Research on Economic Planning and Operation of Electric Vehicle Charging Stations

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Abstract

In response to the call for carbon neutrality, the global energy industry will usher in tremendous changes in all aspects. As a necessity of modern industry, traditional automobiles have produced huge fossil energy emissions. Electric vehicles (EVs), which offering significant potential in improving the eco-friendly environment accelerating the construction of carbon neutrality, become a good alternative to traditional fossil energy vehicles. As the ambitious plans of medium and long-term EV penetration rate proposed by various countries, EV charging stations need to be able to provide EV users with more convenient, efficient, and economical charging services. Appropriately arranging the location and capacity of charging stations can actively guide users' enthusiasm for the use of EVs and significantly stimulate the enthusiasm for investment in the construction of EV charging stations. Applying effective charging energy scheduling strategies based on the built charging stations can make full use of the flexibility of the EV batteries to achieve the purpose of reducing charging losses and even supporting the power grid system.

This dissertation focuses on the investigation of the planning and operation of the EV charging station. Various real constraints in actual operation are discussed and modeled in detail. The main contributions are described as follows:

(i) An EV charging station planning strategy, considering the construction cost and drivers' satisfaction, is proposed in this dissertation. The whole German motorway information and an hourly-based resolution traffic flow are collected, and the existing service areas on motorways are presented as potential locations for charging infrastructure. Close service areas are clustered into a group and the optimal charging station placing locations in this group are calculated. The charging station construction costs, EV drivers waiting costs as well as the EV inconvenient driving costs are defined. By considering the different types of costs mentioned above synthetically, a planning method that can satisfy the charging demand while reducing the construction cost is proposed. In addition, three different planning scenarios to meet different planning requirements have been proposed. The established optimization problem is a mixed-integer nonlinear (MINLP) problem and an improved approach based on the genetic algorithm is proposed to solve this problem. Parallel computing can be adopted which can improve the solving speed. Results verify the efficacy of the proposed method.

(ii) An optimal charging scheduling method by responding to the time-of-used (TOU) electric-

ity price is proposed. First, the uncontrolled charging model to fully charge EVs as fast as possible is established. Then, an optimal charging scheduling model by considering the limited number of chargers is proposed to both reduce the charging cost and guarantee the charging demand of each EV. The proposed model is formulated as a bilevel programming (BP) model. The charger index and available charging duration for each EV are determined at the upper level, while the charging power of each EV at each time slot is determined at the lower level. After that, a solving approach is introduced for the proposed BP model. The efficacy and performance of the proposed charging scheduling method are verified by simulation results.

(iii) A data-driven intelligent EV charging scheduling algorithm is proposed in this dissertation, by scheduling in response to the time-of-use (TOU) electricity price, the limitation of charging facilities, and detailed charger operating process is also considered. First, based on the neural network algorithm, a charging demand forecasting method is introduced to establish the charging task of the charging station. Then, according to the established task, an optimization model that considers the charging costs, battery degradation, and user dissatisfaction comprehensively is proposed. The proposed model is formulated as a mixed-integer nonlinear programming problem, and a corresponding approach for solving the model is also proposed. Finally, the real-time operation process of the proposed scheduling method in the actual charging station is presented. By comparing with the existing methods, better effectiveness and performance of the proposed scheduling method are verified by simulation results.

(iv) A collaborative optimal routing and scheduling (CORS) method is proposed, providing an optimal route to charging stations and designing optimized charging scheduling schemes for each EV. In the order of reporting, whenever an EV reports its charging demand, a CORS optimization model is built and solved so that a specific charging scheme is designed for that EV. Then, the TN and DN status is updated to guide the subsequent EVs operating. The proposed CORS integrates the real-time state of the TN and DN, and effects positive benefits in helping EVs to avoid traffic congestion, improving the utilization level of charging facilities and enhancing the charging economy. The combined distributed biased min consensus algorithm and generalized benders decomposition algorithm are adopted to solve the complex nonlinear optimization problem. Through comparing with the existing methods, better effectiveness is verified by simulation results.

