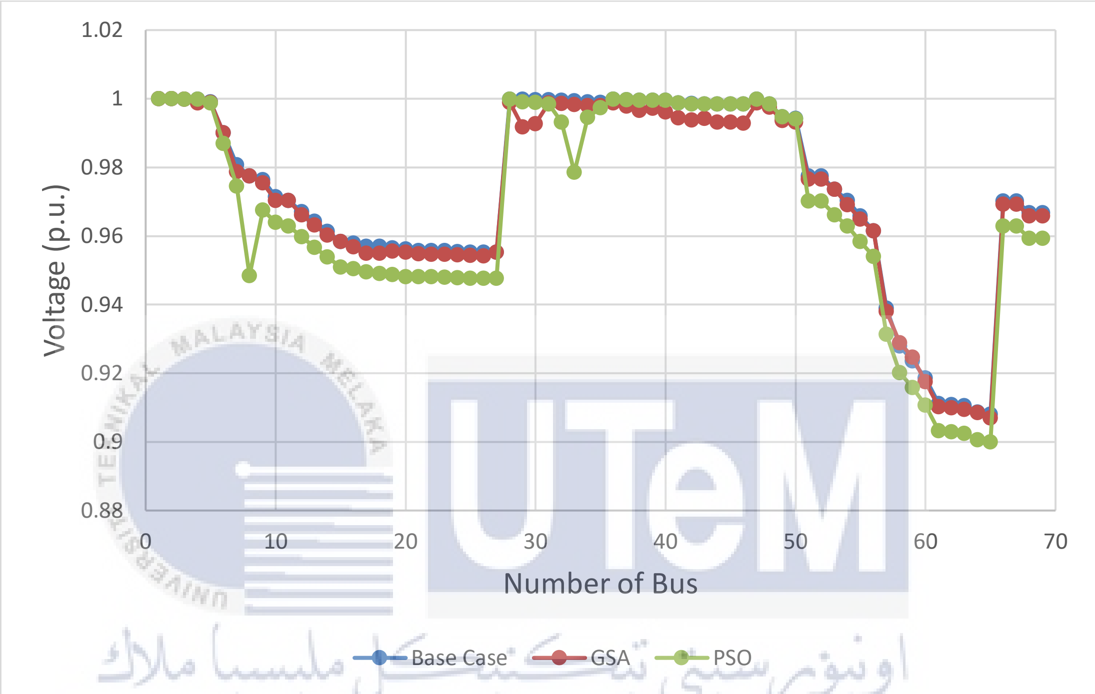

Figure 4.10 Voltage Profile of the GSA and PSO for Two EVCS Installed

4.4 Discussion on EVCS Overall Impacts

In the IEEE 33-bus radial distribution system, the fitness function value increases as the number of EVCS increases. The power losses in the base case with the installation of EVCS increased by 22.94% compared to the base case without any EVCS installation. However, employing the PSO technique led to a reduction of losses by up to 15.16% while the GSA resulted in a reduction of losses by up to 16.83% compared to the base case with EVCS installation.

Regarding voltage deviation, the base case with EVCS installation experienced an increase of 8.35% compared to the base case without any EVCS installation. Subsequently, the application of the PSO technique minimized voltage deviation by up to 6.08% and GSA minimized it by up to 6.49% compared to the base case with EVCS installation. Thus, GSA demonstrated superior performance over PSO in reducing power losses and minimizing voltage deviation when one and two EVCS were installed in the IEEE 33-bus system. Figure 4.11 and Figure 4.12 show the graph of the impact of EVCS installation in the IEEE 33-bus system.

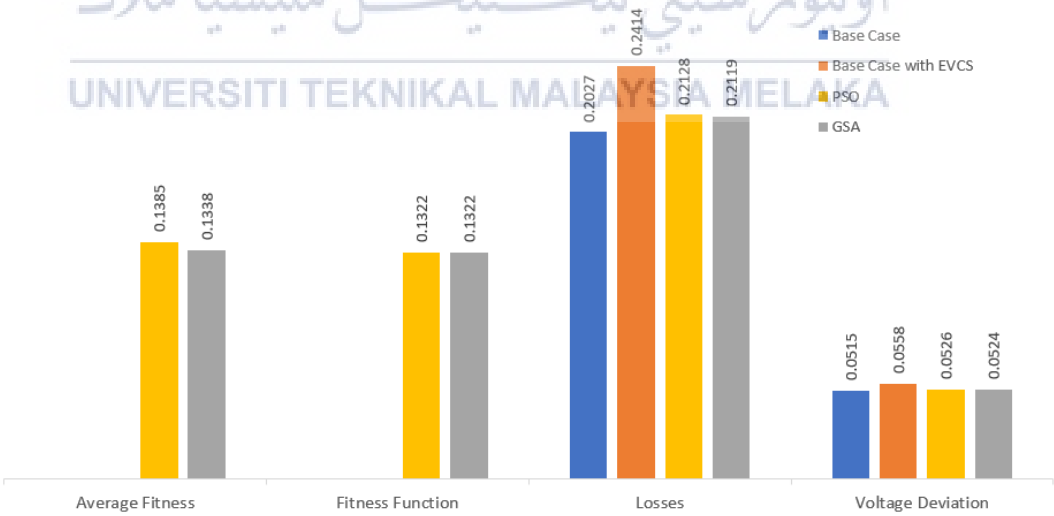

Figure 4.11 Results of 1 EVCS Installation in IEEE 33-Bus

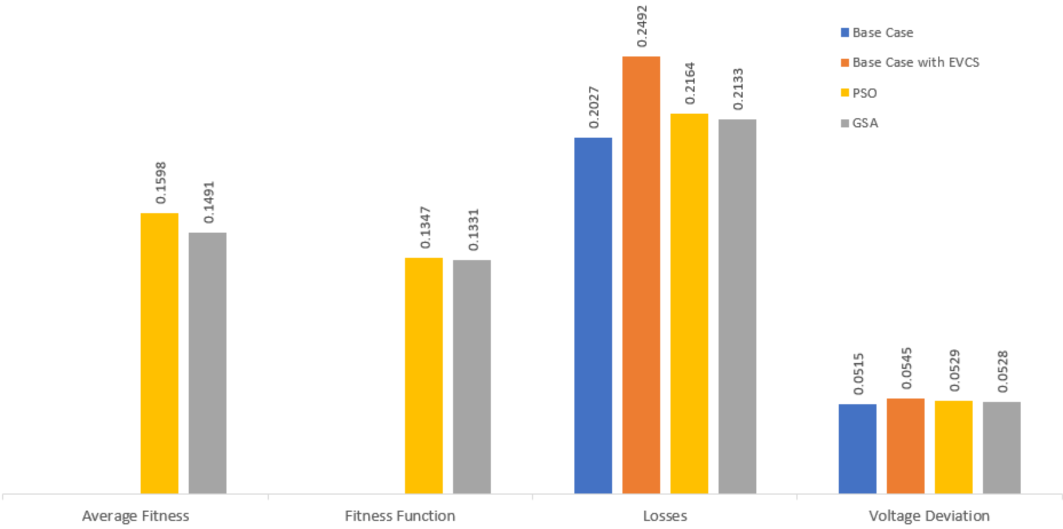

Figure 4.12 Results of 2 EVCS Installation in IEEE 33-Bus

For the IEEE 69-bus radial distribution system, the fitness function value decreases as the number of EVCS increases. The power losses in the base case with installation of EVCS increased by 6.31% compared to the base case without any EVCS installation. However, implementing the PSO technique resulted in a reduction of losses by up to 3.30% and GSA yielded a reduction of losses by up to 4.36% compared to the base case with EVCS installation.

