Planning And Operation of Solar-Hydrogen-Storage Integrated Electric Vehicle Charging Stations in Smart City

A thesis submitted for the degree of Doctor of Philosophy

By

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Abstract

The global push towards carbon neutrality by 2050 has intensified the need for sustainable, energy-efficient electric vehicle charging infrastructure. Traditional charging stations rely heavily on the conventional grid, which presents challenges for integrating renewable energy sources and supporting the widespread adoption of electric vehicles (EVs). This thesis addresses these challenges by developing innovative strategies for energy-efficient electric vehicle charging stations (EVCSs) that incorporate renewable energy sources, enhance energy exchange capabilities, and improve the infrastructure's overall contribution to social welfare and carbon emission reduction.

Although prior research has made strides in enhancing EV charging efficiency and incorporating renewable energy, significant gaps remain. Many existing studies overlook comprehensive models that optimize both energy management and economic viability across EVCS networks. There is a need for solutions that facilitate effective integration of renewable energy sources, such as solar hydrogen and battery storage systems, with minimal reliance on traditional distribution networks. Furthermore, limited attention has been given to optimizing energy transfers between stations and implementing real-time pricing models to balance supply and demand in variable conditions.

This thesis addresses these gaps by presenting a comprehensive model for integrating renewable energy into EVCSs, including solar hydrogen and storage-integrated EVCSs (SHS-EVCSs), supported by advanced simulation and optimization techniques such as the Particle Swam Optimization (PSO) Algorithm, the Non-dominated Sorting Genetic Algorithm (NSGA-II) and the Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D). These methods facilitate the identification of optimal solutions for energy management and cost-effectiveness. Additional contributions include a novel peer-to-peer (P2P) energy dispatch strategy based on game theory, a hierarchical model to enhance driver welfare and operational efficiency, and a Markov decision process with Monte Carlo simulations for accurate demand prediction and real-time pricing. Together, these innovations provide a robust framework for designing future EVCS infrastructure aligned with global carbon neutrality goals, offering practical insights into renewable energy integration, network optimization, and economic impacts on urban transportation systems.

Acknowledgement

Completing this PhD has been a significant journey for me, and it would not have been possible to complete without the support and encouragement of many. I am deeply grateful to those who have contributed to my personal and professional growth during this period.

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My friends have been supported and encouragement during the challenging moments of academic pursuit. Their camaraderie and belief in my abilities have been a constant source of strength. We have shared countless hours playing games, engaging in exhilarating badminton plays, hiking, and travel together, which have all brought joy and balance to my life. They have not only celebrated my birthday with enthusiasm each year but have also stood by my side, providing comfort and guidance when I faced difficult times. I am deeply indebted to them for their unwavering friendship and for being an integral part of my journey.

I am deeply thankful to my parents for their steadfast support and constant encouragement throughout my educational journey and during the demanding process of researching and writing this thesis. Their unwavering belief in me made this accomplishment possible, and for that, I am forever grateful.

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Author’s declaration

The work described in this thesis has not been previously submitted for a degree in this or any other university and unless otherwise referenced it is the author’s own work.

Lijia Duan
May 2024

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Abbreviation

CSs	**Charging stations**
DER	Distributed energy resource
DR	Demand response
DRP	Demand response program
DOD	Depth of discharge
DSM	Demand side management
EV	Electric vehicle
GA	Genetic Algorithm
G2P	Gas to power
FIT	Feed-in Tariff
IMS	Internal Management System
LP	Linear Programmin
MAPE	Mean Absolute Percentage Error
MILP	Mixed integer linear programming.
MOEA/D	Multi-objective Evolutionary Algorithm Based on Decomposition
NSGA-II	Non-dominated Sorting Genetic Algorithm
P2G	Power to gas
P2P	Peer to peer

PV	Photovoltaic
RE	Renewable energy
SA	Simulated Annealing
SHS-EVCSs	Solar-Hydrogen-Battery Storage Electric Vehicle Charging Stations
SoC	State of charge

Chapter 1. Introduction

1.1. Background

As the global economy continues to grow, humanity faces increasing challenges with energy shortages and air pollution. In response, there has been a heightened focus on low-carbon and renewable energy (RE) as key solutions to these issues. Numerous countries have introduced carbon emission standards designed to cut energy consumption, enhance the efficiency of electricity generation, reduce greenhouse gas emissions, and support the development of clean energy alternatives. Although conventional fossil fuel technologies for energy generation are well-developed, offering high capacity and operational stability, they are limited in terms of energy efficiency and lack the flexibility to effectively balance supply and demand. Additionally, the significant carbon and pollutant emissions from these technologies contribute to global warming and environmental degradation, posing a barrier to their further expansion. Clean energy can be divided into renewable and non-renewable categories. Renewable energy includes sources like wind, water, solar, geothermal, and tidal energy. Non-renewable clean energy sources encompass nuclear power, biomass, and hydrogen. While renewable energy offers the benefits of competitive generation costs and low-carbon emissions, its unpredictable and intermittent nature can lead to volatility in energy supply and demand. Hydrogen, as a low-carbon fuel, provides a stable and sustainable energy option, especially when integrated with renewable energy for long-term use.

Electric vehicles (EVs) development can be dated back as far as 1830 when Robert Anderson developed a prototype electric-powered carriage. However, it was until 1884 that the first mass-produced EV was created by British inventor, Thomas Parker [1]. Later in 1897, a New York based taxi company that operated electric cars was founded. However, the EVs at that time were characterized by a range of problems that made it challenge to be rolled out to the larger automotive market. For example, the car batteries could not be reliably recharged and hence the frequent used batteries had to be replaced with new ones. Even in instances where batteries could be recharged, the range anxiety coupled with limited number of charging stations meant that EVs could not be used widely [1]. According to [1, 2], the development of electric ignition systems in 1834 for combustion cars, availability of cheap fuel as well gradual improvement in reliability of such cars further inhibited the development of electric cars.

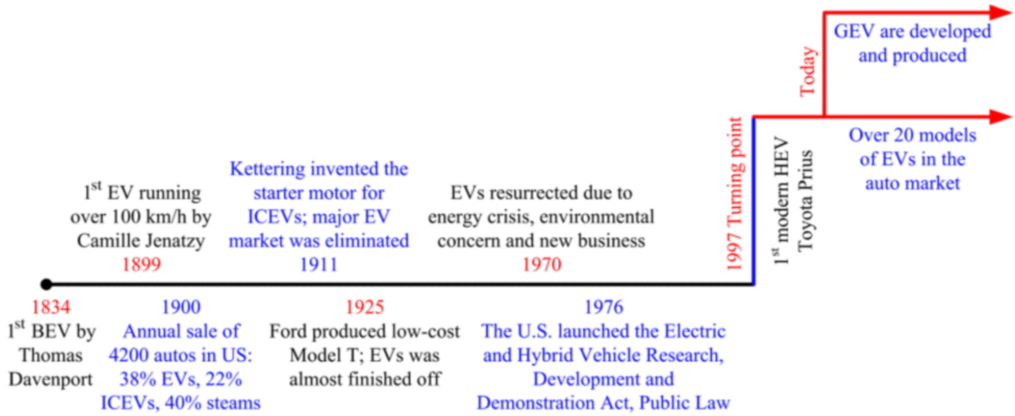


Figure 1-1 EV development history [1]

During the 1960s and 70s, interest in EVs was regained following a spike in global oil prices. However, the interest gradually faded due to persistent drawbacks of EVs such as limited performance and range comparing with combustion vehicles (50-60 miles before recharging) [3]. In 1990 to 1992, regulatory changes particularly in the United States initiated the interest in EV and marked improvements were achieved in aspects such as speeds and performance which helped reduce the gap relative to gasoline-powered vehicles [4]. In 1997, the first major commercial success regarding EVs had occurred following the Toyota’s mass production of hybrid car- Prius. Further in 2006, Tesla Motors began the production of a fully electric car with a range of 200 miles. Coupled with development of nation-wide charging infrastructure in the United States, several models of EVs such as General Motor’s Chevy Volt and Nissan’s LEAF were developed and made commercially available. Another key development in recent times was the decline in battery costs, by 50% in 2013 leading to greater affordability as the battery constitutes the single most expensive part of EVs [4].

Since the early 2000s, there has been an increasing awareness of the need to address greenhouse gas emissions and environmental pollution resulting from the overuse of fossil fuels [5]. This has led to a growing emphasis on RE sources, which are now seen as vital alternatives in many countries across the globe. The electricity generation and transportation sectors are particularly noteworthy, as they are responsible for nearly 64% of global carbon dioxide emissions [5]. This has heightened public concern over the potential for permanent environmental damage. Sources [6] suggest that the integration of RE is crucial for achieving carbon reduction targets in these areas. EVs are considered a promising option for lowering CO_2 emissions. Thorough reviews [7][8] of research on EVs indicate that their use not only reduces environmental impact but also offers cost benefits to owners due to lower operational expenses. However, one of the major challenges in increasing EV adoption is the slow development of charging infrastructure [9]. The lag in establishing sufficient charging facilities discourages potential buyers from making the switch to EVs [10]. Furthermore, high investment costs and uncertainty about future EV demand are additional factors that slow the progress of infrastructure development. For instance, in London, it is estimated that by 2040, more than 500,000 charging points will be needed, with almost 50,000 required in public spaces [11]. This underscores the urgent need for coordinated efforts to expand infrastructure to support the anticipated growth in EV usage.

1.2. Research Aim and Objectives

The aim of this thesis is to explore strategies for constructing new energy-based electric vehicle charging stations (EVCSs) to meet the 2050 carbon emission targets. The focus of the research is on analysing the management of RE used in EVCSs, exploring the mechanisms for energy exchange between multiple charging stations, and how to effectively feed electricity back to the grid to maximize social welfare. Additionally, this study aims to elucidate the crucial role of EVCSs in achieving carbon neutrality goals. To achieve these objectives, the following specific research goals have been set:

1. Review renewable energy technologies, EV charging requirements, and advancements in renewable-powered EVCSs to identify current technology gaps.
2. Propose a super-fast, off-grid, carbon-neutral charging station design to promote urban EV adoption, reduce carbon emissions, and address range anxiety.
3. Conduct an economic analysis comparing SHS-EVCSs with traditional EV stations, focusing on cost-effectiveness, operational efficiency, and sustainability.
4. Develop an optimal scheduling and real-time pricing model for an integrated energy system that leverages multi-energy complementarity, including demand-side management and demand response, tailored to SHS-EVCSs and EV drivers, which called social welfare maximization.

1.3. Contribution

The contributions to this research are:

1. This study focuses on developing a detailed model for EVCSs. It includes a thorough comparative analysis of simulation optimization techniques, specifically comparing the Non-dominated Sorting Genetic Algorithm (NSGA-II) and the Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D) to identifies and selects the optimal solution according to established criteria and performance metrics.
2. The direct transfer of electric energy between EVCSs without using the distribution network. By examining the complexities and outcomes of direct energy exchange, to explore the feasibility, advantages, and obstacles of this innovative approach.
3. Reducing capital costs, O&M expenses, and the costs associated with greenhouse gas emissions. By prioritizing environmental sustainability, it aims to investigate the complex relationship between economic efficiency and environmental impact.

4. The proposal method introduces a peer-to-peer (P2P) optimal dispatch strategy based on game theory for SHS-EVCSs.
5. Examined the synergistic collaborations and operational dynamics among various stakeholders to highlight the shared economic benefits, focusing particularly on methodologies that use SHS-EVSE for energy sharing and economic dispatch optimization, aimed to understand how these interactions enhance collective profitability and operational efficiency.
6. From the perspective of economic market, a model is established based on the master-slave hierarchical relationship between SHS-EVCSs and EV drivers. The model directly considers the welfare of EV drivers, rather than just reducing the operating costs of SHS-EVCSs.
7. Develop a model for EV charging times using a Markov decision process to manage the uncertainties related to charging durations. Furthermore, implement a Monte Carlo simulation to evaluate and forecast EV charging demand, considering that the demand is likely to vary according to the probabilities linked with different charging times.
8. According to the EV charging demand, considering the benefits of both the driver side, the SHS-EVCS side and grid side, improve the social welfare maximization real-time pricing model.

1.4. List of Publications Arising from the PhD

Journal publications:

- **L. Duan**, G. Taylor, C. S. Lai. Solar–Hydrogen-Storage Integrated Electric Vehicle Charging Stations with Demand-Side Management and Social Welfare Maximization. *World Electr. Veh. J.* 2024, *15*, 337.
- **L. Duan**, Y, Yuan, G. Taylor, C. S. Lai. Game Theory-Based Design and Analysis of a Peer-to-Peer Energy Exchange System Between Multi-Solar-Hydrogen-Battery Storage Electric Vehicle Charging Stations. *Electronics* 2024, *13*, 2392.

- **L. Duan**, Z. Guo, G. Taylor, C. S. Lai. Multi-Objective Optimization for Solar-Hydrogen-Battery-Integrated Electric Vehicle Charging Stations with Energy Exchange. Electronics 2023, 12, 4149.

Conference publications:

- **L. Duan**, C. S. Lai, G. Taylor, X. Zhang. Optimal energy exchange of two electric vehicle charging stations with solar-hydrogen-battery storage systems. Accepted for 2023 58th International Universities Power Engineering Conference (UPEC 2023), Aug. 29 - Sep. 01, Dublin, Ireland.
- **L. Duan**, X. Zhang, N. Ozkan, S. Etminan. Design and operation of solar-hydrogen-storage integrated electric vehicle charging station in smart city. CIRED 2021 Conference, Sep. 20-23, Geneva, 2021.

1.5. Structure of the Thesis

Chapter 1- Introduction

This chapter provides a comprehensive introduction to the background of EV, RE, and EV charging infrastructure. It outlines the motivation, aims and objectives of the thesis. Furthermore, it highlights the contributions of this research and the content that will be discussed.

Chapter 2: Literature Review

This chapter provides a review of literature on EV charging and the underlying issues as the adoption of EV continues to increase rapidly. It begins with a review of EV history and the future direction of the sector. Then followed by a review of challenges and opportunities relating to EV charging infrastructure. Further, the chapter reviews the concept of REs and DSM. Other concepts reviewed include vehicle to grid.

Chapter 3: Model and Theory Background

This chapter offers a comprehensive introduction to several key technologies and methodologies in modern energy systems and optimization. It introduces photovoltaic (PV) systems, hydrogen storage systems, and battery storage systems model. Explore optimization algorithms: the non-dominated sorting genetic algorithm-II (NSGA-II) and the multi-objective evolutionary algorithm based on decomposition (MOEA-D), which are pivotal in solving complex optimization problems in energy systems. Furthermore, this chapter explores the foundational principles of Peer-to-Peer (P2P) energy trading working with game theory. Also gives information about social welfare models.

Chapter 4: Design and operate SHS-EV Charging Station

This chapter presents a pioneering design and operational framework for a SHS-EVCS, specifically tailored to meet the demands of future smart cities. The system is designed to provide two key functions: firstly, it enables super-fast and off-grid EV charging; secondly, it offers a multi-energy charging system that integrates solar power, hydrogen fuel, and energy storage technologies. The design and modeling of the SHS-EV charging station involve several critical components: a hydrogen fuel cell generator that facilitates off-grid, high-density power generation; a local solar power generation facility that harnesses renewable energy; a power-to-gas electrolysis unit that produces hydrogen using both grid electricity and solar energy; and advanced storage solutions for hydrogen and batteries, which are crucial for managing local energy balance. Additionally, the framework includes a unique feature where multiple stations are interconnected through an energy exchange system, allowing for the transfer of excess energy between stations, thereby optimizing energy utilization across the network. This innovative approach not only enhances the efficiency and sustainability of EV charging but also contributes to the resilience and adaptability of future urban energy systems.

Chapter 5. Multi SHS-EV charging station power exchange

This chapter introduces an optimization approach for direct energy exchange between geographically dispersed EVCSs in London, UK, and Dali, China.

Part 1 focuses on London, where the proposed SHS-EVCSs are evaluated and compared using two multi-objective optimization algorithms: NSGA-II and MOEA/D. The study's results demonstrate that NSGA-II delivers superior-quality solutions compared to MOEA/D.

Part 2: Dali part introduces a P2P energy trading strategy based on game theory for multi-SHS-EVCSs, this approach sets a fuzzy value based on the prediction errors of renewable energy within each SHS-EVCS. It introduces a day-ahead P2P interactive energy trading model that uses game theory optimization principles to address the variability challenges of renewable energy sources. Then, by applying dual theory, the model is transformed into a linear convex programming problem that can be solved using CPLEX optimization techniques.

Chapter 6 SHS-EV charging stations demand side management

This chapter will examine the practical feasibility of EVCSs by introducing two key models. The first is a non-cooperative game model for SHS, designed to minimize the costs of construction, operation, and maintenance. The second model focuses on internal energy transactions within EVCSs, expanding on concepts discussed in Chapter 5 Part 2. This model integrates operational load and an internal dispatch center for demand response, with the goal of maximizing social welfare by balancing the economic interests of EV owners and minimizing electricity supply costs, including acceptable charging prices. In this broader social welfare model, the capital costs of electricity generation, such as those from the grid, renewable energy, and storage systems, are also important considerations. Additionally, this chapter will explore two distinct scenarios: one scenario addresses day-ahead DSM using fixed load data from Chapter 4, while the other focuses on real-time DSM.

Chapter 7 Conclusion

This chapter provides a comprehensive summary of the overall findings from the entire research project and discusses the key contributions made by this study. Additionally, the chapter outlines potential avenues for future research, suggesting directions that could further enhance understanding and development within the topic area.

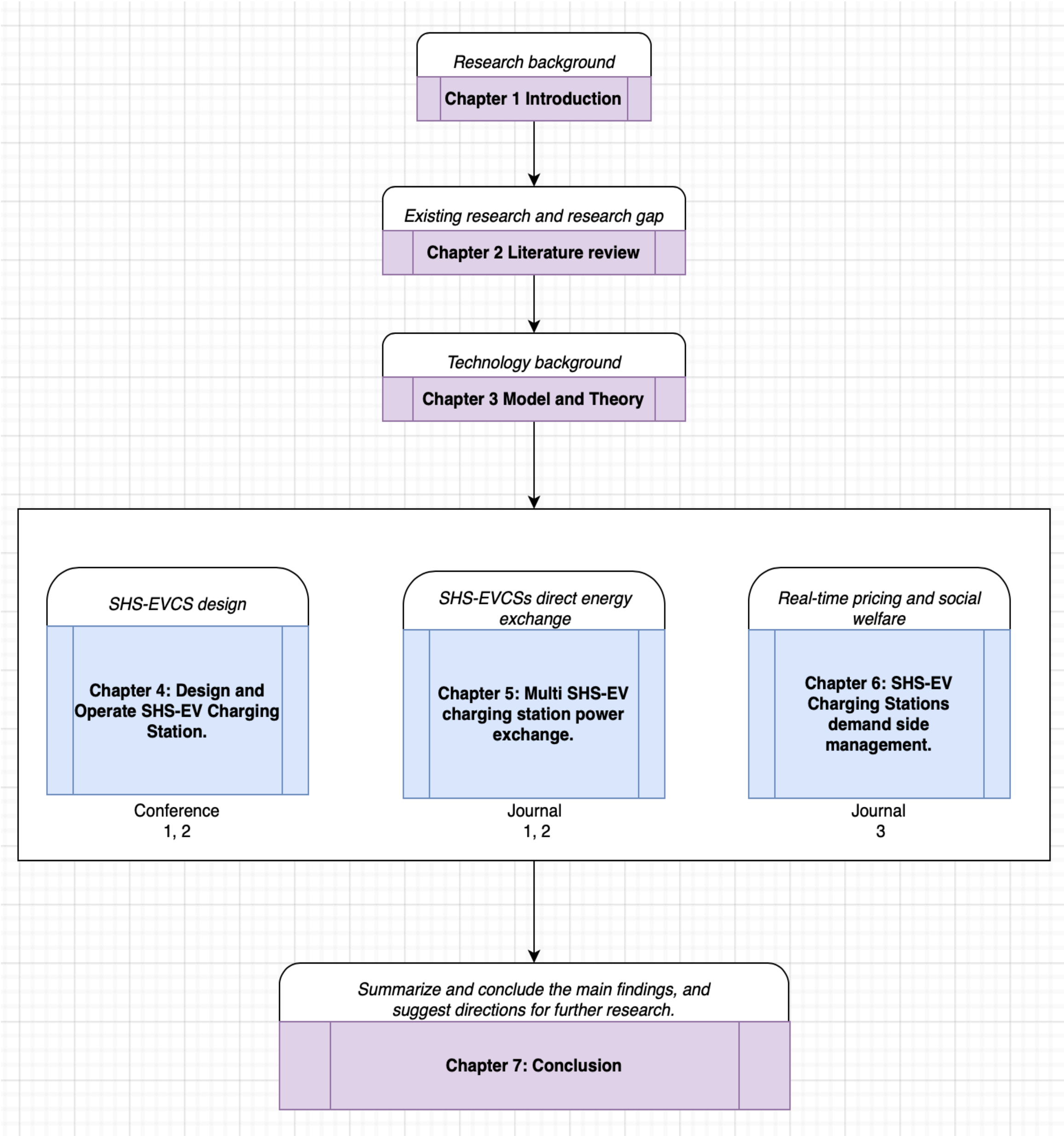


Figure 1-2 Flowchart for thesis structure

Chapter 2. Literature Review

The introduction of renewable energy at EVCSs plays a very important role in the global shift towards sustainable mobility. Due to the rapid development of EVs, the use of renewable energy charging infrastructure can improve energy security and reduce the carbon footprint associated with transportation. Hydrogen storage, battery storage and solar energy comprise the main renewable energy sources. It plays a very important role in this integration, providing solutions that are efficient and sustainable [12][13]. In the process of using these technologies, greenhouse gas emissions are reduced, and the stability of the grid can be achieved by balancing load changes throughout the day [14]. The reduced cost and wide availability are the main features of solar energy, which enables the battery reserve system of the charging station to be supported, and this provides electricity for the charging station. Low-cost grid electricity and excess solar energy are stored in these battery reserves. These batteries can be used if there is insufficient sunlight or during periods of peak demand [15-17]. On the other hand, it enables both high energy density fuels to be supplied and residual renewable energy to be stored [18]. In EV charging infrastructure, these national policies have a big impact on these technologies. In the United Kingdom, for EVs to be promoted and vehicle emissions to be reduced, renewable energy charging infrastructure can be enhanced by the government through the "Road to Zero" strategy [19][20]. At the same time, to increase the deployment of EVs, positive policies can be used in China, including the integration of incentives for renewable energy, so that China can take the lead in the application of renewable energy transportation and EVs [21]. In this literature review, different renewable energy technologies are explored to explore the role of technological advances and integration challenges in the context of EVCSs, as well as the impact of Chinese and UK policies. Within these strategies, within these policies, the global landscape of renewable energy can be shaped.

2.1. EV History and Future

Over the past few decades, changes driven by policy and technology have significantly influenced the development of EVs and their charging infrastructure. The idea of EVs dates to the early 20th century, when researchers first introduced the concept. At that time, EVs competed with internal combustion engines, but they faced challenges such as limited charging options and short driving ranges [23][24]. As a result, EVs did not gain widespread popularity. However, by the late 20th century, advancements in battery technology and growing environmental concerns renewed interest in electric mobility [25]. In recent years, the progress in EV charging infrastructure has been substantial, particularly with the integration of online systems. Wind and solar-powered charging stations are becoming increasingly common, offering sustainable alternatives to traditional electricity sources. Mobile storage units can be enabled through innovations such as bidirectional charging, so that the grid can feedback from energy, thereby integrating renewable energy and energy stability regulatory frameworks and policies [26]. Initiatives such as the Autonomous and Electric Vehicles Act 2018 have been made possible by the government's commitment to reducing carbon emissions [27]. In this act, charging points will be installed in all new homes, thus putting the number of public charging on a rapid growth trend [28]. Figure 1-1 shows the distribution of charging devices across different speed categories, highlighting changes between the old and new classifications [29]. In the former speed categories, there are 53% 'fast' charging devices (7kW to 22kW). In the new categories, the 3kW to 8kW range comprises the largest proportion of charging devices at 59% (31,910 devices) [29].

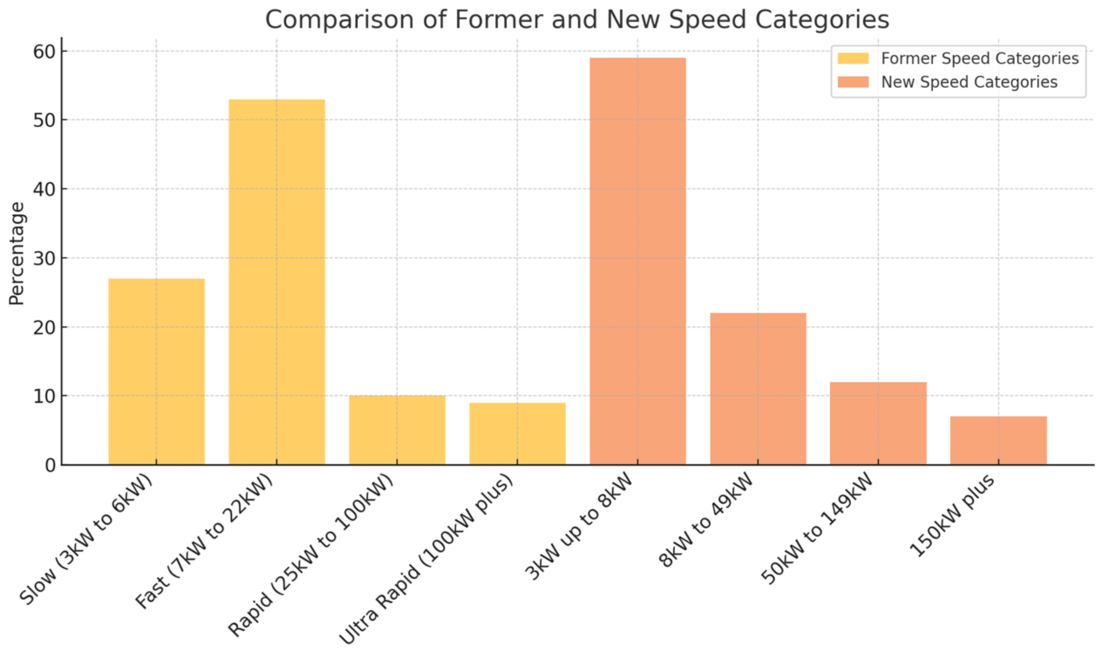


Figure 2-1 public charging devices by charging speed [29]

These efforts complement investment in renewable energy technologies to power stations, as well as subsidies for electric locomotives, such as restrictive policies implemented by the Chinese government for gasoline cars, and EV adoption can be driven by new energy vehicle policies, which can benefit from local subsidies and policy support for construction. In the global EV market, China has gained a leading position by combining renewable energy and EV infrastructure [30-32]. In addition, smart grid technologies can be implemented and explored in both countries so that grid burdens can be managed and charging services can be optimized [33]. These technical demand response systems are included in these technologies, and the renewable energy charging rate can be adjusted by the availability of renewable energy, thus improving the sustainability and efficiency of EV charging stations [34]. In the process of continuous development of charging technology and EVs, the technical exchange framework and international cooperation also support this development, which enables the global standardization of charging systems [35]

2.2. Photovoltaic Energy

Solar charging is used to charge EVs, in the process of promoting sustainable energy solutions, the use of solar power generation of photovoltaic technology has laid a technical role, especially the current main background is based on EV charging [36-38]. Solar energy is used by photovoltaic technology, and electric energy can be directly converted from light energy [39][40]. In this process, electric charge can be generated in photovoltaic cells, and internal power plants in internal batteries can generate electricity [41]. Since fossil fuels are no longer used in the world, the application of EV charging can be innovative and play an important role. The photovoltaic panel is mainly installed on the awning panel or the roof, and the shade can be provided through the solar charging station, which is used by the solar energy. For example, the Solaroad developed by the Netherlands can be integrated by the solar panel. Electricity generation can be charged by EVs at adjacent stations [42][43]. At the same time, solar charging panels are being developed by Vision Solar and Tesla, and battery storage is included in them so that the intermittency of solar energy can be managed. Even with a low solar output, vehicle charging can be achieved [44]. As EV charging infrastructure integrates the sun, various benefits can be brought. From an environmental point of view, the carbon dioxide associated with vehicle charging can be reduced, and greenhouse gas emissions can be reduced. From an economic point of view, the construction provided by utilities can be offset by solar power. Excess power can be sold back through net metering, thereby reducing the costs associated with charging boards [45][46]. In addition, the energy independence of charging stations can be improved by solar loading, and the instability of the grid can be reduced. However, some challenges also exist in the process of charging EVs, the variability of solar energy is a major problem, and factors such as time and weather conditions play an important role [47][48]. To mitigate this problem, the integration of battery storage systems plays an important role. However, in such a system, the capital of the charging station infrastructure will increase, and its complexity will increase in the process of using such a system [49][50]. In addition, geography can also have an impact on the efficiency of solar panels, and if there is less sunlight on this day, then the power station needs to face a major challenge in generating electricity. Some limitations are also reflected in the space requirements for solar panels, especially in some cities where space is at a premium. For these spatial challenges to be overcome, solar panels require innovative design and effective planning, for example, building roofs and parking structures can be integrated with solar panels [51]. Other than that. There are significant upfront costs involved in installing solar panels and managing power management systems, although these energy costs are offset by long-term savings [52]. In the process of realizing sustainable transportation infrastructure, EV charging stations are integrated with solar energy, and the roads provided are very promising. Due to the falling cost and the continuous advancement of technology, it can provide greater power in the future of electric mobility.

2.3. Battery Energy Storage

In the push for sustainable energy solutions, this lays the foundation for the use of photovoltaic technology for solar power generation. In building a resilient, efficient and sustainable infrastructure, EV charging stations are integrated with a variety of renewable energy sources. In these integrations, hydrogen energy systems, battery storage, solar energy play a key role, opportunities and challenges are also brought by their integration, and its availability has a wide range of characteristics [53]. Different types of battery storage technology can be used by EV charging stations, each technology has different characteristics, and different operational needs can be required. Lithium-ion batteries have conventional characteristics, high efficiency and high energy density can be appreciated. Discharge cycles as well as fast charging can be included [54][55]. Technologies such as lead-acid batteries, which are known for their reliability and cost-effectiveness, are also included. Since capacity can be maintained over a long period of time, energy storage can be expressed over a long period of time [56]. Figure 2-2 shows the battery price trend prediction [54].

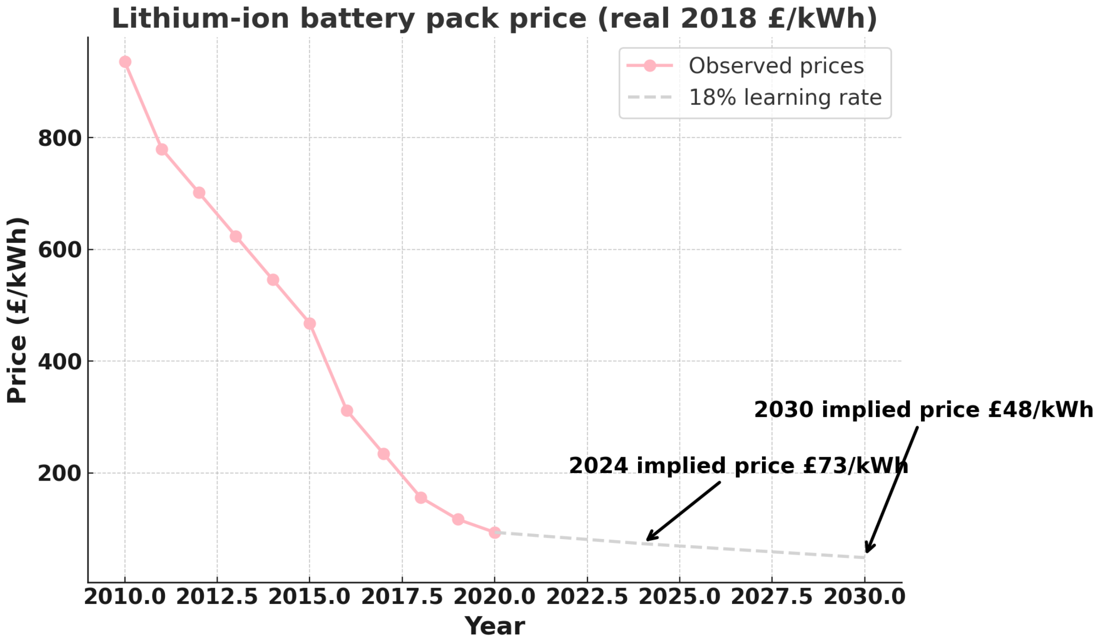


Figure 2-2 Evolution of battery prices over the last 10 years and future predictions [54]

An important role can be played in the process of energy load being balanced by EV charging stations. Excess energy can be generated by peak renewable energy production, and energy can be released during low renewable energy generation periods. For solar power stations, this capability plays an important role. At noon, the peak value can be reached by the energy of the solar power station, and this balance can be optimized by the battery management system, the stability of the grid will be enhanced, the reliability of the power supply of EVs can be ensured, and the fluctuation of renewable energy generation will not be considered [57]. If EV charging stations can be powered by renewable energy, operational efficiency can be ensured by providing energy on demand, service availability, and faster charging times can be promoted. The dependence of the grid on batteries can be reduced, especially during peak load periods, and the carbon footprint of the charging infrastructure can be reduced and operating costs reduced [58]. In addition, due to the continuous development of the Internet of Things and smart technologies, smart grid systems can be integrated by battery storage systems. Remote management as well as data analysis can be allowed through this integration, and predictive maintenance can be optimized so that downtime can be prevented. In addition, the power quality management of charging stations can be supported by adjusting voltage and frequency to be stored by batteries, so that the power quality problems existing in the grid can be checked [59][60]. As the demand for renewable energy integration is on the rise, the role of battery storage can be highlighted. The life cycle of storage systems and energy density can be improved by innovation in battery technology. Higher safety and energy density can be promoted through emerging technologies such as solid-state batteries, and the feasibility of renewable energy applications can be improved [61][62].

2.4. Hydrogen Storage System

In EV charging stations, hydrogen storage solutions offer sustainability and versatility, especially when integrated with renewable energy sources. Electrolysis is the main way to produce hydrogen, hydrogen and oxygen can be separated by water. Power can be provided by battery cars. [63] With EV charging stations as the main background, excess renewable energy can be generated by hydrogen storage through storage, and the balance between supply and demand can be achieved. If wind resources are insufficient, electricity can be converted by stored hydrogen, and a reliable energy supply can be provided by charging EVs. In addition, for fuel cell vehicles, hydrogen, a clean energy source, can become a substitute, and the energy diversification demonstrated by car charging stations can be realized [64][65]. EV charging infrastructure can be integrated with hydrogen systems. High-density energy storage can be achieved by hydrogen storage, especially in urban areas, where the resilience and flexibility of the grid is evident, and backup power options can be provided during outages. In addition, where needed, hydrogen can be transported, and alternatives to direct power plants can be achieved through the expansion of renewable energy coverage [66]. However, some challenges and technologies can be brought about by EV charging stations with integrated hydrogen storage systems. Finiteness is reflected in the efficiency of electrolysis, larger energy can be shown in the storage and compression of hydrogen, and the overall efficiency of the system can be reduced [67]. Compared with traditional fossil fuels, hydrogen fuel has a relatively backward infrastructure, and large upfront investment can be reflected in equipment and new technologies [68]. In the process of hydrogen energy system adoption, safety issues play a very important role, and highly flammable hydrogen is the main feature, which plays an important role in accident prevention and safe storage. As safety standards continue to evolve, additional challenges may be provided by station operators, and the broadness of adoption can be hampered. [69] In addition, more mature methods of energy storage, such as batteries, are less costly than storage technologies. During technological progress, these costs have been reduced [70]. Hydrogen has the potential to decarbonize the transport sector, and EV charging infrastructure can be integrated [71]. Thanks to advances in technology, existing barriers can be overcome by continuous research and development, and the feasibility of hydrogen can be realized in the development of sustainable mobility solutions.

2.5. Multi Energy System

One of the goals of various countries regarding the energy system is to have a smart energy grid that can facilitate efficient and cost-effective EV charging among other power needs [72]. Smart grids are such that the associated energy supply systems comprise of large node networks as well as a variety of energy types at each node. The different sources of energy are then integrated [73]. A key aspect of a smart grid is that it allows for integration and higher penetration of RE. In this respect, there is a consensus that increased use of RE has several benefits. First, RE systems such as wind and solar power have been considered as vital in overcoming the high reliance in fossil fuels which have been associated with global warming. In other words, RE sources contribute towards sustainable energy and reduction in greenhouse gas emissions [74].

Second, RE has the potential to reduces challenges such as transmission and distribution losses experienced in conventional power systems [75].

Despite the benefits associated with the use of RE systems they are characterized by one major disadvantage. Precisely, RE sources such as wind and solar power are intermittent in nature which leads to unreliability and may thus be ineffective for EV charging at certain times of the day [76]. As further explained by [77], the fluctuation in these energy sources possess the challenge of insufficient capacity of transmission lines. Specifically, RE systems are mainly decentralized, have low predictability, and introduce substantially high degree of volatility into energy grids. Considering such challenges, countries and cities relying on RE could thus be inclined to abandon these energy sources. One of the suggested solutions to addressing the unreliability issues of RE sources is the adoption of multi-energy systems. Such systems integrate hydrogen energy, photovoltaic energy and electric storage energy that enhance efficiency through the conversion, storage, and reuse of surplus electrical energy [78]. In detail, [79] elaborates that multi-energy systems which incorporate multiple energy sectors provides additional flexibility which helps in increase system flexibility and stability. Through multi-energy systems it becomes possible to achieve high overall energy efficiency by enhance the capacity to storage seasonal energy from different energy carriers. However, effective functioning of multi-energy systems requires effective design and operation of the grid-based system [79]. In this regard, the choice of energy storage system is an important consideration. Consequently, this section reviews the different energy storage systems that can be applied in a multi-energy system.

In the process of establishing an efficient, resilient and sustainable infrastructure, EV charging stations can integrate renewable energy sources. In integrating hydrogen systems, battery storage, and solar energy, an important role will be played, and opportunities and major technological challenges will arise [80][81]. This option is attractive when it comes to charging EVs, and in conjunction with the battery storage system, the power process can be provided by the sun, even under cloudy conditions, thus improving the reliability of the charging capacity. Hydrogen tank as an energy carrier, excess renewable energy can be stored by it. High-density energy can be provided for backup power and combustion battery vehicles, thus creating energy storage solutions with more multi-functional characteristics [82]. However, in the process of integrating these different energy sources, some technical challenges will be presented in having a cohesive charging infrastructure. Energy management is a major concern. The use, conversion and efficient storage of energy can be ensured through complex systems. In the process of balancing battery solutions, data monitoring and data analysis need to be employed [83]. This battery solution has a high hydrogen system cost, limited life cycle and high-capacity characteristics, and some obstacles exist in the optimization of the system, which is particularly obvious in terms of infrastructure compatibility, and the complex needs of renewable energy can be handled by the installation of EV charging stations. The physical space it contains includes large battery packs and electrolyzes for clear production, as well as the need for smart grid capabilities, energy supply and dynamic management [84]. In addition, some challenges exist in the interoperability of these systems. To enable the seamless operation of different power generation technologies and different storage. Standardized interfaces and protocols are required, and scalability is the main feature of these integrations. The increasing demand for charging stations and the growing demand for EVs can be accommodated [85]. In looking to the future, the performance and integration of renewable energy systems can be developed through the enhancement of EV charging stations. Energy management systems can be enhanced by advances in machine learning and artificial intelligence, and the integration of supply and demand can be achieved through efficient energy use [86]. Fast charging times and high energy densities can be provided through innovations in battery technology. Solid-state batteries are included, and battery storage options at EV charging stations may be changed [87][88]. In addition, hydrogen has a high production efficiency, green electrolysis is driven by renewable energy, and costs can be reduced. In EV charging infrastructure, scalable energy storage solutions can be enhanced by hydrogen [89].

2.6. Peer-to-Peer and Game Theory

P2P energy trading embodies an innovation shift in the energy sector, allowing individuals or businesses to exchange electricity directly, often bypassing traditional energy suppliers. This innovative model harnesses cutting-edge technologies like blockchain and smart grids to facilitate these transactions. By enabling more efficient use of renewable resources, P2P energy trading not only reduces energy costs but also diminishes small business or individuals' reliance on large utility companies. Moreover, it transforms consumers into 'prosumers'—both producers and consumers of energy—fostering a more sustainable energy ecosystem.