Kurzfassung

Als Reaktion auf die Forderung nach Kohlenstoffneutralität wird die globale Energiewirtschaft in allen Bereichen gewaltige Veränderungen herbeiführen. Als eine Notwendigkeit der modernen Industrie haben herkömmliche Automobile enorme Emissionen fossiler Energie erzeugt. Elektrofahrzeuge (EVs), die ein erhebliches Potenzial zur Verbesserung der umweltfreundlichen Umgebung bieten und den Aufbau der Kohlenstoffneutralität beschleunigen, sind eine gute Alternative zu herkömmlichen Fahrzeugen mit fossiler Energie. Angesichts der ehrgeizigen Pläne verschiedener Länder zur mittel- und langfristigen Verbreitung von Elektrofahrzeugen müssen die Ladestationen in der Lage sein, den Nutzern von Elektrofahrzeugen komfortable, effiziente und wirtschaftliche Ladedienste anzubieten. Eine geeignete Anordnung der Standorte und Kapazitäten von Ladestationen kann die Begeisterung der Nutzer für die Nutzung von E-Fahrzeugen aktiv steuern und die Bereitschaft für Investitionen in den Bau von Ladestationen deutlich erhöhen. Die Anwendung effizienter Strategien zur Planung der Ladeenergie auf der Grundlage der errichteten Ladestationen kann die Flexibilität der EV-Batterien voll ausnutzen, um die Ladeverluste zu reduzieren und sogar das Stromnetz zu unterstützen.

Diese Dissertation konzentriert sich auf die Untersuchung der Planung und des Betriebs von EV-Ladestationen. Verschiedene reale Randbedingungen im tatsächlichen Betrieb werden diskutiert und detailliert modelliert. Die wichtigsten Beiträge werden im Folgenden beschrieben:

(i) In dieser Arbeit wird eine Strategie zur Planung von E-Ladestationen vorgeschlagen, die die Baukosten und die Zufriedenheit der Fahrer berücksichtigt. Die gesamte deutsche Autobahninformation und ein stündlich aufgelöster Verkehrsfluss werden gesammelt, und die bestehenden Raststätten auf Autobahnen werden als potentielle Standorte für Ladeinfrastruktur dargestellt. Nahe gelegene Raststätten werden zu einer Gruppe zusammengefasst und die optimalen Standorte für Ladestationen in dieser Gruppe werden berechnet. Die Kosten für den Bau von Ladestationen, die Wartekosten für die EV-Fahrer und die Kosten für unbequemes Fahren werden definiert. Durch die synthetische Berücksichtigung der verschiedenen oben genannten Kostenarten wird eine Planungsmethode vorgeschlagen, die den Ladebedarf befriedigen und gleichzeitig die Baukosten reduzieren kann. Darüber hinaus wurden drei verschiedene Planungsszenarien vorgeschlagen, um unterschiedliche Planungsanforderungen zu erfüllen. Das ermittelte Optimierungsproblem ist ein gemischt-ganzzahliges nichtlineares Problem (MINLP), und zur Lösung dieses Problems wird ein verbesserter Ansatz auf der Grundlage des genetischen Algo-

rithmus vorgeschlagen. Durch den Einsatz von Parallelrechnern kann die Lösungsgeschwindigkeit erhöht werden. Die Ergebnisse bestätigen die Wirksamkeit der vorgeschlagenen Methode.

(ii) Es wird eine Methode zur optimalen Ladeplanung vorgeschlagen, die auf den Strompreis der Nutzungszeit (TOU) reagiert. Zunächst wird ein unkontrolliertes Lademodell erstellt, um die E-Fahrzeuge so schnell wie möglich vollständig aufzuladen. Dann wird ein optimales Ladeplanungsmodell vorgeschlagen, das die begrenzte Anzahl von Ladegeräten berücksichtigt, um sowohl die Ladekosten zu reduzieren als auch den Ladebedarf jedes E-Fahrzeugs zu gewährleisten. Das vorgeschlagene Modell wird als bilevel programming (BP) Modell formuliert. Der Ladeindex und die verfügbare Ladedauer für jedes Fahrzeug werden auf der oberen Ebene bestimmt, während die Ladeleistung jedes Fahrzeugs in jedem Zeitfenster auf der unteren Ebene festgelegt wird. Danach wird ein Lösungsansatz für das vorgeschlagene BP-Modell vorgestellt. Die Wirksamkeit und Leistungsfähigkeit der vorgeschlagenen Ladeplanungsmethode wird durch Simulationsergebnisse verifiziert.