Regarding voltage deviation, the base case with EVCS installation experienced an increase of 9.19% compared to the base case without any EVCS installation. Subsequently, employing the PSO technique minimized voltage deviation by up to 4.58% and GSA achieved a greater reduction of 6.83% compared to the base case with EVCS installation. Thus, GSA exhibited superior performance over PSO in reducing power losses and minimizing voltage deviation when one and two EVCS were incorporated into the IEEE 69-bus system. Figure 4.13 and Figure 4.14 show the graph of the impact of EVCS installation in IEEE 69-bus system.

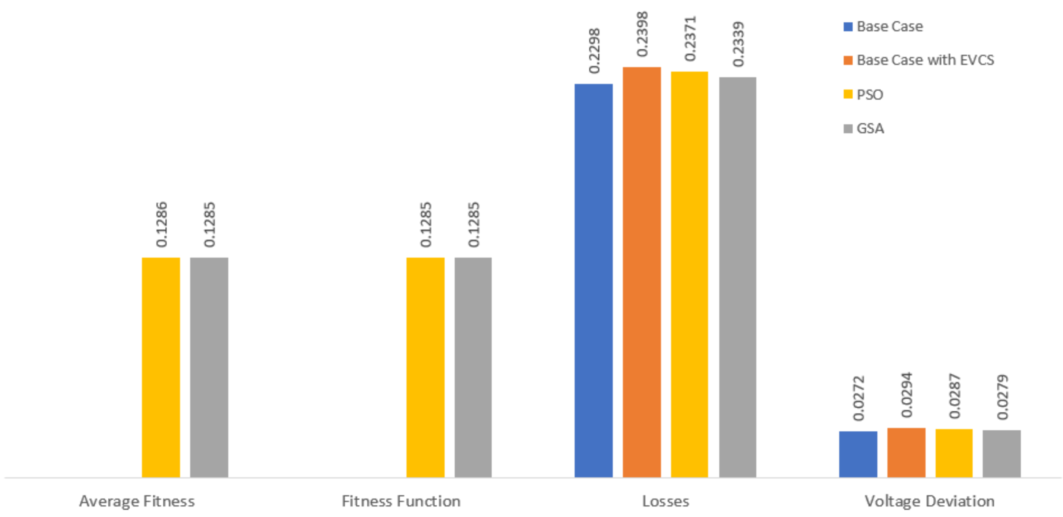

Figure 4.13 Results of 1 EVCS Installation in IEEE 69-Bus

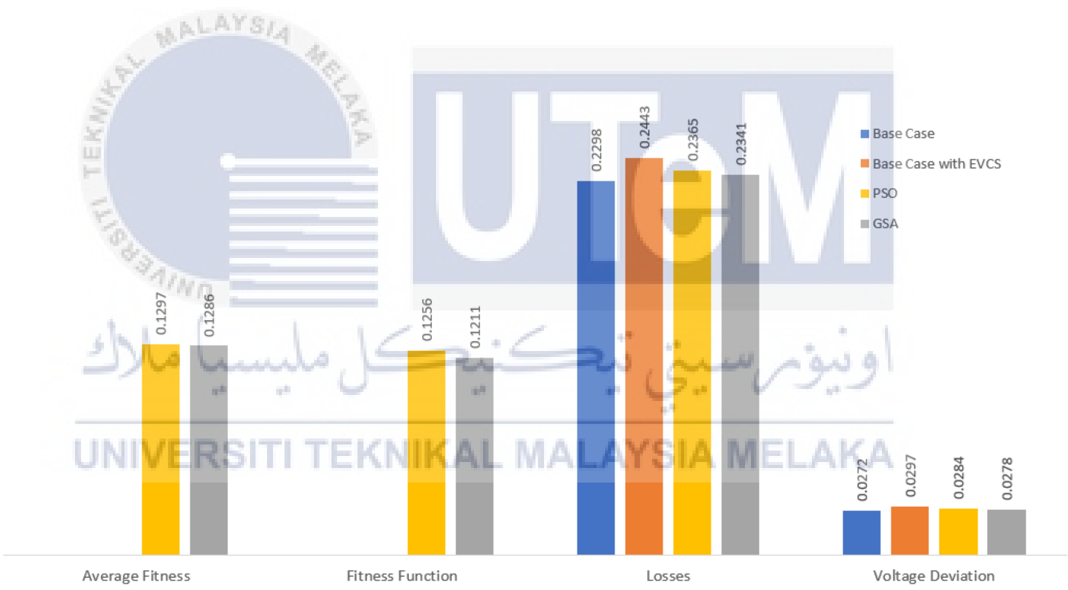

Figure 4.14 Results of 2 EVCS Installation in IEEE 69-Bus

4.5 Summary

In order to achieve Objective 1 of the project, a study was conducted to assess the charging costs associated with different types of EVs in Malaysia. This study aimed to evaluate the advantages of finding the optimal charging power particularly in terms of pricing and time reduction. The evaluation involved calculating and analyzing the charging prices for each EV model offered by Gentari and TNB Electron charging stations. Through this comprehensive evaluation, the most suitable charging power for each EV model was determined by considering factors such as pricing structures and charging time considerations. The results of these evaluations were tabulated and thoroughly discussed.