In Zhou's study [90], the dynamics of P2P energy sharing within smart communities are explored, particularly focusing on its impact on renewable energy adoption. The research categorizes various P2P systems, addresses the challenges they encounter, and examines how artificial intelligence and blockchain technologies could improve energy trading efficiency, highlighting significant economic and operational advantages [90]. The study emphasizes the importance of continued research to enhance the effectiveness of P2P systems in renewable energy markets, especially regarding their operation within community microgrids. A decentralized trading strategy based on game theory is introduced, considering the implications of distributed energy resource (DER) ownership [91]. While P2P trading offers economic benefits to participants, it can result in financial losses in areas with high photovoltaic system penetration, emphasizing the need for strategic DER management to optimize economic results in P2P energy markets [92]. Expanding on this, another study [93] uses fuzzy optimization to balance economic and environmental goals in energy trading, presenting a multi-period P2P model aimed at reducing both electricity costs and carbon emissions. Additionally, research utilizing a distributionally robust optimization technique incorporates a fuzzy set based on Wasserstein distance to address renewable energy prediction errors and proposes a day-ahead microgrid P2P transactive energy model using linear and convex programming methods to manage its nonlinear nature

[94]. A novel approach for optimizing P2P energy trading across multi-microgrid systems employs Nash bargaining theory and data-driven chance constraints, effectively managing uncertainties in renewable energy and load forecasting [95]. Finally, a comprehensive review in Journal [96] analyses 50 international P2P renewable energy trading projects, providing valuable insights into their scope, achievements, and future development prospects.

Game theory, a mathematical method for examining strategic behaviour among rational agents, is effectively utilized in renewable energy markets such as P2P energy trading. In these markets, diverse participants including consumers, prosumers, and utility companies engage in complex interactions [97-99]. Thesis studies show game theory provides a powerful framework to analyse decision-making processes at independent charging stations, where each entity acts as a rational player aiming to optimize their outcomes. This approach models their responses to dynamic shifts in energy supply, demand, and pricing, helping to predict behaviours in a competitive environment.

In the area of P2P energy trading, game theory is instrumental in optimizing energy distribution among participants. It aims to ensure that energy distribution is not only efficient and cost-effective but also equitable, considering the varied production capabilities and demands of different participants. One notable study [97] emphasizes the goal of achieving higher economic returns while maintaining balance among multiple agents. This research employs the finite improvement property and a variable-step iterative convergence method to ensure that the model achieves efficient and precise convergence. The outcomes of this model's simulation highlight improved energy utilization and an increase in economic benefits, illustrating the practical value of applying game theory to real-world scenarios. Another innovative contribution to this field is presented in a study [98] that proposes a new transactive energy market model combining blockchain technology and game theory. This model introduces a Proof-of-Reserve consensus mechanism that enhances transaction efficiency and privacy between prosumers and consumers. By implementing game-theoretic principles, this model strives to maintain a sustainable balance between energy production and consumption while safeguarding the privacy of economic agents [98]. Further expanding on the application of game theory in energy markets, another study [99] introduces a demand response program that leverages game theory. Targeting residential, commercial, and industrial sectors, this program integrates both incentive- and price-based demand response strategies. It assesses various pricing models, such as fixed pricing, time-of-use pricing, and real-time pricing, along with their combinations to optimize outcomes. This strategy aims to maximize utility profits, minimize consumer costs, and produce a more balanced load curve, demonstrating the multifaceted benefits of game theory in managing energy distribution more effectively. Study [100] addresses the issue of the underutilization of renewable energy by creating a bi-level energy optimization model utilizing game theory. Initially, a master-slave game model is set up between power suppliers and consumers to explore the bidding strategies between these two parties. Subsequently, a cooperative game model is employed to examine the distribution of energy demands among users interacting within the framework of the pricing strategies established in the first stage. The findings demonstrate that a game theory-based management model for renewable energy can significantly enhance its economic efficiency. In [101], it develops a bi-level optimization model using cooperative game theory to focus on ensuring the reliability of electricity market consumers. The results of the simulation analysis indicate that the cooperative game model effectively leverages bidirectional communication between the distribution system and its users. The model presents a dual-layer cooperative game approach that considers the reliability needs of electricity market consumers. Through this two-way interaction between users and distribution system utilities, the model offers various solutions to enhance the distribution system's reliability within the power system.

In summary, the integration of game theory into P2P energy trading and broader energy market strategies underscores its potential to foster more sophisticated and beneficial interactions among energy market participants, ultimately contributing to more sustainable and efficient energy systems.

2.7. Demand Side Management

Demand Side Management (DSM) is a critical component in the operation of smart grid systems, allowing end-users to take an active role in optimizing their electricity consumption [102][103]. DSM employs a variety of strategies designed to encourage consumers to use electricity more rationally and efficiently, thereby significantly improving the efficiency of terminal electricity usage. Moreover, DSM is essential for effective resource allocation by integrating the demand side into power market management. This integration helps prevent large-scale power outages that could arise from peak demand or the necessity for additional power generation infrastructure, ultimately leading to cost reductions within the smart grid system [104].

The inherent characteristics of electricity—its immediate consumption and difficulty in storage—necessitate that both supply and demand sides engage in rapid data exchange, make quick decisions, and adjust power consumption strategies in real-time. Achieving this level of responsiveness is challenging within traditional power grids. However, in smart grid systems, the incorporation of advanced technologies such as smart meters, smart homes, and cloud computing significantly enhances the capabilities of DSM, making it possible to achieve these rapid adjustments more effectively [105][106].

As the energy Internet continues to develop and expand, it enables the integration of multiple energy sources and more dynamic management practices. This evolution is transforming the operation of energy systems, promoting more sustainable and efficient energy consumption patterns that align with the broader shift towards comprehensive, interconnected energy networks. The emergence of these networks is not only enhancing the sustainability of energy systems but also paving the way for more resilient and adaptable energy management strategies that can better respond to the complexities of modern energy demands.

Demand response (DR), a key aspect of DSM, involves electricity consumers actively adjusting their power usage in response to market signals or incentives provided by power suppliers [107]. This approach is a fundamental component of DSM, as it significantly improves the efficiency of end-use electricity consumption, reduces resource wastage due to imbalances in power supply, and contributes to the overall stability of the electrical grid [108][109]. The rapid advancement of smart grid technologies, including the adoption of innovations such as smart homes and EVs, provides substantial technical support for the implementation of DR initiatives. These technologies facilitate more precise and real-time adjustments to energy usage, which are crucial for optimizing grid performance.

Additionally, DR benefits consumers by reducing their electricity bills through the modification of traditional consumption patterns and the strategic shifting of electricity usage away from peak periods, thereby helping to prevent large-scale power outages [110]. As distributed energy resources continue to develop, the synergy between regional energy systems—encompassing various forms of energy generation and storage—and power grid systems has enabled DR to evolve from a conventional method to a more comprehensive strategy. This strategy now manages a diverse array of load types, including wind, solar, electrical, and storage, further enhancing the flexibility and resilience of energy systems. This evolution has made the integration of DR into power system dispatch strategies a standard practice, reflecting its growing importance in achieving a more resilient, sustainable, and efficient energy landscape [111][112].

Incorporating DR into energy management not only facilitates greater operational flexibility but also enhances the economic operation of power systems by optimizing the use of available resources. The increasing prevalence of renewable energy sources, with their inherent variability, underscores the necessity for sophisticated DR strategies to maintain grid stability and efficiency [107][112]. As renewable energy becomes a more dominant force in the energy mix, the role of DR in balancing supply and demand will become even more critical. This will require ongoing advancements in DR technologies and strategies to ensure that power systems can continue to operate reliably and economically in an increasingly complex energy environment. The integration of DR into smart grids thus represents a pivotal development in the pursuit of a more sustainable and resilient energy future, where the efficient and flexible management of energy resources is key to meeting the demands of a modern, interconnected world.

2.8. Integration Challenges

Integrating renewable energy sources—such as PV systems, hydrogen storage, and battery technologies—into EVCSs presents a multifaceted set of technical, economic, and regulatory challenges [113]. For this infrastructure to achieve a stable, efficient, and sustainable operation, several critical issues require consideration. Solar energy, being inherently variable and contingent on weather patterns and diurnal cycles, presents reliability issues [114]. This intermittency poses a challenge to maintaining a stable power supply for EV charging, which necessitates a consistent energy source to ensure dependable operation. While hydrogen serves as a promising energy carrier for stabilising energy output, its production—frequently reliant on renewable electricity through electrolysis—can be compromised by the same intermittency issues that affect solar and wind power [115]. Battery storage can offer a degree of energy security, yet these systems face inherent limitations. Not only are large-scale batteries costly, but they also degrade over time, necessitating periodic replacement and incurring significant lifecycle costs [116]. In practice, the balance between the cost of these systems and the level of resilience they provide remains an ongoing dilemma. A high proportion of renewables can jeopardise grid stability, given the inherent variability in their output. EVCSs, therefore, must collaborate closely with grid operators to mitigate stability risks, potentially necessitating costly grid reinforcements to support the fluctuating inputs from renewable sources [117]. Establishing EVCSs powered by renewable energy necessitates a substantial upfront investment. Costs are incurred not only for PV panels and associated equipment but also for battery storage, hydrogen storage systems, and the integration of supportive infrastructure. Without governmental incentives or subsidies, the economic burden of these initial expenditures may hinder widespread implementation [118]. Maintenance and system degradation also contribute to operational costs, particularly with storage solutions such as batteries, which experience performance decline over time. Without a financial model that accommodates these expenses, renewable-powered charging stations may struggle to achieve economic viability [118][119]. Integrating various renewable technologies—such as PV systems, batteries, and hydrogen storage—into a single, cohesive EVCS infrastructure necessitates compatibility across diverse energy management and control technologies. This technical coordination is often challenging, requiring advanced interoperability and control systems to ensure efficiency and reliability. Efficiently managing the multiple energy sources involved demands sophisticated energy management systems capable of optimising energy storage, load distribution, and charging outputs. Developing or procuring these technologies adds operational complexity and, consequently, cost [120][121]. In another hand, consumer behaviour, particularly around peak and off-peak charging times, significantly impacts energy requirements [122]. High demand during peak times may strain a renewable-based system, requiring costly supplemental power or extensive storage to maintain an acceptable level of service reliability.

Addressing these challenges is essential for the successful integration of renewable energy sources into EV charging infrastructure. Collaboration between technology providers, grid operators, regulatory bodies, and EV infrastructure developers will be critical to overcoming these hurdles and advancing the renewable-powered EV charging network.

2.9. Model and Theoretical Background

Constructing and operating a RE EVCS is a complex issue that requires extensive theoretical knowledge. The establishment and operation of a single EVCS can be considered a basic modelling problem. Integrating renewable energy sources such as solar or hydrogen into EVCS requires understanding the intermittent nature of these energy outputs and managing them with storage solutions like batteries. Additionally, designing and constructing the physical infrastructure is critical. This includes selecting suitable chargers, energy storage systems, and necessary hardware to manage high power demands. Compliance with local and national regulations concerning energy, construction, and operation is also crucial, alongside adopting to environmental standards and safety regulations. Furthermore, investing in an EVCS requires a thorough financial viability assessment, involving cost analysis, pricing models, incentives, and an understanding of the economic impacts of fluctuating energy prices on operations. It is also important to predict and meet the demand patterns of EV users by analysing peak usage times, charging durations, and user behaviour analytics.

However, when it involves two EVCSs, it is necessary to consider their cost and profit when they are having energy exchanges, which requires selecting appropriate computational methods to optimize results quickly and effectively. When multiple EVCSs operate together, P2P interactions and decision-making issues arise. As mentioned in the previous chapter, to ensure the minimization of costs and maximization of profits for multiple EVCSs, cooperative game theory is the preferred strategy, which can set the internal price that all gamers need to follow. After solving the technical or physical issues, the management of the power demand of the EVCSs and the charging intentions of EV drivers also need to be considered. Only by integrating these factors can multiple EVCSs operate efficiently. This chapter will introduce the basic theories and methods applied in the configuration and optimization of the model.

2.9.1. Mathematic Model for Renewable Energy

This model integrates photovoltaic, battery storage, hydrogen storage. The fundamental structure of the model is outlined as follows:

2.9.1.1. Photovoltaic model

A photovoltaic power generation model is adopted [123] as follows:

$$P_{pv} = P_{STC} G_{AC} \frac{[1+k(T_c - T_r)]}{G_{STC}} \tag{2.1}$$

Where: P_{pv} is photovoltaic cell output power; G_{AC} is light intensity; P_{STC} is the maximum test power under standard test conditions (sunlight incident intensity of 1000W/m^2, ambient temperature of 25°C); G_{STC} is the illumination intensity under standard test conditions, and its value is 1000W/m. K is the power temperature coefficient; T_c is the operating temperature of the panel; T_r is the reference temperature.

2.9.1.2. Hydrogen system model

Given the unpredictable and often cloudy weather in the UK, it becomes evident that relying solely on photovoltaic energy may not suffice to meet the demands of EVCS. Although there have been significant advancements in battery technology, the high costs associated with batteries remain a major obstacle to widespread adoption and scalability. Considering these challenges, hydrogen presents itself as a promising alternative within the realm of renewable energy options. Its flexibility and ease of transportation make it particularly suitable for urban environments [124]. Hydrogen energy storage is especially noteworthy for its high energy density, which not only boosts energy resilience but also helps balance the grid by providing a reliable, on-demand energy source. This innovative approach is crucial for reducing greenhouse gas emissions, promoting cleaner transportation solutions, and paving the way for a more sustainable energy infrastructure in the future. Additionally, the potential for hydrogen to be generated through processes like electrolysis using surplus renewable energy further enhances its appeal. As the technology and infrastructure for hydrogen production and storage continue to evolve, it could play a pivotal role in addressing the limitations of other renewable energy sources and ensuring a consistent energy supply for various applications.

The equivalent electric power of hydrogen produced by the electrolyze during the time interval *t* is:

$$P_{H_2,i}^{t} = P_{E2H}^{t}\alpha_{E2H} \quad \mathrm{i} \in \mathrm{N_{HSS}} \tag{2.2}$$

The power generation of hydrogen fuel cell is as follows:

$$P_{H2P,i}^{t} = P_{H-FC}^{t}\beta_{E2P}\eta^{FC}, \quad \mathrm{i} \in \mathrm{N_{HSS}} \tag{2.3}$$

The equivalent SOC of hydrogen storage capacity of hydrogen storage tank in *t* interval is as follows:

$$E_{H_2,i}^{t} = E_{H_2,i}^{t-1} - (P_{H-FC,i}^{t} + P_{SH,i}^{t} + P_{H_2,i}^{t})\Delta t, \quad \mathrm{i} \in \mathrm{N_{HSS}} \tag{2.4}$$

Where: P_{E2H}^{t} and P_{H-FC}^{t} are the power consumption of electrolysis and fuel cell respectively; α_{E2H} and β_{E2P} are the conversion efficiency of electrolyser and fuel cell respectively; η^{FC} represent the FC efficiency; $E_{H_2,i}^{t-1}$, $P_{SH,i}^{t}$ and Δt are the residual hydrogen storage equivalent electricity in *t-1* interval, and the equivalent power of hydrogen load and unit time interval respectively; $\mathrm{N_{HSS}}$ is the set of hydrogen system nodes.

2.9.1.3. Battery storage system

This study utilized the battery as the energy storage element. The battery is crucial in stabilizing power fluctuations and enhancing power quality in SHS-EV charging stations. The available battery capacity $S_{Bat,a,t}$ is defined as [125]:

$$P_{Bat,e,t} = P_{Bat,e,t1}\left(1 - \sigma_{Bat,e}\right) + (P_{Bat,e,t}^{cha} * \eta_{Bat,e}^{cha} + \frac{P_{Bat,e,t}^{dis}}{\eta_{Bat,e}^{dis}})\Delta t \tag{2.5}$$

Where $P_{Bat,e,t}$ and $P_{Bat,e,t1}$ are the residual capacity of battery pack *e* in time *t* and *t1*, respectively; $\sigma_{Bat,e}$ is the self discharge rate of battery group *e*; $P_{Bat,a,t}^{cha}$, $P_{Bat,a,t}^{dis}$ are the charging power and discharge power of battery pack *e* in time t respectively, and the power during discharge is negative; $\eta_{Bat,e}^{cha}$, $\eta_{Bat,e}^{dis}$ are the charging efficiency and discharge efficiency of battery pack *e* in interval *t* respectively.

2.9.2. Basic Concepts of Multi-Objective Optimization

The aim of exploring multi-objective optimization problems is to optimize several competing objectives within given constraints to identify the best solution [126]. The three critical elements of multi-objective optimization problems include the objective function, constraints, and decision variables. Generally, multi-objective optimization problems can be formulated as the following mathematical model:

$$\begin{cases} minf(x) = (f_1(x), f_2(x), \dots, f_m(x))^T \\ g_j(x) \leq 0, j = 1,2, \dots, p \\ h_k(x) \leq 0, k = 1,2, \dots, q \end{cases} \quad 2.6$$

Where $x = (x_1, x_2, \dots, x_n) \in X \subset R^n$ is n's decision variable; m is the number of objective functions; $g_j(x)$ is the j's inequality constraints; $h_k(x)$ is k's inequality constraints; p and q are the inequality and equality number.

In multi-objective optimization, enhancing the performance of the target object according to one objective often leads to poorer performance according to another. This implies that in multi-objective optimization, there typically isn't a single optimal solution that excels across all objectives. Moreover, the optimal solution is not singular; rather, a set of optimal solutions, often referred to as Pareto optimal solutions or non-dominated solutions, is usually obtained.

The approaches to solving multi-objective optimization models are primarily categorized into indirect and direct solution methods. Indirect methods convert a multi-objective problem into a single-objective problem for resolution, including techniques such as the constraint method and the linear weighted sum method. Direct methods, on the other hand, are based on Pareto optimization, primarily utilizing multi-objective heuristic algorithms. These heuristic algorithms are less restrictive in terms of model structure and can address large-scale and complex issues.

2.9.2.1. Non-dominated Sorting Genetic Algorithm (NSGA-II) and Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA-D)

NSGA-II employs a ranking-based strategy to identify non-dominated solutions, which represent the best solutions in multi-objective optimization. It organizes individuals by their dominance relationships into different tiers, where those on the top tier are non-dominated, meaning no other individual in the population performs better across all objective functions. NSGA-II also utilizes a crowding distance measure to ensure diversity within the population [127,128]. Conversely, MOEA/D uses a decomposition approach that breaks down the multi-objective optimization problem into several single-objective subproblems. It tackles these subproblems concurrently and integrates their results to form the Pareto optimal front. Throughout the process, MOEA/D continually adjusts the weights given to each objective in the subproblems to enhance solution convergence and diversity [129].

MOEA/D generally converges faster and uses fewer computational resources than NSGA-II, making it ideal for handling large-scale optimization challenges. However, NSGA-II excels in maintaining diversity and is more effective in uncovering the global Pareto front in intricate scenarios [128]. Moreover, NSGA-II is broadly recognized and frequently used as a benchmark in multi-objective optimization across various fields. Both NSGA-II and MOEA/D have proven to be robust algorithms in multi-objective optimization, particularly in applications involving renewable energy. The choice between them should be guided by the specifics of the problem and the desired balance between computational efficiency and the quality of solutions [129]. This thesis will also determine the best algorithm based on the analysis of the Pareto front and Pareto optimal solutions.

2.9.2.2. Game Theory

In the cooperative game model, an alliance is defined as a subset S of the set of participants *N*. For a set of *I* participants, $2^I - 1$ distinct alliances can be established. Specifically, when *S*=*N*, it signifies that all participants are included in a complete cooperative game model. When the participants are divided into several non-overlapping subsets, these groups are termed the alliance structure of the cooperative game. Each alliance structure itself represents a cooperative game model, which can be denoted as $S^C = \{S_{1,} S_{2,} \dots S_I\}$, these must satisfy the condition:

$$\cup_{i=1}^{I} S_i = N, S_i \cap S_j = \emptyset, \forall i \neq j \qquad 2.7$$

A fair and equitable distribution strategy is crucial for forming stable alliances among participants. Widely used allocation strategies include the Shapley value method and the nucleolus method, etc.

Basic Shapley:

$$x(i) = \sum_{S \subset N, i \in S} \frac{(|S|-1)!(n-|S|)!}{n!} [v(S) - v(S \backslash i) \quad 2.8$$

Where n is the single participant in game, N is the set of participants; $|S|$ is the participant in coalition S; v is the pay-out function, and $v \neq 0$.

To distribute the internal interests of the portfolio, the Shapley value can be improved more reasonably to reasonably measure the contribution of each internal unit and ensure the fairness of the distribution strategy. The update model as follow:

$$D(i) = \frac{1}{n-1} \frac{\sum_{j \in \{N \backslash i\}} x(j) - v(N \backslash i)}{x(i) - v(i)} \quad 2.9$$

When $D(i) \geq 1$, it means that the non-cooperative actions of participant i result in losses for other participants that are at least as great as those incurred by participant i themselves. Because of that, participant i is highly likely to reject the proposed allocation strategy. Conversely, when $D(i) < 1$, participant i is inclined to agree to the allocation strategy, and the lower the value of $D(i)$, the greater participant $i's$ readiness to collaborate, leading to increased satisfaction with the allocation strategy.

2.9.3. Social Welfare

Welfare has always been a basic concern for society, and the relationship between individual needs and social interests constitutes the core concern of modern social welfare thought. "Social welfare" is the result of the public's choice in the distribution of social benefits under specific institutional arrangements. It represents a collective or group interest [130]. "Utility" refers to the psychological satisfaction consumers obtain in the consumption process. Economics uses the two most basic concepts of welfare and utility to try to explain and illustrate the possible balance of interests between personal motivations and social choices.

2.9.3.1. Social welfare maximization model

Chapter 6 is primarily exploring a model aimed at maximizing social welfare for EV drivers.

In the society, electricity usage is categorized into three user types: household, commercial, and industrial. Let's assume there are D EV drivers of a particular type within a country or region. Each driver $d \in D = \{1,2, \dots, D\}$, has their consumption over 24 hours segmented into K time interval, and each interval is denoted by $k \in K = \{1,2, \dots, K\}$, x_d^k means driver d at *t-th* interval's electricity consumption, which range from $x_d^k \in [m_d^K, M_d^K]$, where $m_d^K \geq 0$ and $M_d^K \geq 0$, and they are the minimum and maximum consumptions of driver g at interval of k, respectively. G_k represents the production capacity of the SHS-EVCS in the *k-th* interval; $C_k(G_k)$ indicates the cost of producing $G_k$units of electricity in that interval. The utility of the *d-th* driver consuming x_d^k electricity is given by $V_d(x_d^k, \omega_d^k)$, where ω_i^k is the elasticity coefficient of the EV driver, varying across different EV drivers and times, allowing for tailored utility assessments.

An innovative price-based real-time electricity pricing model [131, 132, 133] is proposed to maximize the difference between the EV driver's total utility and the electricity provider's (SHS-EVCS) cost and establish the following optimization problem:

$$\begin{aligned} & max \sum_{k=1}^{K} (\sum_{d=1}^{D} V_1(x_d^k, \omega_d^k) - C_k(G_k)) \\ & s.t. \sum_{d \in D} x_d^k \leq G_k \,, k = 1,2, \dots, K, \\ & x_d^k \geq 0, k = 1,2, \dots, K. \end{aligned} \qquad 2.10$$

The objective function of the optimization problem (2.10) aims to maximize the total social welfare, with a constraint that the total charging amount for all EV drivers does not exceed the overall power generation capacity of the charging station. This optimization problem (2.10) explores strategies for maximizing social benefits given the existing power generation limits, which is referred to as the social welfare maximization model. In this thesis, the total social welfare means both SHS-EVCSs and EV drivers' welfare.

2.9.3.2. Utility function model

In this model, $V(x, \omega)$ is the utility function, $0 < \omega \leq 1$ is the known parameter. For each EV driver, the function value of the utility function represents the driver's satisfaction after using the purchased electricity. Each EV driver in the SHS-EVCS system is an independent individual, and power demand can be characterized by different parameters, such as different times of the day, climate conditions, electricity prices and other factors. Power demand also depends on the type of EV driver or vehicle type. For the same electricity price, different driver will have different reactions. Different utility functions can be used to describe the types of EV drivers, and different EV drivers can be distinguished by elastic coefficients ω. Under the same conditions, the larger the value of ω, the higher the user's optimal electricity consumption. The elastic coefficient directly reflects the driver's electricity consumption preference.

This model can write as [134]:

$$V(x, \omega) = \begin{cases} \omega x - \frac{\alpha}{2} x^2, & 0 \leq x \leq \frac{\omega}{\alpha} \\ \frac{\omega^2}{2\alpha}, & x \geq \frac{\omega}{\alpha} \end{cases} \tag{2.1}$$

Where α and ω are both constant numbers, ω is drivers' willingness of electricity consumption, x is the quantity of electricity that drivers' need.

2.9.4. Methodology

This thesis provides detailed theoretical concepts and mathematical models for integrating renewable energy sources into EVCS. It discusses the models for solar energy, battery storage, and hydrogen storage systems, alongside optimization algorithms such as Particle Swarm Optimization (PSO), NSGA-II and MOEA-D. P2P energy trading strategy based on game theory and social welfare models are also introduced to frame the interaction and economic aspects between multiple energy integrated CS planning and operation.

Chapter 3 of the thesis presents a comprehensive framework for planning and operating a SHS-EVCS. The SHS-EVCS is designed to serve urban smart city needs with capabilities for super-fast and off-grid charging. It integrates multiple energy sources—solar, hydrogen, and batteries—to create a multi-energy system capable of efficient power generation and storage. Hydrogen storage system includes an electrolyser for hydrogen production, a fuel cell generator for power generation, and a hydrogen storage tank for long-term energy reserves. PV system captures solar energy and converts it into electricity, reducing reliance on traditional power grids. Battery storage system ensures energy is available for EV charging during peak demands or when solar power is insufficient. The SHS-EVCS utilizes PSO algorithm to minimize operational and investment costs while maintaining energy storage levels. Implements energy trading strategy and selling electricity, which leverages time-of-use pricing to optimize costs and enhance economic efficiency. Chapter 4 introduces an optimization framework for multiple SHS-EVCSs using NSGA-II and MOEA/D algorithms. The study evaluates energy trading between stations using a peer-to-peer model and game theory. Simulations for stations in London and Dali demonstrate the strategy's efficacy in balancing costs and environmental impact. Chapter 5 create A bi-level optimization model incorporating non-cooperative and cooperative game theories is developed to manage energy dispatch and maximize social welfare. The chapter includes models for real-time pricing and demand response, supported by Markov decision processes and Monte Carlo simulations to forecast EV charging patterns. This strategy optimizes social welfare while minimizing capital and operational costs.

2.10. Research gap and questions

Current discussions around EVCSs tend to focus on aspects like charging status, practical applications, and overall development potential. However, a notable research gap exists in exploring EVCS facilities that combine multiple renewable energy sources, especially hybrid systems like solar-hydrogen-storage. Most studies so far have concentrated on microgrid technology, which integrates renewable energy sources, storage systems, and EV charging through advanced internet-based scheduling. While these studies are valuable, they largely aim to improve individual EV charging methods, manage capacity among various infrastructure components, and enhance control systems for operational efficiency. However, the literature often overlooks the complexities involved in integrating multiple energy sources—particularly in balancing the intermittent nature of renewables, storage demands, and power management in hybrid systems like solar-hydrogen-storage. The challenges of multi-source integration, such as ensuring grid stability, addressing renewable intermittency, and implementing sophisticated energy management systems, remain underexplored. Additionally, limited research examines the relationship between system reliability and user experience in multi-source EVCSs, particularly regarding how factors like charging time and costs affect consumer satisfaction and adoption rates.

This thesis seeks to address the following three main research questions:

1. How can an intricate model for EVCSs be established to facilitate direct energy exchange between stations, bypassing the traditional distribution network?
2. What P2P optimal dispatch strategies, grounded in game theory, can be developed for SHS-EVCSs systems to enhance economic returns and achieve income balance across multiple SHS-EVCSs?
3. How can a bi-level optimization model, integrating both non-cooperative and cooperative game theory, be constructed to minimise capital costs and maximise social welfare within a network of SHS-EVCSs?

2.11. Chapter Summary

This chapter provides a comprehensive review of the theoretical frameworks and modelling approaches about renewable energy sources into EVCS in smart urban environments. It includes various renewable energy models, including photovoltaic, hydrogen, and battery energy systems, which for understanding the complexities and potential of renewable integration. This chapter also incorporates advanced analytical models such as game theory and social welfare models to address the operational and economic aspects of energy systems. Game theory models are employed to strategize the interactions and energy exchanges between multiple EVCS, ensuring that these interactions are optimized for cost efficiency and fairness. The social welfare model integrates economic and social considerations into the planning and operation of EVCS. This model focuses on maximizing societal benefits for both EV drivers and SHS-EVCSs side.

Chapter 3. SHS-EV Charging Station Planning and Operation

3.1 Introduction

Currently, the global EV fleet is estimated at 7.5 million, predominantly consisting of small/light vehicles, though the number of medium and heavy commercial vehicles is rapidly expanding. China holds the largest proportion of EVs at 45%, while Europe is one of the fastest-growing markets, having seen a sales increase of 44% in 2019 [135]. EVs can be categorized based on their battery type into Battery Electric Vehicles (BEVs) and Fuel Cell Electric Vehicles (FCEVs). The primary distinction is that FCEVs operate without the need for external charging systems, whereas BEVs rely entirely on external power from the grid to charge their batteries [136]. The slow pace of growth in the global EV market is often linked to the high production costs. Nonetheless, projections suggest that the number of EVs in use worldwide will surpass 100 million by 2035, with production anticipated to reach 548 million by 2040 [135].

As EVs continue to gain popularity, various initiatives are being launched to expand the charging infrastructure. These efforts include developing a broader network of charging stations, categorized into residential and non-residential types. Charging stations are also differentiated into slow charging (level 1 and level 2) and fast charging stations (level 3 and DC). According to Xi et al. [137], level one charging stations utilize a standard wall outlet with a 110V/15A connection, typically taking 12 to 18 hours to fully charge a battery. Level two stations offer a higher capacity circuit, usually 220V, designed for quicker charging. Fast charging stations, which operate at 400 to 500V, can charge an EV battery in under an hour. In the UK, the number of fast charging stations has seen significant growth over time shows in figure 3-1 and table 3-1[138].

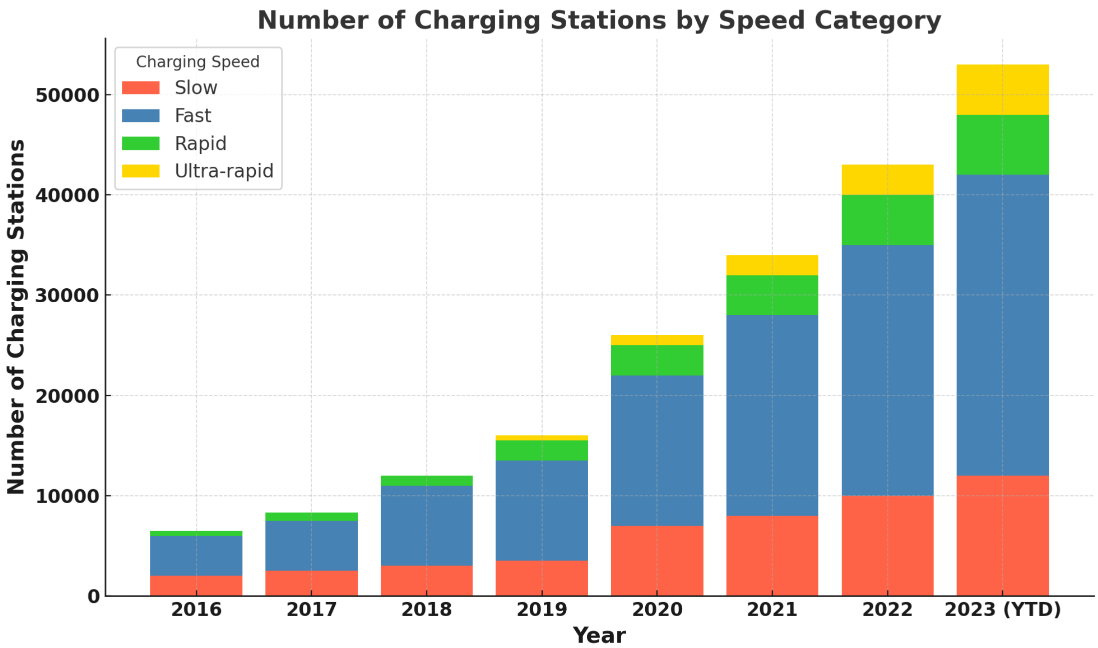


Figure 3-1 Charging stations by type in the UK [138]

Table 3-1 Power rating of four types of charging stations

Type	Slow	Fast	Rapid	Ultra-rapid
Power Rating (kW)	3–6	7–22	25–99	100

This chapter introduces a novel design for a SHS-EVCS for future smart cities. The simulation of the SHS-EVCS encompasses several components: for hydrogen storage system, it has a hydrogen fuel cell generator, an electrolysis unit for hydrogen production and storage systems for hydrogen, a solar power facility for on-site energy capture and batteries to manage local energy equilibrium. This integrated approach not only enhances the efficiency of energy use but also ensures a steady supply of power even in fluctuating environmental conditions or grid outages, which means it has ability to supply the city when it faces to a power shortage. The main contribution of this chapter is to minimize operational costs, which include expenditures for hydrogen fuel and electricity.

This chapter can be seeing as a foundational concept for the subsequent chapters. A simple contribution to this chapter as follows:

- A novel SHS-EVCS with two primary features: super-fast and off-grid charging; a versatile multi-energy charging system that utilizes solar energy, hydrogen, and battery storage.
- Explores the direct transfer of electric energy between SHS-EVCSs, bypassing the traditional distribution network, aiming to illuminate its feasibility, advantages, and challenges within this emerging framework.

3.2 Multi Energy System Planning and Operation

As showed in Figure 3-2, the SHS-EVCS design aims to address and capitalize on the increasing need for sustainable and efficient energy solutions in urban mobility. The SHS-EVCS, through its integrated system design and modelling, includes a hydrogen fuel cell generator designed for off-grid and high-density power generation. Additionally, it features a local solar power generation facility that captures and converts sunlight into usable energy, thereby reducing reliance on traditional power grids. A power-to-gas electrolysis unit is utilized for hydrogen production, sourcing energy from both the power grid and local solar installations, which further supplements the station's energy reserves. The system is rounded out with hydrogen and battery storage facilities that are crucial for maintaining local energy balance and ensuring continuous operation, regardless of external power fluctuations.

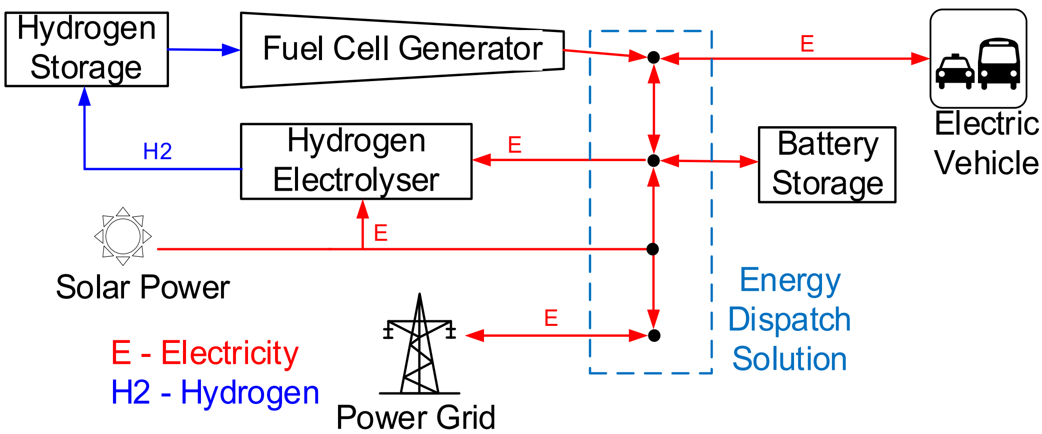


Figure 3-2: Prototype design of SHS-EVCS

The operational model of the SHS-EVCS is particularly innovative due to its ability to engage in energy trading. The station is equipped to buy and sell electricity from and to the power grid, which is incentivized by the daily variations in electricity prices. This capability not only enhances the economic viability of the station by tapping into arbitrage opportunities but also promotes a more dynamic interaction with the energy market. By aligning the charging station’s activity with periods of lower prices, it effectively reduces operational costs and contributes to grid stability during peak demand times. This strategic interaction with the market ensures that the station operates at peak efficiency, leveraging lower-cost energy for charging during off-peak hours and selling back energy during high demand periods.

Moreover, the SHS-EVCS’s design reflects a significant shift towards sustainability in urban infrastructure. The dual use of hydrogen and solar energy not only minimizes the environmental footprint of the charging station but also serves as a model for future developments in RE integration within smart cities. The inclusion of advanced storage solutions further enhances the station’s resilience, allowing it to store excess energy produced during peak solar hours for use during less optimal conditions or at night. By implementing these innovative technologies, the SHS-EVCS not only meets the current demands of EV charging but also anticipates the growth and evolution of urban transportation networks, setting a precedent for future sustainable development projects.

3.3 Model for SHS-EV Charging Station

PV technology is essential for harnessing solar energy, a plentiful renewable resource in the world, despite its reputation for cloudy weather. Solar power contributes to reducing carbon footprints and aligns with the UK’s goal to achieve net-zero emissions by 2050 [19] [20]. The scalability of PV installations allows them to be adapted for residential, commercial, and large-scale utility purposes.

Hydrogen storage systems represent a pivotal technology in the UK’s energy strategy, particularly for balancing intermittent energy supplies from renewables like solar and wind. Hydrogen can be produced through electrolysis (often powered by renewables), stored, transported, and used when needed without direct emissions, offering a clean alternative to fossil fuels.

Battery storage systems are crucial for managing the variability and intermittency of renewable energy sources. By storing excess energy produced during peak production times, batteries enable a steady and reliable supply of electricity, even when solar or wind generation is low, and it helps to reduce the energy loss during the gas to power in hydrogen storage system. This technology enhances grid stability and can reduce the need for backup power from carbon-intensive sources.

Combining these technologies—PV, hydrogen, and battery storage—enhances the flexibility and resilience of the UK's energy system. It allows for higher penetration of renewable resources, reduces dependence on imported energy, and mitigates the impacts of fluctuating energy prices. Furthermore, the integrated approach supports sector coupling, where surplus renewable energy can be utilized across different sectors, such as heating and transportation, optimizing energy use and further reducing emissions.

Hydrogen storage presents several risks due to hydrogen's unique chemical and physical properties. These risks primarily revolve around flammability, leakage, storage requirements, and safety standards [63-71]. Hydrogen is highly flammable and can ignite at a wide range of concentrations (4% to 75% by volume in air). It has a low ignition energy, meaning it can be ignited by even small sparks, static electricity, or high temperatures [66]. When mixed with air in confined spaces, hydrogen can cause explosions if ignited, posing a significant safety risk, especially in populated areas or confined environments [64]. Hydrogen molecules are extremely small, allowing them to permeate through materials that are typically impermeable to other gases. This increases the likelihood of leaks from storage tanks, pipes, and connectors. Hydrogen gas is colourless, odourless, and tasteless, making leaks difficult to detect without specialized sensors. Hydrogen's low density means that it disperses quickly, which is beneficial outdoors, but in enclosed or poorly ventilated spaces, leaked hydrogen can accumulate and present a flammability risk.

Overall, this integrated approach provides a viable pathway toward a sustainable, low-carbon energy future. However, ensuring safety during installation and maintenance is essential, particularly for hydrogen and battery storage, which require continuous monitoring throughout these processes.

3.3.1. Charging Station Data Collect and EV Prediction.

The data utilized for the analysis of EV charging station location selection in this article is sourced from GOV.UK. This includes comprehensive datasets on EV usage and the existing infrastructure of petrol stations (the EV charging station location selection for this thesis), which provide critical insights into the current landscape and potential areas for development. By integrating these data sources, the article aims to present a well-informed discussion on optimizing the placement of new charging stations to best serve the growing number of EV drivers in the region. Table 3-2 shows the total petrol stations in London [139], where the decided location for SHS-EVCS. The bold and Italic is the designed single SHS-EVCS location.

Table 3-2 Total petrol stations [139]

Borough	**2017**	2020
Barking & Dagenham	16	18
Barnet	28	22
Bexley	17	16
Brent	27	16
Bromley	31	34
Camden	7	7
City of London	0	0
Croydon	28	28
Ealing	28	28
Enfield	31	34
Greenwich	23	23
Hackney	8	8
Hammersmith & Fulham	***5***	***5***
Haringey	18	17

Harrow	15	10
Havering	17	20
Hillingdon	24	23
Hounslow	25	24
Islington	6	6
Kensington & Chelsea	8	7
Kingston upon Thames	10	11
Lambeth	13	13
Lewisham	19	16
Merton	12	11
Newham	13	14
Redbridge	16	18
Richmond upon Thames	***15***	***14***
Southwark	18	17
Sutton	12	11
Tower Hamlets	11	10
Waltham Forest	21	21
Wandsworth	18	18
Westminster	11	11
Total Petrol Stations	551	531

The calculation for the average daily flow is estimated by dividing the annual traffic estimate by the road length and the number of days in the year.