(iii) In dieser Dissertation wird ein datengesteuerter intelligenter EV-Ladeplanungsalgorithmus vorgeschlagen, bei dem die Planung als Reaktion auf den Time-of-Use (TOU)-Strompreis, die Begrenzung der Ladeeinrichtungen und den detaillierten Betriebsablauf des Ladegeräts berücksichtigt wird. Zunächst wird auf der Grundlage des Algorithmus eines neuronalen Netzes eine Methode zur Vorhersage des Ladebedarfs eingeführt, um die Ladeaufgabe der Ladestation festzulegen. Dann wird entsprechend der festgelegten Aufgabe ein Optimierungsmodell vorgeschlagen, das die Ladekosten, den Batterieabbau und die Unzufriedenheit der Nutzer umfassend berücksichtigt. Das vorgeschlagene Modell wird als gemischt-ganzzahliges nichtlineares Programmierproblem formuliert und ein entsprechender Ansatz zur Lösung des Modells wird ebenfalls vorgeschlagen. Schließlich wird der Echtzeit-Betriebsprozess der vorgeschlagenen Planungsmethode in einer tatsächlichen Ladestation vorgestellt. Durch den Vergleich mit den bestehenden Methoden werden die bessere Effektivität und Leistung der vorgeschlagenen Planungsmethode durch Simulationsergebnisse verifiziert.

(iv) Es wird eine kollaborative, optimale Routing- und Planungsmethode (CORS) vorgeschlagen, die eine optimale Route zu den Ladestationen bereitstellt und optimierte Ladeplanungsschemata für jedes EV entwickelt. Wenn ein EV seinen Ladebedarf meldet, wird ein CORS-Optimierungsmodell erstellt und gelöst, so dass ein spezifisches Ladeschema für dieses EV entworfen wird. Dann wird der TN- und DN-Status aktualisiert, um den Betrieb der nachfolgenden EVs zu steuern. Das vorgeschlagene CORS integriert den Echtzeit-Status von TN und

DN und hat positive Auswirkungen, indem es EVs hilft, Verkehrsstaus zu vermeiden, den Auslastungsgrad von Ladeeinrichtungen zu verbessern und die Wirtschaftlichkeit des Ladens zu erhöhen. Der kombinierte Distributed Biased Min Con-Sensus Algorithmus und der Generalized Benders Decomposition Algorithmus werden eingesetzt, um das komplexe nichtlineare Optimierungsproblem zu lösen. Durch den Vergleich mit den bestehenden Methoden wird die bessere Wirksamkeit durch Simulationsergebnisse bestätigt.

Nomenclature and Abbreviations

Abbreviations

EV	Electric vehicle
IEA	International Energy Agency
TOU	Time-of-used
MINLP	Mixed-integer non-linear problem
TN	Transportation network
DN	Distribution network
TDN	Traffic-distribution coordination
DICS	Data-driven intelligent EV charging scheduling
CORS	Collaborative optimal routing and scheduling
DBMC	Distributed biased min consensus
GBD	Generalized benders decomposition
STM	Spatiotemporal model
V2G	Vehicle-to-grid
DG	Distributed generation
SOC	State of charge
LIB	Li-ion Battery
DRL	Deep reinforcement learning
MCS	Monte Carlo Simulation
OPF	Optimal power flow
GA	Genetic algorithm
BP	Bilevel programming
ICS	Idle chargers searching
EPS	EV power supplement
UCS	Uncontrolled charging scheduling
WCAS	Optimal charging without chargers assignment scheduling
POCS	Proposed optimal charging scheduling algorithm
LSTM	Long short-term memory
CFO	Convectional forecasting optimization
FCFS	First come first serve scheduling
SWR	Scheduling with real data
SWP	Scheduling without prediction

NROS	Nearby routing with optimal scheduling
ORUS	Optimal routing with uncontrolled scheduling
NRUS	Nearby routing with uncontrolled scheduling