In order to accomplish Objectives 2 and 3 of the projects, a comparative study was conducted to assess and compare the effectiveness of Gravitational Search Algorithm (GSA) and Particle Swarm Optimization (PSO) in determining the optimal location and size for EVCS in a power distribution system. This evaluation focused on two objective functions which are reducing power losses and minimizing average voltage deviation. Two test systems namely IEEE 33-bus and IEEE 69-bus radial distribution systems were used to assess the installation of an EVCS and two EVCS installation situations. Based on the outcomes, the GSA algorithm demonstrated superior performance compared to the PSO algorithm in terms of execution efficiency and rapid convergence in identifying the optimal and precise solution. The number of iterations is crucial for attaining stable and very precise values. Across all scenarios, the displayed outcomes consistently show enhancements in the fitness function values with an increasing number of iterations.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

As a conclusion, the cost of charging for various types of EVs in Malaysia was evaluated successfully and the most suitable charging power of EVCS that offer time efficient and cost-effective was determined at 180 kW. This objective has been successfully achieved through a comprehensive evaluation of charging prices offered by different providers and the identification of optimum charging power for each EV models. Next, the optimal placement and sizing of EVCS in power distribution system had been explored by using the proposed gravitational search algorithm (GSA) optimization technique. The performance of the proposed technique had been compared with other commonly used algorithm which was the particle swarm optimization (PSO) technique. An optimization problem was defined by addressing the challenges encountered in current distribution systems including issues like total real power losses and voltage deviation. These problems are treated as multi-objective optimization problem that aims for minimization through the sum of coefficient factors method with balanced coefficient weights. Two test systems which were IEEE 33-bus and IEEE 69-bus radial distribution systems were utilized to examine the installation of a single EVCS as well as two EVCS cases. Selecting the optimal placement and sizing of EVCS had significantly reduced the total power losses and minimized the average voltage deviation of the system. In summary, this study results can be concluded that the installed of EVCS in the power distribution system at optimal placement and sizing by using GSA optimization can help in improvement of the system performances where the power losses can be reduced up to 16.83% for IEEE 33-bus and up to 4.36% for IEEE 69-bus while the average voltage deviation can be minimized up to 6.49% for IEEE 33-bus and up to 6.83% for IEEE 69-bus compared to the base case with installation of one and two EVCS. Overall, GSA has the ability to determine for a better and optimum solution within faster elapsed time up to 3.72% better compared to PSO for all cases.

5.2 Recommendations for Future Works/Improvements

This study has tackled numerous challenges related to distribution system issues. However, several potential areas remain unexplored and available for further investigation and extension. First, this study was tested and compared only between GSA and PSO techniques. For future improvements, this optimization could be explored more with another optimization techniques such as Improved Gravitational Search Algorithm (IGSA), Improved Particle Swarm Optimization (IPSO) or other new optimization technique to identify the optimal placement and sizing of EVCS in power distribution system. An analysis of the performance of these methods in comparison to the proposed Gravitational Search Algorithm (GSA) would yield significant insights regarding the strengths and weaknesses of each respective approach. Lastly, various objectives could be included in the multi-objective approach such as by considering the overall EVCS installation cost, waiting time and other more complex objective function that accounts for additional factors like grid reliability, environmental impact and long-term sustainability could enhance the comprehensiveness of the study.

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APPENDICES

APPENDIX A CALCULATIONS

Table 1.1: CT and CP Offered by TNB Electron for Nissan Leaf 2023

Level of Charger	Prices (RM/min)	Charging Price for Nissan Leaf
Level 3 DC Fast Charger	(80kW) – RM2.05/min	$CT = \frac{40}{50} \times 60 = 48\ minutes$ $CP = 48 \times RM2.05 = RM98.40$
	(90kW) – RM2.20/min	$CT = \frac{40}{50} \times 60 = 48\ minutes$ $CP = 48 \times RM2.20 = RM105.60$
	(100kW) – RM2.35/min	$CT = \frac{40}{50} \times 60 = 48\ minutes$ $CP = 48 \times RM2.35 = RM112.80$

Table 1.2: CT and CP Offered by Gentari for Nissan Leaf 2023

Level of Charger	Prices (RM/kWh)	Charging Price for Nissan Leaf	Prices (RM/min)	Charging Price for Nissan Leaf 2023
Level 2 AC Charger	All Charger (7kW, 11kW, 22kW) RM0.55/kWh	$CP = 40 \times RM0.55$ $CP = RM22.00$	All Charger (7kW, 11kW, 22kW) RM0.10/min	$CT = \frac{40}{11} \times 60 = 218\ minutes$ $CP = 218 \times RM0.10 = RM21.80$
Level 3 DC Fast Charger	180kW RM1.00/kWh	$CP = 40 \times RM1.00$ $CP = RM40.00$	(30kW) – RM0.60/min	$CT = \frac{40}{30} \times 60 = 80\ minutes$ $CP = 80 \times RM0.60 = RM48.00$
			(50kW) – RM1.20/min	$CT = \frac{40}{50} \times 60 = 48\ minutes$ $CP = 48 \times RM1.20 = RM57.60$
	350kW RM1.20/kWh	$CP = 40 \times RM1.20$ $CP = RM48.00$	(60kW) – RM1.40/min	$CT = \frac{40}{50} \times 60 = 48\ minutes$ $CP = 48 \times RM1.40 = RM67.20$
			(180kW) – RM3.60/min	$CT = \frac{40}{50} \times 60 = 48\ minutes$ $CP = 48 \times RM3.60 = RM172.80$

Table 2.1: CT and CP Offered by TNB Electron for Hyundai Ioniq 5

Level of Charger	Prices (RM/min)	Charging Price for Hyundai Ioniq 5
Level 3 DC Fast Charger	(80kW) – RM2.05/min	$CT = \frac{72.6}{80} \times 60 = 55\ minutes$ $CP = 55 \times RM2.05 = RM112.75$
	(90kW) – RM2.20/min	$CT = \frac{72.6}{90} \times 60 = 48\ minutes$ $CP = 48 \times RM2.20 = RM105.60$
	(100kW) – RM2.35/min	$CT = \frac{72.6}{100} \times 60 = 44\ minutes$ $CP = 44 \times RM2.35 = RM103.40$

Table 2.2: CT and CP Offered by Gentari for Hyundai Ioniq 5

Level of Charger	Prices (RM/kWh)	Charging Price for Hyundai Ioniq	Prices (RM/min)	Charging Price for Hyundai Ioniq 5
Level 2 AC Charger	All Charger (7kW, 11kW, 22kW) RM0.55/kWh	$CP = 72.6 \times RM0.55$ $CP = RM40.00$	All Charger (7kW, 11kW, 22kW) RM0.10/min	$CT = \frac{72.6}{11} \times 60 = 396\ minutes$ $CP = 396 \times RM0.10 = RM39.60$
Level 3 DC Fast Charger	180kW RM1.00/kWh	$CP = 72.6 \times RM1.00$ $CP = RM72.60$	(30kW) – RM0.60/min	$CT = \frac{72.6}{30} \times 60 = 145\ minutes$ $CP = 145 \times RM0.60 = RM87.00$
			(50kW) – RM1.20/min	$CT = \frac{72.6}{50} \times 60 = 87\ minutes$ $CP = 87 \times RM1.20 = RM104.40$
	350kW RM1.20/kWh	$CP = 72.6 \times RM1.20$ $CP = RM87.12$	(60kW) – RM1.40/min	$CT = \frac{72.6}{60} \times 60 = 73\ minutes$ $CP = 73 \times RM1.40 = RM102.20$
			(180kW) – RM3.60/min	$CT = \frac{72.6}{180} \times 60 = 24\ minutes$ $CP = 24 \times RM3.60 = RM86.40$