Table 3-3 Motor vehicle flow by road class and region and country in Great Britain, 2020 [140]

Thousand vehicles per day	Motorway	Rural	Urban
North East	43.8	12.4	15.9
North West	62.5	9.0	13.1
Yorkshire and the Humber	58.5	9.7	14.1
East Midlands	74.0	11.9	14.3
West Midlands	62.5	10.0	15.5
East of England	84.9	16.4	14.9
London	***89.2***	***29.7***	***21.6***
South East	71.6	14.7	14.7
South West	59.5	9.5	14.4
England	66.4	11.9	15.7
Wales	53.0	6.6	13.4
Scotland	36.2	3.7	10.9
Great Britain	62.0	9.3	15.0

Figure 3-3 shows a traffic flow map of the United Kingdom, categorizing roads based on the volume of vehicles per day. Each colour on the map represents a different range of daily vehicle traffic:

- Light Blue: Up to 5,000 vehicles;
- Blue: 5,000 to 10,000 vehicles;
- Green: 10,000 to 15,000 vehicles;
- Light Yellow: 15,000 to 20,000 vehicles;
- Yellow: 20,000 to 25,000 vehicles;
- Orange: 25,000 to 30,000 vehicles;
- Light Red: 30,000 to 35,000 vehicles;
- Red: 35,000 to 40,000 vehicles;
- Dark Red: 40,000 to 45,000 vehicles;
- Maroon: Over 45,000 vehicles.

From the colour distribution in London that black circle pointed, the major traffic volumes are between 20,000-45,000, sometimes over 45,000, compare to table 3-2, both give the clue for EV prediction in London.

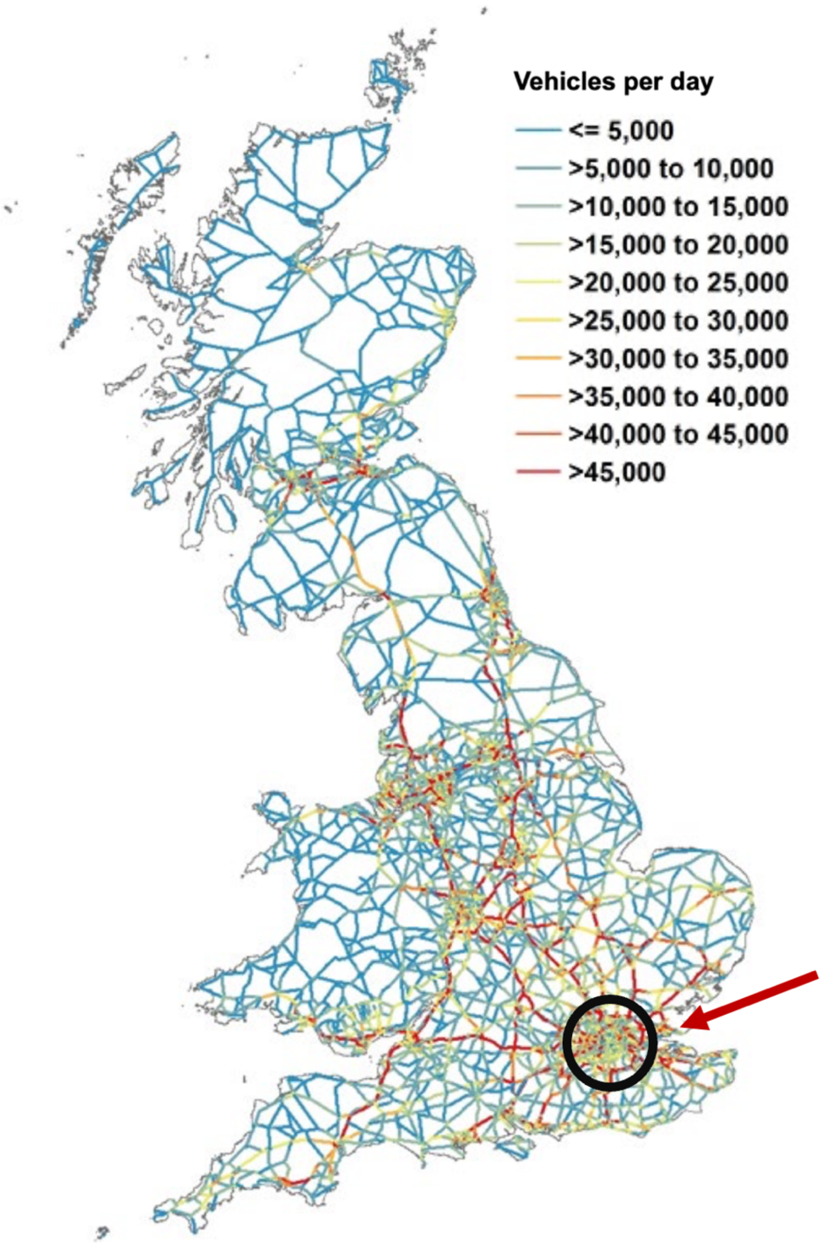


Figure 3-3 Average daily flows on motorways and ‘A’ roads in Great Britain, 2021 [141]

3.3.2. SHS-EV Charging Station Model

3.3.2.1. Objective Function

➢ *Single SHS-EVCS objective function*

The goal of the design is to reduce both the investment and operational costs of SHS-EVCS. This goal can be broken down into three main parts: the initial construction investment costC_0, the selling and buying cost from grid C_S, and the ongoing SHS-EVCS operational cost C_1. The initial investment includes the costs of building and equipping each distributed unit within the charging system, with the energy storage capacity influencing these expenses.

$$minF = min\,(C_0 + C_S + \textstyle\sum_{m=1}^{N} \sum_{n=1}^{Y} C_1\,[m, n]) \qquad 3.1$$

Where N is the subsystem, Y is 24 hours. C_S is the SHS-EVCSs is buying and selling the electricity to grid.

As the SHS-EVCSs is buying and selling the electricity to grid, the profit of selling electricity model in this chapter is giving as follow:

$$C_S = \textstyle\sum_{t=1}^{24} (C_{grid}^{t} \sum_{i=1}^{Ngrid} P_{G,i}^{t} + C_{SHS} \sum_{j=1}^{N_{SHS}} P_{SHS,j}^{t}) \qquad 3.2$$

Where: C_{grid}^{t} and C_{SH} are the price of selling or purchasing electricity to the power grid and the price of hydrogen generated per unit of electricity consumed in t period respectively; $P_{G,i}^{t}$ and $P_{SHS,j}^{t}$ are the electricity generated by the grid and SHS-EVCS in t perid.

The investment cost model in this chapter is updated to follows:

$$C_0 = C_{0,PV} + C_{0,BS} + C_{0,HSS} \qquad 3.3$$

$$C_{0,PV} = \frac{P_{PV}(1 + r_{PV})^{yPV}}{365\,[(1 + r_{PV})^{yPV} - 1]} c_{0,PV} \sum_{i=1}^{N_{PV}} P_{PV,CAP,i}$$

$$C_{0,BS} = \frac{P_{BS}(1 + r_{BS})^{yBS}}{365\,[(1 + r_{BS})^{yBS} - 1]} c_{0,BS} \sum_{k=1}^{N_{BS}} P_{BS,CAP,k} \qquad 3.4$$

$$C_{0,HSS} = \frac{P_{HSS}(1 + r_{HSS})^{yHSS}}{365\,[(1 + r_{HSS})^{yHSS} - 1]} c_{0,HSS} \sum_{j=1}^{N_{HSS}} P_{HSS,CAP,j}$$

Where: y and r are the design life and discount rate of equipment respectively(y=25, r=6%); $C_{0,PV}$, $C_{0,BS}$, $C_{0,HSS}$ are the unit capacity investment cost of PV, BS and HSS respectively; $P_{PV,CAP,i}$, $P_{BS,CAP,k}$, $P_{HSS,CAP,j}$ are the installation capacity of PV and energy storage system (both BS and HSS) of the *I, k, j* node respectively; $c_{0,PV}$, $c_{0,BS}$, $c_{0,HSS}$ are the average daily investment cost of PV, BS and HSS after discount respectively.

The SHS-EVCS O&M cost is:

$$C_1[m,n] = C_{OM}[m,n] + C_{Fuel}[m,n] \tag{3.5}$$

$C_{OM}[m,n]$ and $C_{Fuel}[m,n]$ are the operating and maintenance cost, fuel cell cost.

- *Two SHS-EVCS energy exchange objective function*

The energy exchange objective function is similar to the single one, but it includes an additional energy exchange component in C_1.

$$C_1[m,n] = C_{OM}[m,n] + C_{Fuel}[m,n] + C_{grid}[m,n] + \left(M_{buy1} - M_{sell1}\right) \tag{3.6}$$

M_{buy1} and M_{sell1} indicate the prices for purchasing and selling electricity to another EV charging station, with the values potentially being positive or negative.

3.3.2.2. Photovoltaic Power Output Constraints

Given the unpredictability and variability of solar energy, the photovoltaic power output is adjusted based on the forecasted power levels.

$$P_{Pv,k,t}^{for}, 0 \leq P_{Pv,k,t} \leq P_{Pv,k}^{n} \tag{3.7}$$

where $P_{Pv,k,t}^{for}$ and $P_{Pv,k}^{n}$ are the predicted power and rated power of the *k* photovoltaic cells at time *t*, respectively.

3.3.2.3. Battery Storage Output Constraints

The battery does not produce electric energy but acts as a backup to the remaining energy. There is no difference in coordination time, so there is no capacity increase.

$$S_{Bat,a,T} = S_{Bat,a,0} \tag{3.8}$$

Where $S_{Bat,a,T}$ and $S_{Bat,a,0}$ are the ending capacity and initial capacity of the battery pack *a* in the coordination period.

3.3.2.4. Hydrogen Storage System Output Constraints

$$E_{H_2,i}^{min} \leq E_{H_2,i}^{t} \leq E_{H_2,i,CAP}, i \quad \in \mathrm{N_{HSS}} \tag{3.9}$$

Where $E_{H_2,i,CAP}$, $E_{H_2,i}^{min}$ are the capacity and lower limit of hydrogen storage tank respectively, and the lower limit is 20%

3.3.3. Minimize the Investment and Operational Costs of SHS-EVCS using Particle Swarm Optimization (PSO) Algorithm

In this chapter, Particle Swarm Optimization (PSO) is chosen as it offers a practical and effective approach to tackling complex, multi-objective optimization problems—particularly relevant for managing the dynamic operations of renewable-powered EV charging stations. PSO is well-suited to handle the nonlinear, intricate systems that characterize these stations, where variables like energy sources, demand fluctuations, and cost factors interact in real time [142]. Unlike some traditional optimization methods, PSO is also less computationally demanding, making it suitable for the real-time applications needed in EV charging systems. Additionally, PSO is relatively straightforward to implement, especially when compared to more complex algorithms like genetic algorithms or simulated annealing, which makes it a convenient and efficient choice for this study.

The decision matrix below compares PSO with other optimization methods commonly used for similar applications, including Genetic Algorithms (GA), Simulated Annealing (SA), and Linear Programming (LP). Each method is evaluated on criteria relevant to the thesis objectives, using a scoring scale from 1 to 5 (where 5 is the best).

Criterion	**PSO**	**GA**	**SA**	**LP**
Handling Nonlinear Complexity	5	4	3	2
Convergence Speed	4	3	3	5
Multi-Objective Capability	5	5	3	2
Scalability and Flexibility	5	4	3	2
Ease of Implementation	5	3	3	4
Suitability for Real-Time Applications	4	3	2	2
Computational Efficiency	4	3	3	5
Total Score	32	25	20	22

With a total score of 32, PSO stands out, excelling across multiple important criteria. Its strengths include managing non-linear complexities and adapting well to real-time applications, making it an ideal choice for this thesis. While GA also support the optimization and offer flexibility, it tends to converge more slowly. SA and LP, meanwhile, are less suited for the complex, dynamic demands of renewable-powered EV charging systems.

In the PSO algorithm, each particle's state is characterized by its position and velocity vectors. These vectors indicate the particle's current solution to the problem and its direction through the search space [142]. As the particle moves, it consistently updates its direction based on the best global solution found by any particle and the best solution it has personally achieved, aiming to locate the global optimum [143] [144]. The formulas to update the particle's velocity and position are as follows:

$$v_{ij}^{t+1} = \omega v_{ij}^{t} + c_1 r_1 \left(P_{best\,ij}^{t} - x_{ij}^{t}\right) + c_2 r_2 \left(g_{best\,ij}^{t} - x_{ij}^{t}\right) \tag{3.10}$$

$$x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1} \tag{3.11}$$

Where: t is the number of iterations; ω is the inertia weight factor; c_1 and c_2 are the accelerator factors, which have ability to adjust the proportion of individual cognitive and social components in the speed of particle swarm; r is random number in [0, 1]; $P_{best\,ij}^{t}$ is the best position of individual optimal value of particles; $g_{best\,ij}^{t}$ is the best position of global optimal value; v is the velocity of the particles, in general, the speed is control in $[-v_{max}, v_{max}]$; x_{ij}^{t} is the position of particles in t iterations, and the searching zone is limit in $[-x_{max}, x_{max}]$.

The traditional PSO algorithm operates on the principle of adjusting individual behaviours based on the shared information within the group and personal experiences to ultimately arrive at the best solution [145,146]. To enhance the diversity of the initial population and the convergence rate of the algorithm, this chapter initially implements a competitive learning approach to boost the fitness of the initial population.

Subsequently, it integrates an elite retention strategy to accelerate the convergence of the algorithm in its later phases.

In the optimization process, the direction of optimization in traditional PSO is often influenced by the globally optimal state, which can restrict the diversity of the algorithm's initial population and lead to premature convergence. To overcome these issues, the traditional PSO algorithm has been enhanced by integrating a competitive learning strategy, which improves the overall fitness of the algorithm's particles compared to the conventional method. This competitive learning strategy operates differently from standard PSO algorithms, as it is not confined by the population's optimal state. Instead, it uses competition among the populations to eliminate particles, thereby mitigating the influence of the global optimum on the optimization process [147]. However, competition among particles with significant performance disparities might be harmful for the transmission of optimal particles to subsequent generations. Therefore, the variance and standard deviation of the fitness levels in the initial population are computed to assess this risk. The formulas for calculating the mean and standard deviation are as follows:

$$f' = \frac{\sum_{i=1}^{M} f_i}{M} \tag{3.12}$$

$$\sigma = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(f_i - f')} \tag{3.13}$$

The fitness value of the *i-th* particle is represented by f_i, with M denoting the total number of particles. The average fitness of the particles is denoted by f', and σ represents the standard deviation of the particle fitness values. Subsequently, the particles are categorized into three distinct groups: the "optimal area", "reasonable area" and "distance area" based on their characteristics. The competitive learning strategy is specifically applied to particles within the "reasonable area " and "distance area" fostering competition within these groups. Particles that do not perform well in the "distance area" learn from those in the "reasonable area" updating their velocity and position data, which are then carried forward to the next generation. The formula for updating is as follows:

$$x_{ij}^{(t+1)} = c_1 x_{ij}^t + c_2(x_{ij}^t - x_{kj}^t) + c_3\alpha(f' - x_{ij}^t) \quad 3.14$$

In this configuration: c_1, c_2, and c_3 are acceleration coefficients. From equation (3.13), $x_{ij}^{(t+1)}$ contains three components. The first component x_{ij}^t is same as the standard PSO update formula. The second component, x_{kj}^t indicates that particles in 'distant area' update their states by learning from those particles in "optimal area". The third component introduces a new parameter, α (where α is a smaller positive number), indicate that the update process is also influenced by the central position of the particle, which helps to control the update extent and enhance the convergence of the algorithm. For particles in the "reasonable area", an adaptive balance between global exploration and local exploitation is necessary, a new designed learning is made for these particles. The particle update formula in the "reasonable area" varies based on the situation:

1) When the population is not caught in a local optimum, particles in the reasonable zone employ the traditional particle update methods (formulas 3.10 and 3.11) to evolve. This approach aims to gradually steer the population towards the global optimum and ensure the algorithm's convergence.

2) When the population is fall into a local optimum, and the fitness value of a particle's current position is the same as the fitness value from the previous generation, indicating no improvement, which means $f(x_{ij}^t) - f(x_{ij}^{t-1}) = 0$, the particles in the reasonable zone use formula (3.13) for updates, aiming to improve the search capabilities of the population, thereby increasing the chances of escaping the local optimum.

In the PSO algorithm, "population diversity" and "selection pressure" are two significant factors to lead high selection pressure, which can often lead to slow convergence in the later stages of the algorithm [147]. This chapter rank the fitness of particles using the algorithm described above and compare it to the fitness function, retaining those particles with superior performance for the next generation. This strategy not only prevents the loss of the best individuals during the genetic operations but also directs the search trajectory of the algorithm, thus hastening convergence.

At the beginning of the algorithm, an optimal point $x_{ini}, y_{ini}, z_{ini}$ is first identified, and the fitness function is defined as$f(x_{ini}, y_{ini}, z_{ini})$:

$$f(x_{ini}, y_{ini}, z_{ini}) = \frac{1}{F(x_{ini}, y_{ini}, z_{ini})} \qquad 3.15$$

Where $F(x_{ini}, y_{ini}, z_{ini})$ is the distance of particle to the optimal area.

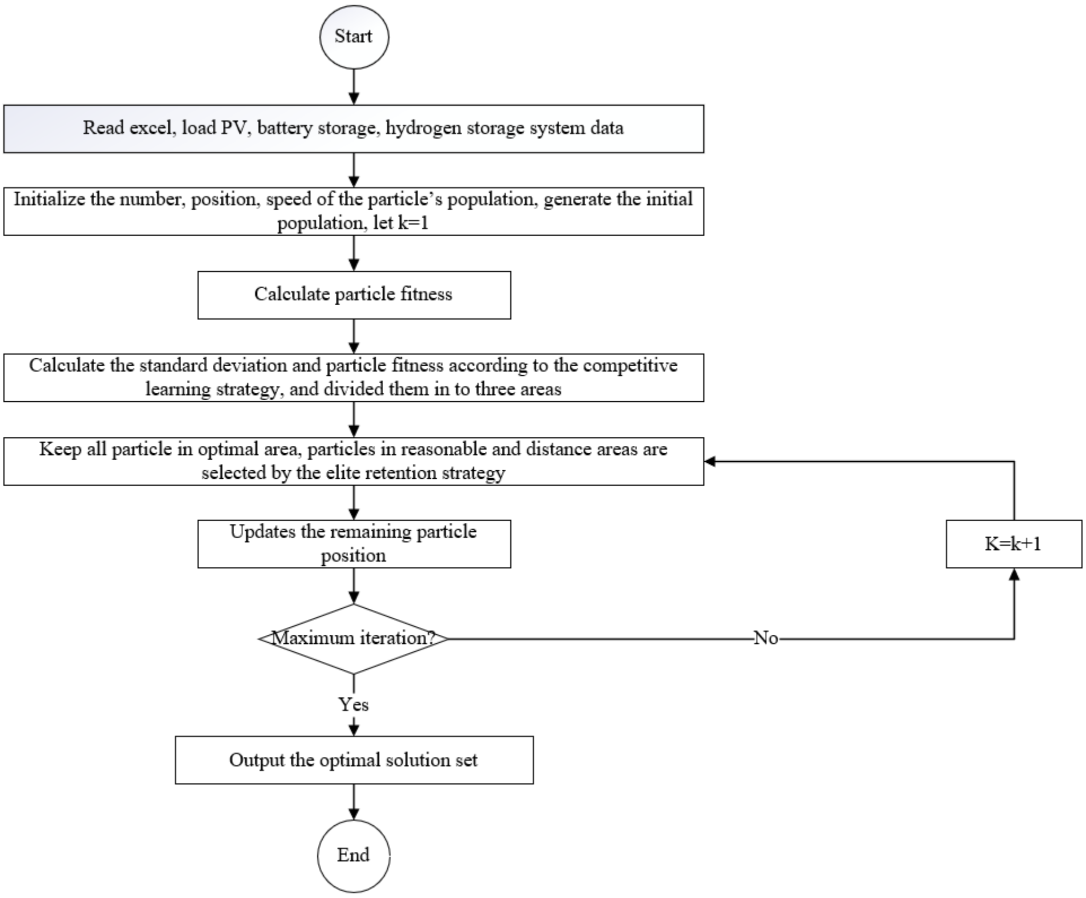


Figure 3-4 Flowchart of PSO algorithm

3.4 Results and Analysis

This thesis is using the assumption EV number to verify the total load for the SHS-EVCS based on table 3-2, 3-3, and figure 3-3.

This EV is taking place in London (Hammersmith & Fulham), and its complementary clean energy: hydrogen, photovoltaic and battery storage, as an example to analyse the above optimal model. The main characteristic parameters of the station are shown in Table 3-4. Taking 24 hours as the scheduling cycle, every 1 hour as a scheduling period, summer as the reference day. For the case study, a 24-hour scheduling period was employed, with an hourly energy dispatch solution used on a summer reference day. The common parameters of the charging stations include:

- Charging capacity (kW): 360.
- PV capital cost (£/kW): 1112.
- PV maintenance cost (£/kW): 0.01.
- Battery capital cost (£/kW): 331.55.
- Battery maintenance cost ((£/kW): 0.01.
- Battery initial state of charge (%): 40.
- Rated charge and discharge power of battery (kW): 500.
- Minimum battery state of charge (%): 25.
- Maximum battery state of charge (%): 100.
- Battery charge and discharge efficiency (%): 85.
- Initial capacity of gas tank (%): 30.
- Hydrogen tank cost (£/kW): 27.63.
- Hydrogen tank maintenance cost (£/kW): 0.01.
- Tank storage efficiency (%): 95.
- Fuel cell generator capacity (kW): 600.
- Fuel cell generator capital cost (£/kW): 705.9.
- Fuel cell generator maintenance cost ((£/kW): 0.15.
- Electric to gas efficiency (%): 75.
- Electricity-to-gas coefficient (kWh/m^3): 0.2.
- Gas-to-electric efficiency (%): 65.
- Gas-to-electricity coefficient (m^3/kWh): 0.295.

Renewable energy feed-in tariff (£/kW): 0.019.

Table 3-4 The parameters of SHS-EV charging stations.

Parameter	**Hammersmith & Fulham**	**Richmond upon Thames**
Number of chargers per station	3	8

PV installed capacity (kW)	500	1000
Battery capacity (kW)	1000	800
Hydrogen tank capacity (m^3)	1000	1000
Fuel cell generator capacity (kW)	800	1500

The Feed-in Tariff (FIT) policy serves as the primary incentive for small-scale renewable energy generation projects in the UK [148]. Under this policy, power suppliers are required to compensate for electricity produced by small renewable energy installations and fed into the grid. The policy is applicable to solar photovoltaic, wind, hydropower, and anaerobic digestion power generation projects with an installed capacity of up to 5MW, as well as combined heat and power units with a capacity of no more than 2kW. The compensation for generated power is calculated based on the cost of solar photovoltaic generation, while the compensation for power sold is based on the grid-connected solar electricity price.

3.4.1 Single SHS-EV Charging Station Simulation Results.

A case study on the SHS-EV charging station was performed using EV charging data from Hammersmith & Fulham. The energy systems, including hydrogen, photovoltaic, and battery storage, were modelled according to the methodology described earlier. Table 3-4 details the primary technical and economic parameters of the SHS-EV charging station. The study covers a 24-hour period, utilizing hourly energy dispatch solutions, based on a representative summer day.

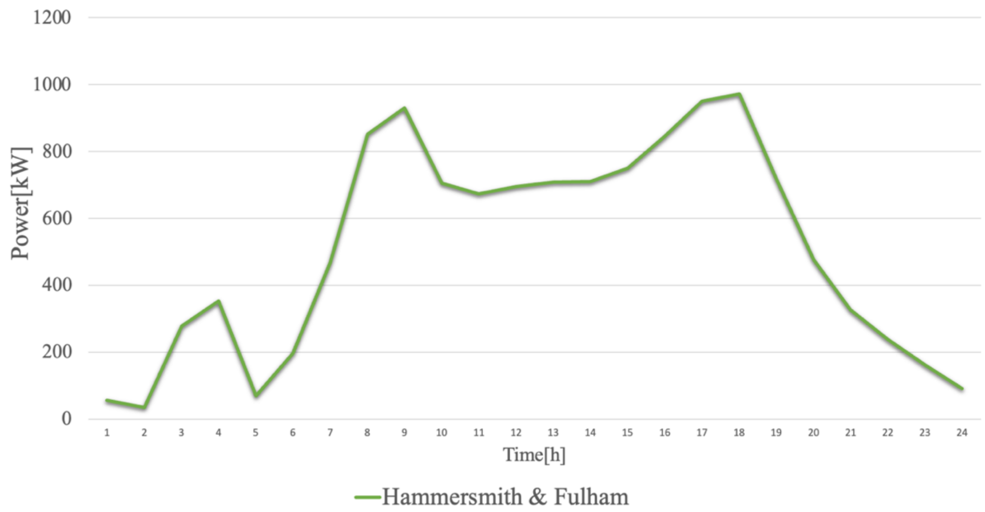


Figure 3-5 Case studies in London boroughs for SHS-EVCS

Figure 3-5 shows the estimated EV charging demand profile (load curve) in the London boroughs in the SHBS-EVCS. Firstly, the SHS-EV charging load curve belongs to one SHBS-EVCS. It is assumed that there will be 5 SHBS-EVCS in Hammersmith & Fulham, based on the existing number of petrol stations in this London boroughs. For SHS-EVCS, Hammersmith & Fulham received the EV charging load with peak value of 1.0 MW. This requires 3 chargers in the charging stations to meet such peak charging load. This is calculated as 360kW charger is required to charge an EV with 60kWh batteries, therefore 3 chargers can charge 3 x 360kW to meet the peak charging load in Hammersmith & Fulham.

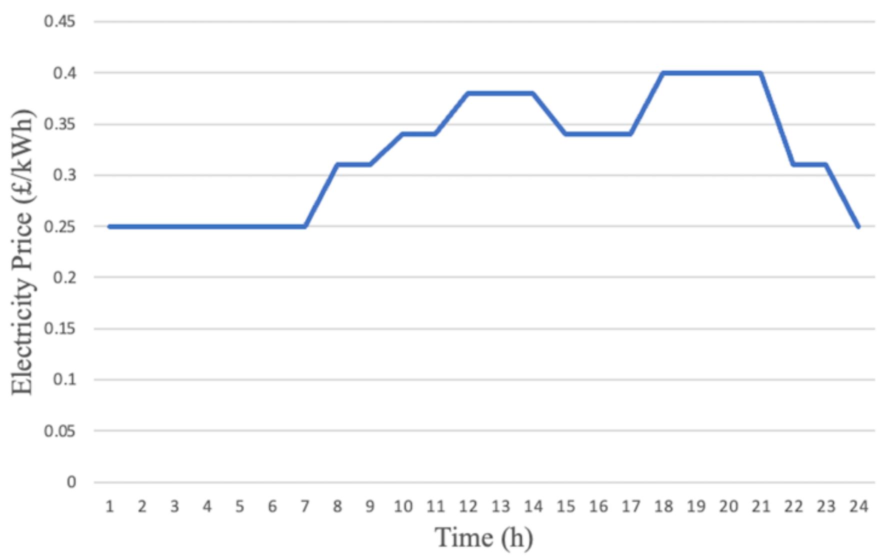


Figure 3-6 Daily electricity price

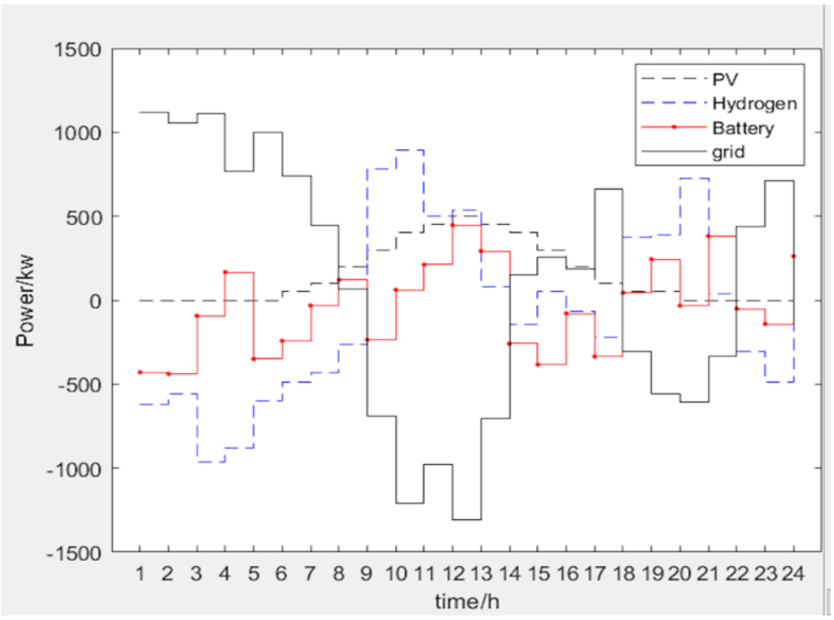


Figure 3-7 Optimal energy dispatch solution

When electricity prices drop to their lowest during the night, the cost of producing hydrogen from electricity is more economical than at other times. As illustrated in Figures 3-6 and 3-7, from 1 a.m. to 6 a.m., there is no photovoltaic energy production. During this window, 1000 kW of hydrogen is stored for future use in power generation. This hydrogen is then utilized between 9 a.m. and 1 p.m., and from 6 p.m. to 10 p.m., when electricity prices from the grid are at their peak. The integration of the hydrogen system allows the power grid to manage peak loads more cost-effectively, at a lower compensation rate than other energy sources. The charging station also produces and stores hydrogen to support peak load regulation, ensuring that the fuel cell generator can handle high EV charging demands when photovoltaic output is insufficient. Additionally, the SHS-EV charging station is programmed to sell electricity back to the grid during high-price periods, making it more cost-effective for the grid to purchase electricity from the station. This is reflected as negative grid output in Figure 3-7, corresponding to the high-price periods shown in Figure 3-6.

During the hours from 6 a.m. to 6 p.m., photovoltaic energy is the primary source of power for the charging station. Outside of peak charging times, the hydrogen fuel cell generator, battery storage, and photovoltaic systems work in tandem to supply electricity for EV charging. During off-peak periods, hydrogen and battery storage are being replenished, as indicated by their negative energy states. Between 6 p.m. and 11 p.m., when photovoltaic energy is no longer available, energy is supplied from hydrogen storage, battery storage, and the grid.

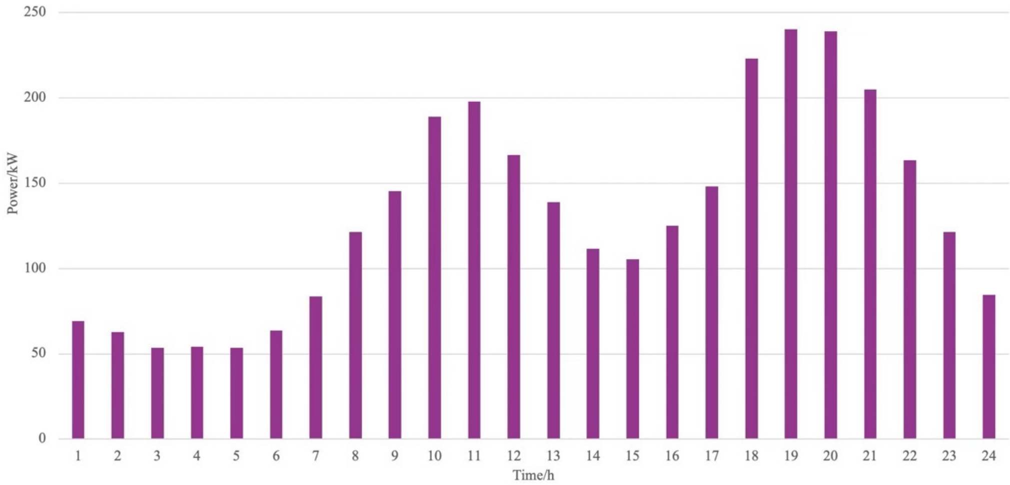


Figure 3-8 EV equivalent charging load curve

Figure 3-8 shows the EV equivalent charging load for the SHS-EV charging station. This load is calculated by modifying a standard EV charging load to incorporate a fast-charging model, which assumes that an EV can be fully charged within just 10 minutes. The resulting charging load curve reveals two distinct peaks: one occurring during the daytime from 9 a.m. to 1 p.m., and another in the evening between 6 p.m. and 10 p.m. These peaks reflect the periods when EVs are most charged, indicating concentrated charging activities during these hours.

These two charging peaks are particularly significant as they coincide with the periods of highest electricity prices in UK. By comparing Figures 3-6 and 3-8, it becomes clear that the times of increased charging activity align closely with the peak electricity pricing periods. This alignment suggests a strong correlation between the charging behaviour of EV users and the fluctuations in electricity prices.

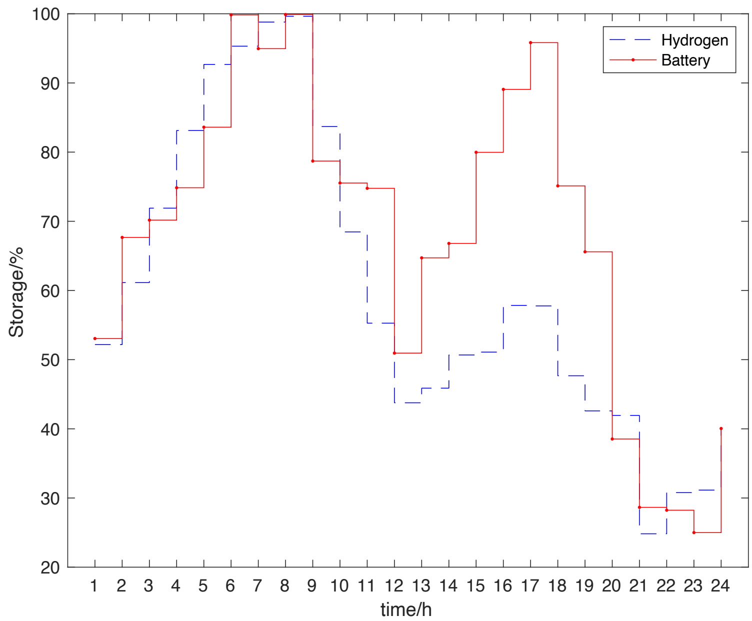


Figure 3-9 Optimal energy dispatch solution

Figure 3-9 shows the behaviour of energy reserves in battery and hydrogen storage systems during periods of varying electricity prices. Notably, during times of high electricity prices, such as between 8 p.m. and 10 p.m., the reserve levels in both systems drop significantly. Specifically, battery storage capacity falls below 30%, while hydrogen storage dips to less than 20%. This reduction indicates that during peak pricing periods, these stored energy reserves are heavily utilized to meet the demand, likely as a strategy to avoid purchasing expensive grid electricity. Conversely, during the period from 11 a.m. to 1 p.m., electricity is predominantly supplied by photovoltaic energy. This reliance on solar power reduces the consumption of stored hydrogen and battery energy, allowing these reserves to remain relatively stable. Additionally, during periods of low electricity prices, such as from 1 a.m. to 8 a.m., coupled with reduced EV charging demand at night, both hydrogen and battery storage systems are recharged, approaching their maximum capacity.

On economic side, operating the SHS-EV charging station for a single day would typically cost £4195.88 if all the electricity were sourced directly from the power grid. However, by incorporating SHS energy sources, the operational cost is significantly reduced to £1313.32, resulting in a substantial daily savings of £1882.56. This reduction highlights the financial benefits of integrating sustainable energy solutions into the charging station's operations. For instance, charging an EV like a Tesla Model 3 for a 10-minute session costs £6.39, making it an affordable option for users while still ensuring the station remains profitable.

To meet the peak charging demand, the station requires up to three chargers operating simultaneously. During the four-hour peak period each day, the station can charge up to 120 vehicles, demonstrating its capacity to handle high demand efficiently. Outside of these peak hours, the station can still service an average of 8 cars per hour, ensuring continuous operation and revenue generation throughout the day. This steady flow of customers enables the station to generate a daily revenue of £1789.2, which, after accounting for operational costs, translates to a net profit of £475.88 per day.

The initial capital investment for setting up the SHS-EV charging station is calculated at £534,835. Given the daily profit margins, it is projected that the station will be able to recoup its total investment within three years. After this break-even point, the station will start generating a consistent profit, making it a financially viable and sustainable in the long term.

3.4.2 2 SHS-EV Charging Stations Simulation Results.

Figure 3-10 depicts the design of energy systems for two SHS-EVCSs. The SHS-EVCSs can both purchase and sell electricity from the grid, with these transactions influenced by fluctuations in daily electricity prices. The concept of energy exchange between EVCSs improves energy resource utilization. By sharing and distributing power among stations, it helps to lower the overall demand for grid electricity during peak periods. This system not only reduces electricity costs for station operators and users by allowing access to more affordable energy from neighboring stations or renewable sources, but it also supports the adoption of renewable energy by facilitating the sharing of excess energy. Furthermore, energy exchange enhances the resilience and reliability of the energy grid, ensuring that charging stations can continue operating even during outages or disruptions.

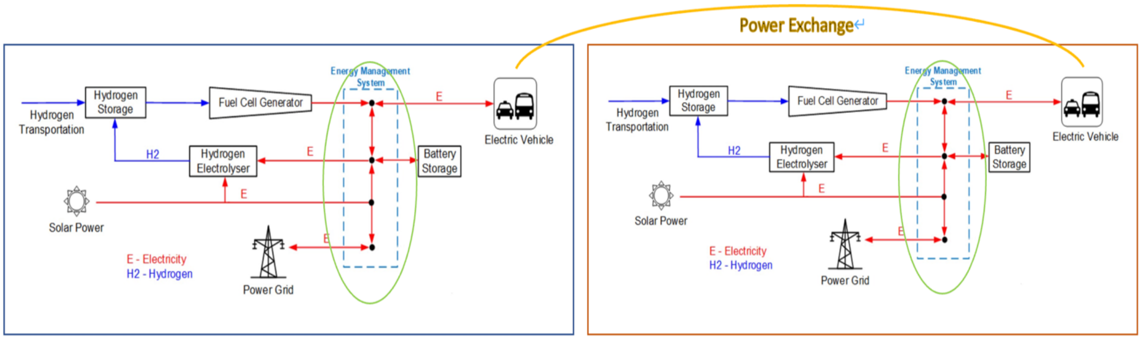


Figure 3-10 Energy system design for SHS-EVCSs with power exchange using EVs

Figure 3-11 illustrates the anticipated EV charging demand profiles (load curves) for the SHS EVCSs in two London boroughs. Each load curve represents the demand at a specific SHS-EVCS within these areas. Based on current infrastructure, it is estimated that Hammersmith & Fulham will host 5 SHS-EVCSs, while Richmond upon Thames will have 14, reflecting the existing number of petrol stations in these regions. Richmond shows the highest EV charging demand among the two boroughs, with peak loads reaching up to 2.8 MW. To effectively handle this peak demand, 8 chargers are required at these stations. This calculation assumes each charger has a capacity of 360 kW, which is sufficient to charge an EV equipped with a 60 kWh battery in a reasonable time frame.

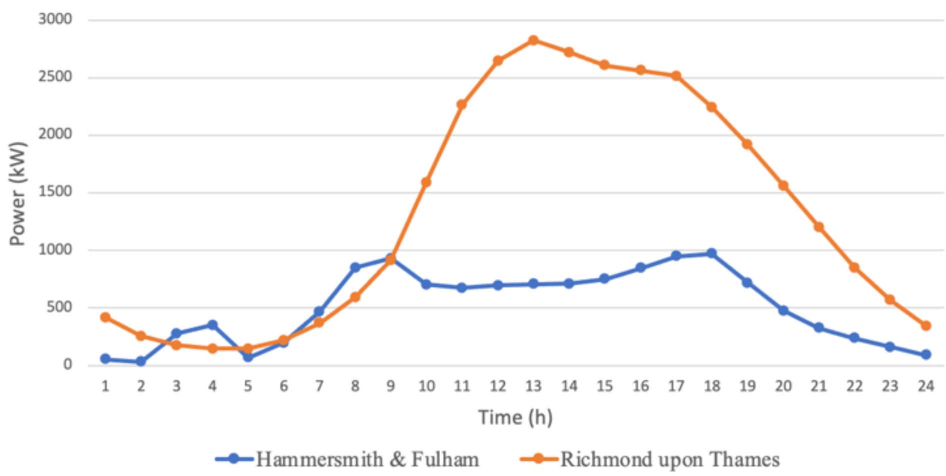


Figure 3-11Case studies in two London boroughs for SHS-EVCSs

In contrast, the SHS-EVCSs in Hammersmith & Fulham experience a significantly lower peak charging load, which remains under 1000 kW. Due to this lower demand, only 3 chargers with a capacity of 360 kW each are necessary to meet the charging needs at these stations. This difference in infrastructure requirements between the two boroughs highlights the variability in charging demand based on regional factors such as population density, vehicle ownership rates, and existing energy infrastructure.