Indices and Sets

k/Ω^k	Index and set of a candidate service area cluster
g/Ω^g	Index and set of a candidate service area
t/T	Index and set of time slot
s/Ω^s	Index and set of service areas
$\Omega^s(k)$	Set of service areas in cluster k
M	Number of chargers
m	Index of charger
M_s	Number of chargers in charging station s
$n/\boldsymbol{\Omega}^E$	Number and set of EVs
N	Number of charging EVs in one optimization duration
T	Total number of time slot
$\boldsymbol{VEC}_n$	Set of charging information of n-th EV
$\boldsymbol{VEC}$	Set of sorted EVs
$\boldsymbol{P}_{ch}$	Matrix of charging power of each charger in every time slot
$P_{ch(m,t)}$	Charging power of m-th charger at time slot t
$\boldsymbol{P}_{ev}$	Matrix of charging power of each EV in every time slot
$P_{ev(i,t)}$	Charging power of i-th EV at time slot t
$\boldsymbol{\delta}$	Matrix of the chargers assignment
$\delta_{(k,m)}$	Binary coefficients, which is equal to 1 if the i-th EV charge at the m-th charger, otherwise, zero
t_n^a	Arrival time of EV n
t_n^d	Departure time of EV n
t_n^s	Time of EV n start charging
t_n^e	Time of EV n end charging
t_n^{full}	Minimum time required to fully charge of EV n
E_n^{req}	Required energy of EV n
P_{max}	Maximum power per time slot provided by one charger

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1 Introduction

1.1 Background and Motivation

The depletion of fossil energy and the change of climate is urgent issues for countries around the world. Electric vehicles (EVs), which offer significant potential in improving sustainability and ecofriendly environment, become a good alternative to traditional fossil energy vehicles. Ambitious EV development plans have been drawn up by countries and corresponding policies to promote EV deployment are designed. The European Union (EU) will aim to have at least 30 million zero-emission vehicles on its roads by 2030, as it seeks to steer countries away from fossil fuel-based transport. China plans to achieve about 20% of the total sales of EVs by 2025. By 2035, pure EVs will become the mainstream of newly sold vehicles, and public vehicles will be fully electrified. The International Energy Agency (IEA) [1] has established the Sustainable Development Scenario trajectory that will require putting 230 million EVs on the world's roads by 2030, which occupies 17.3% of the total amount of vehicles. The annual number and proportion of sold electric vehicles are shown in Figure 1.1.