Table 3.1: CT and CP Offered by TNB Electron for BYD Atto 3

Level of Charger	Prices (RM/min)	Charging Price for BYD Atto 3
Level 3 DC Fast Charger	(80kW) – RM2.05/min	$CT = \frac{60.5}{80} \times 60 = 45\ minutes$ $CP = 45 \times RM2.05 = RM92.25$
	(90kW) – RM2.20/min	$CT = \frac{60.5}{80} \times 60 = 45\ minutes$ $CP = 45 \times RM2.20 = RM99.00$
	(100kW) – RM2.35/min	$CT = \frac{60.5}{80} \times 60 = 45\ minutes$ $CP = 45 \times RM2.35 = RM105.75$

Table 3.2: CT and CP Offered by Gentari for BYD Atto 3

Level of Charger	Prices (RM/kWh)	Charging Price for BYD Atto 3	Prices (RM/min)	Charging Price for BYD Atto 3
Level 2 AC Charger	All Charger (7kW, 11kW, 22kW) RM0.55/kWh	$CP = 60.5 \times RM0.55$ $CP = RM33.28$	All Charger (7kW, 11kW, 22kW) RM0.10/min	$CT = \frac{60.5}{11} \times 60 = 330\ minutes$ $CP = 330 \times RM0.10 = RM33.00$
Level 3 DC Fast Charger	180kW RM1.00/kWh	$CP = 60.5 \times RM1.00$ $CP = RM60.50$	(30kW) – RM0.60/min	$CT = \frac{60.5}{30} \times 60 = 121\ minutes$ $CP = 121 \times RM0.60 = RM72.60$
			(50kW) – RM1.20/min	$CT = \frac{60.5}{50} \times 60 = 73\ minutes$ $CP = 73 \times RM1.20 = RM87.60$
	350kW RM1.20/kWh	$CP = 60.5 \times RM1.20$ $CP = RM72.60$	(60kW) – RM1.40/min	$CT = \frac{60.5}{60} \times 60 = 61\ minutes$ $CP = 61 \times RM1.40 = RM85.40$
			(180kW) – RM3.60/min	$CT = \frac{60.5}{80} \times 60 = 45\ minutes$ $CP = 45 \times RM3.60 = RM162.00$

Table 4.1: CT and CP Offered by TNB Electron for Kia EV6 GT

Level of Charger	Prices (RM/min)	Charging Price for Kia EV6 GT
Level 3 DC Fast Charger	(80kW) – RM2.05/min	$CT = \frac{77.4}{80} \times 60 = 58\ minutes$ $CP = 58 \times RM2.05 = RM118.90$
	(90kW) – RM2.20/min	$CT = \frac{77.4}{90} \times 60 = 52\ minutes$ $CP = 52 \times RM2.20 = RM114.40$
	(100kW) – RM2.35/min	$CT = \frac{77.4}{100} \times 60 = 46\ minutes$ $CP = 46 \times RM2.35 = RM108.10$

Table 4.2: CT and CP Offered by Gentari for Kia EV6 GT

Level of Charger	Prices (RM/kWh)	Charging Price for Kia EV6 GT	Prices (RM/min)	Charging Price for Kia EV6 GT
Level 2 AC Charger	All Charger (7kW, 11kW, 22kW) RM0.55/kWh	$CP = 77.4 \times RM0.55$ $CP = RM42.57$	All Charger (7kW, 11kW, 22kW) RM0.10/min	$CT = \frac{77.4}{11} \times 60 = 422\ minutes$ $CP = 422 \times RM0.10 = RM42.20$
Level 3 DC Fast Charger	180kW RM1.00/kWh	$CP = 77.4 \times RM1.00$ $CP = RM77.40$	(30kW) – RM0.60/min	$CT = \frac{77.4}{30} \times 60 = 155\ minutes$ $CP = 155 \times RM0.60 = RM93.00$
			(50kW) – RM1.20/min	$CT = \frac{77.4}{50} \times 60 = 93\ minutes$ $CP = 93 \times RM1.20 = RM111.60$
	350kW RM1.20/kWh	$CP = 77.4 \times RM1.20$ $CP = RM92.88$	(60kW) – RM1.40/min	$CT = \frac{77.4}{60} \times 60 = 77\ minutes$ $CP = 77 \times RM1.40 = RM107.80$
			(180kW) – RM3.60/min	$CT = \frac{77.4}{180} \times 60 = 26\ minutes$ $CP = 26 \times RM3.60 = RM93.60$

Table 5.1: CT and CP Offered by TNB Electron for Ora Good Cat

Level of Charger	Prices (RM/min)	Charging Price for Ora Good Cat
Level 3 DC Fast Charger	(80kW) – RM2.05/min	$CT = \frac{63.1}{80} \times 60 = 47\ minutes$ $CP = 47 \times RM2.05 = RM96.35$
	(90kW) – RM2.20/min	$CT = \frac{63.1}{90} \times 60 = 42\ minutes$ $CP = 42 \times RM2.20 = RM92.40$
	(100kW) – RM2.35/min	$CT = \frac{63.1}{100} \times 60 = 38\ minutes$ $CP = 39 \times RM2.35 = RM91.65$

Table 5.2: CT and CP Offered by Gentari for Ora Good Cat

Level of Charger	Prices (RM/kWh)	Charging Price for Ora Good Cat	Prices (RM/min)	Charging Price for Ora Good Cat
Level 2 AC Charger	All Charger (7kW, 11kW, 22kW) RM0.55/kWh	$CP = 63.1 \times RM0.55$ $CP = RM34.71$	All Charger (7kW, 11kW, 22kW) RM0.10/min	$CT = \frac{63.1}{11} \times 60 = 344\ minutes$ $CP = 344 \times RM0.10 = RM34.40$
Level 3 DC Fast Charger	180kW RM1.00/kWh	$CP = 63.1 \times RM1.00$ $CP = RM63.10$	(30kW) – RM0.60/min	$CT = \frac{63.1}{30} \times 60 = 126\ minutes$ $CP = 126 \times RM0.60 = RM75.60$
			(50kW) – RM1.20/min	$CT = \frac{63.1}{50} \times 60 = 76\ minutes$ $CP = 76 \times RM1.20 = RM91.20$
	350kW RM1.20/kWh	$CP = 63.1 \times RM1.20$ $CP = RM75.72$	(60kW) – RM1.40/min	$CT = \frac{63.1}{60} \times 60 = 63\ minutes$ $CP = 63 \times RM1.40 = RM88.20$
			(180kW) – RM3.60/min	$CT = \frac{63.1}{100} \times 60 = 38\ minutes$ $CP = 38 \times RM3.60 = RM136.80$

Table 6.1: CT and CP Offered by TNB Electron for Audi RS e-tron GT

Level of Charger	Prices (RM/min)	Charging Price for Audi RS e-tron GT
Level 3 DC Fast Charger	(80kW) – RM2.05/min	$CT = \frac{85}{80} \times 60 = 64\ minutes$ $CP = 64 \times RM2.05 = RM131.20$
	(90kW) – RM2.20/min	$CT = \frac{85}{90} \times 60 = 57\ minutes$ $CP = 57 \times RM2.20 = RM125.40$
	(100kW) – RM2.35/min	$CT = \frac{85}{100} \times 60 = 51\ minutes$ $CP = 51 \times RM2.35 = RM119.85$