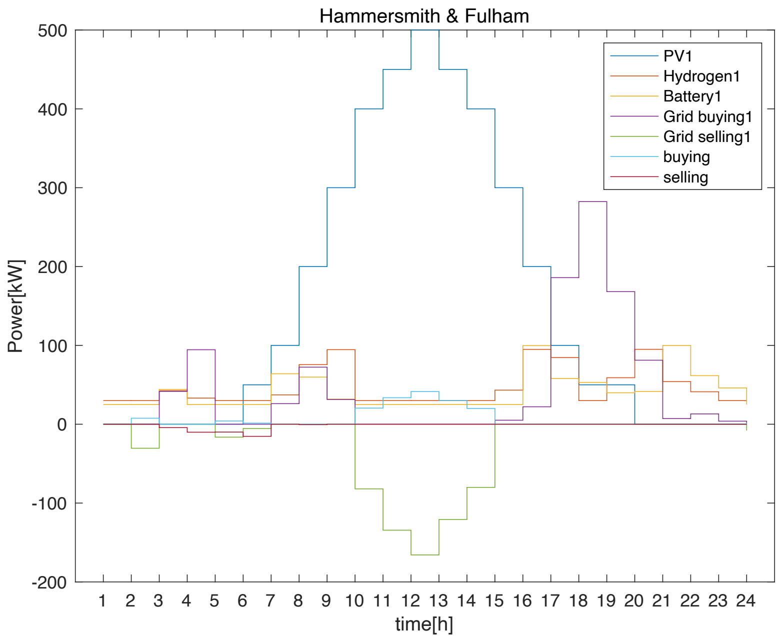


Figure 3-12 Hammersmith &Fulham optimal energy dispatch

Figure 3-12 shows that solar energy is the primary source of power for the charging station between the crucial daylight hours of 7 a.m. and 7 p.m., with the station's solar panels capable of generating a maximum output capacity reaching up to 500 kW. This substantial reliance on solar energy during these hours is essential for meeting the charging demands of EVs, particularly as the demand for clean energy continues to rise. The availability of solar power during these peak sunlight hours not only ensures a renewable and environmentally friendly energy supply but also reduces the station's dependency on fossil fuels, thereby contributing to lower carbon emissions. The solar energy harnessed during this period plays a vital role in ensuring that EVs can be charged efficiently, meeting the increasing demands as more vehicles transition from traditional fuels to electric power. To further enhance energy reliability, the station employs both hydrogen and electric energy storage systems, which operate in tandem. These systems are designed to store excess energy during periods of high solar output and release it during periods of low solar generation, ensuring that the station can consistently meet energy needs throughout the day and avoid interruptions in service. Moreover, during periods when electricity prices peak, particularly from 10:00 a.m. to 3:00 p.m., the charging station strategically engages with the power grid to supplement its energy supply. This approach ensures that the station can meet high demand even when solar power generation may not be sufficient. However, the reliance on the grid during these peak times can be financially burdensome due to the higher cost of electricity during these hours. To mitigate these expenses, the charging station adopts a time-of-use pricing strategy, which is an effective cost management technique. By purchasing electricity during off-peak hours—typically in the evening or at night when prices are significantly lower—the station can store this cheaper energy in its advanced storage systems for later use during peak demand periods. This management of energy sources not only helps in reducing operational costs but also stabilizes the energy supply, ensuring that the station can deliver a reliable and uninterrupted charging service. Overall, by carefully managing and integrating diverse energy sources, leveraging advanced storage solutions, and utilizing dynamic pricing strategies, the charging station can ensure a sustainable, reliable, and cost-effective energy supply, positioning itself as a key player in the transition to a greener transportation infrastructure.

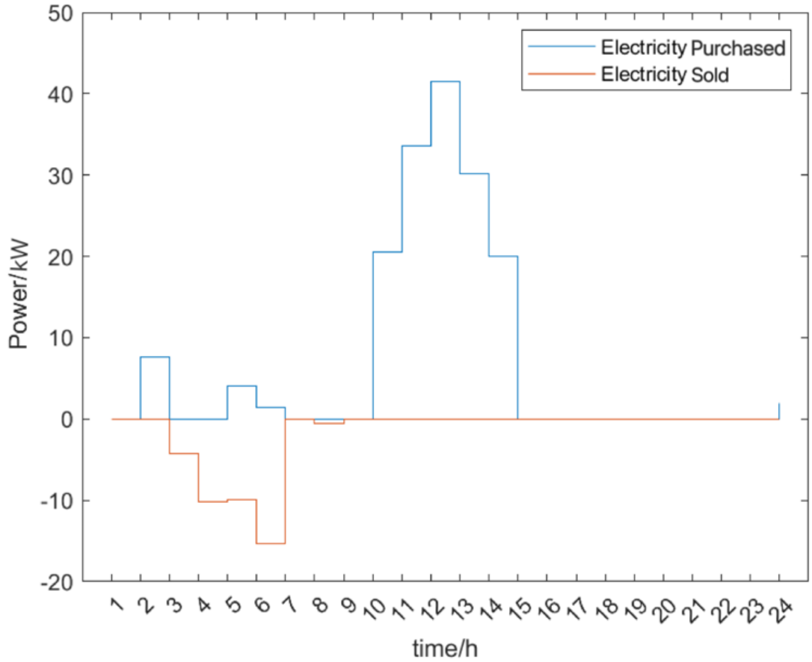


Figure 3-13 Energy exchange between two SHS-EVCSs

Figure 3-13 offers a detailed depiction of the power transfer between two charging stations over specific time periods, with a maximum transfer capacity of 50 kW. This energy exchange, though seemingly straightforward, plays a crucial role in the efficient operation of these charging stations. To thoroughly understand and optimize this exchange, a PSO algorithm is employed. This algorithm is a powerful tool for analyzing complex systems, and in this context, it helps in achieving the lowest possible operational costs by determining the most efficient patterns of energy transfer between the stations. The results, as shown in Figure 3-6, provide an intriguing insight. When an autonomous energy generation system is integrated into the charging stations and these stations are connected to the grid, the power exchange between them becomes nearly insignificant. This finding is particularly interesting because it suggests that, under these conditions, the energy generated and stored by each station is largely sufficient to meet its own needs, thereby reducing the need for inter-station energy transfers. This minimal power exchange indicates that such exchanges have a negligible effect on reducing the overall costs of operating the stations. In other words, the stations can operate more independently, relying on their own generated energy rather than needing to balance energy levels between each other.

Table 3-5 SHS-EVCSs minimum investment and operation cost

Cost	**Hammersmith & Fulham**	**Richmond upon Thames**
Capital cost for initial years (£) C_m^0	1,338,720	1,828,410
Discounted capital cost (£) C_0	181,889.15	248,422.33
Grid electricity purchase per day (£)	575.09	1994.36
Power exchange per day (£)	77.12	30.25
Maintenance and operating cost per day (£)	205.65	232.79
Minimum daily cost (£) *minF*	1273.32	2887.81

Table 3-6 SHS-EVCS cost only buy electricity from grid

Cost	**Hammersmith & Fulham**	**Richmond upon Thames**
Daily cost (£)	4,195.88	11,225.81

Table 3-5 presents a detailed analysis of the economic dimensions associated with two SHS-EVCSs, focusing on both their initial investment and ongoing operational costs. One of the most striking aspects highlighted in Table 3-5 is the cost efficiency of SHS-EVCSs over their operational lifespan. Assuming a lifespan of 10 years, and accounting for daily maintenance and the periodic replacement of components every decade, the daily cost of operating an SHS-EVCS is remarkably low—only £4,163.13. Table 3-6, the contrast becomes even more pronounced. The daily operational costs for the two charging stations listed there are three times higher than those of the SHS-EVCS. This significant difference underscores the financial advantages of SHS-EVCSs, particularly in terms of ongoing expenses. From an economic perspective, the lower daily costs associated with SHS-EVCSs suggest that they offer a more financially sustainable model for long-term operation, especially in scenarios where cost minimization is a priority.

Moreover, the ability to optimize energy utilization through the energy exchange between SHS-EVCSs further enhances their cost-effectiveness. This energy conversion process not only improves efficiency but also reduces the operational costs associated with running these stations. By facilitating a more balanced distribution of energy, these systems can operate more efficiently, thereby lowering the overall cost burden on operators. However, it is important to recognize that the integration of SHS-EVCSs with the larger power grid requires certain adjustments. These adjustments could involve additional infrastructure investments, regulatory considerations, and potential changes to grid management practices. While these modifications may introduce additional costs, they also offer the potential for greater energy efficiency and reliability, particularly in areas with fluctuating energy demands.

From an economic standpoint, the decision to invest in and maintain SHS-EVCSs must be informed by a careful analysis of both the costs and benefits. On one hand, the lower operational costs and improved energy efficiency of SHS-EVCSs make them an attractive option for supporting the transition to sustainable transportation. On the other hand, the costs associated with integrating these systems into the broader power grid must be weighed against the potential long-term savings and environmental benefits.

In conclusion, Tables 3-5 and 3-6 offers valuable insights into the financial dynamics at play, and these insights should guide both policymakers and investors in their efforts to create a more sustainable and economically viable energy infrastructure.

3.5 Chapter Summary

In this chapter, the isolated microgrid SHS-EVCS with photovoltaic power, battery storage, and a hydrogen storage system including a fuel cell generator, an electrolyze, and a hydrogen storage tank has been investigated in this chapter, proposing the method based on the isolated microgrid energy management with a minimum cost and stable energy storage state. While learning cost reduction of the energy storage system, they use a minimum algorithm of the energy storage system to maintain the energy storage state. Achieve an optimal control of the system cost, and energy storage level. The proposed energy management verified in terms of cost and other indicators is put into operation by MATLAB in this chapter. The results prove that compared to the traditional one, this SHS-EVCS greatly reduces the cost. Energy storage always guarantees itself at the expected level so that its utilization is high, thus increasing the system reliability.

This chapter also focuses on the economic assessment of power exchange between two SHS-EVCSs, with each charging station's power distribution involving a variety of energy production, conversion, and storage equipment. A thorough economic analysis is conducted, factoring in the electrical load demands of charging stations in Hammersmith & Fulham and Richmond upon Thames during different time frames, as well as the energy interactions between the two stations. Additionally, the study examines how to optimize the system's operation when connected to the grid for electricity sales. In the coordinated planning process, accounting for the interactions among charging stations and power lines can improve the efficiency of distributed generation use while reducing the necessity for additional grid investments. Within SHS-EVCS coordinated planning, the charging stations can interact flexibly with other smart devices, leading to more efficient equipment use and increased economic benefits overall.

Chapter 4. Multi SHS-EV Charging Station Energy Exchange

4.1. Introduction.

Energy exchange, often called point-to-point power transmission, offers several advantages compared to conventional distribution network approaches. There are two main approaches to direct energy exchange: the first involves transmitting electricity via high-voltage lines from one location to another, and the second uses EVs as part of a Vehicular Energy Network for energy transfer [149]. The high-voltage transmission method is particularly effective for long-distance energy transfer, reducing losses and improving efficiency. On the other hand, utilizing EVs for energy exchange not only supports grid stability but also promotes the integration of renewable energy sources by enabling flexible energy storage and distribution across different regions. The first method leverages high-voltage transmission lines that incur lower resistive losses than distribution networks, allowing for efficient power transmission over greater distances with fewer losses [150][151]. In contrast, traditional distribution networks involve multiple transformers and lines that lead to higher energy losses. The second method, using EVs for direct energy exchange, offers enhanced routing flexibility [152]. It permits direct electricity transfer from specific sources to destinations without dependence on intermediary distribution systems, which is vital for large-scale power transactions across distant locations. However, relying on distribution networks exposes energy transfers to potential network faults, outages, and capacity constraints. Although establishing a direct energy exchange infrastructure demands initial investment, it often proves more cost-effective over time by minimizing transmission losses and enhancing overall efficiency. This can lead to significant cost savings as opposed to relying on distribution networks, which may require continuous maintenance and upgrades.

This chapter for London part is focuses on the use of EVs for direct energy exchange, given its relevance to the research's multi-objective functions. For Dali part, it uses high voltage transmission line. It is important to note that both direct energy exchange and traditional methods have their respective advantages and can be utilized under different circumstances. The selection of the most appropriate method depends on various factors including geographical limitations, the scale of the energy transactions, existing infrastructure, and specific power system needs. These considerations are crucial in determining the most efficient and reliable method for power transmission.

The ongoing discussion of the EVCS is mainly held with various aspects, ranging from the present status of charging applications and future development prospects. Less discussion is available regarding the exploration of facility CS that integrate several types of multi-energy, including solar-hydrogen storage systems. The current research [153-155] in this field is based on microgrid technology comprising renewable energy sources, energy storage systems, and EV charging through scheduling over the internet. These studies centre on the objective for improving individual EV charging techniques that provide an optimum allocation of capacity among the various constituents of the charging system and optimization of the control systems. The focus is on the improvement in the economic operation of the system. This will include focusing research efforts on raising the utilization rate of renewable energy (particularly photovoltaics), and the design of the EV charging modes, based on the charging system scheduling within individual EVCS. This chapter conducts a detailed investigation into EVCSs with a focus on several key areas, making notable contributions as follows:

London section:

- This section introduced a comprehensive model for EVCSs and conducted a comparative analysis of simulation optimization methods. It thoroughly examines and compares two distinct algorithms: the Non-dominated Sorting Genetic Algorithm (NSGA-II) and the Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA-D).

- A further critical aspect of the research focuses on minimizing capital and operational & maintenance (O&M) costs, along with costs associated with greenhouse gas emissions. Aim to achieve an optimal balance between cost reduction and environmental preservation by employing a holistic optimization strategy.

Dali (China) section:

- This section introduces a P2P optimal dispatch strategy based on game theory for SHS-EVCSs, designed to maximize economic returns by ensuring income balance across multiple SHS-EVCSs.
- Designed and addresses linear-based simulation queries using a CPLEX solver, primarily used for locational analysis. This solver has been integrated with an SHS-EVCHs model to enhance its practical application.
- Analyse the synergistic interactions and operational dynamics among various stakeholders, focusing on understanding the collective economic advantages. Also analyse the methods that rely on SHS-EVSC to facilitate energy sharing and optimize economic dispatch.

This chapter is organized as follows: Section 4.2 focuses on the London area, which includes an analysis of two SHS-EVCS topologies, the NSGA-II and MOEA-D algorithms, and the corresponding simulation results. Section 4.3 covers the Dali (China) area, featuring four SHS-EVCS simulations, a game theory-based P2P energy trading model, and an economic analysis.

4.2. Two SHS-EV Charging Station Power Exchange in London

4.2.1. 2 SHS-EV Charging Station Location Chosen and Topology.

Figure 4-1 shows two SHS-EVCSs that harness solar energy, hydrogen storage, and battery storage as their primary power sources. These stations are engineered to reduce carbon emissions while lowering both capital and operational expenses. The solar component features photovoltaic panels that convert sunlight into electricity, which can be used immediately to charge EVs or stored in batteries for later use. The hydrogen storage system includes an electrolyze that splits water into hydrogen and oxygen, with the hydrogen stored in high-pressure tanks until required. This stored hydrogen is then used in a fuel cell, where it combines with oxygen to generate electricity for vehicle charging. Additionally, the station is equipped with a lithium-ion battery storage system to store surplus electricity produced by the solar panels or fuel cells. This stored energy is especially useful for charging vehicles when solar or hydrogen energy is unavailable. The SHS-EVCS is designed to maximize the utilization of renewable energy, significantly reducing dependence on fossil fuels and contributing to the reduction of carbon footprints and the fight against climate change. The inclusion of battery storage ensures reliable EV charging, even when renewable energy sources are intermittent. This hybrid approach also enhances the SHS-EVCSs' overall resilience, enabling it to better manage fluctuations in energy supply and demand. Consequently, these SHS-EVCSs represent a significant advancement in sustainable transportation infrastructure, offering a scalable solution for future urban development.

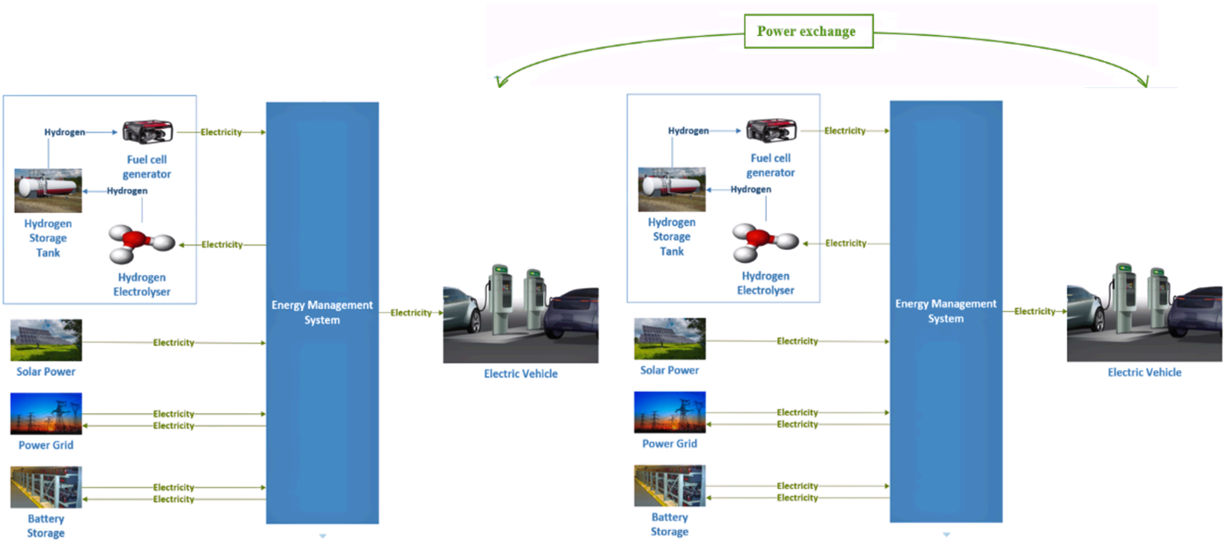


Figure 4-1 Energy exchange between two SHS-EVCSs

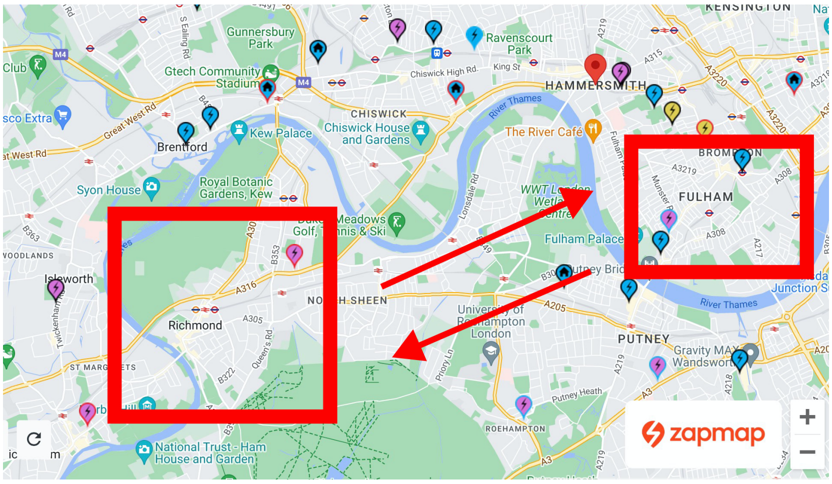


Figure 4-2 Hammersmith & Fulham and Richmond upon Thames Geographic location [156]

The placement and capacity of EVCSs are pivotal decisions that require a thorough understanding of local EV adoption trends, the existing infrastructure's capabilities, and EV drivers’ preferences. These factors are essential to ensure the network balances accessibility, convenience, and scalability effectively, supporting the rapidly expanding EV market [157]. Figure 4-1 illustrates that when two SHS-EVCSs are linked to the grid, they possess the capability to exchange power between them. This functionality is particularly beneficial when one station has surplus energy while another faces high demand; the station with excess power can transfer energy to the other, optimizing the use of renewable resources and reducing reliance on fossil fuels.

Moreover, this power-sharing capability reflects a grid-interactive approach that enhances the overall energy efficiency of the network. Figure 4-2 provides a visual representation of the geographic layout of these two stations, offering crucial insights into their spatial relationship. This visual tool aids in understanding how these stations are positioned relative to one another and the broader grid.

To further enhance the accessibility and convenience of the charging infrastructure, strategic planning has led to the establishment of a direct connection between the two nearest charging stations. This connection not only facilitates efficient energy transfer but also improves the resilience and reliability of the charging network. By linking these stations, the aim is to boost the overall effectiveness and EV drivers’ experience of the charging infrastructure, making it more adaptable to the needs of EV drivers and contributing positively to the sustainability of urban transportation systems.

4.2.2. Problem Formulation.

Although the SHS-EVCS is connected to the grid, it prioritizes maintaining self-sufficiency in its power supply. The primary aim is to rely on the energy generated internally by the EVCS to meet its daily load requirements. If the internal energy production falls short, the system may consider purchasing electricity from the grid or another EVCS to cover the deficit. The main objective of the SHS-EVCS design is to minimize both capital and operational costs. This optimization objective includes two key components: the initial capital cost C_0 which covers the construction and procurement of each distributed unit within the system, including the size of the energy storage device, and the subsequent O&M costs C_1, which relate to the operation and maintenance of each system component, such as fuel cell expenses and transaction costs between the system and the grid or between two charging stations. The system aims to find the optimal size for the energy storage device through this optimization process. O&M costs are managed by allowing energy storage and other distributed units to function as controllable loads during scheduling, while adhering to operational constraints. Additionally, the second objective function addresses environmental protection by analysing the greenhouse gas emission costs associated with each unit. A comprehensive benefit optimization model is developed to balance environmental impacts with overall benefits [158][159]. This model seeks to optimize both capital and O&M costs while effectively managing emission reduction targets for the SHS-EVCS. Even though the SHS-EVCS is grid-connected, the emphasis remains on ensuring that the EVCS can independently meet its energy demands. Should the internal energy generation prove insufficient, the system will consider drawing power from the grid or other EVCSs to maintain operations.

In summary, the problem formulation emphasizes minimizing costs and emissions while maintaining self-sufficiency in energy generation for EVCS. The optimization model addresses economic and environmental objectives, ensuring an efficient and sustainable energy management system.

4.2.3.1. Objective Function

$$minF = min\ (C_0 + \sum_{m=1}^{N} \sum_{t=1}^{T} C_1\ [m,t]) \quad 4.1$$

$$minF_{GE} = \sum_{t=1}^{T} \sum_{j=1}^{J} \zeta_j \left(\sum_{i=1}^{N} \delta_j P_{mt} + \gamma_j Q_{mt}\right) \quad 4.2$$

$$C_0 = \sum_{m=1}^{N} C_m^0 \times \frac{r \times (r+1)^y}{(r+1)^y - 1} \quad 4.3$$

$$C_1[m,t] = C_{OM}[m,t] + C_{Fuel}[m,t] + C_{grid}[m,t] + \left(M_{buy1} - M_{sell1}\right) \quad 4.4$$

$$minF = min\ (C_0 + \sum_{m=1}^{N} \sum_{t=1}^{T} C_1\ [m,t]) \quad 4.5$$

where *N* is the number of subsystems, which is 2; T is the time period, which is 24 hours; C_m^0 is the initial capital cost in the *m* subsystem; j is the greenhouse gases in class j (including CO_2, SO_2, and NO_x); *J* is the number of greenhouse gases, which is 3; ζ_j is the disposal cost for class j greenhouse gases (GBP/kW); δ_j and γ_j are the coefficients for class j greenhouse gases for the SHS system and grid (GBP/kW); P_{mt} and Q_{mt} are the power outputs (kW) of the SHS system and grid at time *t*; $C_{OM}[m,n]$, $C_{Fuel}[m,n]$, and $C_{grid}[m,n]$ are the operating and maintenance costs, fuel cell costs, and costs associated with buying and selling electricity from the grid, respectively; *r* is the discount rate, which is 6%; and M_{buy1} and M_{sell1} are the costs and revenues associated with buying and selling electricity to another EV charging station, respectively.

$$C_{OM}[m,t] = C_{OM(pvn)}[m,t] + C_{OM(hsn)}[m,t] + C_{OM(batn)}[m,t] \quad 4.6$$

$$C_{OM(pv)}[m,t] = K_{OMpv} P_{pv}[m,t] \quad 4.7$$

$$C_{OM(hs)}[m,t] = K_{OMhs} P_{H_2,i}^{t}[m,t] \quad 4.8$$

$$C_{OM(es)}[m,t] = K_{OMbat} P_{Bat,a,t}[m,t] \quad 4.9$$

$$C_{Fuel}[m,t] = a_m f_m \quad 4.10$$

$$C_{grid}[m,t] = bP_{g,buy} - cP_{g,sell} \quad 4.11$$

$$M_{buy1} = dP_{EVCS,buy1} \quad 4.12$$

$$M_{sell1} = eP_{EVCS,sell1} \quad 4.13$$

where $C_{OM(pvn)}[m,t]$, $C_{OM(hsn)}[m,t]$, and $C_{OM(batn)}[m,t]$ are the O&M cost for photovoltaic, hydrogen, and battery storage, respectively; K_{OMpv}, K_{OMhs}, and K_{OMbat} are the O&M cost, which is 28.70 GBP/kW, 14.18 GBP/kW, and 4.75 GBP/kW, respectively; $P_{pv}[m,t]$, $P^{t}_{H_2,i}[m,t]$, and $P_{Bat,e,t}[m,t]$ are the output power for PV, hydrogen, and battery storage, respectively; a_m and f_m are the price and capacity for the fuel cell, respectively; *b* and *c* are the buying and selling prices for the grid (these prices are changeable depending on the time period, but in this paper, the selling price *c* is 0.33 GBP/kWh), respectively; $P_{g,buy}$ and $P_{g,sell}$ are the buying and selling power for the grid, respectively; and *d* and *e* are the buying and selling prices from another SHS-EVCS, which are also variable depending on the time period, but in this paper, the buying price *d* is 0.24 GBP/kWh and selling prices *e* are 0.31 GBP/kWh. $P_{EVCS,buy1}$ and $P_{EVCS,sell1}$ are the buying and selling power from the EVCS, respectively.

4.2.3.2. Constraints

i. Photovoltaic Power Output Constraints

$$P^{for}_{Pv,k,t}, 0 \leq P_{Pv,k,t} \leq P^{n}_{Pv,k} \quad 4.14$$

where $P^{for}_{Pv,k,t}$ and $P^{n}_{Pv,k}$ are the predicted power and rated power of the *k* photovoltaic cells at time *t*, respectively.

ii. Battery Storage Output Constraints

$$S_{Bat,e,T} = S_{Bat,e,0} \quad 4.15$$

where $S_{Bat,e,T}$ and $S_{Bat,e,0}$ are the ending capacity and initial capacity of the battery pack *e* in the coordination period, respectively.

iii. Hydrogen Storage Output Constraints

$$E^{min}_{H_2,i} \leq E^{t}_{H_2,i} \leq E_{H_2,i,CAP}, i \quad \in \mathrm{N_{HSS}} \quad 4.16$$

where $E_{H_2,i,CAP}$ and $E^{min}_{H_2,i}$ are the capacity and lower limit of the hydrogen storage tank, respectively, and the lower limit is 20%.

iv. The Power Output of each Energy Source

$$\begin{cases} P_{min}^{in,electrolyser} \leq P_t^{in,electrolyser} \leq P_{max}^{in,electrolyser} \\ P_{min}^{FC} \leq P_t^{FC} \leq P_{max}^{FC} \\ SOC_{min} \leq SOC \leq SOC_{max} \end{cases} \quad 4.17$$

where P_t^{pv} is the power consumed of PV at time slot t; $P_{min}^{in,electrolyser}$ and $P_{max}^{in,electrolyser}$ are the upper and lower limits of $P_t^{in,electrolyzer}$, respectively; and P_{min}^{FC} and P_{max}^{FC} are the upper and lower limits of fuel cell generation, respectively.

v. Power Balance Constraint

$$\sum_{t=1}^{T} P_{pv}(t) + P_{H_2,i}^{t}(t) + P_{Bat,e,t}(t) + P_g(t) + P_{EVCS}(t) = P_{load}(t) \quad 4.18$$

P_g and P_{EVCS} are the grid and another EV charging station are involved in energy exchange at time *t,* where a positive value indicates electricity is being purchased, and a negative value indicates it is being sold. P_{load} represents the load power at time *t*.

4.2.3. NSGA-II and MOEA/D Algorithm Analysis.

This chapter addresses multiple algorithms to solve optimization problems, such as Multi-Objective Particle Swarm Optimization (MO-PSO), Non-dominated Sorting Genetic Algorithm III (NSGA-III), MOEA-D, and NSGA-II. In this part, MOEA-D and NSGA-II are more adapted to solve the problems, employing distinct methods for tackling multi-objective optimization problems. MOEA-D divides the problem into multiple subproblems and optimizes each individually, whereas NSGA-II utilizes a non-dominated sorting technique to evolve a population of solutions. Comparing these two approaches can provide insights into how their differing methodologies influence performance on specific problems. The primary configurations of the two algorithms are detailed in Table 4-1.

Table 4-1 Key Setting in the Algorithms

NSGA-II	
Population Size	100
Stopping Criteria	200

Crossover Percentage	0.8
Number of Parents	80
Mutation Percentage	0.4
Number of Mutants	40
Mutation Rate	0.01
MOEA-D	
Population Size	100
Stopping Criteria	200
Number of Neighbours	10
Crossover Percentage	0.5

4.2.3.3. NSGA-II

This section introduces the use of NSGA-II to solve the optimization problems of SHS-EVCS, ensuring that the constraints of SHS-EVCS are met in each iterative step between layers. A challenge that arises when integrating this method with SHS-EVCSs needs to manually set some parameters. However, in this chapter, both algorithms use the same manual parameter settings method as a solution, so the impact is considered negligible. Figure 4-3 presents the flowcharts for two SHS-EVCS systems optimized using the NSGA-II algorithm. The algorithm for using NSGA-II in the SHS-EVCS optimization process can be described as follows [155]:

Data input: Topological matrix. n: generation number; $minF$; $minF_{GE}$.

Algorithm 1: Non-dominated Sorting Genetic Algorithm (NSGA-II)

1. Problem definition.
   a. Define the objective function.
   b. Define the constraints.
2. Initialization.
   a. Generate an initial set of solutions.
   b. Evaluate these solutions based on the objective function and constraints.
3. Fast Non-dominated Sorting.
4. Create the offspring population.
   a. Perform crossover and mutation operations.
   b. Evaluate the offspring solutions using the objective function and constraints.

5. Merge the parent and offspring populations.
6. Environmental selection.
    a. Choose the solutions for the next generation.
    b. Prioritize solutions with the lowest non-domination level and highest crowding distance.
7. Repeat from Step 3.
8. Output the best solution.

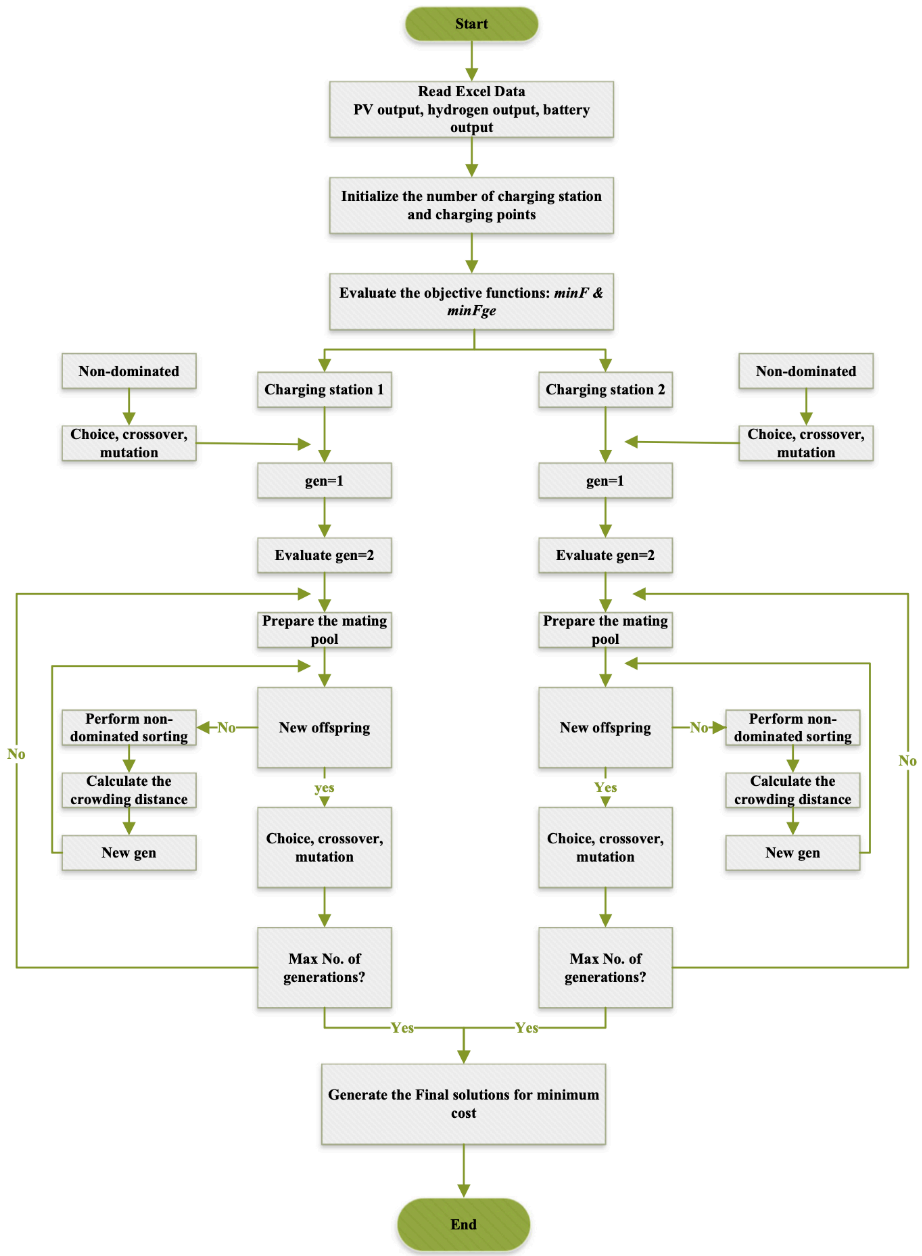


Figure 4-3 The flowchart of SHS-EV charging station using NSGA-II optimization

4.2.3.4. MOEA-D

This section explains how MOEA/D works in MATLAB. MOEA/D is in search of a solution set that is well known as the Pareto front. This algorithm incorporates the concept of mathematical programming, which not only accelerates the convergence speed of the algorithm but also ensures a more uniform distribution of solutions. Figure 4-4 shows the flowcharts of two SHS-EVCS optimized using MOEA/D. MOEA/D can summarized as follow:

Algorithm 2: Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D)
1. Input: Maximum number of iterations (200); population size (N); decision-making criteria; preference information. 2. Set the iteration counter ItrCounter = 1. 3. Generate the initial population using a uniform sampling method. 4. Evaluate the objective values of the population. 5. Determine the Pareto-based non-dominated rank using a fast-sorting operator. 6. Compute the decision-making preference degree. 7. Calculate the weighted distance for each individual. 8. Rank individuals based on the weighted distance. 9. Choose the top N individuals to form the new parent population.

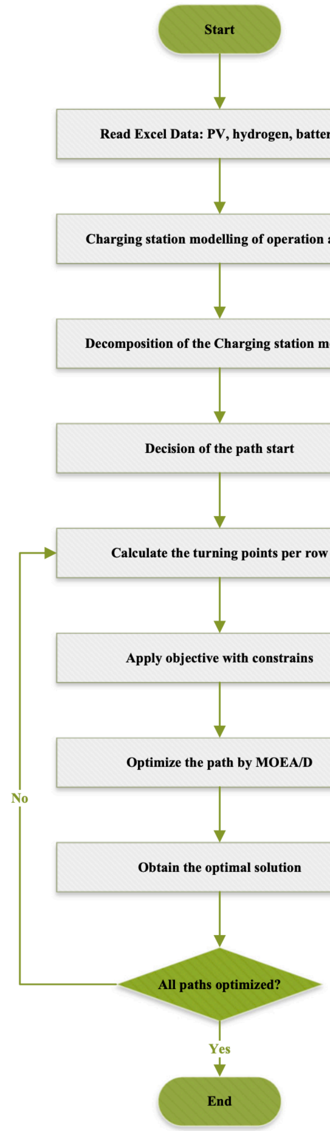


Figure 4-4 The flowchart of SHS-EVCSs using MOEA/D optimization

4.2.4. Simulation Results and Analysis Compare with Single SHS-EV Charging Station Results.

In the methodology section of the study, two SHS-EVCSs were modelled. Key technical and economic parameters for each station are detailed in Tables 4-2 and 4-3, providing insights into the functionality and financial aspects of these systems. Table 4-4 presents data on the greenhouse gas emission coefficients and disposal costs, which were key factors included in the objective function designed to optimize environmental protection operations. Table 4-5 shows the design variables using for SHS-EVCSs.

Table 4-2 Technical parameters of SHS-EVCS in two London boroughs [158][159]

Parameters	**Hammersmith & Fulham**	**Richmond upon Thames**
Charger capacity (kW)	360	360
Number of chargers per station	3	8
PV installed capacity(kW)	500	1000
Battery capacity (kWh)	500	800
Hydrogen tank capacity (m^3)	1000	1500
Fuel cell generator capacity (kW)	800	1000
Battery initial state of charge (%)	40	40
Minimum battery state of charge (%)	25	25
Maximum battery state of charge (%)	100	100
Battery charge and discharge efficiency (%)	85	85
Initial capacity of gas tank （%）	30	30
Tank storage efficiency (%)	95	95
Electric to gas efficiency (%)	75	75
Electricity-to-gas coefficient (kWh/m^3)	0.2	0.2
Gas-to-electric efficiency (%)	65	65
Gas-to-electricity coefficient (m^3/kWh)	0.295	0.295

Table 4-3 Economic parameters of SHS-EVCS in two London boroughs

Parameters	**Hammersmith & Fulham**	**Richmond upon Thames**
PV capital cost (£/kW)	1112	1112
Battery capital cost (£/kWh)	331.55	331.55
Hydrogen tank cost (£/m^3)	27.63	27.63

Table 4-4 Greenhouse gases emission costs [123][162]

Type	**Fuel cell generator eco-efficiency (kg/kWh)**	**Grid eco-efficiency (kg/kWh)**	**Disposal cost (£/kg)**
CO_2	1.596	1.432	0.088
SO_2	0.008	0.454	6.237
NO_x	0.014	21.8	26.46

Table 4-5 Design variables for SHS-EVCS

Input	Technical Specification
Replace time (y) [year]	10
PV O&M cost (K_{OMpv})[£/kW]	28.70 [159]
Hydrogen O&M cost (K_{OMhs})[£/kW]	14.18 [159]
Battery O&M cost (K_{OMbat})[£/kW]	4.75 [31]
PV output power ($P_{pv}[m,t]$) [kW]	$P_{STC} G_{AC} \frac{[1+k(T_c-T_r)]}{G_{STC}}$ [124]
Hydrogen output power ($P_{H_2,i}^{t}[m,t]$) [kW]	$E_{H_2,i}^{t-1} - (P_{H-FC,i}^{t} + P_{SH,i}^{t} + P_{H_2,i}^{t})\Delta t$ [124]
Battery output power ($P_{Bat,a,t}[m,t]$) [kW]	$P_{Bat,e,t1}\left(1-\sigma_{Bat,e}\right) + (P_{Bat,e,t}^{cha} * \eta_{Bat,e}^{cha} + \frac{P_{Bat,e,t}^{dis}}{\eta_{Bat,e}^{dis}})\Delta t$ [33]
Discount rate [%]	6
Buying and selling prices from grid (b, c) [£/kW]	0.33
Buying prices from another charging station (d) [£/kW]	0.24
Selling prices from another charging station (e) [£/kW]	0.31

Figure 4-5 illustrates the projected EV charging demand profile, or load curve, for the SHS-EVCS across two London boroughs. Each load curve represents a different SHS-EVCS. The analysis assumes Hammersmith and Fulham will host 5 SHS-EVCSs, while Richmond upon Thames will have 14, based on their current petrol station numbers [46]. Richmond displays the highest charging load, peaking at 2.8 MW, requiring eight 360 kW chargers to handle this demand. This is based on the need to charge an EV with a 60 kWh battery. In contrast, Hammersmith & Fulham's SHS-EVCS experiences the lowest load, staying under 1000 kW, where three 360 kW chargers are considered sufficient. These variations highlight the importance of location-specific infrastructure planning to meet varying demands. Properly addressing these differences is crucial for ensuring efficient and reliable EV charging across different areas.