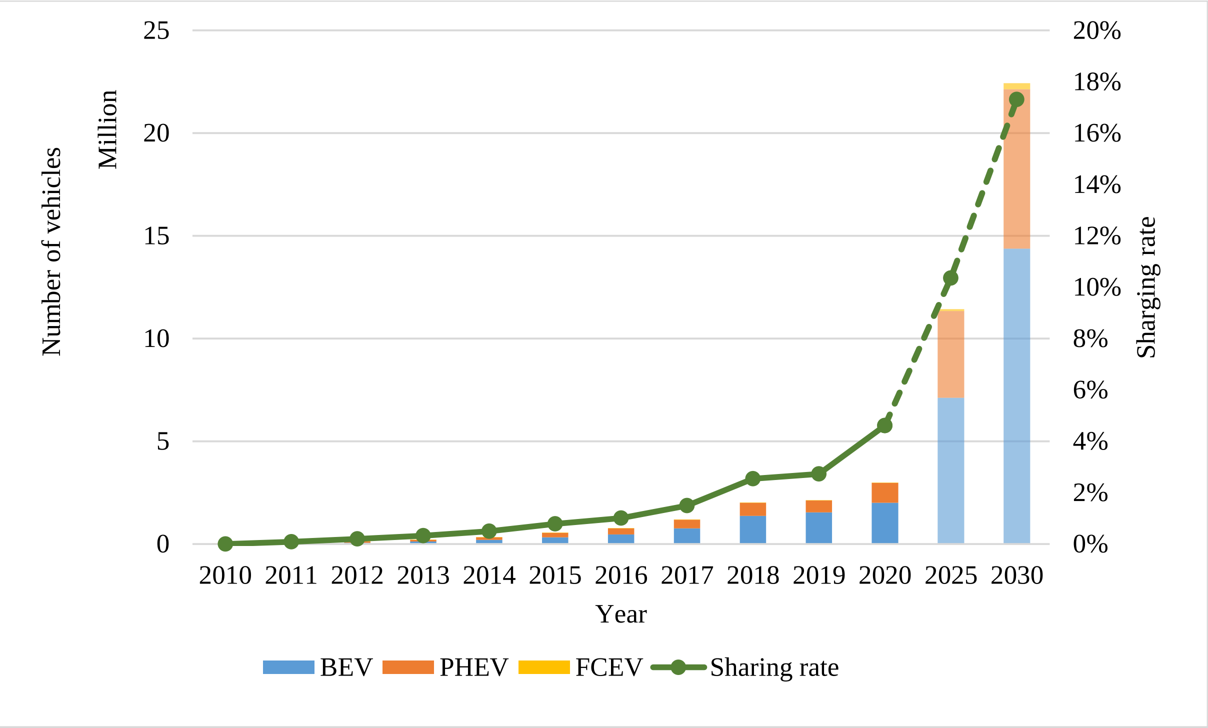


Figure 1.1 The annual number and proportion of sold electric vehicles.

With the increase in the number of EVs, the demand for supporting charging facilities is also increasing. Generally speaking, the types of chargers are divided into fast charging chargers and slow charging chargers corresponding to DC chargers and AC chargers respectively. The AC charger is simple to use and install, which can be directly connected to the grid without special transformation. The power of the AC charger is relatively small, a single pile is mostly 3.5kW and 7kW. A single charge often takes several hours to fully charge. Constructing an AC charger, as a cheaper method, is suitable for spreading the scale of charging stations at the initial stage of investment to ensure the basic charging needs of EV users. However, the slow charging speed is one of the main reasons for extinguishing the enthusiasm of potential EV buyers. In contrast, the DC chargers are more access to 380V power supply with large power supply current and short charging time. 60%-80% of the battery power can be fully charged within 20-30 minutes by DC chargers. However, DC fast charging has high requirements on the power grid and more complex harmonic suppression devices, so the investment cost is relatively high.

The lack of charging facilities has been the main obstacle to the widespread use of EVs [2]. More than 67% of respondents agree that right now lack of charging facilities and 54% of respondents claim that long charging time is one of the main barriers to EV adoption [3]. However, from the perspective of charging operation companies, the main source of income is charging service fees, which is difficult to offset the construction investment and maintenance costs. Low utilization rate is currently the biggest obstacle to profitability in the EV charging field, according to the report in [4], in China 2019, the average daily usage time of a single charger is only 0.93 hours, which means the usage rate is only 3.9%. Therefore, both the user side and the operator side put forward requirements for reasonable planning and sizing of charging stations.

Charging station plays an important role in providing charging services to EVs. As discussed above, chargers in a charging station have a lot of idle time, meanwhile, the parking time of an EV is generally much longer than the required time to fully charge its batteries [5, 6]. Many countries, such as Germany, have introduced time-of-use (TOU) electricity pricing mechanisms to increase market competition, thereby encouraging the consumption of renewable energy and increasing system flexibility. China’s power market is also reforming in this direction. Since the charging demand of EVs has obvious sequential characteristics, the optimal scheduling method that considers the TOU electricity price has been widely adopted to promote the total utility for the charging operator markets [7] and minimize the total charging cost and the energy cost from the substation [8].

Meanwhile, with the spread of the scale of charging stations, the charging power of EVs will bring a significant impact on the power grid. On the one hand, due to the charging of EVs, there is a sudden increase in load which results in voltage instability. On the other hand, large charging power can significantly change the power demand on the load side and bring new challenges to the power flow regulation of the power grid [9]. In addition, the increase in the charging demand of EV users will also change the flow of the transportation network. Inappropriate charging station routing strategies will cause congestion in dense areas of charging stations. Meanwhile, when users have charging demands, a reasonable selection of charging stations for them can also effectively alleviate traffic congestion, reduce the charging waiting time and improve the efficiency of charging facilities.

As countries actively promote the development of the EV industry, the scale of EVs will trigger a huge change in the existing power grid and transportation network structure. Corresponding technical guarantees for the large-scale application of EVs are required in the era of rapid development. The main motivation to carry out this research is to formulate reasonably charging station sizing and planning schemes and design optimal scheduling methods with fully activating charging flexibility, which will help to improve the economic operation of the transportation and power network, increase the profitability of charging stations and encourage the confidence of EV users.