Table 6.2: CT and CP Offered by Gentari for Audi RS e-tron GT

Level of Charger	Prices (RM/kWh)	Charging Price for RS e-tron GT	Prices (RM/min)	Charging Price for Audi RS e-tron GT
Level 2 AC Charger	All Charger (7kW, 11kW, 22kW) RM0.55/kWh	$CP = 85 \times RM0.55$ $CP = RM46.75$	All Charger (7kW, 11kW, 22kW) RM0.10/min	$CT = \frac{85}{11} \times 60 = 464\ minutes$ $CP = 464 \times RM0.10 = RM46.40$
Level 3 DC Fast Charger	180kW RM1.00/kWh	$CP = 85 \times RM1.00$ $CP = RM85.00$	(30kW) – RM0.60/min	$CT = \frac{85}{30} \times 60 = 170\ minutes$ $CP = 170 \times RM0.60 = RM102.0$
			(50kW) – RM1.20/min	$CT = \frac{85}{50} \times 60 = 102\ minutes$ $CP = 102 \times RM1.20 = RM122.4$
	350kW RM1.20/kWh	$CP = 85 \times RM1.20$ $CP = RM102.00$	(60kW) – RM1.40/min	$CT = \frac{85}{60} \times 60 = 85\ minutes$ $CP = 85 \times RM1.40 = RM119.0$
			(180kW) – RM3.60/min	$CT = \frac{85}{180} \times 60 = 28\ minutes$ $CP = 28 \times RM3.60 = RM100.80$

Table 7.1: CT and CP Offered by TNB Electron for Porsche Taycan Turbo S

Level of Charger	Prices (RM/min)	Charging Price for Porsche Taycan Turbo S
Level 3 DC Fast Charger	(80kW) – RM2.05/min	$CT = \frac{93.4}{80} \times 60 = 70\ minutes$ $CP = 70 \times RM2.05 = RM143.50$
	(90kW) – RM2.20/min	$CT = \frac{93.4}{90} \times 60 = 62\ minutes$ $CP = 62 \times RM2.20 = RM136.40$
	(100kW) – RM2.35/min	$CT = \frac{93.4}{100} \times 60 = 56\ minutes$ $CP = 56 \times RM2.35 = RM131.60$

Table 7.2: CT and CP Offered by Gentari for Porsche Taycan Turbo S

Level of Charger	Prices (RM/kWh)	Charging Price for Taycan T S	Prices (RM/min)	Charging Price for Porsche Taycan Turbo S
Level 2 AC Charger	All Charger (7kW, 11kW, 22kW) RM0.55/kWh	$CP = 93.4 \times RM0.55$ $CP = RM51.37$	All Charger (7kW, 11kW, 22kW) RM0.10/min	$CT = \frac{93.4}{11} \times 60 = 509\ minutes$ $CP = 509 \times RM0.10 = RM50.90$
Level 3 DC Fast Charger	180kW RM1.00/kWh	$CP = 93.4 \times RM1.00$ $CP = RM93.40$	(30kW) – RM0.60/min	$CT = \frac{93.4}{30} \times 60 = 187\ minutes$ $CP = 187 \times RM0.60 = RM112.2$
			(50kW) – RM1.20/min	$CT = \frac{93.4}{50} \times 60 = 112\ minutes$ $CP = 112 \times RM1.20 = RM134.4$
	350kW RM1.20/kWh	$CP = 93.4 \times RM1.20$ $CP = RM112.08$	(60kW) – RM1.40/min	$CT = \frac{93.4}{60} \times 60 = 93\ minutes$ $CP = 93 \times RM1.40 = RM130.20$
			(180kW) – RM3.60/min	$CT = \frac{93.4}{180} \times 60 = 31\ minutes$ $CP = 31 \times RM3.60 = RM111.60$

APPENDIX B CONFERENCE PUBLICATION

Conference

1) Abdul Kadir, A. F., Sulaima, M. F., Ab Aziz, N. H., Zin, A. N. M., Shareef, H., & Rahman, Z. A. (2023). Evaluation of Charging Costs for Various Types of EVs in Malaysia. *2023 10th International Conference on Power and Energy Systems Engineering, CPESE 2023*, 317–322. https://doi.org/10.1109/CPESE59653.2023.10303243

Evaluation of Charging Costs for Various Types of EVs in Malaysia

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***Abstract* - The growing popularity of electric vehicles (EVs) has increased the demand for electric vehicle charging stations (EVCS) in power distribution systems. Numerous benefits can be obtained from integrating EVCS with the optimum charging power of various EVs, such as cost-effectiveness and time reduction. Therefore, this research aims to evaluate the charging cost and charging time for various types of EVs in Malaysia. In this paper, the charging cost and charging time for different EVs in Malaysia are compared and evaluated by considering the constant charging rate of the Battery Management System (BMS) relative to the battery's capacity. The results highlight the significance of contemplating pricing structures and charging time reductions when selecting a charging provider. The evaluation provides valuable insights into the charging costs of EVs, thereby facilitating the identification of potential user bases and the estimation of charging needs for EVs in Malaysia.**

Keywords – Electric Vehicle, Charging Cost, Type of EVs, Optimum Charging Power, Electric Vehicle Charging Station (EVCS)

I. Introduction

In Malaysia, the rapid adoption of electric vehicles (EVs) has gained significant momentum, driven by the need to reduce greenhouse gas emissions and dependency on fossil fuels [1]. As the nation strives to achieve its sustainable development objectives and transition to a greener transportation sector, it is essential to evaluate the charging costs associated with various types of EVs. Malaysia's unique geographical and economic landscape provides unique challenges and opportunities for EV owners and charging infrastructure [2]. With an increasing number of EV models on the market, ranging from purely electric vehicles to plug-in hybrids, it is essential to evaluate the financial implications of owning and charging these vehicles by considering the various factors that affect charging costs [3].

This evaluation aims to comprehensively analyse the charging costs for various types or models of electric vehicles in Malaysia. It will consider important factors such as electricity rates, the availability of charging infrastructure and the cost impact of charging methods. This evaluation will involve data collection, analysis and modelling techniques. Real-world charging data, information on electricity tariffs and vehicle specifications will be the primary sources for assessing the charging costs of various EV types. Therefore, the findings of this study will provide an understanding of the financial implications of owning and operating EVs in Malaysia.

In a simple explanation, due to affordability and consumer adoption, the cost of charging impacts the affordability and attractiveness of EVs to potential buyers. A research article by [3] highlights the significance of analysing charging costs for effective planning of EVCSs. At the same time, the International Energy Agency (IEA) has suggested that analysing the cost of charging for several types of EVs is crucial data for policymakers to develop effective policies and regulations [4]. Understanding the cost of charging for different types of EVs helps to evaluate the buyer's financial feasibility and ensures that EVs remain an attractive option for consumers. Hence, there is a need to explore the cost of charging for various types of EVs in Malaysia.