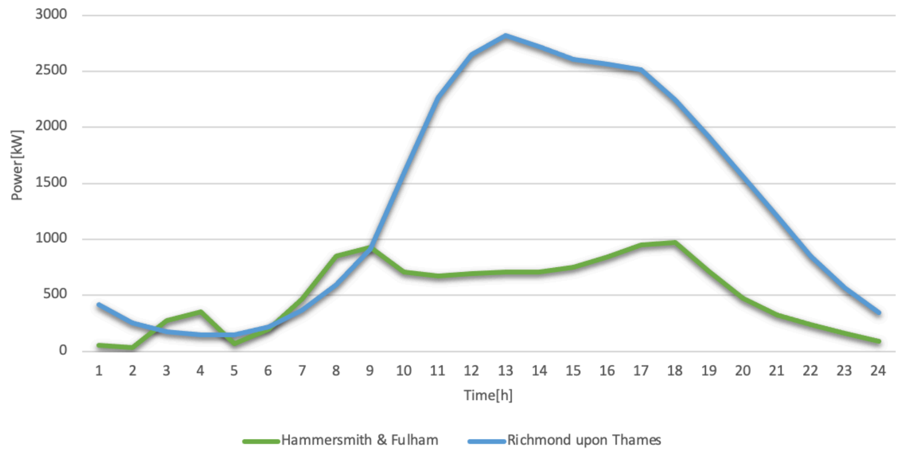


Figure 4-5 EV load curve in two London boroughs for SHS-EV charging station

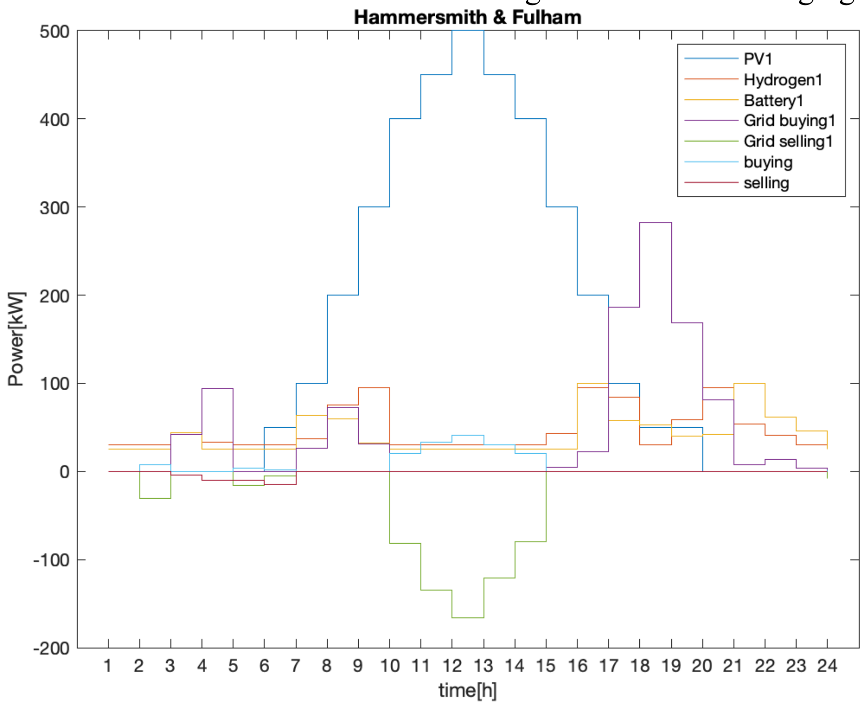


Figure 4-6 Hammersmith & Fulham optimal energy dispatch solution (with energy exchange, 4-12)

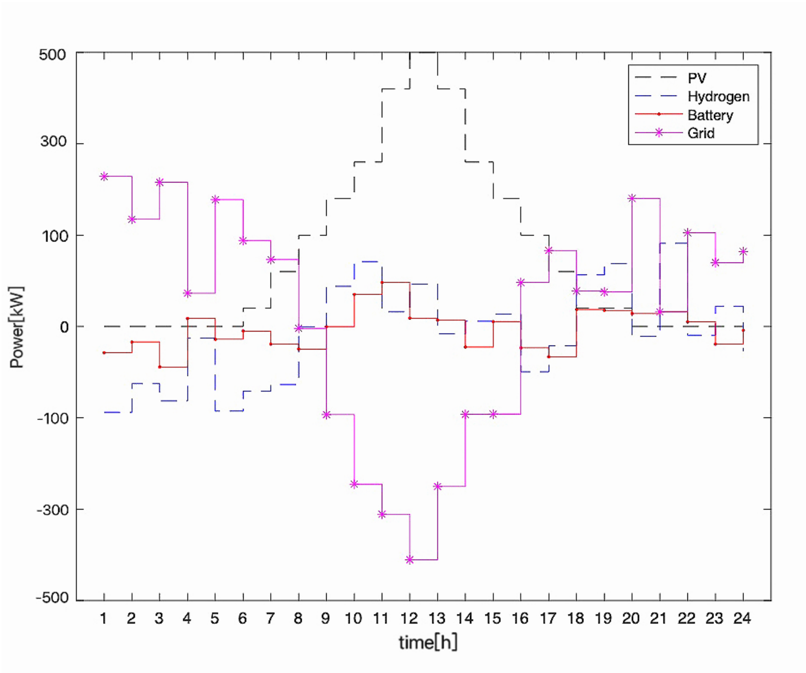


Figure 4-7 Hammersmith & Fulham optimal energy dispatch solution (without energy exchange)

Figure 4-6 shows that solar energy serves as the main power source from 7 a.m. to 7 p.m., reaching a peak capacity of 500 kW. This significant reliance on solar power underscores the critical importance of leveraging renewable energy to meet the charging demands of EVs at SHS-EVCSs during daylight hours. To ensure a stable and continuous energy supply throughout this period, the charging station incorporates hydrogen and electric storage systems, which operate in tandem to effectively manage the fluctuating daily energy requirements.

Moreover, during the hours of 10:00 a.m. to 3:00 p.m., when electricity prices are at their highest, the SHS-EVCS engages with the power grid to secure an adequate electricity supply. While tapping into the grid during these peak hours can result in increased costs, it becomes necessary to satisfy the heightened energy demands for EV charging. To mitigate these expenses, the station implements a time-of-use pricing strategy, purchasing electricity at lower rates during off-peak hours and storing it for use during peak times. This strategic approach not only helps in minimizing the financial impact of high electricity prices but also improves the overall cost efficiency of the station's operations.

Figure 4-7 offers an energy dispatch analysis for a single SHS-EVCS in Hammersmith and Fulham, which operates without energy exchange. A comparison of the two figures reveals only minor differences in the procurement of electricity from the grid. Despite the absence of detailed price information, a thorough examination of the graphs provides valuable insights into capital expenditures, operational and maintenance costs, and the financial benefits associated with reduced greenhouse gas emissions. These findings align with the two main objectives of optimizing costs and minimizing environmental impact.

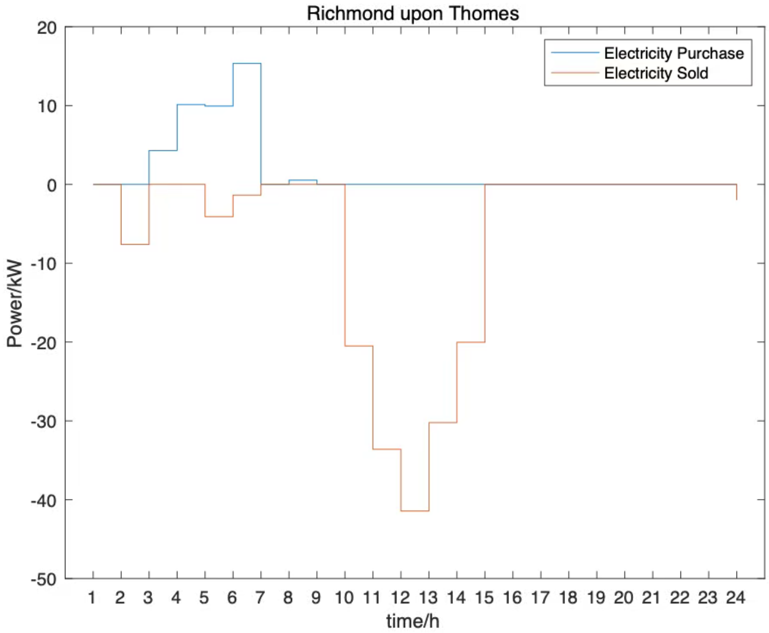


Figure 4-8 Energy exchange between two SHBS-EV charging stations

Figure 4-8 shows the energy exchange dynamics between two SHS-EVCSs over specific time intervals, showing power transfers within a 50 kW range. The analysis in Figure 4-8 indicates that when EVCSs are equipped with independent energy generation systems and connected to the grid, the energy exchange between them becomes minimal. This suggests that energy exchange has a negligible effect on the cost reduction objectives of the SHS-EVCSs. Through a thorough analysis and optimization of these energy exchange dynamics, it is possible to minimize overall operating costs while still ensuring an adequate energy supply.

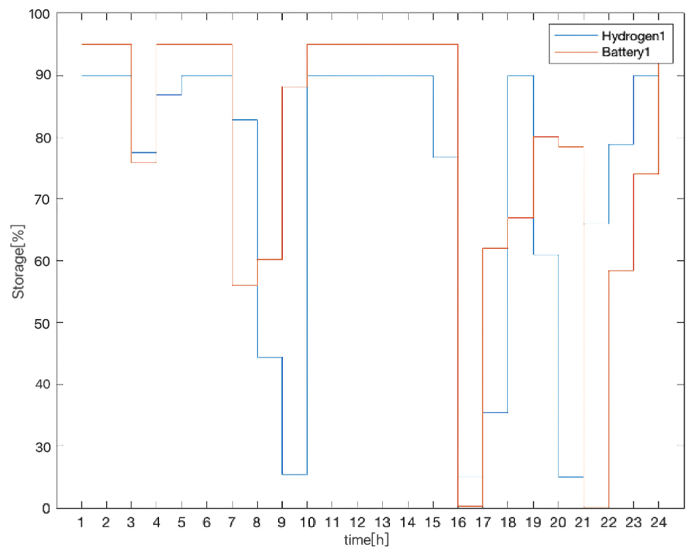


Figure 4- 9 Hydrogen and battery energy storage for 24 hours (with energy exchange)

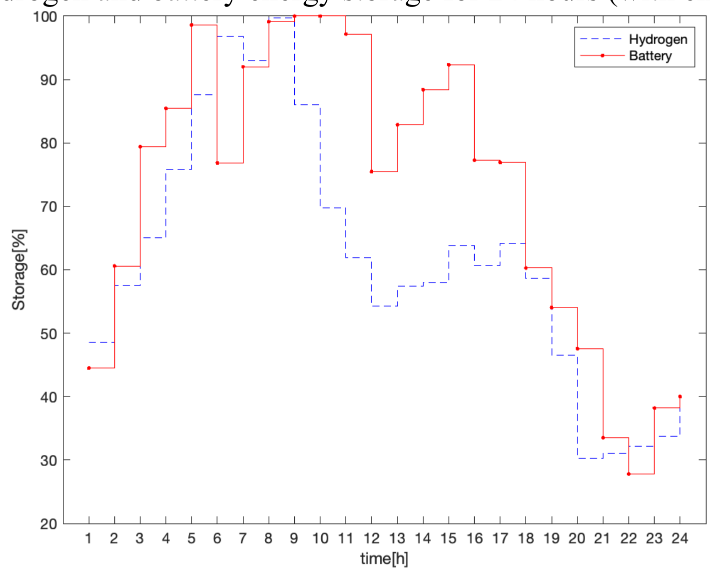


Figure 4-10 Hydrogen and battery energy storage for 24 hours (without energy exchange)

Figures 4-9 and 4-10 reveal that hydrogen and battery energy storage are primarily utilized during specific times of energy exchange, particularly from 8:00 a.m. to 10:00 a.m., 4:00 p.m. to 5:00 p.m., and 9:00 p.m. to 10:00 p.m. Additionally, these energy sources are most active during the midnight hours when no energy exchange occurs, highlighting their role in maintaining energy stability during off-peak periods.

Figure 11 highlights that point A represents the Utopia point, while area B denotes the Pareto front, containing valid Pareto optimal solutions. The research clearly shows that NSGA-II performs better than MOEA/D, especially in optimizing cost objectives.

NSGA-II demonstrates superior efficiency and practicality in achieving the desired outcomes, making it the more advantageous method for optimization in this context. This superiority is particularly evident in scenarios requiring complex multi-objective optimization, where NSGA-II consistently delivers more balanced and cost-effective solutions. As a result, the study suggests that NSGA-II is the preferred approach for achieving optimal performance across multiple criteria. The presence of outliers in this Pareto front can be attributed to a combination of algorithmic limitations, the inherent complexity of multi-objective trade-offs, and potential issues with parameter settings and model constraints. Specifically, MOEA/D, while effective in decomposing complex optimization problems, may face challenges in maintaining a balanced distribution across objectives, particularly in non-linear and non-convex problem spaces. This can result in solutions that optimize either capital and operational costs or greenhouse gas emissions but fail to achieve an efficient trade-off between the two, leading to outliers with disproportionately high emissions costs. Additionally, the complexity of multi-energy systems—where diverse energy sources interact dynamically—compounds the difficulty of finding well-balanced solutions, as the trade-offs between capital costs, operational expenses, and environmental impacts become highly sensitive to the configuration of each component.

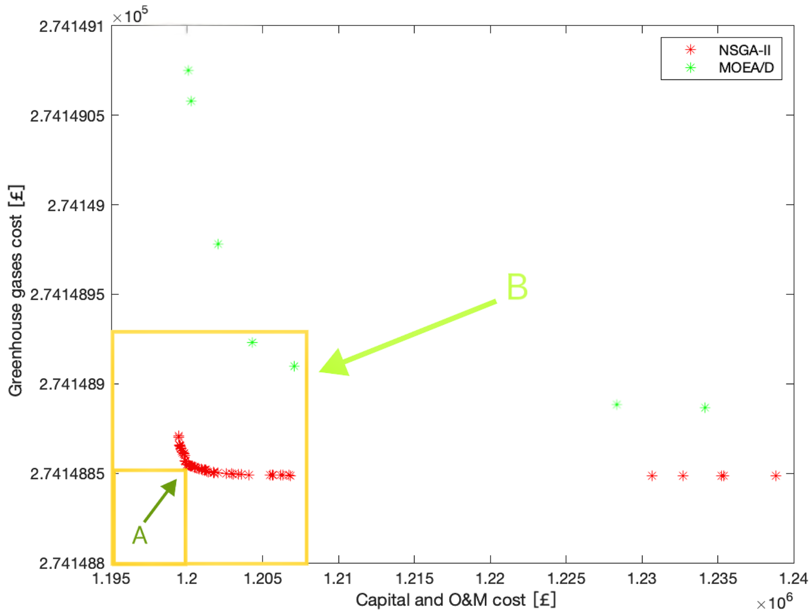


Figure 4-11 NSGA-II and MOEA/D comparison

Table 4-6 SHS-EVCS minimum cost.

Cost (£)	Hammersmith & Fulham	Richmond upon Thames
Capital cost for initial years	1,478,720	2,128,410
Discounted capital cost	201,889.15	268,422.33
Grid electricity purchase per day	575.09	1994.36
Energy exchange per day	77.12	30.25
O&M cost per day	205.65	232.79
Minimum daily cost	1673.32	3087.81
Daily cost without hydrogen storage	2152.26	3552.24

Table 4-7 EVCS cost only buy electricity from grid.

Cost (£)	Hammersmith & Fulham	Richmond upon Thames
Daily cost	4,695.88	12,225.81

Table 4-6 outlines the key economic factors for two SHS-EVCS, focusing on both capital and operating costs. The SHS-EVCS has an expected service life of ten years, with a daily maintenance cost of £4761.13, which includes regular upkeep, and the replacement of components as needed over this period. In contrast, Table 4-7 shows that the daily operating cost for two traditional charging stations is three times higher than that of the SHS-EVCS. This significant difference highlights the cost-effectiveness of the SHS-EVCS, which optimizes energy use and reduces operating expenses compared to traditional charging stations.

Given the safety concerns associated with hydrogen, an alternative design approach could involve eliminating hydrogen energy use in SHS-EVCSs. Opting out of hydrogen energy would increase the minimum daily expenditure by at least £500. Although this is still more economical than relying solely on grid electricity, it does not meet the minimum cost threshold. Other factors, such as supply chain costs, labor expenses, energy prices, and taxes, also influence installation and O&M costs, though this paper primarily addresses the technical aspects, with these additional factors to be explored in future work.

Nevertheless, integrating these stations with the broader power grid requires careful consideration of necessary adjustments, which will inevitably incur extra costs. Balancing these costs with the associated benefits is crucial, especially when aiming to promote sustainable transportation solutions. Furthermore, as the industry evolves, future advancements in technology and energy management strategies may further reduce costs, making SHS-EVCSs even more competitive. Continued research and development in this area will be essential for maximizing both economic and environmental benefits.

4.3. Multi-SHS-EV Charging Station Energy Exchange in Dali

As global subsidies for renewable energy gradually decline, EVCS powered by renewable sources need to adopt market-based strategies to remain competitive. The unpredictable nature of renewable energy generation creates significant challenges for strategic planning. To address the uncertainties caused by forecasting inaccuracies, this study proposes a game theory-based P2P energy trading strategy specifically designed for SHS-EVCS. Firstly, by accounting for the prediction errors of renewable energy within each SHS-EVCS, set a fuzzy value. Secondly, this section applies the optimization principles of game theory to develop a day-ahead P2P interactive energy trading model designed to address the volatility challenges associated with renewable energy. Thirdly, the model is reformulated as a linear convex programming problem using duality theory, making it solvable with CPLEX optimization techniques. The results of the case study show that this approach not only increases SHS-EVCS revenue to £6,187.71 through P2P trading but also helps manage operation and maintenance expenses, thereby fostering the growth of the renewable energy industry.

Key infrastructure for sustainable transportation: By integrating various renewable energy sources such as solar, wind, hydrogen, and battery storage, these charging stations offer a versatile solution that helps balance grid load and optimize energy use. The multi-energy EV charging system features an intelligent management system capable of adjusting charging power and technology in real time according to fluctuations in energy supply and demand. This enhances energy efficiency, reduces operating costs, and supports the green transformation of the power grid [161]. As a crucial component of urban green infrastructure, the multi-energy EV charging system addresses the evolving needs of EV owners and plays a significant role in achieving carbon neutrality goals.

4.3.1. 4 SHS-EV Charging Station Planning and Operation.

The traditional energy transition towards sustainable energy systems is accelerating, and in this context, EVCSs that incorporate various energy storage methods, including solar, hydrogen, and batteries, are playing a significant role. Integrating these diverse energy sources demands creative management techniques to ensure the efficiency, affordability, and dependability of the power supply. Against this backdrop, utilizing game theory and linear programming stands out as an effective method for designing and analysing P2P energy exchange systems.

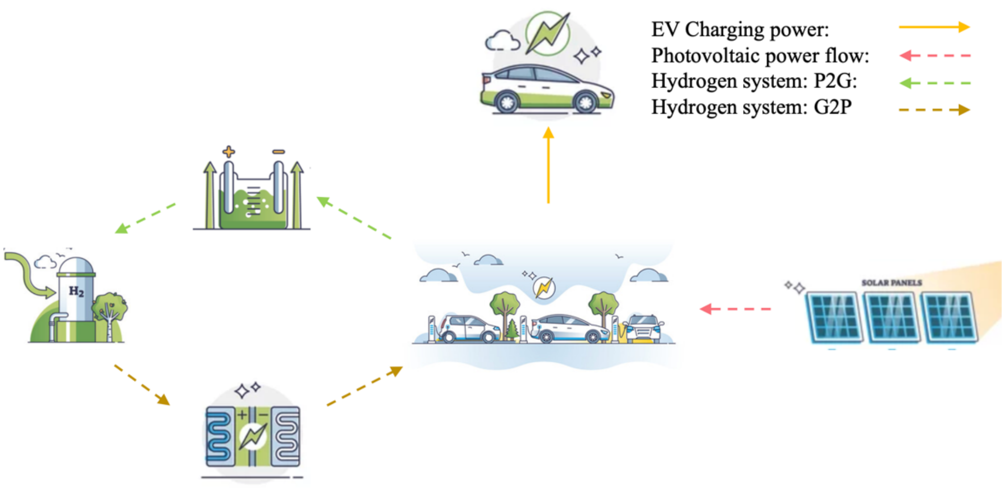


Figure 4-12 single SHS-EVCS topology

Figure 4-12 shows the SHS-EVCS, which utilizes photovoltaic panels, hydrogen storage, and batteries to charge EVs. The EVCS features a solar array equipped with photovoltaic panels that capture sunlight and convert it into electrical energy. This energy can be used directly to charge EVs, sent to the grid, or stored in battery and hydrogen systems for later use. For hydrogen storage, the system employs an electrolyze to split water into hydrogen and oxygen. The hydrogen is then compressed and stored for future use. During peak demand periods, this stored hydrogen is converted back into electricity via a fuel cell to charge EVs. Additionally, a battery storage system collects surplus energy from either the solar array or the fuel cell, ensuring a steady energy supply to charge EVs, even when solar and hydrogen sources are not active.

4.3.2. P2P Energy Trading Model.

The internal P2P transaction contains each SHS-EVCSs, battery system and grid. Therefore, the P2P model can be written as follow equations:

P2P internal trading revenue [94].

$$C_{n,t}^{sell} = \rho_{n,t}^{inter} P_{n,t}^{load} \tag{4.18}$$

$\rho_{n,t}^{inter}$ is the price of number *n* SHS-EVCS selling electricity to other SHS-EVCS using internal load.

4.5.2.1. P2G Trading with Grid.

$$C_{n,t}^{grid} = \rho_{n,t}^{B} P_{n,t}^{B} - \rho_{n,t}^{g} P_{n,t}^{g} \tag{4.19}$$

$\rho_{n,t}^{B} and\ P_{n,t}^{B}$ are the price and electricity purchased by SHS-EVCS *n* from shared battery energy storage at time *t*. $\rho_{n,t}^{g}\ and\ P_{n,t}^{g}$ are the price and power selling to grid. Usually, $\rho_{n,t}^{g}$is much lower than $\rho_{n,t}^{B}$, which can increase the profits or reduce costs through P2P trading.

4.3.2.2. P2P Transaction Energy Trading Cost.

$$C_{n,t}^{p2p} = \sum_{N}^{1} \rho_{n,t}^{N}\, P_{n,t}^{N} \tag{4.20}$$

Where *N* is the set of charging stations in P2P trading. $\rho_{n,t}^{N}$ is the transaction price between SHS-EVCS *n* and SHS-EVCS *N* at time *t*. $P_{n,t}^{N}$ is the transaction power between them at time *t*.

4.3.2.3. P2P Transactive Energy Trading Constraints.

For any time, the electricity sold and purchased should be balance.

$$P_{n,t}^{N} = -P_{n,t}^{N} \tag{4.21}$$

4.3.3. Game Theory Model.

Typically, purchasing electricity from the grid is costly, while buying and selling electricity within SHS-EVCSs can be achieved at lower prices. As a result, EVCSs often engage in internal transactions with other EVCSs that have excess electricity. During periods when multiple EVCSs have surplus energy or face electricity shortages, competition arises. Surplus EVCSs aims to sell as much excess electricity as possible to those EVCSs that are energy deficient.

In such situation, if EVCSs acting competitively adjust their electricity prices out of self-interest—to maximize their sales revenue or minimize their purchase costs—they will not hesitate to do so, even though it may impact other EVCSs. Without a binding agreement in place, these competitive EVCSs may continually alter prices to benefit themselves, which will lead to unfair and unstable energy scheduling among EVCSs.

To address this, the involved EVCSs engage in discussions to set an appropriate electricity price, which then becomes the standardized rate for energy transactions. This approach treats energy exchange price as the basis for the game strategy. The game model considers the difference between energy sales revenue and purchase costs as the benefit for each participant, constructing the following game model:

Cooperative game theory:

Gamer: N(SHS-EVCS1(1), SHS-EVCS2, SHS-EVCS3… SHS-EVCSN)

Strategy: electricity prices (ρ); power transaction value set (P)

Matrix:

$\rho = \left[\rho_{1,1}^{cs} \dots \rho_{N,t}^{cs} \dots \rho_{n,t}^{cs} \dots \rho_{N,t}^{cs} \dots \rho_{N,T}^{cs}\right]$ All gamers' pricing in different time.

$P = \left[P_{1,1}^{cs} \dots P_{N,t}^{cs} \dots P_{n,t}^{cs} \dots P_{N,t}^{cs} \dots P_{N,T}^{cs}\right]$ All gamers' transaction value.

Benefits: $U = [U_{1,1}^{cs} \dots U_{N,1}^{cs} \dots U_{n,t}^{cs} \dots U_{N,t}^{cs} \dots U_{N,T}^{cs}]$ Benefit set matrix consisting of the benefits of purchasing and selling electricity at different times for all players in the game.

Buyer: if energy exchange between charging stations, the upper limit is $P_{n,t}^{g}$ (electricity buying from grid), then $\left|P_{n,t}^{cs}\right| \leq P_{n,t}^{g}$, the SHS-EVCS is called buyer at time *t*.

Seller: if energy exchange between charging stations, the upper limit is $P_{n,t}^{g*}$ (electricity selling to grid), then $P_{n,t}^{cs} \leq P_{n,t}^{g*}$, the SHS-EVCS is called seller at time *t*.

When $SHS - EVCS_n \in Sellers$, the benefits at time *t* are:

$$U_{n,t}^{cs} = \rho_{n,t}^{cs} P_{n,t}^{cs} \Delta t + \rho_{n,t}^{g} \left(P_{n,t}^{g*} - P_{n,t}^{cs}\right) \Delta t = \sum_{j \in buyers} \rho_{n,t}^{cs} P_{nj,t}^{cs} \Delta t + \rho_{n,t}^{g} (P_{n,t}^{g*} - \sum_{j \in buyers} P_{nj,t}^{cs}) \Delta t \quad 4.22$$

When $SHS - EVCS_n \in Buyers$, the benefits at time *t* are:

$$U_{j,t}^{cs} = \sum_{n \in sellers} \rho_{n,t}^{cs} P_{jn,t}^{cs} \Delta t + \rho_{n,t}^{g*} (P_{n,t}^{g} - \sum_{n \in sellers} \left|P_{jn,t}^{cs}\right|) \Delta t \quad 4.23$$

Where $P_{jn,t}^{cs}$ means SHS-EVCS j follow the SHS-EVCS n pricing rule $\rho_{n,t}^{cs}$ to buy the power at time t, $P_{jn,t}^{cs} < 0$

For game theory constraint, it should be followed by this rule: All players will not change the electricity price strategy and believe that this electricity price strategy is the optimal electricity price strategy that does not harmful for all players.

Under the cooperative game model, within the SHS-EVCSs P2P trading model, each EVCS serves as producer and consumer, means this is multiple entities reach an agreement. Therefore, the game theory follows as figure 4-13:

a) Start trading.
b) All SHS-EVCSs request the energy exchange.
c) With the goal of maximizing the profits of the coalition, according to the energy trading needs of each EVCS, analyse whether each EVCS meets the constraints of the model running time (if the energy trading meets the best profit for the coalition in time *t*), and the energy trading plan is calculated.
d) Confirm the energy trading flow and profit calculate.
e) If the profit follows the coalition maximization, go to step f); if not, go back to the step c), recalculate the energy exchange quantity.

f) Profit allocates depends on the constraints.

g) Energy trading end.

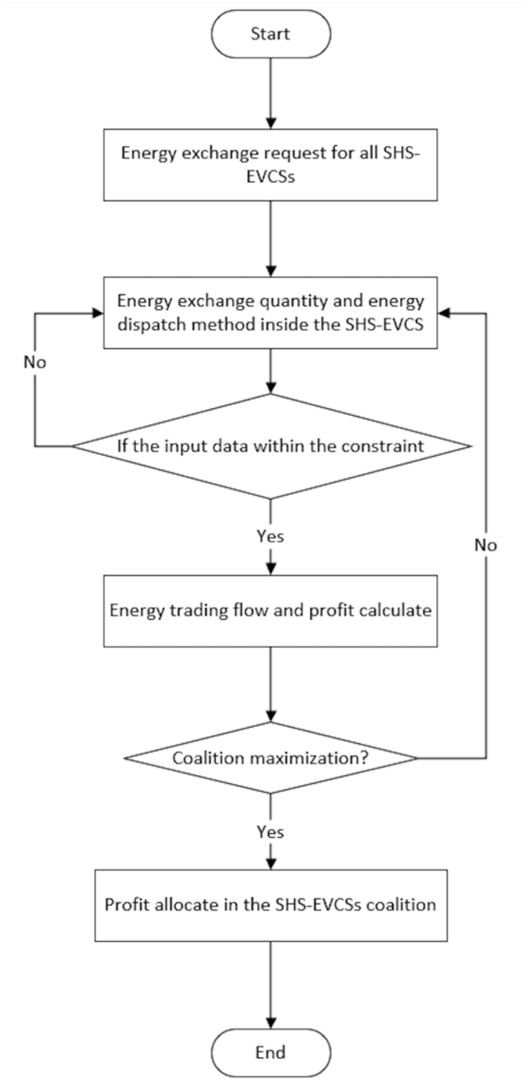


Figure 4-13 Game theory flowchart

4.3.4. Main model

4.3.4.1. Objective function

To reduce anticipated costs, the objective function F of SHS-EVCS includes the cost of hydrogen energy storage, gas turbine costs, solar energy costs, grid costs, battery storage costs, and P2P costs, minus the revenue from selling electricity (1).

$$F = min \sum_{n \in N}^{1} F_n = min \sum_{n}^{N} \sum_{t}^{T} (C_{n,t}^{E_H} + C_{n,t}^{FC} + C_{n,t}^{grid} + C_{n,t}^{Pv} + C_{n,t}^{p2p} + C_{t}^{Bes} - C_{n,t}^{sell}) \quad 4.24$$

Where: $C_{n,t}^{E_H}$ is hydrogen cost
$C_{n,t}^{FC}$ is fuel cell generator cost
$C_{n,t}^{grid}$ grid cost
$C_{n,t}^{Pv}$ solar cost
$C_{n,t}^{p2p}$ p2p trading cost
C_{t}^{Bes} battery energy storage
$C_{n,t}^{sell}$ sale revenue

4.3.4.2. Hydrogen constraints.

- Electrolyser Constraint:

$$u_{hs}(t)E_{hs,min}^{o} \leq E_{ae}^{o}(t) \leq u_{hs}(t)E_{hs,max}^{o} \quad 4.25$$

Where $E_{hs,min}^{o}$is the lower output limit of the electrolyser, $E_{hs,max}^{o}$ is the upper output limit of the electrolyser, $u_{hs}(t)$ is the state variable of the electrolyser.

- Hydrogen Tank Constraints:

$$\begin{cases} u_{hs}^{in}(t)E_{hs,min}^{in} \leq E_{hs}^{in}(t) \leq u_{hs}^{in}(t)E_{hs,max}^{in} \\ u_{hs}^{out}(t)E_{hs,min}^{out} \leq E_{hs}^{out}(t) \leq u_{hs}^{out}(t)E_{hs,max}^{out} \\ E_{hs,min} \leq E_{hs}(t) \leq E_{hs,max} \\ u_{hs}^{in}(t) + u_{hs}^{out}(t) \leq 1 \end{cases} \quad 4.26$$

Where $E_{hs,min}^{in}$ is the lower input limit of the electrolyser, $E_{hs,max}^{in}$ is the upper input limit of the electrolyser, u_{hs}^{in} is the hydrogen tank storage state variable， u_{hs}^{out} hydrogen tank release state variable.

- Fuel Cell Generator Constraint:

$$0 \leq P_{FC}^{out}(t) \leq P_{FC,max}^{out} \quad 4.27$$

Where $P_{FC,max}^{out}$ is the maximum power output for fuel cell generator.

4.3.4.3. Photovoltaic Constraint.

$$P_{pv,min} < P_{PV}(t) < P_{pv,max} \quad 4.28$$

Where $P_{pv,min}$ and $P_{pv,max}$ are the minimum and maximum PV power output.

4.3.4.4. Battery Storage Constraint.

$$E_{BSS}^{min} \leq E_{BSS,j}(k) \leq E_{BSS}^{max} \tag{4.29}$$

$$\begin{cases} E_{BSS}^{min} = (1 - DOD)E_{BSS}^{max} \\ E_{BSS}^{max} = N_{BSS}E_{rate\_BSS} \end{cases} \tag{4.30}$$

Where E_{rate_BSS} is the self-discharge rate of the battery, DOD is the depth of discharge, valued at 90%.

4.3.5. Case Study

Figure 4-14 shows the energy exchange between the four SHS-EVCS. The yellow line represents the charging of EVs, while the grey double-headed arrows indicate the buying and selling of electricity between the charging stations and either shared storage or the grid. The green dashed line connected to the hydrogen storage system shows the conversion of electricity into hydrogen gas through electrolysis, and the dark yellow dashed line depicts the conversion of hydrogen gas back into electricity using a fuel cell generator. The green dashed line associated with solar energy represents photovoltaic power generation. The blue double-headed arrows show the energy exchange occurring between the four SHS-EVCS.

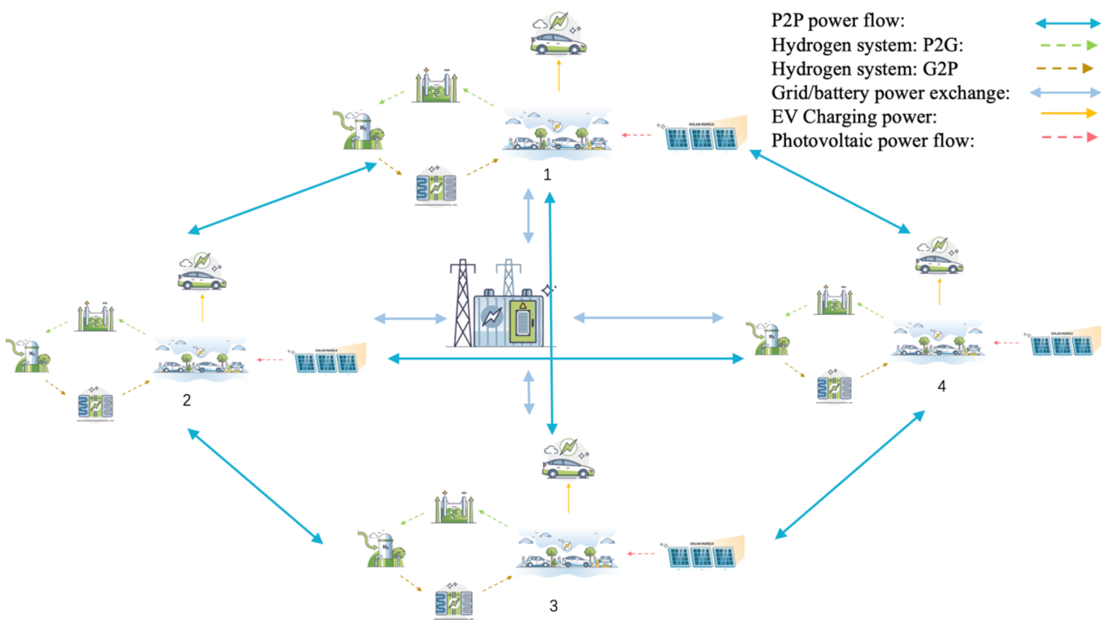


Figure 4-14 Topology of multi-SHS-EVCSs

In the simulation method, Tables 4-8 and 4-9 provide a comprehensive summary of the technical and economic parameters for the four SHS-EVCS. These tables offer a detailed overview of each station's operational capabilities and financial aspects, including energy production capacity, operational efficiency, maintenance costs, operating expenses, and potential revenue sources. Table 4-10 introduces a set of design variables essential for the simulation process. These variables play a critical role in modelling the stations' performance and economic feasibility under various scenarios, such as energy demand fluctuations, market price changes, and shifts in operational conditions. By incorporating these variables, the simulation provides valuable insights into optimizing the design and operation of SHS-EVCSs to maximize efficiency and profitability.

Dali, located in Yunnan Province, China, was selected for this case study primarily because of its unique geographic features and the booming tourism sector. Located between Cangshan mountain and Erhai lake, Dali's transport infrastructure heavily relies on two major north-south highways, as depicted in figure 4-15. The consistent influx of tourists throughout the year intensifies the demand for effective transportation solutions. Consequently, the construction of charging stations has become a crucial initiative to enhance the transportation infrastructure and promote sustainable development. This strategy not only eases traffic congestion but also promotes the adoption of eco-friendly transportation methods like EVs, thus improving Dali’s tourism experience and its environmental stewardship. Although there are several charging points available in the parking areas, most of them charge fees for both parking and charging, posing an inconvenience for users. In response, SHS-EVCS provides a more cost-effective and user-friendly option for EV owners. Furthermore, SHS-EVCS places a high priority on creating a safer and more secure charging environment, offering peace of mind to all EV drivers.

Figure 4-15 Topology of 2 main roads in Dali.

Table 4-8 Technical parameters of SHS-EVCS in four Dali boroughs

Parameters	**Longzu 1(EVCS1)**	**Longzu 2(EVCS2)**	**Qiliqiao (EVCS3)**	**Fuyuan (EVCS4)**
Charger capacity (kW)	360	360	360	360
Number of chargers per station	10	10	12	8
PV installed capacity(kW)	1500	1500	2000	1000
Shared Battery capacity (kWh)	10000	10000	10000	10000
Hydrogen tank capacity (m^3)	2000	2000	3000	1500
Fuel cell generator capacity (kW)	800	800	1000	600
Battery initial state of charge (%)	40	40	40	40
Minimum battery state of charge (%)	25	25	25	25
Maximum battery state of charge (%)	100	100	100	100
Battery charge and discharge efficiency (%)	80	80	80	80
Initial capacity of gas tank（%）	30	30	30	30
Tank storage efficiency (%)	98	98	98	98

Energy to gas efficiency (%)	70	70	70	70
Electricity-to-gas coefficient (kWh/m^3)	0.2	0.2	0.2	0.2
Hydrogen conversion efficiency (%)	75	75	75	75
Gas-to-electricity coefficient (m^3/kWh)	0.295	0.295	0.295	0.295

Table 4-9 Economic parameters of SHS-EVCS in four Dali boroughs [162-164].

Parameters	**Longzu 1**	**Longzu 2**	**Qiliqiao**	**Fuyuan**
PV capital cost (£/kW)	286	286	286	286
Battery capital cost (£/kWh)	39.6	39.6	39.6	39.6
Hydrogen tank cost (£/m^3)	7.5	7.5	7.5	7.5

Table 4-10 Design variables for SHS-EVCS

Input	**Technical Specification**
PV output power [kW]	$P_{STC} G_{AC} \frac{[1+k(T_c-T_r)]}{G_{STC}}$
Hydrogen output power [kW]	$E_{H_2,i}^{t-1} - (P_{H-FC,i}^{t} + P_{SH,i}^{t} + P_{H_2,i}^{t})\Delta t$
Battery output power [kW]	$P_{Bat,e,t1}\left(1-\sigma_{Bat,e}\right) + (P_{Bat,e,t}^{cha} * \eta_{Bat,e}^{cha} + \frac{P_{Bat,e,t}^{dis}}{\eta_{Bat,e}^{dis}})$

4.3.6. Results and Discussion

Figure 4-16 illustrates the changes in grid electricity prices and internal electricity trading prices over time. The grid electricity price remained relatively stable at £0.018/kWh until shortly after 8 a.m., when it increased slightly to £0.05/kWh, likely reflecting a base price adjustment. The internal electricity purchase price briefly rose to £0.048/kWh around 7 a.m., followed by another increase to approximately £0.075/kWh at 11 a.m., where it remained until 1 p.m. After 6 p.m., the purchase price climbed again to £0.075/kWh, holding steady until it began to decline after 8 p.m.

In contrast, the internal electricity sales price increased to around £0.47/kWh at 7 a.m., peaked again at 11 a.m., and then decreased after 2 p.m., showing an inverse relationship with the purchase price trend. After 6 p.m., the selling price surged to £0.75/kWh, maintaining this level until it began to decline after 8 p.m. These price variations reflect shifts in internal market supply and demand or strategic adjustments in electricity trading. A rise in price typically indicates increased demand or reduced supply, while a decrease suggests lower demand or increased supply. The difference between internal purchase and sales prices not only highlights potential trading margins but also underscores opportunities for cost management and revenue optimization.