1.2 Challenges and Research Questions

The research in this article focuses on how to appropriately plan the size and location of charging stations and use limited charging facilities to design reasonable and feasible charging power scheduling schemes. Especially, there are following problems which are worthy of more in-depth investigation:

(1) *Problem of how to optimally plan the charging system into the motorway*. Proposing appropriate charging station planning strategies is currently one of the important means to activate the enthusiasm of EVs. It can not only effectively reduce the investment cost of charging stations, but also provide users with charging guarantees and higher service quality. At present, there are many planning schemes for urban scenes, but less research work focuses on motorway charging station planning. The anxiety of cruising range is one of the most common problems faced by EV users. To ensure economy and user satisfaction, the charging planning problem needs to be considered from the construction cost, the average waiting time for charging, and the convenience of finding a charging station. In addition, the established model is usually a mixed-integer non-linear (MINLP) problem which should be solved by a specific algorithm.

(2) *Problem of how to formulate charging scheduling strategy with limited charging facilities*. Charging scheduling is an attractive research direction that can utilize the flexibility characteristics brought by that the staying time of EVs in a charging station is usually longer than the required charging time. Lack of charging facilities is still a significant barrier to the electrification of the logistic system. How to effectively schedule the EV charging power to reduce the charging station operating cost when the number of chargers was limited becomes an important issue. However, many of the current scheduling research works ignore the characteristics of limited charging station facilities, or some works simply the number of chargers to the capacity limit of the charging station, which means it is impossible to know how each EV connects to a specific charger. Thus, it is necessary to propose a scheduling method to assign specific chargers to each individual EV while adopting power scheduling.

(3) *Problem of how to establish scheduling algorithm in consideration of traffic uncertainty*. In the time dimension, charging scheduling is to allocate the corresponding power to the EV staying in the charging station at different times. However, in the actual scheduling, the uncertainty of subsequent charging demand will affect the current scheduling performance. Therefore, the prediction of subsequent charging demand is necessary to improve the efficiency of scheduling. At present, there have been studies to develop scheduling strategies around the uncertainty of future charging demand. However, some of the existing works simplified the demand scenarios to keep the problem computationally tractable [10, 11], some [12] neglect the flexibility of the scheduling charging power and battery degradation, and some [13] [14] regard the power demand of the charged EV as a whole that ignoring the traffic flow information of each individual EV. To improve the operating profit, it is essential to propose scheduling schemes that consider both the charging demand uncertainty and the operating of limited charging facilities in such form of charging stations.

(4) *Problem of how to operate the power distribution and traffic networks collaboratively*. The increasing of EVs alleviates the faced environmental problems but brings challenges to the optimal operation of transportation network (TN) and distribution network (DN). The charging power scheduling schemes of the charging station for the electrical part can only be formulated according to the actual number and type of EVs arriving at the station. Similarly, in the navigation of the charging EV in the traffic part, it is necessary to refer to the traffic congestion situation on the driving path and whether the charging station has idle charging facilities. However, the most of existing research

works consider EV charging station assignment and navigation services in the TN separately from charging station power scheduling services in the DN, which leads to the fact that the obtained optimal operation strategies cannot be realized in the actual execution process. Therefore, in order to cope with the increasingly complex TN and DN interactive system, it is necessary to propose a joint operation method that can ensure the economic operation of charging stations and avoid traffic congestion.

1.3 Objectives of the Dissertation

The overall objective of the dissertation is to propose the optimal planning and operation methods of electric vehicle charging stations to improve the flexibility and economy of electric vehicle charging applications. Specifically, the objectives of the dissertation include mainly the following aspects:

(1) *Design the charging station sizing and placing strategy on motorways*. The designed planning method needs to combine the specific situation of the motorway and the driving behaviors of EV users on the motorway and design a charging station planning method that is economical and considers the user experience.

(2) *Achieve optimal EV charging scheduling considering the limited number of chargers*. In order to ensure that the EVs' charging demands can be satisfied in the case of limited chargers, the proposed algorithm is required to provide the specific service EVs for each charger. Corresponding power scheduling should be implemented in response to the TOU price to achieve the operating economy.