II. Type of Electric Vehichle

Electric cars have undergone various changes and continuous development by providing users with various options [5]. There are generally four categories of electric vehicles which are Hybrid Electric Vehicles (HEVs), Fuel Cell Electric Vehicles (FCEVs), Plug-in Hybrid Electric Vehicles (PHEVs) and Battery Electric Vehicles (BEVs) [6].

A. Hybrid Electric Vehicles (HEVs)

This type of hybrid vehicle is often called HEV. HEVs have an internal combustion engine (ICE) and an electric motor. In this type of electric car, the ICE is powered by traditional fuels

2023 10th International Conference on Power and Energy Systems Engineering (CPESE) | 979-8-3503-2762-5/23/$31.00 ©2023 IEEE | DOI: 10.1109/CPESE59653.2023.10303243

such as gasoline, while the electric motor drives its power from batteries. The ICE and electric motor rotate the transmission, which drives the wheels [7]. The primary difference between HEVs and other types of electric vehicles, such as BEVs and PHEVs, is that the batteries in HEVs can only be charged by the ICE, regenerative braking or a combination of both. Unlike other electric vehicles, HEVs do not have a charging port, meaning the battery cannot be recharged from an external power source such as the electricity grid [8].

In Malaysia, several HEV models are available, including the Honda RS e: HEV, Honda Insight, Toyota Corolla Cross Hybrid, Toyota Prius, Nissan Serena Hybrid, Proton X90, Perodua Ativa Hybrid and others—the key components of an HEV as illustrated in Fig. 1.

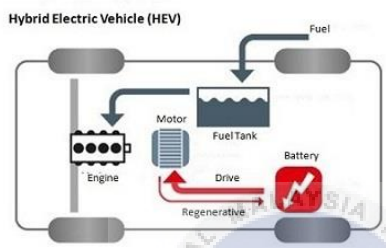

Fig. 1 Components of HEV [9]

B. Plug-in Hybrid Electric Vehicles (PHEVs)

A Plug-in Hybrid Electric Vehicle (PHEV) is a subcategory of the hybrid vehicle category. This electric vehicle category allows drivers to select their power source. This category of electric vehicles gets their propulsion from a combination of traditional fuels like gasoline and rechargeable battery packs. Gasoline powers the internal combustion engine, while the rechargeable battery pack powers the electric motor. By plugging the car into an electrical outlet or an EVCS or generating electricity through regenerative braking, the battery can receive a charge of electricity and become fully charged [10].

The standard PHEV can operate in at least two different modes. These modes are the All-Electric Mode and the Hybrid Mode. In the All-Electric Mode, the car gets all its energy from the motor and the battery. In the Hybrid Mode, the vehicle uses electricity and petrol [11]. Some PHEVs can travel more than 70 km on electricity alone.

In Malaysia, several PHEV models are available, including the Volvo S90 Recharge T8, Volvo XC60 Recharge T8, Mercedes C350e, BMW i8, and BMW X5 xDrive40e—the primary components of a PHEVs as shown in Fig. 2.

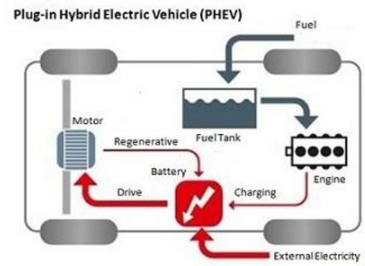

Fig. 2 Components of PHEV [12]

C. Fuel Cell Electric Vehicles (FCEVs)

Fuel Cell Electric Vehicles (FCEVs), also known as fuel cell vehicles (FCVs) or Zero Emission Vehicles, are different kinds of electric cars that use "fuel cell technology" to create the electricity required to run the vehicle by employing a fuel cell powered by hydrogen. This technology is often called "fuel cell electric vehicles" (FCEVs). In this electric vehicle category, the fuel's potential chemical energy is directly transferred into the potential electrical energy of the vehicle [13]. Hydrogen is a unique element in electrochemical processes because it can be converted into electricity in the fuel cell system. This ability makes the conversion of hydrogen into electricity in the fuel cell system significantly more efficient than the conversion of ordinary fuels into mechanical energy [14].

In Sarawak, Malaysia, only five units of Toyota Mirai are available as of 16th January 2023. East Malaysia received the first units of the second-generation Toyota Mirai in Malaysia when UMW Toyota Motor handed over four hydrogen fuel-cell electric vehicles (FCEVs) to SEDC Energy and one unit to the Sarawak Premier [15]—the primary components of an FCEV as shown in Fig. 3.

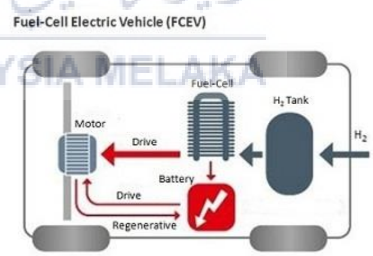

Fig. 3 Components of FCEV [16]

D. Battery Electric Vehicles (BEVs)

An electric vehicle that gets its power exclusively from a battery pack that can be recharged is known as a Battery Electric Vehicle (BEV). Since BEVs do not rely on petrol or any other type of combustion for power, these cars are considered zero-emission vehicles because they do not emit emissions from their tailpipes [17]. A BEV's battery pack is the primary power source for the vehicle, and it may be charged by connecting the car to an electrical outlet or a charging station specifically designed for that purpose. The electric motor subsequently uses the energy stored in the battery to power the car, resulting in a quiet and smooth driving experience [18]. The primary components of a BEV are illustrated in Figure 4.

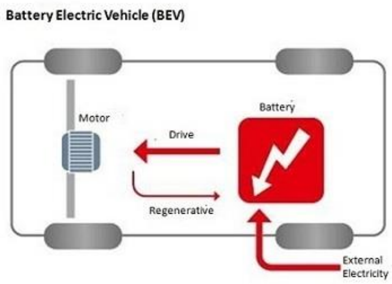

Figure 4 Components of BEV [19]

A BEV's operational concept involves converting power from the DC battery to AC for the electric motor. The accelerator pedal transmits a signal to the controller, which modifies the vehicle's velocity by altering the frequency of the AC power from the inverter to the motor. The motor turns and rotates the wheels via a drive train. During deceleration or when the brakes are applied, the motor functions as an alternator and generates power fed back to the battery [18]. In Malaysia, several BEV models are available, including the Hyundai Ioniq 5, Kia EV6, BYD Atto 3, Tesla Model 3, Mercedes Benz EQA, and others.