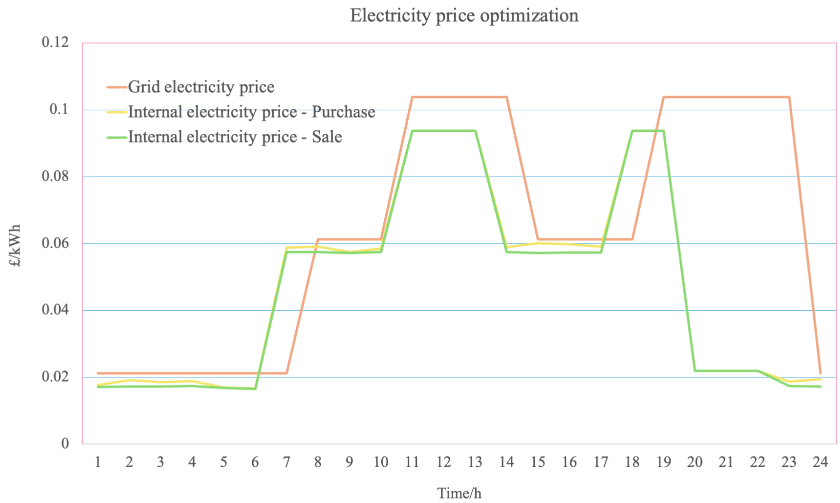


Figure 4-16 Electricity price optimization

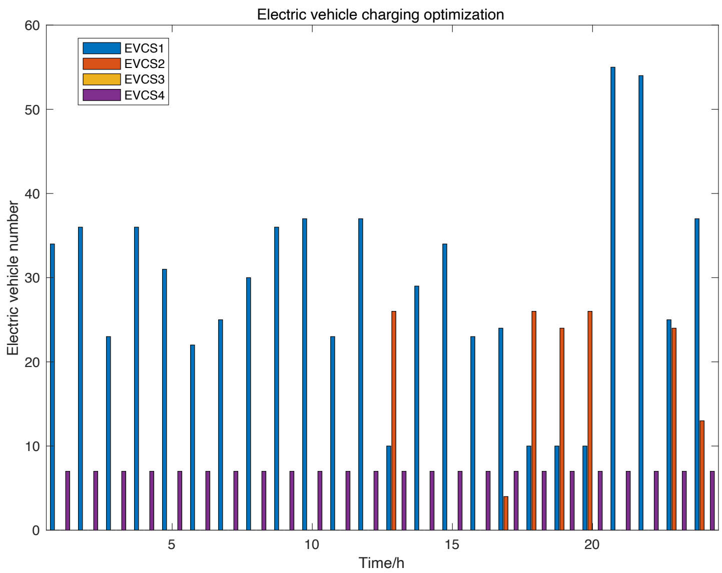


Figure 4-17 Number of electric vehicles charging stations optimization

Figure 4-17 presents the number of EVs at each charging station after optimization. SHS-EVCS 1 shows a slight decrease in vehicle numbers after 2 a.m., followed by another small drop after 6 a.m., and a significant reduction after 1 p.m., where the number of vehicles charging declines sharply. At SHS-EVCS 2, 25 vehicles begin charging at 1 p.m., with the same number observed at 8 p.m., 11 p.m., and 12 a.m. For SHS-EVCS 3, only 26 vehicles charge at 6 p.m. SHS-EVCS 4 maintains a relatively consistent number of vehicles throughout the day, with a slight increase in charging activity at 11 p.m.

The figure illustrates the results of traffic flow optimization for the four SHS-EVCSs. In designing this simulation model, factors such as geographical constraints, traffic control measures, and energy exchange were considered. The analysis of these factors allowed the simulation to generate an optimal traffic flow management strategy. The increases and decreases shown in the figure correspond to adjustments in traffic flow at each charging station under specific conditions, based on the optimal solutions produced by the simulation. By fine-tuning traffic flows, the distribution and use of charging resources can be optimized, helping to prevent congestion during peak charging times. This comprehensive plan offers guidance on effectively managing and scheduling vehicle access to charging stations, ensuring efficient charging and enhancing the overall experience for EV drivers. The insights gained from this analysis could be valuable for future research focused on optimizing operations, such as reducing power supply or staffing during periods of low demand.

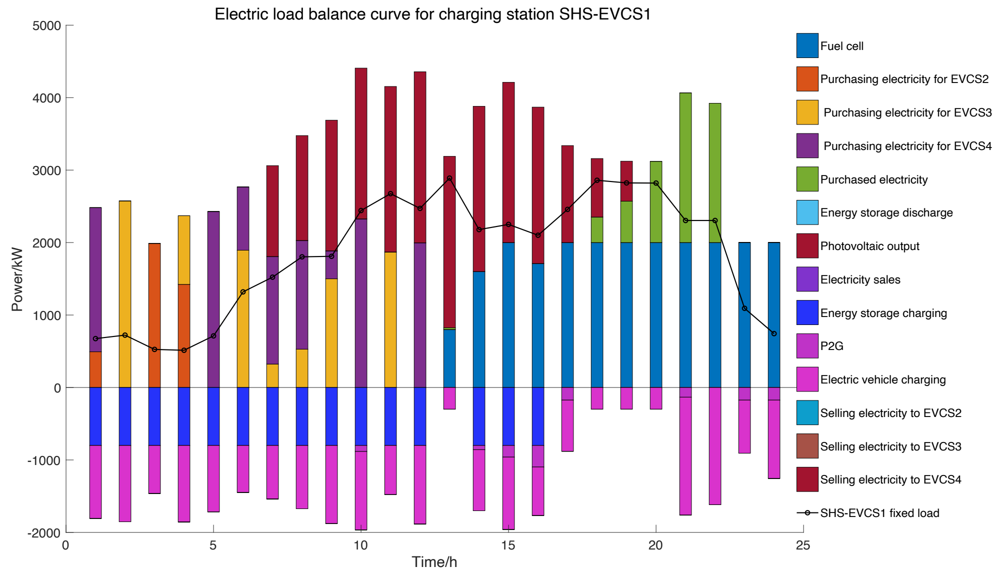


Figure 4-18 SHS-EVCS1 renewable energy usage and electricity load curve

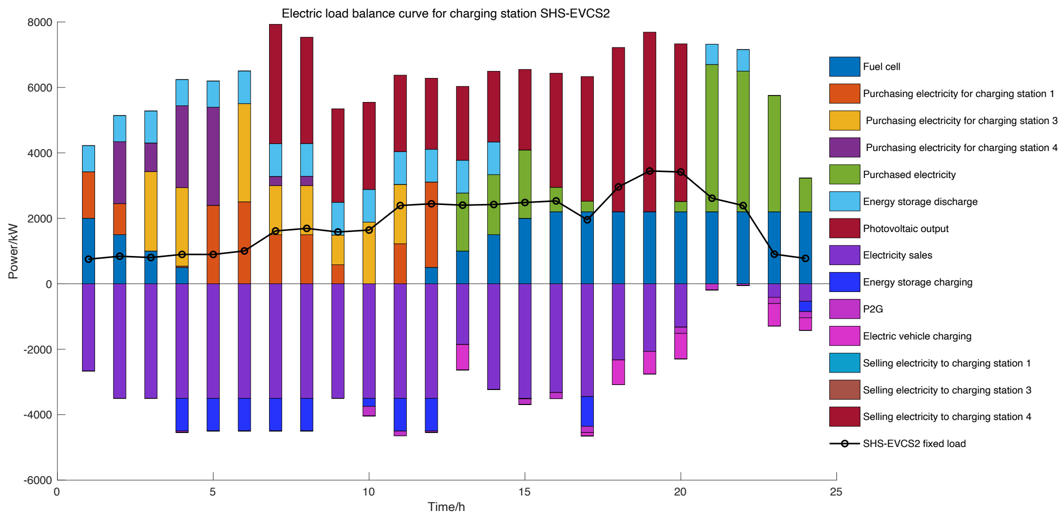


Figure 4-19 SHS-EVCS2 renewable energy usage and electricity load curve

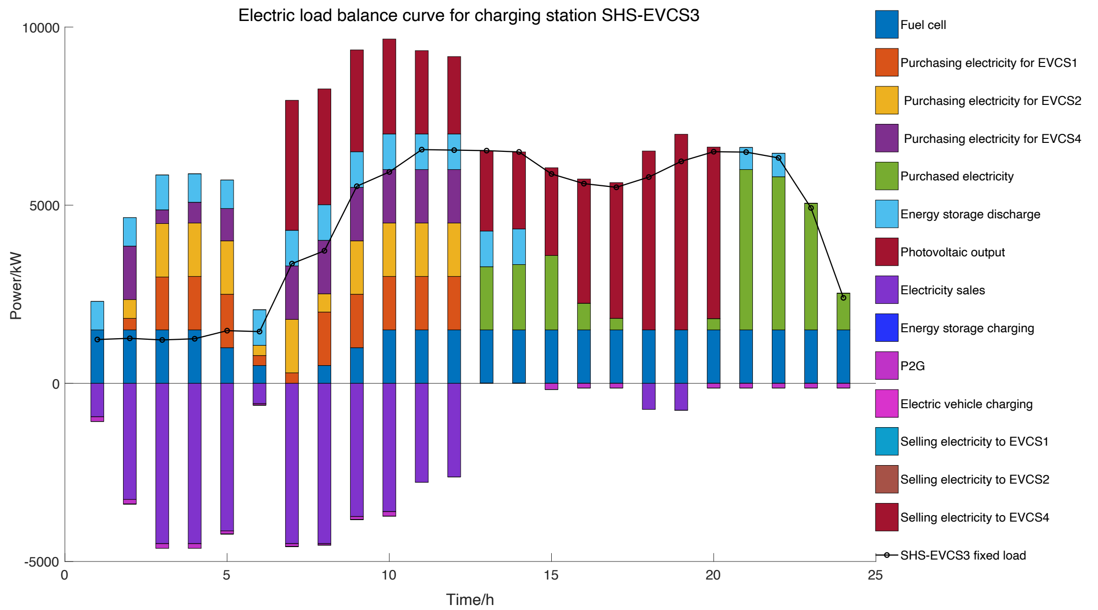


Figure 4-20 SHS-EVCS3 renewable energy usage and electricity load curve

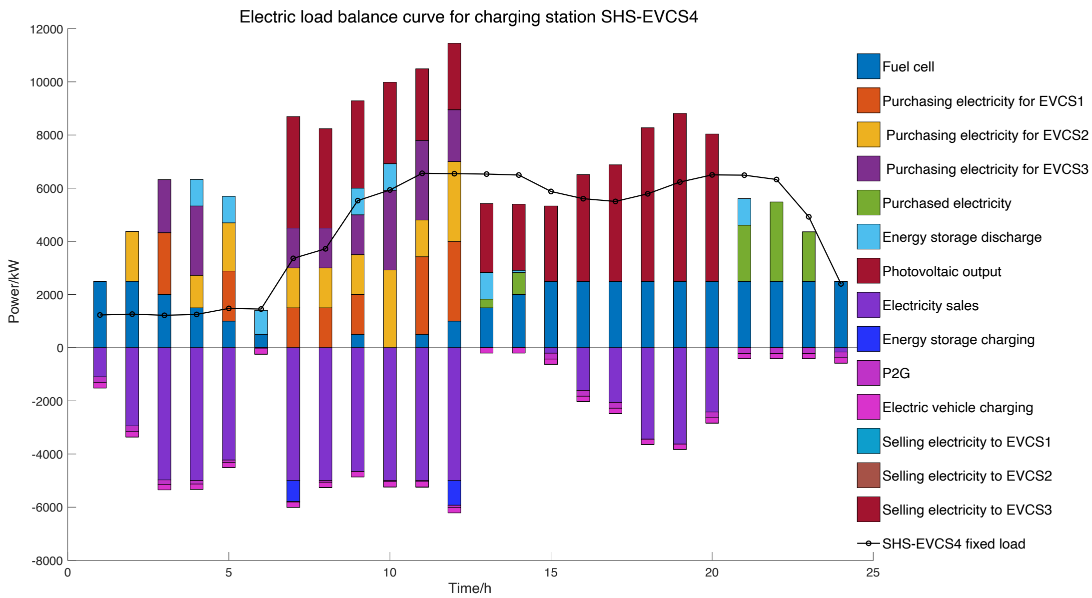


Figure 4-21 SHS-EVCS4 renewable energy usage and electricity load curve

Figures 4-18 to 4-21 present the energy usage and electricity load profiles for four different SHS-EVCSs. Photovoltaic generation is the primary source of electricity during daylight hours, capturing solar energy efficiently. Figures 4-20 and 4-21 display similar patterns in energy consumption and load, largely due to their comparable residential locations. After sunset, the electricity supply shifts to hydrogen fuel cells, supplemented by electricity from a shared battery storage system. This transition highlights the flexibility of the integrated energy systems within the SHS-EVCS framework.

Furthermore, these stations participate in inter-station power trading, demonstrating the advantages of a decentralized energy network. Optimizing the energy management strategies depicted in these figures can maximize economic benefits and reduce infrastructure costs. This approach enhances the operational efficiency of each SHS-EVCS and contributes to a more sustainable power grid by utilizing diverse energy storage and generation methods. Strategic energy management is crucial for developing resilient, intelligent power grids and advancing toward energy self-sufficiency. This optimization strategy not only improves the cost-effectiveness of energy use but also supports the integration of renewable energy sources on a larger scale. By leveraging such strategies, SHS-EVCSs can play a pivotal role in the transition to a greener, more resilient energy infrastructure, ultimately aiding in the reduction of carbon footprints and the promotion of sustainable urban development.

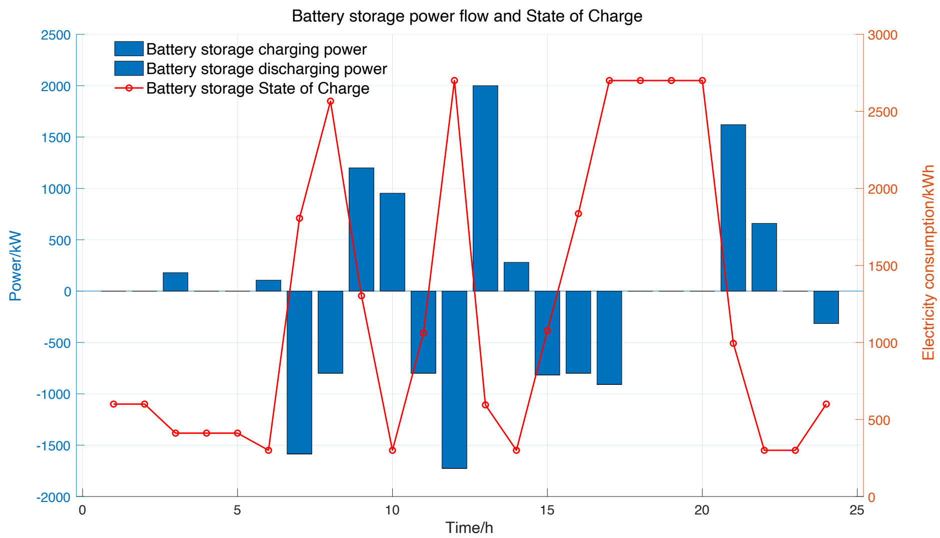


Figure 4-22 Battery storage power flow and electricity consumption

Figure 4-22 displays a composite graph featuring both a bar chart and a line graph to illustrate the operational dynamics of an energy storage system over a 24-hour period. In the bar chart, positive values indicate charging power, representing periods when the energy storage system is actively accumulating energy. Negative values signify discharging power, indicating times when the system is supplying energy to the four

SHS-EVCSs. The bars fluctuate throughout the day, with significant charging activity observed around hours 1, 6, 9, 10, 13, 14, 20, 21, and 22, likely corresponding to off-peak hours or times of surplus energy production. Discharging occurs intermittently, with the highest power output during hours 7, 8, 11, 12, 15, 16, 17, and 24, possibly aligning with peak demand periods or when grid support is needed.

The state of charge decreases during positive bar periods and increases during negative bar periods, illustrating the charging and discharging cycles of the energy storage system. This cyclical pattern continues, with the state of charge peaking at various points throughout the day, reflecting a strategy of charging during low-demand times and discharging during high-demand periods or when energy generation is insufficient, or electricity prices from the shared battery system are high. The graph highlights a well-managed energy storage system that actively adjusts its charge and discharge cycles to take advantage of fluctuating energy prices, maximize the use of renewable energy, and enhance the stability of the SHS-EVCSs. This operational strategy is key to ensuring efficient energy use and maintaining grid stability.

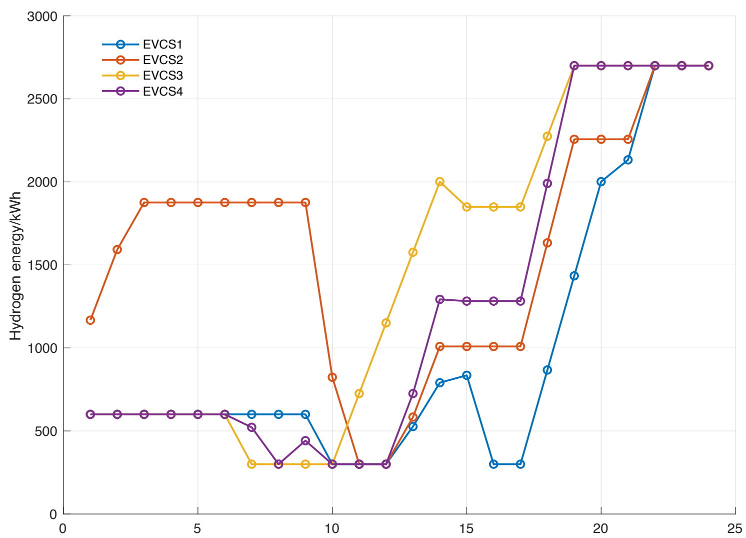


Figure 4-23 4 SHS-EVCSs hydrogen usage

Figure 4-23 shows the daily hydrogen consumption patterns across four SHS-EVCSs, revealing distinct variations in usage over the course of the day. During the early morning hours, from midnight to 10 a.m., EVCS 1 maintains a steady level of hydrogen use, while EVCS 2 shows a slight increase. In contrast, EVCS 3 and EVCS 4 experience a decrease in usage, with EVCS 3 showing a particularly sharp decline. After 10 a.m., there is a notable rise in hydrogen consumption at EVCS 3, indicating increased operational activity or demand. The other stations—EVCS 1, EVCS 2, and EVCS 4—also exhibit minor increases in usage. All SHS-EVCSs see a marked increase in hydrogen consumption until 5 p.m., reflecting higher demand or intensified charging activities. EVCS 1 records the most significant rise, followed by EVCS 2, EVCS 4, and EVCS 3. In the late evening, from 10 p.m. to midnight, hydrogen consumption stabilizes across all stations, reaching a steady level of demand. This pattern of usage aligns with typical daily trends, showing a dip in the early morning and a peak in the evening, likely reflecting standard consumer charging habits or the operational cycles of the SHS-EVCS network.

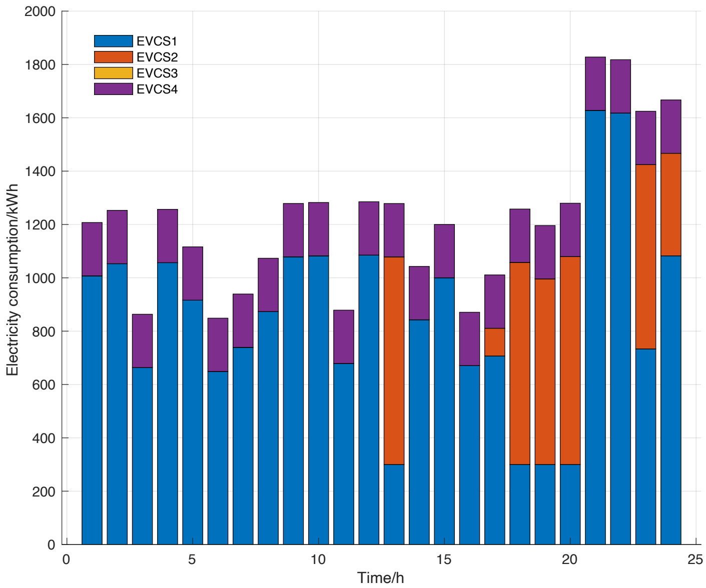


Figure 4-24 4 SHS-EVCSs EV charging optimization over 24 hours

Figure 4-24 shows the optimization of charging over a 24-hour period, providing a detailed electricity consumption patterns across four different SHS-EVCSs throughout the day. The bar graph uses differentiated colour to clearly indicate the electricity usage for each SHS-EVCS, with the height of each segment within the hourly bars representing specific consumption levels. When compared with Figure 4-18, which likely shows EV charging quantities at corresponding times, a clear correlation emerges. The electricity consumption profile in this figure mirrors the fluctuations in charging activities shown in Figure 4-18, indicating a direct relationship between the electricity used by the SHS-EVCSs and the volume of charging operations. This parallelism suggests that electricity consumption is closely aligned with the demand for charging services, allowing for better predictive modelling of energy needs based on anticipated charging loads. Understanding this relationship is crucial for optimizing energy allocation and improving the overall efficiency of SHS-EVCS operations, ensuring that energy resources are used most effectively throughout the day.

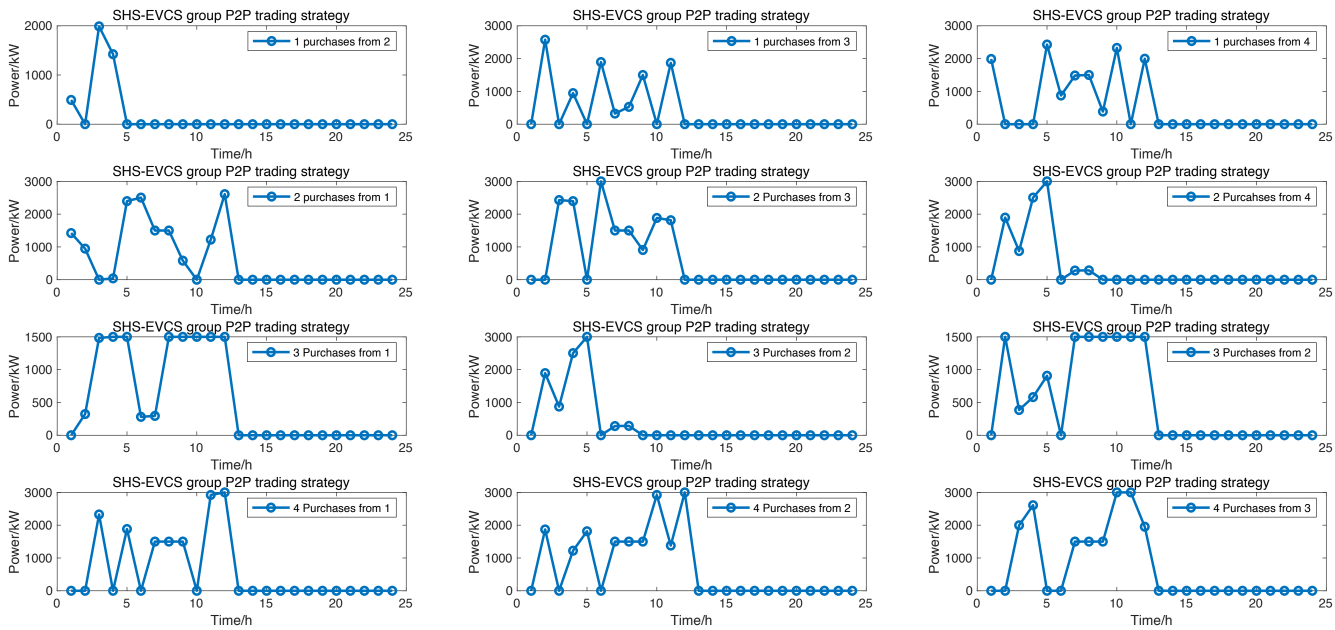


Figure 4-25 P2P trading strategy between 4 SHS-EVCSs

Each figure in figure 4-25 indicates the buyer and seller (for example, "EVCS1 purchases from EVCS2" suggests that source EVCS1 is buying from source EVCS2) with time represented in 24 hours. The data points are connected by lines to indicate the change in purchasing activity over time.

a) EVCS1 purchases from EVCS2: This figure shows the variation in purchases made by source EVCS1 from source EVCS2 over time. There are several distinct peaks in purchasing activity, especially around the 3am and 6am.

b) EVCS1 purchases from EVCS3: In this figure, purchasing activity by source EVCS1 from source EVCS3 also shows several peaks, particularly at 2am, 4am, 6am and 9am.

c) EVCS1 purchases from EVCS4: This figure shows peaks in purchases by source EVCS1 from source EVCS4 at 1am, 5am, 8am and 12pm.

d) EVCS2 purchases from EVCS1' EVCS2's purchases from source EVCS1 show peaks from 2am to 12pm.

e) EVCS2 purchases from EVCS3: This figure displays several peaks in purchases by source EVCS2 from source EVCS3, especially at 6am.

f) EVCS2 purchases from EVCS4: In this figure, source EVCS2's purchases from source EVCS4 peak at 5am.

g) EVCS3 purchases from EVCS1: Purchases by source EVCS3 from source EVCS1 are higher between 2am and 12pm.

h) EVCS3 purchases from EVCS2: In this figure, source EVCS3's purchases from source EVCS2 show notable peaks at am and 5am.

i) EVCS3 purchases from EVCS4: This figure indicates that source EVCS3's purchases from source EVCS4 peak before 12pm.

j) EVCS4 purchases from EVCS1: Source EVCS4's purchases from source EVCS1 show peaks at 12pm.

k) EVCS4 purchases from EVCS2: In this figure, source EVCS4's purchases from source EVCS2 peak at 10am and 12am.

l) EVCS4 purchases from EVCS3: Source EVCS4's purchases from source EVCS3 have peaks at 4am, 10am and 11am.

These figures represent the fluctuation of transaction volumes between different suppliers or products over time. Peaks can indicate high demand or bulk transactions at specific points in time. Analyzing these figures could provide insights into the patterns and trends of trade activity between different sources, which may be valuable for optimizing inventory management, forecasting future demands, or adjusting supply chain strategies.

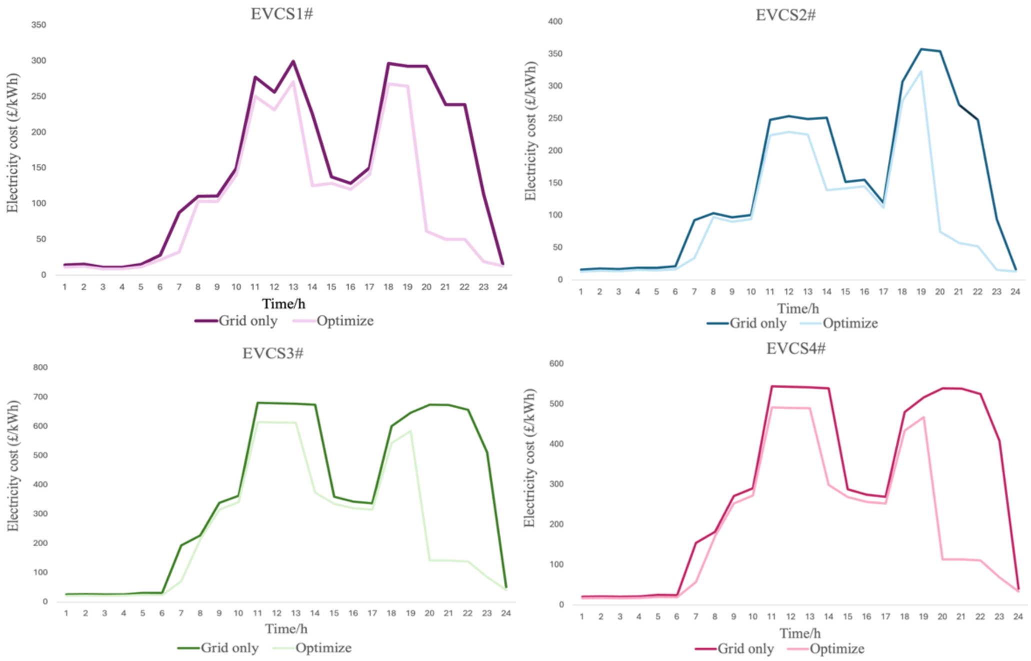


Figure 4-26 Comparison of internal electricity purchasing versus grid procurement for SHS-EVCSs

Figure 4-26 compares the internal power procurement costs of SHS-EVCS with those of grid power. The figure clearly demonstrates that internal energy trading is more cost-effective than relying entirely on grid power. This comparison emphasizes the economic benefits of optimizing power trading within SHS-EVCS, showcasing the potential for significant cost savings. It effectively illustrates the cost-efficiency of utilizing internal energy resources, promoting the adoption of such strategies to improve the economic performance of SHS-EVCS operations.

This economic analysis is crucial not only for evaluating the feasibility of SHS-EVCS configurations but also for informing decisions on scaling and expanding these systems. The significant difference between total daily costs and potential revenue highlights considerable profit opportunities, which could play a key role in encouraging investment in EV charging infrastructure and supporting the wider adoption of renewable energy technologies.

4.4. Chapter Summary

Part 1 of this chapter introduces an innovative multi-objective optimization design approach that integrates both economic and environmental considerations. Utilizing NSGA-II and MOEA/D algorithms, this approach optimizes the distributed generation power rating and energy storage system capacity of SHS-EVCS. By comparing the optimization results from these two algorithms, the proposed method in this study reveals significant advantages, offering a comprehensive analysis that incorporates a wide range of influencing factors to derive the most effective trade-off solutions. The energy flows from various sources, including solar energy, hydrogen storage, battery storage, and the grid, are meticulously managed to ensure that the EVCS delivers an economical and efficient energy supply. This thorough energy optimization strategy not only enables charging stations to adapt to the variable energy demands of EV charging but also minimizes operational costs and maximizes environmental sustainability. Furthermore, this approach contributes to reducing the carbon footprint of transportation infrastructure, supporting broader efforts to combat climate change.

Part 2 introduces a game theory-based P2P energy trading strategy, specifically tailored for multiple SHS-EVCSs, which addresses the challenges posed by the intermittency and volatility of renewable energy generation. This strategy is designed to mitigate the uncertainties that arise from inaccurate renewable energy forecasts, which can severely impact the operational efficiency and economic viability of SHS-EVCS. A key innovation in this study is the introduction of a cooperative game theory approach grounded in P2P trading, which functions as a mechanism to resolve conflicts of interest and ensure mutually beneficial cooperation among participating SHS-EVCSs. Such cooperation is essential for maintaining system stability, preventing any single SHS-EVCS from destabilizing the network through strategies like aggressive electricity price adjustments. The proposed energy trading strategy not only enhances the operational efficiency of SHS-EVCS but also fosters a collaborative environment, ensuring the long-term sustainability and economic efficiency of renewable energy use within EV charging infrastructure. This cooperation can also lead to more resilient energy networks, capable of adapting to fluctuations in both supply and demand, ultimately contributing to a more reliable and sustainable energy future.

However, this chapter is not without limitations, which highlight areas for future research. It does not currently incorporate demand-side management strategies, particularly demand response, into its framework, which could further optimize energy use and enhance the system's responsiveness to fluctuating demand. Additionally, the study does not fully explore the distinctions between cooperative and non-cooperative game theory approaches, which may lead to different outcomes and strategies in energy trading scenarios. Moreover, the social welfare aspects, such as the impact on EV drivers and broader community benefits, have not been comprehensively addressed. These aspects are crucial for ensuring that the proposed solutions are not only economically viable but also socially equitable. Future research should aim to address these gaps, exploring more sophisticated models that integrate demand-side management, a deeper analysis of game theory approaches, and a thorough consideration of social welfare impacts. By doing so, the robustness and applicability of the findings can be enhanced, making the proposed strategies more effective in a wider context and contributing to the broader adoption of sustainable energy practices in urban infrastructure.

Chapter 5 SHS-EV charging stations demand side management considering social welfare maximization

5.1. Introduction

To ensure the stable operation of a power system, it's crucial to maintain a real-time balance between supply and demand. However, achieving this balance solely through supply-side adjustments is challenging. Consequently, effective DSM becomes essential [167]. Among DSM methods, real-time pricing stands out as the most straightforward and effective. It uses electricity price signals to motivate consumers to shift their usage to off-peak periods, thereby reducing peak demand and smoothing out consumption fluctuations [134][167]. The study in [131] was the first to apply a social welfare maximization model to real-time pricing in smart grids, aiming to optimize user utility and minimize costs for power providers. The objective function combines the user's utility function and the power provider's cost, using the balance between supply and consumption as a constraint. This dual optimization approach determines supply, demand, and real-time prices.

Chapter 3 confirms the feasibility of SHS-EVCS, while Chapter 4 explores the potential for multiple SHS-EVCSs to complement each other, especially in energy trading. This chapter will evaluate the practical feasibility of EVCSs, focusing on two main models. The first model is a non-cooperative game model for a single charging station, aimed at minimizing costs related to construction, operation, and maintenance. The second model extends the internal EVCS energy transaction cooperation model discussed in Chapter 4 Part 2, incorporating operational load management and an internal dispatch centre for demand response. This model also focuses on maximizing social welfare by considering the economic interests of EV owners, particularly in terms of acceptable charging prices, which effectively minimizes the cost of electricity supply. In the general social welfare model, capital costs of electricity generation (including grid, renewable energy, and storage systems) are significant. However, in the SHS-EVCS model, these capital costs are already accounted for in the non-cooperative game model for a single charging station, so they are excluded from the social welfare maximization model.

The chapter makes three key contributions:

- Develop an EV charging time model, which employs a Markov decision process to manage the uncertainty of charging times, combined with Monte Carlo simulation to predict EV charging demand based on the probability of various charging durations.
- Create a bi-level optimization model that integrates both non-cooperative and cooperative game theory to tackle the dual challenges of minimizing capital costs and maximizing social welfare.
- Enhance a duality theory-based real-time pricing model aimed at maximizing social welfare, which accounts for EV charging demand while considering the interests of drivers, SHS-EVCS, and the grid.

This chapter is structured as follows: Section 5.2 describes the bi-level model of multi-SHS-EVCSs, covering three layers—information, economic, and energy. Section 5.3 presents the EV charging time and demand model. Section 5.4 develops the social welfare model. The case study is discussed in Section 5.5, and the chapter concludes in Section 5.6.

5.2. Bi-level Model

This chapter divides the multi-SHS-EVCSs system into two levels. The first level addresses the single SHS-EVCS level, which utilizes a non-cooperative game theory model to reschedule energy dispatch in order to meet the Level 1 objective function-minimize the capital cost. The second level similar as part 2 of Chapter 4 but an Internal Management System (IMS), which is also called demand response centre, will be acceded to the SHS-EVCSs coalition to manage the ordering of charging and discharging. In this stage, there will be two scenarios, the first scenario will calculate the uncertainty of EV charging time to predict the EV charging demand; the second scenario will using the fixed load data from chapter 4. The objective function at this level aims to maximize the coalition's profit. The final objective for this bi-level model is to maximize social welfare.

5.2.1 First Level SHS Model

This section integrates solar energy, hydrogen storage system, battery storage (SHS), and the grid as player in a non-cooperative game theory for CS, which hydrogen storage provides long-term energy buffering, batteries offer rapid response to demand fluctuations, solar energy contributes renewable generation, and the grid ensures stable supply. The objective is to minimize construction, operation, and maintenance costs while optimizing energy allocation. The specific interaction model is illustrated in Figure 5-1.

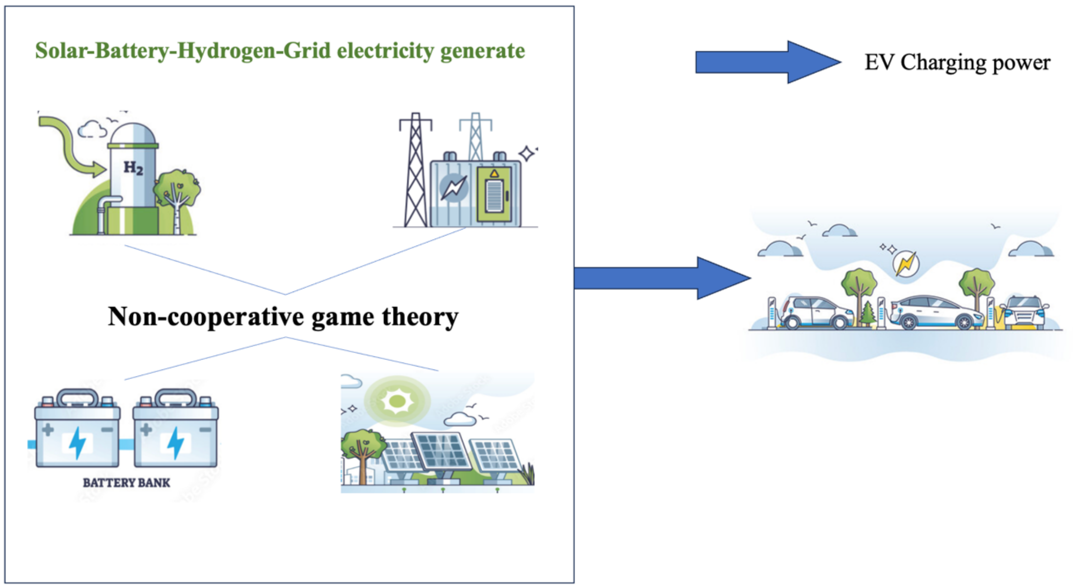


Figure 5-1 Electricity dispatch depends on non-cooperative game theory within SHS system

The objective function for this part is similar as 4.1-4.11, but 5.1-5.9 are not considering energy exchange inside the SHS system. The formular is shown as:

$$minF = min\ (C_0 + \sum_{m=1}^{N} \sum_{t=1}^{T} C_1\ [m,t]) \quad 5.1$$

$$C_0 = \sum_{m=1}^{N} C_m^0 \times \frac{r \times (r+1)^y}{(r+1)^y - 1} \tag{5.2}$$

$$C_1[m,t] = C_{OM}[m,t] + C_{Fuel}[m,t] + C_{grid}[m,t] \tag{5.3}$$

$$C_{OM}[m,t] = C_{OM(pvn)}[m,t] + C_{OM(hsn)}[m,t] + C_{OM(esn)}[m,t] \tag{5.4}$$

$$C_{OM(pv)}[m,t] = K_{OMpv} P_{pv}[m,t] \tag{5.5}$$

$$C_{OM(hs)}[m,t] = K_{OMhs} P_{H_2,i}^{t}[m,t] \tag{5.6}$$

$$C_{OM(es)}[m,t] = K_{OMes} P_{es,a,t}[m,t] \tag{5.7}$$

$$C_{Fuel}[m,t] = a_m f_m \tag{5.8}$$

$$C_{grid}[m,t] = bP_{g,buy} - cP_{g,sell} \tag{5.9}$$

where *N* is the subsystem, which is 2; T is 24 h; C_m^0 is the initial capital cost in the *m* subsystem; $C_{OM}[m,n]$, $C_{Fuel}[m,n]$, and $C_{grid}[m,n]$ are the operating and maintained cost, fuel cell cost, and selling and buying electricity price from grid cost, respectively; *r* is the discount rate, which is 6%; $C_{OM(pvn)}[m,t]$, $C_{OM(hsn)}[m,t]$, and $C_{OM(batn)}[m,t]$ are the photovoltaic, hydrogen, and battery storage O&M cost; K_{OMpv}, K_{OMhs}, and K_{OMbat} are the operation and maintenance cost, which is 28.70 GBP/kW, 14.18 GBP/kW, and 4.75 GBP/kW, respectively; $P_{pv}[m,t]$, $P_{H_2,i}^{t}[m,t]$, and $P_{es,e,t}[m,t]$ are the output power for PV, hydrogen, and battery storage, respectively; a_m and f_m are the price for the fuel cell and capacity for the fuel cell, respectively; *b* and *c* are the buying and selling prices for the grid (these prices are changeable depending on the time period, but in this paper, the selling price *c* is 0.33 GBP/kWh), respectively; $P_{g,buy}$ and $P_{g,sell}$ are the buying and selling power from the grid, respectively.

This chapter is also using the PSO to solve the first level problem, using the equation 3.9-3.14, and energy constrains are same as equation 4.14-4.17.

5.2.1.1. Non-Cooperative Game Theory

The model presented in this section is a multi-agent framework where each participating piece of equipment focuses on cost minimization. The strategic decisions of each participant are independent of others, establishing a scenario of mutual interaction and fair competition. This setup characterizes a typical non-cooperative game model. The non-cooperative interactions among all energy sources can be described as follows:

$$G = \{P; N; E\} \tag{5.10}$$

Where P is the game player; N is the strategy set; E is the payoff function.