III. Levels of EV Charging Station

Electric vehicles (EVs) are becoming increasingly popular, which has led to an increased demand for charging stations. EV charging levels are determined by power, location, charging time, equipment, cost and their impact on the electrical grid [20]. The availability of charging infrastructure has become a significant factor in reducing EVs' energy storage requirements and costs. Charging components, such as cords, plugs, charge stands for residential or public use, power outlets, protection devices and EV connectors, are commonly designed in two configurations which are wall or pedestal-mounted boxes and specialized cord sets. These configurations may differ in detail depending on the location, voltage, frequency, electrical grid connections and utility standards [21]. Charging stations are categorized into three levels based on their charging rate and voltage: Level 1, Level 2, and Level 3 of charging stations, as shown in Fig. 5.

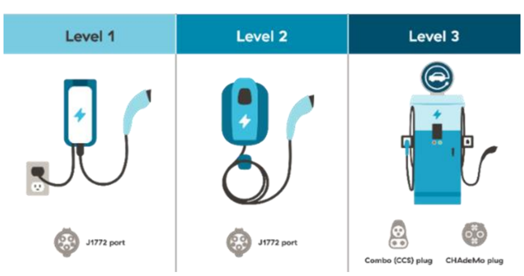

Fig. 5 Levels of EVCS [22]

A. Level 1: Slow AC Charger

When recharging an electric vehicle (EV), a Level 1 charging station is the most fundamental and uncomplicated solution. It employs a conventional socket outlet with a maximum capacity of 16 Amps and a maximum voltage of 230 Volt for AC single-phase configuration and 400 Volt for AC three-phase configuration. This outlet is comparable to the one used to plug in a typical home appliance [23].

The Level 1 charging station typically comes with the EV as part of the standard equipment and can charge the battery from zero to total capacity overnight. Level 1 charging provides a charging output rate of 1.4kW-2.0kW. This rate is relatively slow and would take between 8 and 20 hours to fully charge an electric vehicle, depending on the battery size [22]. However, Level 1 charging is the most generally available option because it can be utilized with any ordinary electrical outlet. As a result, it is a charging solution that is accessible to owners of electric vehicles.

Level 1 charging is ideal for people who drive short distances regularly and can charge their vehicles overnight while at work or asleep. This kind of charging is also appropriate for workplace use, allowing employees to charge their electric vehicles (EVs) while at work or to leave their cars plugged in overnight to charge at home [24]. The charging equipment required for Level 1 usually consists of a connector cable and a charging module that may be plugged into a regular outlet. The charging module monitors the charging process and adjusts the charging rate to prevent the battery from overcharging or overheating. Because Level 1 charging stations do not need to have their installation performed by a professional or require any additional electrical work, they are the most cost-effective choice for owners of electric vehicles.

B. Level 2: Moderate AC Charger

A Level 2 charging station is a faster and more robust option for electric vehicles (EVs) than a Level 1 charging station. It provides a higher charging output rate of 3kW to 20kW and would take between 4 and 8 hours to fully charge an electric vehicle, depending on the size of the battery, which is roughly four times faster than a Level 1 charger. Level 2 charging stations use a 230 Volt AC single-phase or 400 Volt AC three-phase electrical supply, which requires a dedicated circuit and a professional installation by a licensed electrician [23]. The installation involves running new wiring from the electrical panel to the charging location, installing a new circuit breaker and mounting the charging station on the wall or a pedestal.

Level 2 charging stations are commonly found in public areas such as shopping centres, parking lots and on-street parking. They are also famous for residential use, especially for EV owners who frequently drive long distances and require a faster charging option. Equipment for Level 2 charging consists of a connector cable and a charging module. The charging module controls the charging process and adjusts the charging rate to prevent the battery from overcharging or overheating. Some Level 2 chargers can connect with the electric vehicle and offer data on the vehicle's charging state, energy usage, and charging history [22].

One benefit of Level 2 charging stations is that, in comparison to Level 1 charging stations, they offer a greater degree of flexibility. They are compatible with various electric vehicle models and battery capacities, making them a more general alternative for charging. In addition, Level 2 charging stations give owners of electric vehicles who need to charge their vehicles rapidly and effectively more flexibility when charging their vehicles [24].

C. Level 3: DC Fast Charger

The most efficient method for charging electric cars (EVs) is accomplished at a Level 3 charging station which may also be referred to as a DC fast charger or DCFC. It has a very high charging output rate of 20 kW up to 350 kW, and it would take between 30 minutes and 2 hours to fully charge an electric vehicle, depending on the battery size. This is more than ten times quicker than a Level 1 charger and up to six times faster than a Level 2 charger. Charging stations of level 3 utilize a direct current (DC) electrical supply, which necessitates the installation of specialized electrical infrastructure and the services of a licensed electrician [23].

The installation procedure requires extensive work to be done with electricity, including upgrading the existing electrical service, installing a DC transformer, and mounting the charging station. Level 3 charging stations are commonly found along highways, major roadways and at rest stops, providing a quick and convenient charging solution for long-distance travel [22].

The advantage of Level 3 chargers is their compatibility with a wide range of EVs. Most Level 3 chargers use standardized connectors such as the CCS (Combined Charging and System) and CHAdeMO, which are compatible with most electric cars from various manufacturers. This makes it easier for EV drivers to find a compatible charging station regardless of their vehicle model. Level 3 charging stations require high DC power, which leads to expensive installation compared to lower-level chargers. However, they are more efficient and cost-effective in the long run. Level 3 chargers typically have higher utilization rates and can generate more revenue for charging station operators [24].

Overall, level 3 charging stations are the most rapid and robust chargers available for EVs, making them ideal for long-distance travel because they allow drivers to turn off their batteries quickly and easily. They are compatible with various electric vehicles and can assist companies and public facilities attract more people who drive electric vehicles. Even though they demand a more significant investment up front, Level 3 chargers are more cost-effective and efficient over the long term, which makes them a crucial component of the expanding electric vehicle charging infrastructure.

IV. Evaluation of Charging Cost and Time

To gain a comprehensive understanding of the economic potential and accessibility of electric vehicle (EV) ownership and utilization in Malaysia, it is essential to evaluate the costs associated with charging each of the various types of EVs currently on the market. To do the evaluation, it is necessary to take into consideration a few numbers of variables that influence the charging prices of various EV models as well as the charging requirements that are specific to each model. This study assumes that the constant charging rate for the EV's BMS system, which is relative to the battery's capacity, has been applied to evaluate the charging cost and time for various EV types.

Firstly, the amount of time it takes to charge an EV and the associated cost is heavily influenced by the charging capacity of the battery as well as the rate of power at which it can be charged. In general, electric vehicles with enormous battery capacities take more power to charge fully, resulting in higher charging costs when compared to EVs with smaller batteries.

Several companies have ventured into the electric vehicle charging sector in the Malaysian market. The charging rates offered by these companies differ due to various factors, including cost structure, charging speed, technology provided and market competition. Within the range of available EV charging service providers, this project focuses on Gentari and TNB Electron as baseline references to calculate and analyze the prices for charging various types of EVs in Malaysia.