- Game player: in the context of this game, each entity with decision-making authority is referred to as a game player. The game participants in this study include solar energy (S), hydrogen energy storage (H), battery energy storage (B), and the power grid (G). The collective set of these participants is represented as follows:

$$P = \{S, H, B, G\} \tag{5.11}$$

- Strategy Set: during the game, each participant selects a set of strategies to maximize their own benefits. In this context, the strategies correspond to minimizing costs for each energy source: solar energy (N_S), hydrogen energy storage (N_H), battery energy storage (N_B), and the power grid (N_G). The strategy set is represented as follows:

$$N = \{N_S;\ N_H;\ N_B;\ N_G\} \tag{5.12}$$

- Payoff: the payoff function evaluates the cost of each participant in the game and serves as crucial feedback for adjusting strategies in subsequent rounds. The payoff function for each participant depends not only on their own strategy but also on the strategies of other participants. It is represented as a function of the strategy combination, as shown in Equation (5.13), E_{SHS} is the minimum cost for the SHS system:

$$E_{SHS}(N_S;\ N_H;\ N_B;\ N_G) \tag{5.13}$$

In general, non-cooperative games will expect to find a Nash equilibrium and obtain the optimal objective function.

To satisfy the condition for Nash equilibrium minimize the cost for grid, which can be tell as less power buying from grid. Therefore, the optimal solution for grid P_g^t needs to fix the power of P_{pv}^t, P_{hs}^t, and P_{es}^t. For solar power optimal solution P_{pv}^t, fix the power of P_g^t, P_{hs}^t, and P_{es}^t; For battery storage optimal solution P_{es}^t, fix the power of P_g^t, P_{hs}^t, and P_{pv}^t; For hydrogen storage system optimal solution P_{hs}^t, fix the power of P_g^t, P_{es}^t, and P_{pv}^t. Decision variables are the power generated or purchased from P_g^t, P_{hs}^t, P_{es}^t, and P_{pv}^t at time t.

To solve Nash Equilibrium

1) Initialization: set initial strategies N_S, N_H, N_B, N_G, replace by P_g^t, P_{pv}^t, P_{hs}^t, and P_{es}^t.
2) Iterative optimization:
   - Grid:
     - Fix P_{pv}^t, P_{hs}^t, and P_{es}^t.
     - Solve the optimal P_g^t.
   - Solar power:
     - Fix P_g^t, P_{hs}^t, and P_{es}^t.
     - Solve the optimal P_{pv}^t.
   - Battery storage:
     - Fix P_g^t, P_{hs}^t, and P_{pv}^t
     - Solve the optimal P_{es}^t.
   - Hydrogen storage system:
     - Fix P_g^t, P_{es}^t, and P_{pv}^t
     - Solve the optimal P_{hs}^t.
3) Check convergence:
   - Verify if all participants' strategies converge to a fixed point.
   - If not converged, return to step 2 for further iteration.
4) Verify Nash Equilibrium:

- Confirm that all strategy combinations satisfy the Nash equilibrium condition, meaning each participant cannot further reduce its cost by changing its strategy while others' strategies remain unchanged.

5.2.1.2. EV Uncertainty Model

To capture the randomness of EV charging times, this chapter adopts the Markov chain probability model, which is particularly well-suited for describing random processes with discrete time and states. A key feature of this model is that the next state depends solely on the current state, independent of previous states. The transition probabilities between these states help simplify the complexity of the random process. Each power level of the EV battery can be considered a discrete state, making the random fluctuations in battery power a non-stationary Markov chain. This approach effectively represents the probability of future events based only on the current state [168].

$$P\left\{x_f^{dis}\middle|x_1^{dis}=s_1^{dis},x_2^{dis}=s_2^{dis},\dots,x_{f-1}^{dis}=s_{f-1}^{dis}\right\}=P\left\{x_f^{dis}\middle|x_{f-1}^{dis}=s_{f-1}^{dis}\right\} \quad 5.14$$

$$s_f^{dis}\in S^{dis},1\le f\le f_{max}$$

Where x_f^{dis} is the $f'th$ discrete variables; s_f^{dis} is the $f'th$ discrete state; S^{dis} is the discrete state space; f_{max} is the maximum number of discrete variables.

Based on 5.14, it is also needs to satisfy:

$$P\left\{x_f^{dis}\middle|x_{f-1}^{dis}=s_{f-1}^{dis}\right\}=P\left\{x_{f+1}^{dis}\middle|x_f^{dis}=s_f^{dis}\right\} \quad 5.15$$

To describe the randomness and reversibility of the EV charging and driving power consumption process, the detailed balance condition is incorporated into the Markov sampling process. This ensures reversibility between any two states:

$$p_{ij}P\left\{x_{f+1}^{dis}=s_j^{dis}\middle|x_f^{dis}=s_i^{dis}\right\}=p_{ji}P\left\{x_{f+1}^{dis}=s_i^{dis}\middle|x_f^{dis}=s_j^{dis}\right\} \quad 5.16$$

Where p_{ij} is the transition probability of state i to j; p_{ji} is the transition probability of state j to i.

EVs can be categorized into two operating states: charging and non-charging (waiting). These correspond to two distinct modes: charging mode and waiting mode [168-171].

In charging mode, the vehicle is connected to the SHS-EVCS and actively charging. In waiting mode, the vehicle is at the SHS-EVCS but not connected for charging, essentially in a parked state. The variable c_f represents the probability that the vehicle is in the charging state, highlighting the randomness of the charging process, while d_f represents the probability of charging interruption, capturing the uncertainty in the charging process.

The state transition probabilities show in figure 5-2. Here, EVC_f and EVD_f denote the states of the charging mode and waiting mode, respectively. The probabilities of transition between these states are represented by d_f and c_f, while a_f indicates the waiting probability. ΔT_1 and ΔT_2 represent the charging time and waiting time, respectively.

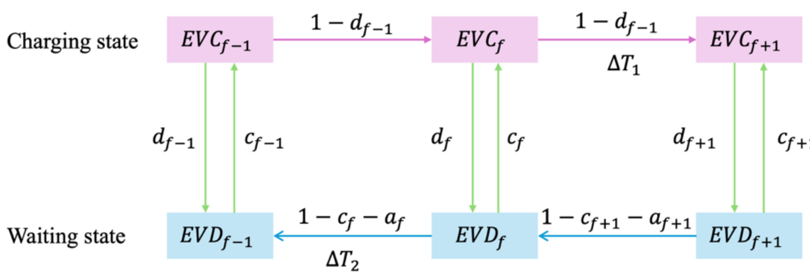


Figure 5-2 State transition diagram

If the EV drivers are anxiety of battery level, in this paper, the level is $B_{min}^{arrive} \leq 35\%$, the drivers will charge their EV. When charging the car, if $B_{min}^{leave} \geq 95\%$, the EV drivers will choose to discharge their cars. *N* is the full battery level which is 100. Suppose that battery capacity consumption is no more than 50%, the probability for c_f and d_f can be demonstrate as [168,169,170]:

$$c_f = \begin{cases} \frac{1}{1+e^{(f-0.5(B_{min}^{arrive}+N))^{0.14}}} & f \geq B_{min}^{arrive} \\ 1 & f < B_{min}^{arrive} \end{cases} \tag{5.17}$$

$$d_f = \begin{cases} \frac{1}{1+e^{(0.5(B_{min}^{leave}+N)-f)^{0.32}}} & f \geq B_{min}^{leave} \\ 0 & f < B_{min}^{leave} \end{cases} \tag{5.18}$$

The state probability EVC_f and EVD_f of EV can be denoting as [168, 169, 170]:

$$P_s(EVC_f) = \begin{cases} (1-d_{f-1})P_s(EVC_{f-1}) + c_f P_s(EVD_f) \\ 1 \le f \le N \\ c_0 P_s(EVD_0) \\ f = 0 \end{cases} \quad 5.19$$

$$P_s(EVD_f) = \begin{cases} d_f P_s(EVC_f) + a_f P_s(EVD_f) + (1 - c_{f+1} - a_{f+1})P_s(EVD_{f+1}) \\ 0 \le f \le N-1 \\ d_N P_s(EVC_N) + a_N P_s(EVD_N) \\ f = N \end{cases} \quad 5.20$$

Where $P_s(EVC_f)$ is the state probability of EVC_f, and $P_s(EVD_f)$ is the state probability of EVD_f.

These variables subject to:

$$\sum_{f=0}^{100}\{P_s(EVC_f) + P_s(EVD_f)\} = 1 \quad 5.21$$

$$d_0 = 0, c_0 = 1, d_{100} = 1, c_{100} = 0 \quad 5.22$$

Equation (5.21) states that at any given time, the sum of all state probabilities for the EV must equal 1. Equation (5.22) specifies that when the battery power is at 0, the EV must be in the EVC_f mode, and when the battery is fully charged, it must be in the EVD_f mode.

ΔT_1 and ΔT_2 are [168]:

$$\Delta T_1 = min\left\{\frac{B_{cap}\Delta(+f)}{N\eta_c P_c}, T_{leave} - T_{arrive}\right. \quad 5.23$$

$$\begin{cases} \Delta T_2 = \frac{B_{cap}\Delta(-f)}{NE_{km}v} \\ 1 \le \Delta(-f) \le N \end{cases} \quad 5.24$$

Where:

η_c is the EV battery efficiency, which is 95%

P_c is the fixed charging power, which is 7kW

B_{cap} is the battery capacity, which is 60kWh (Tesla model 6 battery capacity)

$\Delta(-f)$ is the electricity loss when driving the EV

E_{km} is power consumption, which is 16.25kWh/100km

v is the average driving speed, which is 32km/h

To forecast electricity demand across all SHS-EVCSs for numerous EV drivers, it's crucial to start by creating a model to predict the charging demand of a single EV. This model serves as the foundation for understanding broader consumption patterns. Then, by summing the individual charging demands using the Monte Carlo random simulation method, the total electricity demand for all EVs can be calculated. The total charging power demand at any given moment can be expressed as follows:

$$P_{cha,sum} = \sum_{i}^{N_{ev}} P_{cha,i} \quad 5.25$$

Where $P_{cha,sum}$ is the total charging power; $P_{cha,i}$ is the $i'th$ EV charging power; N_{ev} is the total EV number.

For each EV's SOC, it should follow:

$$SOC_{start} = \frac{1}{SOC_{start,max} - SOC_{start,min}} \quad 5.26$$

Where SOC_{start} is the initial SoC of EV, $SOC_{start,max}$ and $SOC_{start,min}$ are the maximum and minimum SoC for EV.

For EV's battery SOC_{arrive} when arriving at SHS-EVCS, it denotes as:

$$SOC_{arrive} = SOC_{start} - \frac{D_{EV} E_{km}}{B_{cap}} \quad 5.27$$

Where D_{EV} is the EV driving distance and subject to:

$$0 \leq D_{EV} < \frac{B_{cap}}{E_{km}} \quad 5.28$$

Meanwhile, for all the EV drivers, they have z times charging opportunity:

$$1 \leq z \leq 3 \quad 5.29$$

Although the Monte Carlo method offers high prediction accuracy, it requires prior knowledge of the probability distribution of input samples. Predicting EV charging demand involves many uncertainties that typically do not follow standard probability distributions, making it challenging to determine the corresponding probability density functions [168]. For example, the probability that an EV owner opts for a simple trip chain for commuting and the probability that an EV charges from the grid often belong to discrete probability distributions [168–170]. Therefore, it is essential to first define the probability distribution of the relevant uncertainties before applying the Monte Carlo method to predict EV charging demand.

The EV charging forecast algorithm is follow as (Algorithm 5.1):

Algorithm 5.1: EV Charging Demand Forecast Algorithm

Input: the EV data: B_{cap}, η_c, P_c, E_{km}, v, $N_{ev}\ldots$

a) Repeat 1: calculate the EVs charging demand
b) Get initial EV data SOC_{start} , $P_{cha,sum}$ through Monte Carlo random simulation method
c) Repeat 2: calculate single EV charging demand
d) Update the current battery level
e) Calculate the charging and discharging probability c_f, d_f
f) Calculate the charging duration ΔT_1
g) Calculate the waiting duration ΔT_2
h) Get the charging frequency $1 \leq z \leq 3$
i) Repeat 2 to calculate the single EV charging demand
j) End repeat 2
k) Repeat 1 based (5.25) to get the total EV charging demand
l) End repeat 1
m) **End:** Output the total EV charging demand to get the SHS-EVCS charging load

5.2.2 Second Level for SHS-EVCSs

The second level, similar to Chapter 4.3, incorporates information transfer and load demand considerations. Figure 5-3 shows how the second level operates: the blue line represents internal P2P energy trading, showing how energy is exchanged within the SHS-EVCSs. The pink line shows the flow of information, detailing the communication between each EVCS and the information centre, as well as the interactions between each EVCS and individual EVs. The yellow line represents EV charging flow, each EVCS will receive the EVs' information when they are charging or waiting for charging. This information will use into the Markov decision process to estimate EV charging demand in real time scenario.

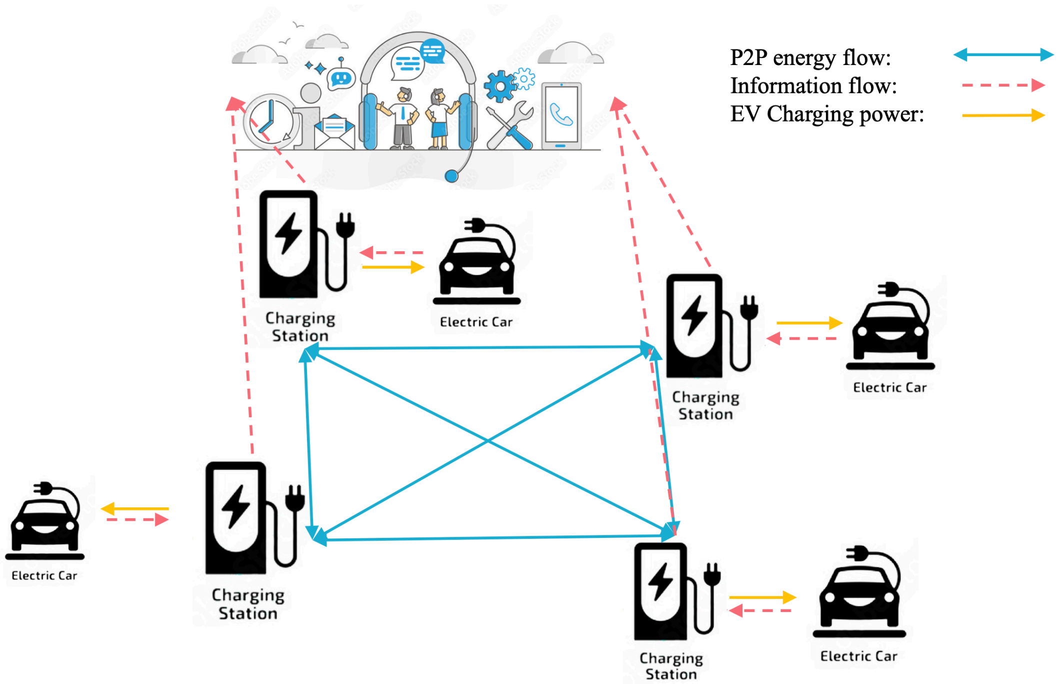


Figure 5-3 topology for SHS-EVCSs coalition information and energy flow

In the SHS-EVCSs coalition, which consists of four EVCSs, D users, and an IMS, each SHS-EVCS generates electricity to meet the demand of EV drivers in its area. EV drivers, SHS-EVCS, and IMS are connected via a communication network to exchange real-time information on electricity prices and power requirement. A power consumption cycle is divided into k time periods. At the start of each period, the IMS sets an electricity price based on the power market. EV drivers and SHS-EVCS then determine their optimal power consumption and supply based on this price and relay this information back to the IMS. The IMS updates the electricity price based on the received consumption and supply data. This iterative process continues with drivers and SHS-EVCS adjusting their consumption and supply according to the new price information and reporting back to the IMS until supply and demand are balanced, establishing the electricity price for that time. This price becomes the real-time electricity price for the period.

The social welfare maximization model 2.10 can be defined in this problem as:

$$max \sum_{k=1}^{K} \left(\sum_{d=1}^{D} V_d\left(x_d^k, \omega_d^k\right) - C_k(G_k) \right) \qquad 5.30$$

$$s.t. \sum_{d \in D} x_d^k \leq G_k \,, k = 1,2, \dots, K$$

$$m_d^k \le x_d^k \le M_d^k, d = 1,2,\dots,D; k = 1,2,\dots,K$$

$$G_k^{min} \le G_k \le G_k^{max}, k = 1,2,\dots,K$$

Where x_d^k is the electricity consumption of EV driver d at time k; m_d^k and M_d^k are the minimum and maximum electricity consumption of EV driver d at time k, and it satisified $m_d^k \le x_d^k \le M_d^k$; G_k is SHS-EVCS's electricity supply at time k, G_k^{min} and G_k^{max} are the minimum and maximum electricity supply of SHS-EVCS, and $G_k^{min} \le G_k \le G_k^{max}$; generally, $G_k^{min} \ge \sum_{d=1}^{D} m_d^k$ and $G_k^{max} \ge \sum_{d=1}^{D} M_d^k$; $C_k(G_k)$ means the cost of SHS-EVCS to provide electricity for G_k at time k, and it is the convex function of G_k; C_k is the capital cost for SHS-EVCS from first level output; $V_d(x_d^k, \omega_d^k)$ is the utility that EV driver d using x_d^k at time k, and it is the concave function of x_d^k; ω_d^k is the driver d's elastic of charging his EV at time k, for $\omega_d^k \in [1, 3.5]$.

The objective function for maximizing social welfare is a concave function, and the constraint set is a convex set, making this a convex programming problem that can be effectively addressed using traditional convex programming techniques. However, the decision variables in equation (5.30) are the driver's electricity consumption x_d^k and the power supply of SHS-EVCS G_k. The real-time electricity price, which is the core variable of the problem, does not appear in the model and making it invalid to solve (5.30) directly. For convex optimization problems, the original problem is equivalent to the dual problem, where the decision variable of the dual problem, the Lagrange multiplier in the original problem's Lagrange function, corresponds to the shadow price in economics. Shadow prices are considered theoretically optimal and are often used to guide pricing. Therefore, this chapter will employ dual theory to determine the real-time electricity price [131, 134,172-174].

Each interval in (5.30) is independent of each other, so a distributed algorithm can be used to solve each interval separately. The optimization problem corresponding to the *k-th* interval is:

$$max \sum_{d=1}^{D} V_d(x_d^k, \omega_d^k) - C_k(G_k) \qquad 5.31$$

$$s.t. \sum_{d=1}^{D} x_d^k \le G_k$$

$$m_d^k \le x_d^k \le M_d^k, d = 1,2, \dots, D$$
$$G_k^{min} \le G_k \le G_k^{max}$$

The Lagrange function for (5.31) denotes as:

$$L(x_d^k, G_k, \lambda_k) = \sum_{d=1}^{D} V_d\left(x_d^k, \omega_d^k\right) - C_k(G_k) + \lambda_k\left(G_k - \sum_{d=1}^{D} x_d^k\right) \quad 5.32$$
$$= \sum_{d=1}^{D}(V_d\left(x_d^k, \omega_d^k\right) - \lambda_k x_d^k) + (\lambda_k G_k - C_k(G_k))$$

Where $\lambda_k > 0$ is the Lagrangian multiplier, according to the dual theory, (5.32) can be transform to:

$$\min\ \max\ \ L\left(x_d^k, G_k, \lambda_k\right) \quad 5.33$$

Where $\lambda_k > 0, x_d^k \in [m_d^k, M_d^k], G_k \in [G_k^{min}, G_k^{max}]$.

Remark:

$$x_d^{k*} = argmax((V_d\left(x_d^k, \omega_d^k\right) - \lambda_k x_d^k) \quad 5.34$$
$$x_d^k \in [m_d^k, M_d^k]$$
$$G_k^* = argmax(\lambda_k G_k - C_k(G_k)) \quad 5.35$$
$$G_k \in [G_k^{min}, G_k^{max}]$$
$$A(\lambda_k) = \max\ \ L(x_d^k, G_k, \lambda_k)$$
$$x_d^k \in [m_d^k, M_d^k]$$
$$G_k \in [G_k^{min}, G_k^{max}]$$
$$= \sum_{d=1}^{D}(V_d\left(x_d^{k*}, \omega_d^k\right) - \lambda_k x_d^{k*}) + (\lambda_k G_k^* - C_k(G_k^*)) \quad 5.36$$

If λ_k is the time of use (TOU) or real time electricity price for *k-th* interval, then (5.34) is the driver's optimal charging electricity consumption for personal welfare maximization (the difference between utility and electricity purchase fee). (5.35) is the SHS-EVCS maximizes its welfare (the difference between electricity sales revenue and power supply cost) to obtain the optimal charging electricity supply. Thus, using Lagrangian multiplier λ_k as real time electricity is reasonable. To solve the dual problem $\min A(\lambda_k), \lambda_k > 0$, can use the following method [175, 176]:

$$\lambda_k^{h+1} = \lambda_k^h + \gamma_k^h a_k^h \quad 5.37$$

Where h is the iteration time; γ_k^h is the distance and ≥ 0; a_k^h is the down direction of function $A(\lambda_k)$; let $a_k^h = \sum_{d=1}^{D} x_d^{k*} - G_k^*$; (5.37) prove that when $\sum_{d=1}^{D} x_d^{k*} > G_k^*$, $a_k^h > 0$, while $\lambda_k^{h+1} > \lambda_k^h$ due to the demand and supply theory, the electricity price increase; when $\sum_{d=1}^{D} x_d^{k*} < G_k^*$, $a_k^h < 0$, then $\lambda_k^{h+1} < \lambda_k^h$, the electricity price decrease; when $\sum_{d=1}^{D} x_d^{k*} = G_k^*$, while $\lambda_k^{h+1} = \lambda_k^h$, the electricity price keep balance. In paper [131, 134, 174], γ is a fixed positive number, which is 0.8.

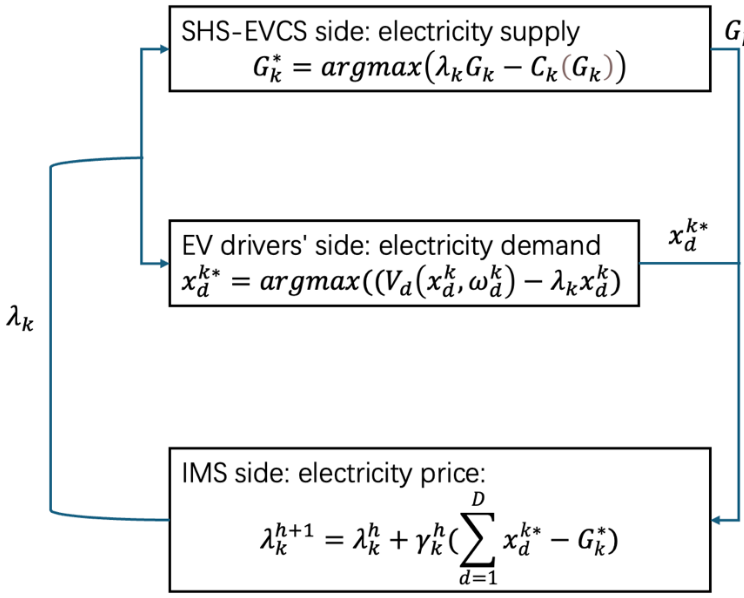


Figure 5-4 power and information interaction between SHS-EVCS, EV drivers, and IMS

Algorithm 5.2: **Real-time electricity price distributed algorithm**

Initialization parameters: γ, D, k, m_d^k, M_d^k and stop error ε (ε is a positive number 0.1), for h=0. IMS randomly release electricity price λ_k^h to SHS-EVCS and EV driver.

1. According to the random electricity price, using (5.34) to calculate the optimal electricity consumption $x_d^{k*}(\lambda_k^h)$ by EV driver, and report the optimal electricity consumption to ISM
2. Using $G_k^* = argmax(\lambda_k G_k - C_k(G_k))$ to calculate the optimal electricity supply $G_k^*(\lambda_k^h)$ by SHS-EVCS, and report it to ISM
3. Accept the optimal $x_d^{k*}(\lambda_k^h)$ and $G_k^*(\lambda_k^h)$, using $\lambda_k^{h+1} = \lambda_k^h + \gamma_k^h a_k^h$ to calculate the optimal electricity price

4. If $0 < G_k^*(\lambda_k^h) - \sum_{d=1}^{D} x_d^{k*}(\lambda_k^h) \leq \varepsilon$, let $\lambda_k = \frac{1}{2}(\lambda_k^h + \lambda_k^{h+1})$; if not, input λ_k^{h+1} to 1

End: output the optimal solution for x_d^{k*} and G_k^*

5.2.2.1. Game Theory Model

It is same as game theory model in chapter 5.

Under the cooperative game model, within the SHS-EVCSs P2P trading model, each EVCS serves as producer and consumer, means this is multiple entities reach an agreement. Therefore, the game theory follows as figure 5-15:

a) Start trading.
b) All SHS-EVCSs request the energy exchange.
c) With the goal of maximizing the profits of the coalition, according to the energy trading needs of each EVCS, analyse whether each EVCS meets the constraints of the model running time (if the energy trading meets the best profit for the coalition in time *t*), and the energy trading plan is calculated.
d) Confirm the energy trading flow and profit calculate.
e) If the profit follows the coalition maximization, go to step f); if not, go back to the step c), recalculate the energy exchange quantity.
f) Profit allocates depends on the constraints.
g) Energy trading end.

5.2.3 Economic Analyse

Integrating renewable energy sources into EVCSs brings substantial economic benefits, as highlighted by various studies. Adding solar power to EVCSs, for example, can greatly reduce operating costs. One study published in 'Renewable and Sustainable Energy Reviews' found that solar-powered charging stations help cut down on grid reliance, resulting in lower energy expenses and boosting financial viability for operators [177]. Another study [178] showed that incorporating a 100 kW PV system could decrease net present costs by around 122%, saving about $61,492 annually compared to stations reliant solely on the grid.

Demand response strategies further enhance savings by allowing EVCSs to adjust charging operations based on real-time electricity prices, which means charging can be timed for off-peak periods when rates are lower. Research [179] found that these strategies not only reduce operating costs but also improve profitability by aligning energy consumption with cheaper electricity rates. Similarly, battery storage integration enables stations to store excess renewable energy for use during peak times. A study [180] reported that combining battery storage with EVCSs led to a 29.4% drop in CO_2 emissions and a 96.16% reduction in unburned hydrocarbons, offering clear economic and environmental advantages. This setup also reduces the need for energy purchases during peak price periods and opens up additional revenue through energy arbitrage [181].

The bi-level optimization model explored in this article is designed to maximize social welfare by balancing the financial interests of both EVCS operators and EV users. This approach ensures that the cost savings and benefits of renewable integration are shared equitably, strengthening the long-term economic sustainability of EV charging networks [182]. By incorporating renewable energy and demand response strategies, the model strikes an optimal balance between cost-efficiency and user convenience, further enhancing the economic sustainability of EV infrastructure [183]. Techno-economic assessments back this up, showing that renewable-powered EVCSs are more economically viable, with significantly lower levelized energy costs than traditional grid-reliant stations. For instance, combining solar PV and battery storage brought the LCOE down to $0.0549/kWh, compared to $0.409/kWh for grid-only systems [180].

5.3. Results and Analysis

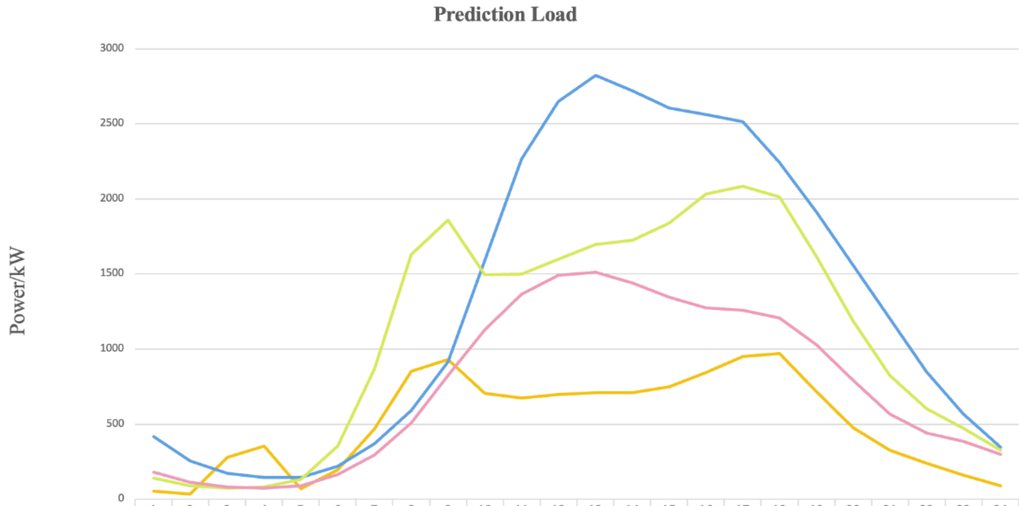
There will be three scenarios for analysis: one is day-ahead without TOU strategy (EV uncertainties), another involving day-ahead and real-time without TOU strategy , and the last one is day-ahead and real-time prediction with TOU. In the day-ahead TOU scenario, load management decisions are made based on predicted demand and supply conditions from the department for transportation. This allows for strategic planning and optimization of energy resources in advance. The real-time TOU scenario, on the other hand, utilizes a Markov decision process to dynamically adjust and optimize load in real-time. This involves comparing the differences between fixed loads, which are inflexible and must be met regardless of conditions, and flexible loads, which can be adjusted based on real-time data. The goal of this comparison is to assess two ways' impact on social welfare, aiming to enhance overall efficiency, reduce costs, and improve the balance between energy supply and demand.

Table 5-1 and Figure 5-5 present the initial scenario featuring fixed loads, where the parameters for the SHS-EVCSs are derived from forecasting and scheduling approaches that utilize transport statistics obtained from gov.uk, as detailed in paper [184]. These statistics play a crucial role in shaping the parameters, ensuring that they accurately reflect real-world conditions. In Figure 5-6, the fixed load values for Hammersmith & Fulham and Hounslow are based on weekday averages, which accounts for the observed charging peaks that occur before and after standard working hours. This pattern is consistent with typical weekday commuting behaviour, where EVs are charged primarily outside of office hours.

For the other two EVCSs, the fixed load values are based on weekend averages, reflecting different usage patterns when people tend to have more flexibility in their schedules, leading to varied charging times. Figure 5-6 provides a detailed visualization of the SHS-EVCSs load curves for both day-ahead and real-time forecasts within a non-TOU system. This figure demonstrates that critical factors, such as EV charging times, battery capacities upon arrival and departure, and charging rates, remain consistent regardless of the forecasting method used. This consistency suggests that the system is robust under various conditions, although it also highlights areas where future optimization could further enhance efficiency.

Table 5-1 London four area SHS-EVCS parameters

Parameters	Hammersmith & Fulham	Richmond upon Thames	Hounslow	Ealing
Charger capacity (kW)	360kW	360kW	360kW	360kW
Number of chargers per station	3	8	14	21
PV installed capacity(kW)	500	1000	1000	1000
PV installed cost (£/kW)	1112	1112	1112	1112
Battery capacity (kW)	1000	800	800	800
Battery installed cost (£/kW)	331.55	331.55	331.55	331.55
Battery initial state of charge (%)	40	40	40	40
Rated charge and discharge power of battery (kW)	500	500	500	500
Minimum battery state of charge (%)	25	25	25	25
Maximum battery state of charge (%)	100	100	100	100
Battery charge and discharge efficiency (%)	85	85	85	85
hydrogen tank capacity (m^3)	1000	1000	1000	1000
Initial capacity of gas tank （%）	30	30	30	30
Hydrogen tank cost (£/m^3)	27.63	27.63	27.63	27.63
Tank storage efficiency (%)	95	95	95	95
Electric to gas efficiency (%)	75	75	75	75
Electricity-to-gas coefficient (kWh/m^3)	0.2	0.2	0.2	0.2
Fuel cell generator capacity (kW)	800	1500	1000	1200
Gas-to-electric efficiency (%)	65	65	65	65
Gas-to-electricity coefficient (m^3/kWh)	0.295	0.295	0.295	0.295
RE feed-in tariff (£/kWh)	0.03	0.03	0.03	0.03



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Hammersmith & Fulham	54.99	33.84	277.3	352.5	69.09	196.5	467.7	851.7	931.1	705	674	695.6	707.9	709.7	749.2	844.6	949.9	972	718.2	476.1	325.7	238.3	161.7	90.25
Richmond upon Thames	418	255.2	172.9	144.4	144.4	218.2	369.3	592.6	916.6	1591	2266	2647	2822	2718	2607	2563	2515	2241	1915	1559	1202	849.4	565.7	344.1
Hounslow	140	88.13	72.46	82.26	131.2	352.5	868.6	1631	1859	1493	1498	1599	1698	1725	1838	2031	2086	2012	1618	1189	823.5	603.2	473	328
Ealing	178.8	111.6	80.58	74.7	88.13	163.7	293.8	507.8	823.4	1128	1366	1492	1511	1439	1346	1275	1260	1208	1028	792.3	568.2	442.3	383.6	299.6

Figure 5-5 SHS-EVCSs prediction load using chapter 4's method

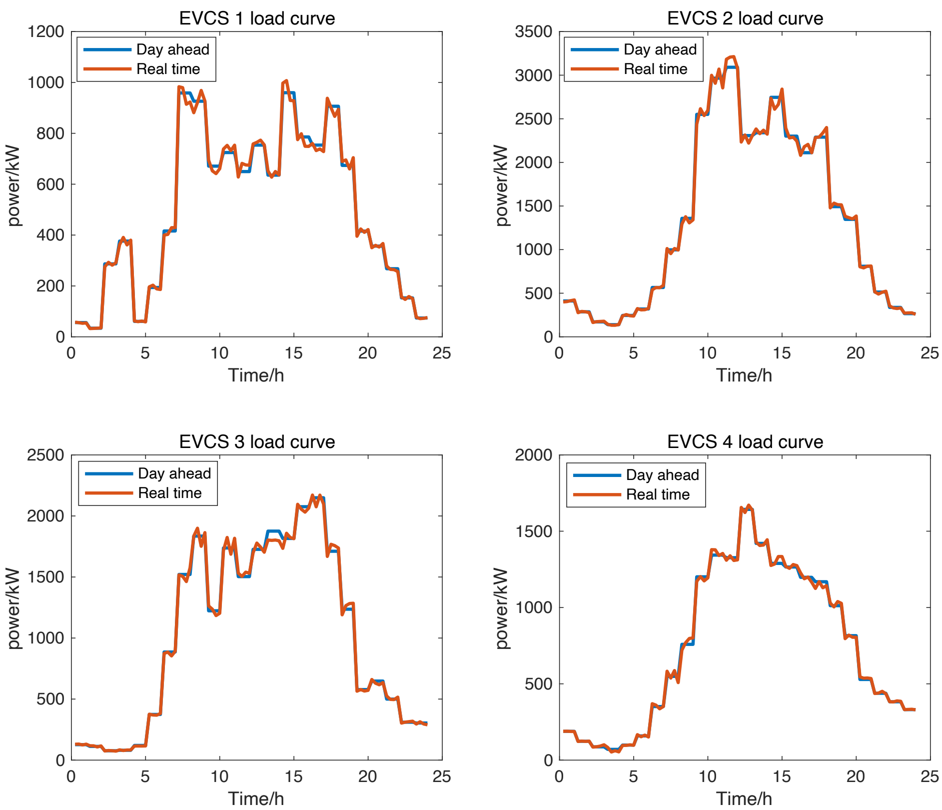


Figure 5-6 SHS-EVCSs day ahead and real time load curve without TOU strategy

Figure 5-7 shows the EV prediction load and load after TOU strategy. The blue curve shows typical EV charging patterns without any TOU interventions. Notable peaks for

SHS-EVCS 1 and 3 are around the 9 am and 7 pm, likely corresponding to typical EV charging times. Lower power demand during early morning hours (0 to 5am). For SHS-EVCS 2 and 4, the peak load at noon, the lower power demands similar to 1 and 3. The orange curve shows the load after TOU strategies have been applied. The TOU appears to effectively reduce the peaks for all SHS-EVCSs, indicating successful peak shaving. For SHS-EVCS 2 and 4, there is only one peak load at noon, demonstrating the effectiveness of the TOU strategy.

For the implications of TOU strategy , the significant reduction in peak load (as seen in the reduction from the blue to the orange line) helps in alleviating stress on the power grid, potentially reducing the need for grid reinforcement and lowering electricity costs. By distributing the load more evenly, TOU strategy can enhance the efficiency of power generation and distribution systems, contributing to more stable grid operations. TOU strategy can lead to cost savings for both utilities and consumers by minimizing the need for peak power generation, which is often more expensive and environmentally detrimental.

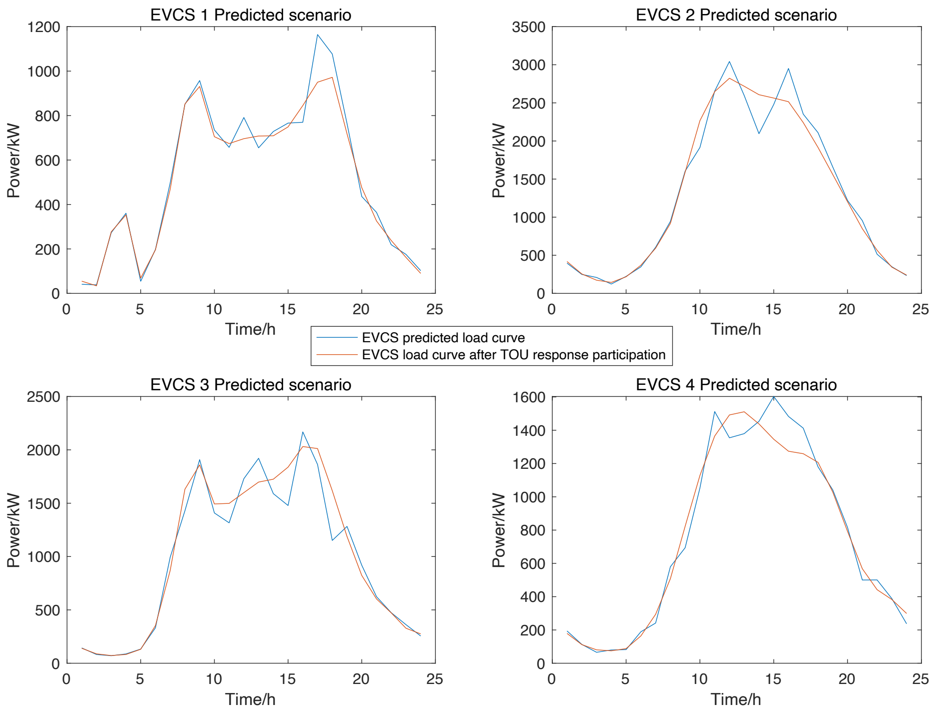


Figure 5-7 EV prediction load and load after demand side management

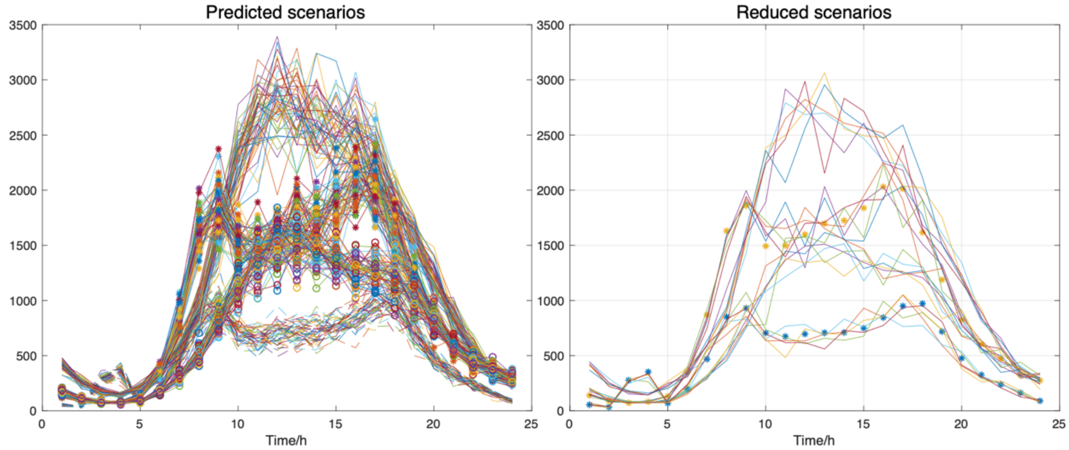


Figure 5-8 Prediction scenarios and reduced scenarios

Figure 5-8 compares the predicted scenarios with the reduced versions for SHS-EVCSs forecasting. Initially, 50 scenarios were generated for each SHS-EVCS. The scenario reduction process involves selecting a subset of these scenarios and adjusting their probabilities to closely match the overall probability distribution of the original set. This process minimizes the difference between the probability distribution of the selected subset and the initial group of scenarios. To systematically reduce the number of scenarios, the one with the lowest probability is removed in each iteration. By the end of the iterations, at least the five most probable scenarios remain. This approach effectively reduces the total number of scenarios while preserving those that best represent the key probabilistic features of the original set. This method not only simplifies the computational process but also maintains the accuracy of the statistical representation. Over the course of the day, the original prediction scenarios show significant variation and complexity, with multiple intersecting lines and extraneous data points. In contrast, the reduced scenarios offer a more concise and focused view, clearly highlighting the main trends in electricity demand. Peak demand times at 9 a.m. and 6 p.m. are prominent in both sets of scenarios, but the reduced versions eliminate minor fluctuations and outliers, making the data easier to interpret and more useful for strategic planning.

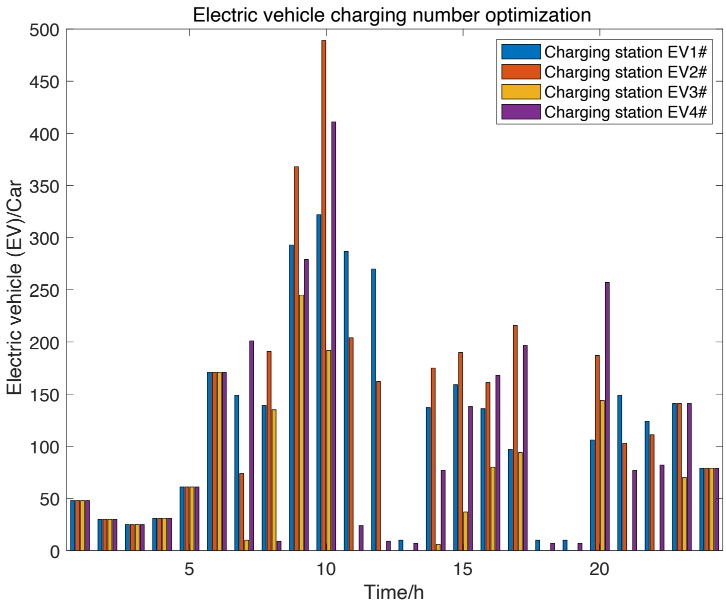


Figure 5-9 EV number optimization

The figure 5-9 provides each SHS-EVCS's EV traffic flow over a 24-hour period, showcasing distinct peaks and valleys in demand. The primary peak occurs at approximately the 10 am, where all stations experience a significant increase in vehicle numbers, indicating a morning charging rush. Specifically, EVCS 2 reaches its highest vehicle count during this period, suggesting it is a preferred station or location for morning charging, which is because it is in a commercial area. Conversely, EVCS 3 exhibits lower overall usage but still shows noticeable peaks at the 6am and 9am, indicating targeted high-demand periods. During the night at 8 pm, highlights another surge in charging activity, likely corresponding to evening charging. This trend is observed across all stations, with each showing increased vehicle numbers. EVCS 4 also sees a significant peak currently, demonstrating consistent demand during evening hours. Early morning around 0-5 am show the lowest vehicle numbers across all stations, indicating minimal charging activity, which could reflect lower overall travel and charging needs during these hours and effective TOU strategies already in place, shifting demand away from this period.

The observed charging patterns likely result from typical daily routines, where morning peaks correspond to pre-work charging and evening peaks to post-work or end-of-day charging needs. Most of EV drives are preferring to charge their car before work and after work. Implementing strategies to manage these peaks, such as increasing charging station capacity or optimizing charging schedules, can enhance overall system efficiency and user experience.

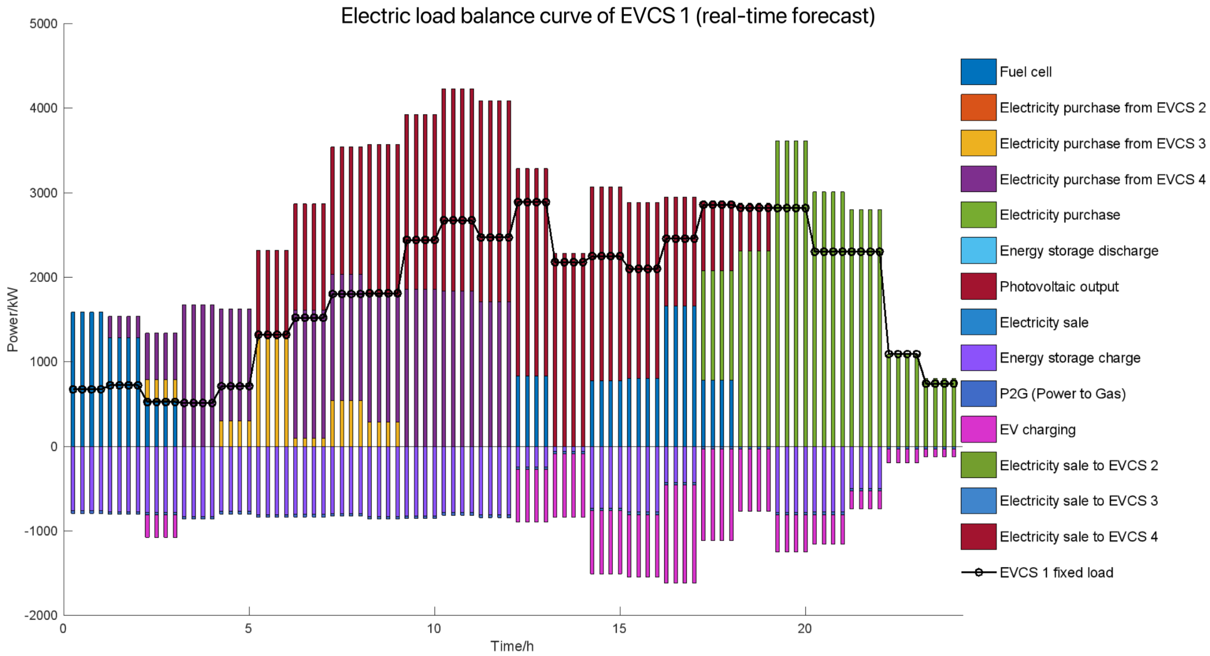


Figure 5-10 SHS-EVCS1 renewable energy usage and electricity load curve

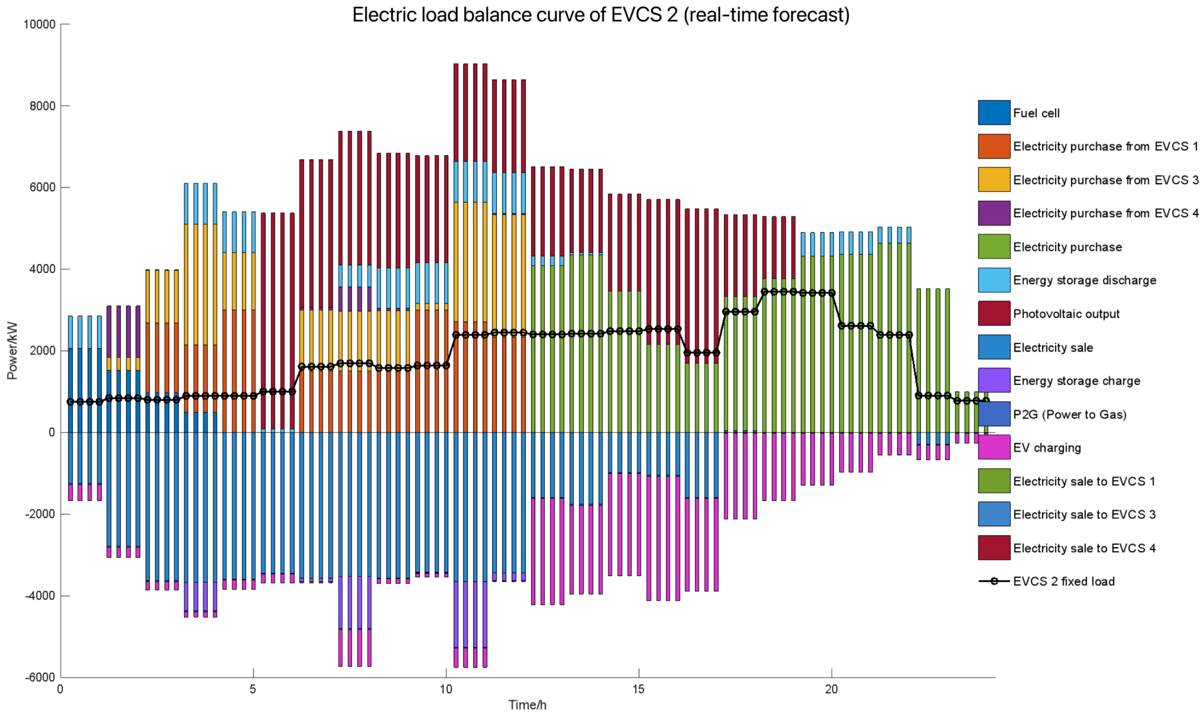


Figure 5-11 SHS-EVCS2 renewable energy usage and electricity load curve.

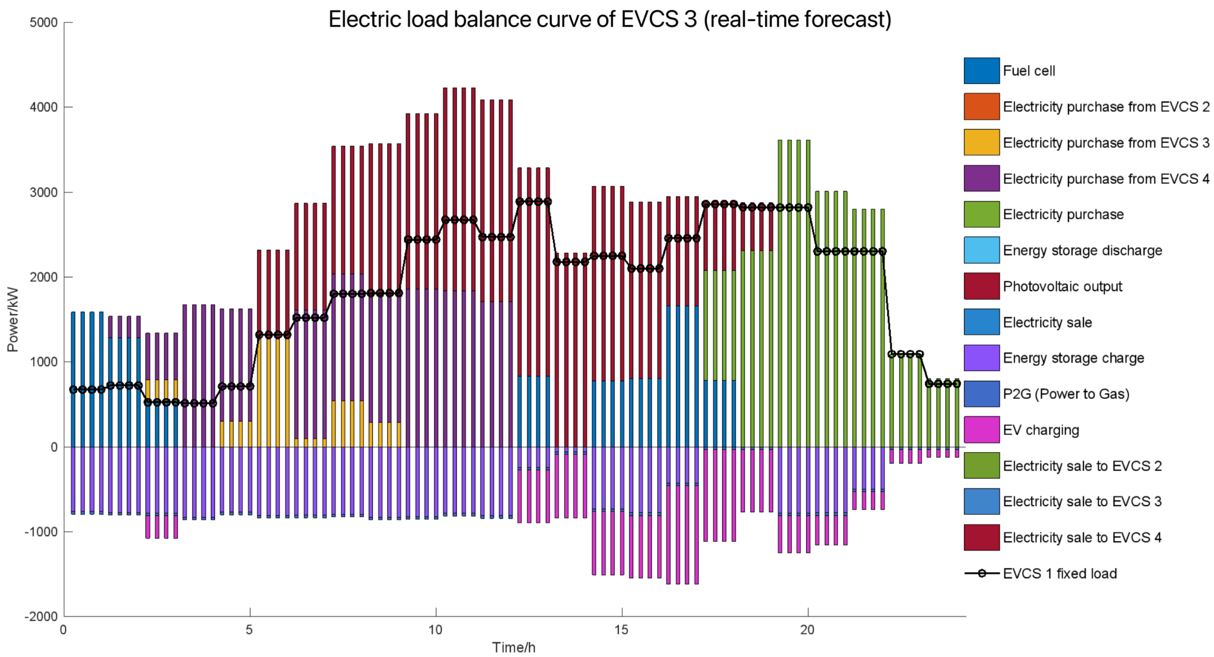


Figure 5-12 SHS-EVCS3 renewable energy usage and electricity load curve.

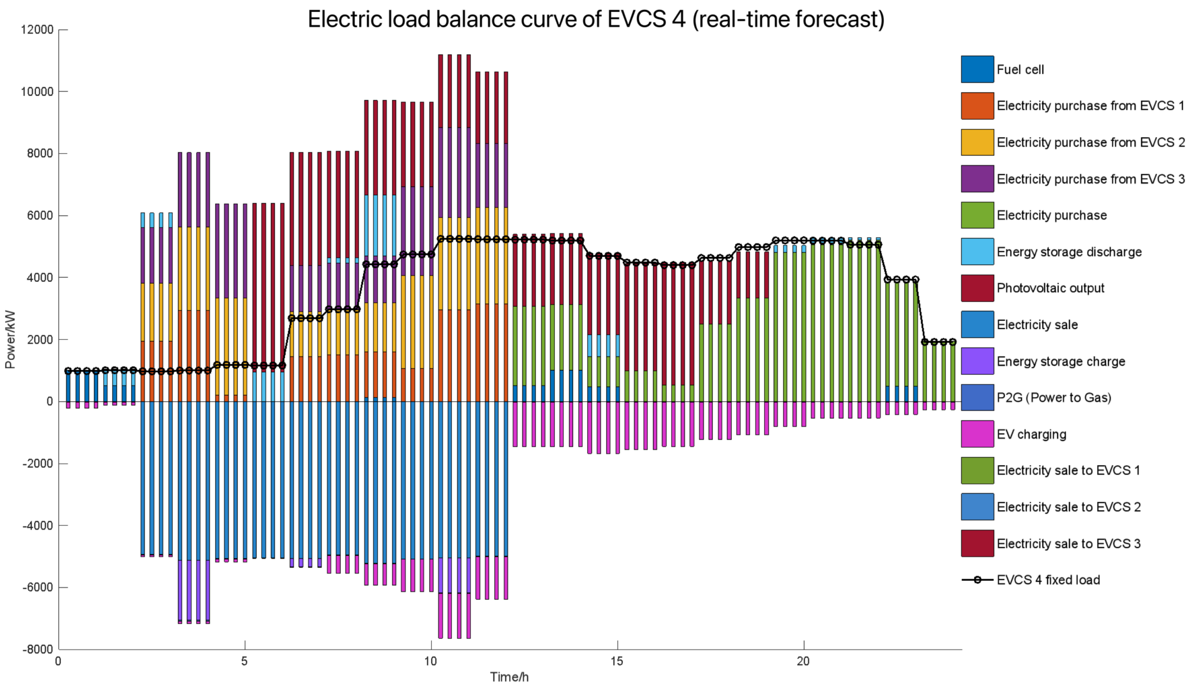


Figure 5-13 SHS-EVCS4 renewable energy usage and electricity load curve.

Figures 5-10 to 5-13 shows the energy utilization and electricity load profiles for four SHS-EVCSs. During the daytime, PV generation is the primary source of electricity. The efficiency and sustainability of PV systems make them an ideal choice for daytime power, reducing the need for grid electricity and minimizing carbon emissions. This reliance on solar power not only decreases operational costs but also aligns with renewable energy goals. After sunset, when solar power is no longer available, the SHS-EVCSs shifts to hydrogen fuel cells for electricity generation. The hydrogen storage system used in EVCS can be generated during periods of low electricity demand or excess solar production, ensuring a sustainable and continuous energy supply. Supplementing hydrogen storage system, electricity is also drawn from battery storage system. These batteries store excess energy generated during the day, particularly from PV systems, and release it during peak demand periods or when renewable generation is low. The integration of battery storage ensures a stable and reliable power supply, balancing the intermittency of renewable energy sources. Additionally, each SHS-EVCS has the capability to purchase electricity from other stations within the network based on cost-minimization strategies. This inter-station electricity trading allows for a more flexible and efficient energy management approach, ensuring that each station can maintain optimal operations while minimizing expenses. By leveraging diverse energy sources and trading capabilities, the SHS-EVCSs can adapt to fluctuating energy demands and market conditions, enhancing the overall stability and sustainability of the power grid.

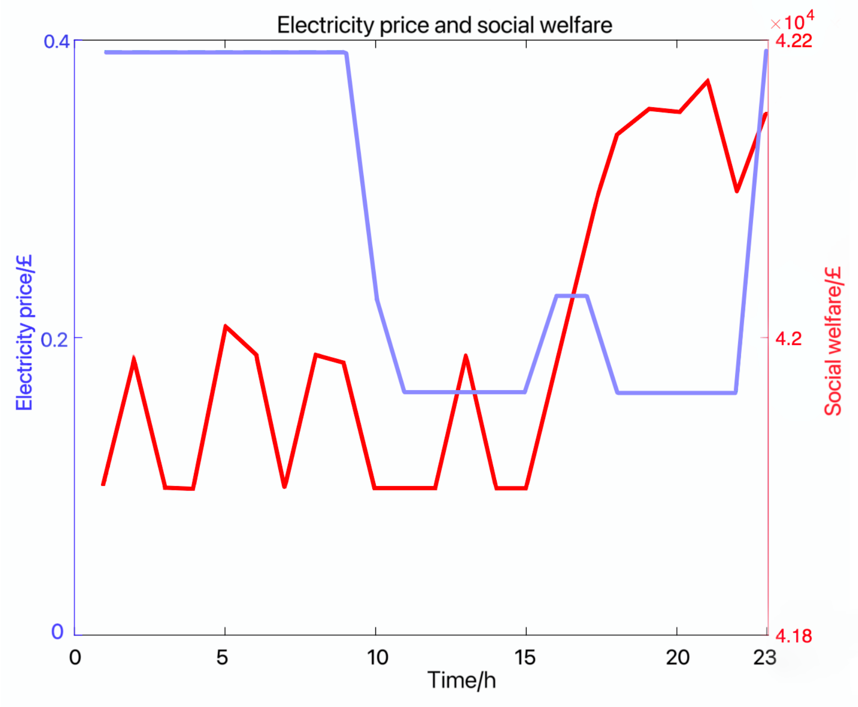


Figure 5-14 electricity price and social welfare

Figure 5-14 shows the interaction between electricity prices and social welfare over a 24-hour period. Initially, electricity prices are relatively high, around £0.4. From 11 a.m. to 11 p.m., prices drop significantly and stabilize at approximately £0.2. After 11 p.m., prices begin to rise again, peaking around £0.35. In contrast, social welfare is lower when electricity prices are high, but it increases as prices decrease, highlighting an inverse relationship between the two. This inverse pattern is most pronounced between 3 p.m. and 11 p.m., where lower electricity prices correspond to higher and more stable levels of social welfare. This suggests that lower electricity prices may enhance social welfare, likely due to improved energy affordability, which benefits consumers and contributes to overall social well-being.

Typically, fluctuations in electricity prices are driven by changes in demand and supply, peak versus off-peak hours, and other market factors. In this chapter, however, these fluctuations are influenced by the dynamics within the SHS-EVCSs alliance itself. Despite these variations, the overall trend indicates that as electricity prices fall, social welfare stabilizes or even increases slightly.

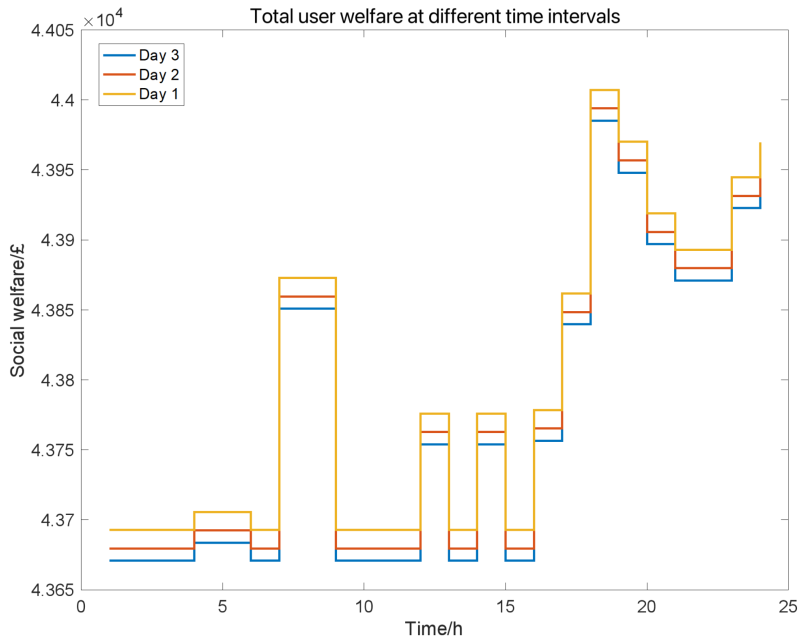


Figure 5-15 total user welfare in different time interval

Figure 5-15 shows the connection between social welfare and time across various intervals, specifically over three distinct days: day 1, day 2, and day 3. The recurring patterns that emerge across these intervals suggest that short-term forecasting, which focuses on more immediate time frames, can be almost as reliable as long-term forecasting for effectively addressing and planning for social welfare outcomes. This observation is particularly relevant in scenarios where quick decision-making is required, highlighting that energy management strategies do not necessarily need extended forecasts to be effective. Moreover, the figure provides the ability to achieve similar levels of social welfare with short-term forecasts suggests that in the further case study, the MATLAB simulation can potentially optimize resources and make informed decisions without always relying on extensive long-term data.

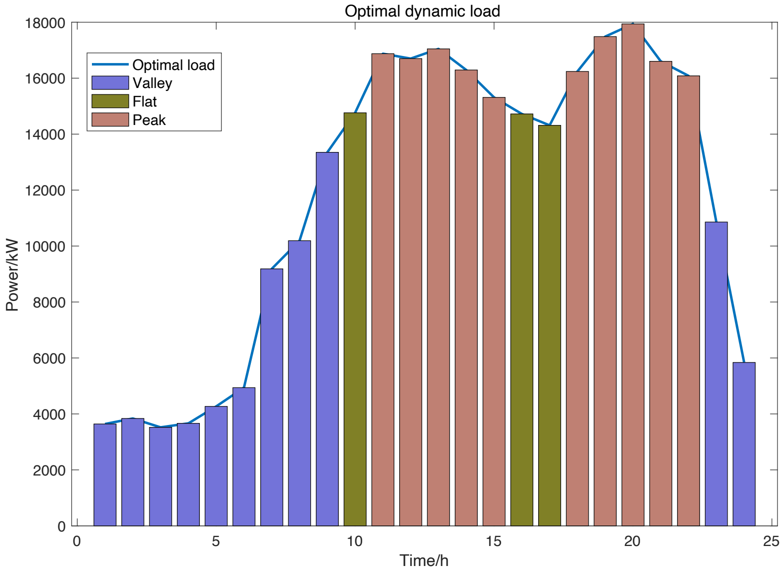


Figure 5-16 Total optimal dynamic load

Figure 5-16 shows the optimal dynamic power load over a 24-hour period. During the low-demand period from 11:00 PM to 9:00 AM, the power load gradually rises from approximately 2,000 kW to 12,000 kW. This period sees low charging demand for EVs since many owners charge overnight, with some vehicles already fully charged or no longer charging. The sharp increase in load between 6:00 AM and 7:00 AM likely reflects a surge in charging activity as drivers prepare to leave for work. The SHS-EVCS system optimizes EV charging loads through demand response, load forecasting algorithms, and TOU pricing, improving power utilization and balancing the internal grid load. Additionally, it regulates power distribution to prevent resource wastage during off-peak hours, ensuring efficient energy use throughout the system.

Around 10:00 AM and between 4:00 PM and 5:00 PM, the power load stabilizes at about 14,000 kW, indicating a steady demand for EV charging. Implementing dynamic pricing during these periods can help further smooth the load curve and reduce fluctuations in grid pressure, contributing to a more resilient power system. Peak load periods are observed from 11:00 AM to 3:00 PM and from 6:00 PM to 10:00 PM, with loads exceeding 16,000 kW and peaking at 18,000 kW. These peaks are largely due to increased charging demand, particularly in the evening when many drivers charge their vehicles after returning home. To manage these peaks, strategies such as time-based charging fees, peak time restrictions, and intelligent scheduling systems can be employed, which can also encourage more even distribution of charging times among users. By adjusting the output power of charging stations and coordinating power demand, grid stress during peak periods can be mitigated, ensuring that energy distribution remains efficient and reliable. Furthermore, SHS-EVCS leverages energy storage systems to return excess power to the grid during peak times, effectively contributing to peak shaving and valley filling, which helps in maintaining grid stability. Alongside IMS, this setup allows for real-time monitoring and dynamic management of EV charging demand, enhancing the reliability and stability of both internal and external grids, and giving an advice for more sustainable energy practices in the future.

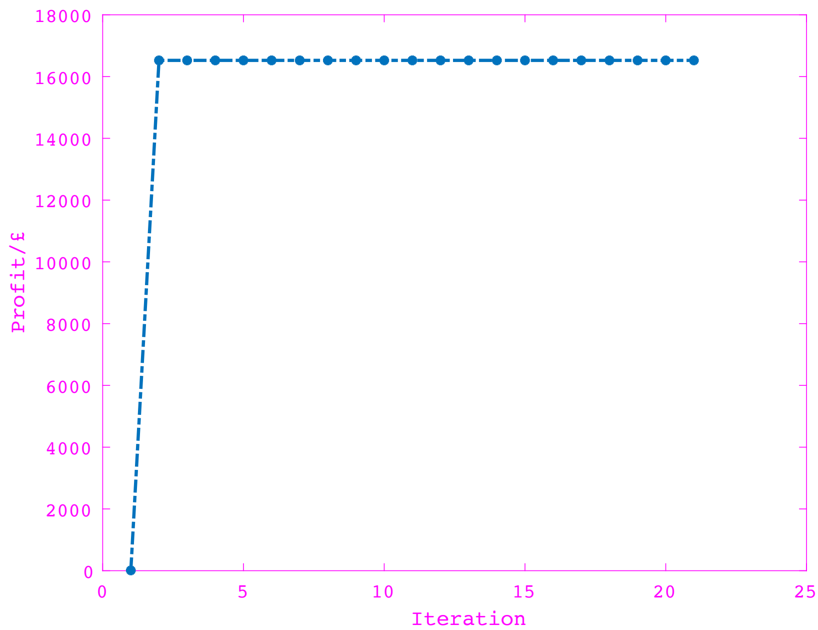


Figure 5-17 Convergence of real-time electricity price distributed (SHS-EVCS profit) algorithms

Figure 5-17 shows the relationship between profit and iteration, where iterations span from 0 to 25, and corresponding profit values range between £0 and £18,000. The graph shows a significant and rapid surge in profit between the first and second iterations, quickly reaching nearly £16,800. After this sharp increase, the profit levels off, indicating a stabilization around this peak for the subsequent iterations. This pattern suggests that the process efficiently achieves its optimal profit level early on, requiring minimal adjustments to maintain profitability thereafter.

The rapid convergence of the solution within only two iterations, especially in the context of a complex network of charging stations, suggests that the optimization algorithm effectively reached a near-optimal solution almost immediately. This could be due to several reasons: The algorithm may have started with an initial population or solution that was already close to the optimal. In some cases, well-designed initialization strategies can lead to fast convergence because the initial points are in favourable regions of the search space. Although the EVCS network is complex, the model used for optimization may have been simplified, with fewer variables or constraints than expected. This reduction in complexity could allow the algorithm to identify the optimal solution with minimal iterations. PSO algorithm used in this simulation can be configured with high convergence rates under specific settings. This would allow the process to quickly focus on the best or nearly best solutions in just a few steps. The last reason is the optimization problem includes effective constraints that limit the search space significantly, the algorithm may need fewer iterations to find feasible solutions that also meet profitability objectives.

Table 5-2 Energy optimal parameters and cost

Parameters	Hammersmith & Fulham	Richmond upon Thames	Hounslow	Ealing
Battery storage system (kWh)	800	1762.6758	1000	2000
Battery storage system investment & O/M cost (£/kWh)	265,240	584,415.16	497,325	663,100
Hydrogen storage tank capacity (kWh)	1369.49	1524.98	1379.1612	1277.0575
Hydrogen storage tank investment & O/M cost (£/kWh)	55,100.09	61,356.08	55,489.204	51,381.16
Fuel cell capacity (kWh)	1582.5	1988	1500	1000
Fuel cell investment & O/M cost (£/kWh)	79,3845.3	997,260.32	752,460	501,640

Table 5-2 presents the energy storage and generation technologies deployed in Hammersmith and Fulham, Richmond upon Thames, Hounslow, and Ealing, highlighting key trends and strategic differences in the adoption of battery and hydrogen storage systems. The analysis reveals that Ealing has the highest battery storage capacity at 2,000 kWh, reflecting a focused investment strategy in this technology. In contrast, Richmond upon Thames has adopted a more diversified approach, investing significantly across all technologies. Richmond leads in battery system investment with a capacity of 1,762.68 kWh at a cost of £584,415.16, and leads in fuel cells with a capacity of 1,988 kWh at a cost of £997,260.32, underscoring its commitment to a balanced and resilient energy infrastructure.

Hydrogen storage capacity is relatively consistent across all regions, ranging from 1,300 to 1,500 kWh. However, Richmond again slightly exceeds others in both capacity and cost, indicating a strategic emphasis on this technology as well. Richmond's substantial investment in fuel cells is particularly noteworthy, likely due to their higher efficiency and operational flexibility compared to other energy storage and generation methods.

Table 5-3 MAPE for 4 SHS-EVCSs

	Hammersmith & Fulham	**Richmond upon Thames**	**Hounslow**	**Ealing**
MAPE/%	13.04	11.37	11.8	13.56

Table 5-3 shows the MAPE percentages for four regions: Hammersmith & Fulham (13.04%), Richmond upon Thames (11.37%), Hounslow (11.8%), and Ealing (13.56%). Richmond upon Thames exhibits the lowest MAPE, signifying the most accurate predictions, with Hounslow following closely. Conversely, both Hammersmith & Fulham and Ealing have higher MAPE values, with Ealing's figure being the highest, indicating the least accuracy in predictions. While these values are generally within an acceptable range, there is a clear opportunity to enhance forecasting methods in the future.

5.4. Chapter Summary

The chapter conducted in this thesis has thoroughly explored the optimization and economic feasibility of SHS systems integrated with EVCS, utilizing both non-cooperative and cooperative game theory frameworks. The development and implementation of a bi-level optimization model have proven to be a robust method in addressing the dual goals of minimizing capital and operational costs while maximizing social welfare. The use of non-cooperative game theory at the individual SHS-EVCS level allows for strategic cost minimization by treating each RE supplies as independent players. The solutions ensure that no single RE can reduce its cost further without increasing the costs of others, thus achieving an optimal balance in the energy dispatch strategy. At the second level, the cooperative game theory framework facilitates internal energy trading and demand response among multiple SHS-EVCSs. This collaborative approach, managed by an IMS, enhances overall system efficiency by dynamically adjusting electricity prices based on real-time supply and demand data. This iterative process not only stabilizes the electricity market but also ensures that EV charging demands are met effectively, even under conditions of uncertainty.

The use of Markov decision processes to simulate EV charging times, combined with Monte Carlo simulations to forecast charging demand, is crucial for capturing the unpredictability of EV usage patterns. These methods ensure high forecasting accuracy and enable the optimization model to adapt to changing conditions, thereby enhancing the reliability of the SHS-EVCS system. Additionally, the application of duality theory in setting real-time electricity prices helps manage energy consumption on the demand side. By implementing these theoretically optimized prices, the system encourages off-peak charging, alleviates peak load pressure, and improves grid stability. This approach aligns with the broader goals of demand-side management, such as peak load shaving, ultimately reducing overall energy costs and enhancing system sustainability. Empirical analysis and case studies illustrate the effectiveness of the TOU strategy in reducing peak loads and balancing demand. The comparison between forecasted and actual load scenarios underscores the critical role of TOU in preventing demand surges and promoting efficient energy use. This not only benefits the grid by minimizing the need for additional infrastructure investment but also provides economic advantages to EVCS operators and consumers through lower electricity prices and reduced operating costs.

To conclude, the implementation of optimization strategies and game theory models within SHS-EVCSs systems presents a significant opportunity to greatly improve the sustainability and efficiency of energy infrastructures. By applying these sophisticated methods, energy systems can be managed in a way that balances various demands more effectively. The findings from this study offer crucial insights into the complex interactions between renewable energy sources, storage capacities, and the demands of EV charging. These insights provide a clearer understanding of how to optimize these elements for better performance and efficiency. A particularly noteworthy result is the potential for social welfare to reach as high as £4.218*10^4, contingent upon maintaining EV charging electricity prices below £0.20. This highlights the critical role of pricing in achieving both economic benefits and enhanced social welfare. Overall, the study underscores the importance of integrating these advanced models to foster more sustainable and economically beneficial energy systems.

Chapter 6 Conclusion.

This thesis has contributed the planning and operation of Solar-Hydrogen-Storage Integrated Electric Vehicle Charging Stations (SHS-EVCS) within smart cities. It encompasses the design of SHS-EVCS capacity, energy exchanges among various SHS-EVCSs, and case studies across different countries. This work also develops real-time forecasts of EV charging demand to optimize SHS-EVCS charging loads and employs Time-of-Use (TOU) strategies to maximize social welfare for both EV drivers and SHS-EVCS operators.

6.1 Basic knowledge using for SHS-EVCS

Chapter 2 gives a detailed review of the theoretical frameworks and modelling techniques to incorporating renewable energy sources into EVCS within smart city. It covers a range of renewable energy models, such as photovoltaic, hydrogen storage system, and battery storage systems. Additionally, this chapter introduces an analytical tool including game theory and social welfare models that tackle both the operational and economic dimensions of energy systems. Game theory is using to arrange the interactions and energy transactions among various EVCSs, optimizing these relationships for both cost-effectiveness and equity. Meanwhile, the social welfare model aiming to enhance benefits for all EV drivers to SHS-EVCSs.

6.2 Planning and operating a single SHS-EVCS

In chapter 3, it provides an isolated microgrid SHS-EVCS, which integrates photovoltaic power, battery storage, and a hydrogen storage system, which including a fuel cell generator, an electrolyser, and a hydrogen storage tank. It introduces an energy management approach designed for isolated microgrids that aims to minimize costs and maintain a stable energy storage state. By employing a PSO algorithm to reduce the costs of the energy storage system, it ensures the maintenance of the energy storage state at optimal levels. The energy management strategy is validated through MATLAB simulations, demonstrating that the proposed system significantly lowers costs compared to traditional way to buying electricity from grid. The findings confirm that the energy storage maintains its desired level consistently, enhancing the overall system reliability and efficiency.

6.3 Multi-SHS-EVCSs energy exchange planning and operating

Chapter 4, Section 4.2, introduces a novel multi-objective optimization design approach that accounts for both economic and environmental factors. The NSGA-II and MOEA/D algorithms are employed to optimize the distributed generation power rating and energy storage system capacity of SHS-EVCS. By comparing the optimization results from both algorithms, the proposed approach in this study demonstrates clear advantages, providing a comprehensive analysis of various influencing factors to achieve the best trade-off results. The management of energy flows from sources such as solar energy, hydrogen storage, battery storage, and the grid are effectively optimized, ensuring that the EVCS delivers a cost-effective energy supply. This thorough optimization approach enables charging stations to meet the variable energy demands of EV charging while minimizing costs and maximizing sustainability.

Section 4.3 introduces a game theory-based P2P energy trading strategy specifically designed for multiple SHS-EVCSs, addressing the challenges of intermittency and volatility inherent in renewable energy generation. The strategy aims to mitigate the uncertainties caused by inaccurate renewable energy forecasts, which can significantly impact the operational efficiency and economic viability of SHS-EVCS. A notable advancement in this study is the introduction of a cooperative game theory approach based on P2P trading, which serves as a mechanism to resolve conflicts of interest and ensure mutually beneficial cooperation among participating SHS-EVCSs. Such cooperation is crucial for maintaining system stability and preventing any single SHS-EVCS from destabilizing the network through actions like electricity price adjustments. The proposed energy trading strategy enhances the operational efficiency of SHS-

EVCS and fosters a collaborative environment, ensuring the long-term sustainability and economic efficiency of renewable energy use in EV charging infrastructure.

However, this study has several limitations that require further investigation. It does not incorporate demand-side management strategies, particularly demand response, into its framework. Additionally, it overlooks important distinctions between cooperative and non-cooperative game theory approaches, which could influence the results. Moreover, social welfare aspects, such as the well-being of EV drivers, have not been fully considered. Future research should address these gaps to improve the robustness and applicability of the findings in a broader context.

6.4 SHS-EVCS demand side management consider as social welfare maximization

The chapter 5 conducted in this thesis has thoroughly explored the optimization and economic feasibility of SHS systems integrated with EVCS, utilizing both non-cooperative and cooperative game theory frameworks. The development and implementation of a bi-level optimization model have proven to be a robust method in addressing the dual goals of minimizing capital and operational costs while maximizing social welfare. The use of non-cooperative game theory at the individual SHS-EVCS level allows for strategic cost minimization by treating each RE supplies as independent players. The solutions ensure that no single RE can reduce its cost further without increasing the costs of others, thus achieving an optimal balance in the energy dispatch strategy. At the second level, the cooperative game theory framework facilitates internal energy trading and demand response among multiple SHS-EVCSs. This collaborative approach, managed by an IMS, enhances overall system efficiency by dynamically adjusting electricity prices based on real-time supply and demand data. This iterative process not only stabilizes the electricity market but also ensures that EV charging demands are met effectively, even under conditions of uncertainty.

By combining Markov decision processes to model EV charging times with Monte Carlo simulations to forecast charging demand, these methods effectively capture the stochastic nature of EV usage patterns. They provide highly accurate forecasts and enable the optimization model to adapt to varying conditions, thereby enhancing the reliability of the SHS-EVCS system. Additionally, duality theory is applied to determine real-time electricity prices, aiding in the management of demand-side energy consumption. By leveraging these theoretically optimal prices, the system incentivizes off-peak charging, reduces peak load pressure, and contributes to grid stability. This aligns with the broader objectives of demand-side management, which aim to achieve peak load reduction, ultimately lowering overall energy costs and improving system sustainability.

The proposed empirical analysis and case studies demonstrate the effectiveness of the TOU strategy in reducing peak loads and balancing energy demand. The comparative results between forecasted and actual load scenarios underscore the significant impact of TOU in mitigating demand peaks and promoting efficient energy utilization. This approach not only benefits the grid by reducing the need for additional infrastructure investment but also offers economic advantages to EVCS operators and consumers through lower electricity prices and operating costs. In summary, the integration of advanced optimization techniques and game theory models in managing SHS-EVCS systems presents a promising pathway toward achieving sustainable and efficient energy infrastructure. The findings in this chapter provide valuable insights into the complex interactions between renewable energy, storage systems, and EV charging requirements. Future research should continue to explore the scalability of these models and their applicability in diverse geographic and economic contexts, thereby supporting the global transition to cleaner and more resilient energy systems.

In conclusion, the integration of advanced optimization techniques and game theory models in the management of SHS-EVCS systems offers a promising pathway toward sustainable and efficient energy infrastructure. The findings from this chapter provide valuable insights into the complex interplay between renewable energy sources, storage systems, and EV charging demands. Future research should continue to explore the scalability of these models and their application in diverse geographical and economic contexts, thereby contributing to the global transition toward cleaner and more resilient energy systems.

6.5 Future Research

All the questions and conclusions intended to be addressed in this paper have been presented. However, there are still areas where the research direction can be expanded. This section will outline some potential future work that can be extend follow the current study.

a) Future research could explore the uncertainties associated with renewable energy sources in EVCSs. For instance, it could examine how seasonal variations in solar energy affect the operation of charging stations in different regions or countries. Additionally, research could investigate the selection of various renewable energy sources, such as wind energy or geothermal energy, based on differences in locations or climate. The integration of these new energy sources would also need to address their inherent uncertainties.

b) Due to the lack of widespread adoption of networked EVs and CSs, empirical analysis is currently not feasible. Existing research primarily tests algorithms and models through simulations, lacking the necessary analysis of feasibility. In the future, more robust validation can be achieved through extensive empirical analysis using actual network data.

c) In Chapter 5, this research considers the uncertainty related to when EV drivers decide to start or stop charging their EVs. However, in reality, EV charging uncertainty involves many more factors. For example, the distance between home or workplace and nearby EVCSs can influence the choice of CS. Additionally, personal charging preferences and behaviours, such as range anxiety, charging habits, and acceptable electricity price range etc. These uncertainties affect the charging load on EVCS and the internal distribution of RE supply. This presents an interesting and meaningful research topic that warrants further exploration in future studies.

d) It will be essential for future research to further investigate the scalability of these models and explore their applicability in a wide range of geographical and economic contexts. Such exploration is crucial for ensuring that these advanced methods can be adapted to different regions and circumstances, ultimately supporting the global transition towards more sustainable, resilient, and adaptable energy systems. This research not only contributes to the academic understanding of energy management but also has practical implications for the development of cleaner and more secure energy solutions worldwide.

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