Next, the charging infrastructure and the price structure of that infrastructure both affect the cost of recharging an EV. A variety of price structures may be used at public charging stations, including hourly rates, flat rates and payments based on the amount of time spent charging. Additionally, private charging stations such as those installed at homes or businesses may have different electricity tariffs, which can further influence the overall charging costs. Thus, the charging cost and charge time can easily be calculated by using the formula as follows:

$$\textit{Charging Cost} = \textit{Battery capacity} \times \textit{Electricity Cost} \quad (1)$$

$$\textit{Charge Time} = \frac{\textit{Battery Capacity}}{\textit{Charging Power}} \quad (2)$$

where the battery capacity is in kWh, electricity cost in RM/kWh and the charging power in kW. In this paper, the charging price rate from Gentari and TNB Electron and EV specifications are referred to calculate the estimated charging costs for different EV models based on their battery capacities, charging times, and the applicable electricity costs.

V. Result and Discussion

Evaluating the cost of charging for different varieties of EV in Malaysia based on EV specifications requires considering variables like battery capacity, estimated range, maximum charge power and vehicle weight. However, for this study, only battery capacity of EVs is taken into consideration. This evaluation aims to assess the cost implications of charging and identify the most efficient and cost-effective charging power for each electric vehicle model. Table 1 shows the specifications of various EV types.

TABLE 1 SPECIFICATION OF VARIOUS EV TYPES

EV Model	Battery Capacity (kWh)	Estimated Range (km)	Max. Charge Power (kW)	Weight (kg)
Hyundai Ioniq 5	72.6	430	350	2100
Kia EV6 GT	77.4	506	350	2105
Audi RS e-tron GT	85.0	501	270	2420
Porsche Taycan Turbo S	93.4	416	270	2295

BMW i4 M50 EV	83.9	510	200	2290
Volvo C40 Recharge	78.0	438	150	2045
Tesla Model Y	75.0	514	250	2003

Table 2 provides a comprehensive overview of the charging prices offered by TNB Electron, with charging powers ranging from 80kW and 100kW. This analysis evaluates the charging costs for various popular EV models by considering their various battery capacities and charging times. As shown in Table 2, the cost per minute increases as charging power increases. Thus, each EV model will experience a reduction in charging time and cost. TNB Electron only offers charging powers of 80kW, 90kW and 100kW, so using a charger with a higher power rating can result in more affordable services.

TABLE 2 COMPARISON BETWEEN CT AND CP FOR CHARGING POWER OFFERED BY TNB ELECTRON

Charging Power	80kW (RM2.05/min)		100kW (RM2.35/min)	
EVs Model (Battery Capacity)	CT (min)	CP (RM)	CT (min)	CP (RM)
Hyundai Ioniq 5 (72.6kWh)	55	112.75	44	103.40
Kia EV6 GT (77.4kWh)	58	118.90	46	108.10
Audi RS e-tron GT (85kWh)	64	131.20	51	119.85
Porsche Taycan Turbo S (93.4kWh)	70	143.50	56	131.60
BMW i4 M50 EV (83.9kWh)	63	129.15	50	117.50
Volvo C40 Recharge (78kWh)	59	120.95	47	110.45
Tesla Model Y (75kWh)	56	114.80	45	105.75

The following Table 3 provides a comparison of the charging prices and charging times that Gentari offers for various charging powers, and the charging rate was expressed in RM/min. According to Table 3, the charging rate increases as the charging power increases. The findings of the study indicate that recharging an electric vehicle with a charging capacity of 180 kW results in a reduction in both the amount of time required and the cost spent. Therefore, charging an electric vehicle with a power rating of 180 kW contributes to an increase in both the convenience and satisfaction experienced by users as an outcome of the efficient operation of the charging services provided.

TABLE 3 COMPARISON BETWEEN CT AND CP FOR CHARGING POWER OFFERED BY GENTARI

Charging Power	60kW (RM1.40/min)		180kW (RM3.60/min)	
EVs Model (Battery Capacity)	CT (min)	CP (RM)	CT (min)	CP (RM)
Hyundai Ioniq 5 (72.6kWh)	73	102.20	24	86.40
Kia EV6 GT (77.4kWh)	77	107.80	26	93.60
Audi RS e-tron GT (85kWh)	85	119.00	28	100.80
Porsche Taycan Turbo S (93.4kWh)	93	130.20	31	111.60
BMW i4 M50 EV (83.9kWh)	84	117.60	28	100.80
Volvo C40 Recharge (78kWh)	78	109.20	31	111.60
Tesla Model Y (75kWh)	75	105.00	25	90.00

The evaluation of charging prices for different EV models in Malaysia offers helpful insights into identifying the optimum charging power and predicting the charging requirements of each EV. The charging power of 180 kW is appropriate for consideration when determining the cost of the charge in RM/min. This indicates that the selection of charging power should also take advantage of the pricing structure that various charging providers provide. Electric vehicle owners can select the most cost-effective power for their charging needs.

A charging power specification of 180kW offers significant price and charging time reduction advantages. Higher charging power ratings promote faster charging, allowing EV owners to recharge their vehicles less. This is especially beneficial for drivers who are on the move and need to recharge their batteries rapidly. EVs with a power rating of 180kW contribute to an increase in user convenience and satisfaction by providing efficient charging services.

Moreover, chargers with higher power ratings, such as 180kW, can result in more affordable charging services. This means that EV users will pay lower costs per unit of energy consumed, making the charging procedure more cost-effective.

The evaluation is essential for determining the optimum charging capacity for various EV models and estimating their charging requirements. The government involved in the planning of EV infrastructure can make educated decisions regarding installing charging stations if they are aware of the optimum charging power. This ensures that the charging infrastructure satisfies the needs of EV users. Thus, it promotes efficient charging services and contributes to the expansion and adoption of electric vehicles in Malaysia.

VI. Conclusion

In conclusion, evaluating charging prices for various EV models in Malaysia provides beneficial information for identifying the optimum charging capacity or power and predicting the charging needs of each vehicle. The use of a charger with a higher power rating provided by TNB Electron still does not offer the most significant advantages in terms of pricing and charging time reduction compared to the charging power offered by Gentari. The results indicate that a charging power of 180 kW offers an EV owner cost structure compared to other options. In addition, higher charging power ratings, such as 180 kW, result in quicker charging, decreasing charging time and improving user convenience. Moreover, the evaluation indicates that higher power ratings can result in more cost-effective charging services with reduced costs per unit of energy consumed. Overall, this evaluation will be necessary for the government to make reliable choices regarding the installation of charging stations by providing the efficiency of charging services and promoting the growth and adoption of electric vehicles in Malaysia.

Acknowledgment

The authors would like to acknowledge the FRGS grant given by the Ministry of Higher Education, (FRGS/1/2020/TK0/UTEM/02/66) through which the financial support is received for this research project. The authors also would like to thank to Universiti Teknikal Malaysia Melaka for their endless support from the beginning of this study.

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