(3) *Realize a data-driven charging station scheduling scheme*. The proposed method should be able to establish a future charging demand model based on historical data, and then design a corresponding scheduling plan based on the predicted future data, also the limitations of charging facilities should not be ignored. Meanwhile, historical data should also be updated over time, to realize real-time updating scheduling operations.

(4) *Propose the collaborative EV routing and charging scheduling strategy*. The proposed method should consider the status of the TN and DN comprehensively, formulate the charging assignment and navigation route for all EVs according to their actual charging demand, and then, develop a specific charging scheduling plan for each individual EV based on the charging station assignment results.

1.4 Outlines of the Dissertation

By considering the practical problems that may be faced in the planning and optimal operation of EV charging stations, this dissertation designs different planning and operation schemes in response to the problems raised above and the research goals formulated. The content and structure of the dissertation are demonstrated in Figure 1.1 and organized as follows:

In Chapter 2, the status of art about investigations on EV charging stations is summarized. It mainly reviews the research carried out in recent years from three aspects: the review of charging station planning and routing approaches, the optimized operation modes from the perspective of charging station operators, and the coordinated operation of the charging station considering transportation and distribution networks interaction.

In Chapter 3, a charging station planning method based on the existing service areas is proposed. An EV charging station planning model for motorways, which is based on the existing service area and does not require additional motorway retrofit costs, is proposed. Comprehensive consideration of the construction cost of charging stations, the waiting time for charging, and the inconvenient driving cost. The proposed planning method can reduce the total cost as much as possible while guarantee the distribution density of charging stations and the number of charging facilities in charging stations that can meet the EV drivers' requirements. An improved genetic algorithm is designed to solve the proposed MINLP optimization problem. Three different planning scenarios: orientation to minimize social cost, orientation to minimize charging station operating, and orientation to minimize charging station construction, are defined to meet the different planning requirements.

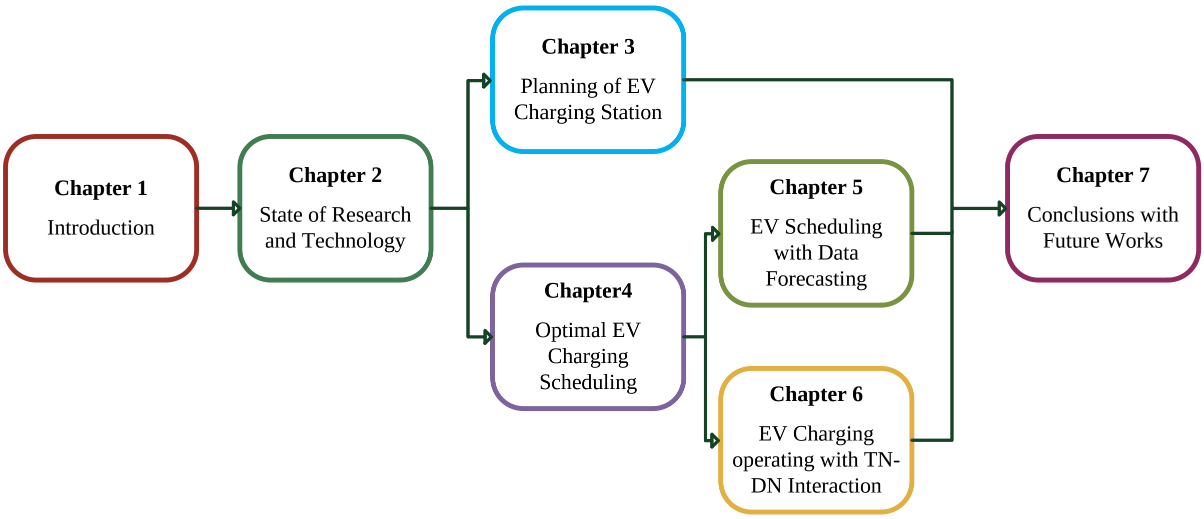


Figure 1.2 Structure of the dissertation.

In Chapter 4, considering the limited number of chargers, an optimal charging power scheduling method based on TOU electricity price is proposed. Firstly, the uncontrolled charging scheduling model is designed for fully charging EVs as fast as possible. There is no coordination among charging EVs, and no charging power optimization scheduling is implemented. Then, considering the limited chargers assignment scheme, an EV optimal charging scheduling model to minimize the total charging cost is proposed. The established model is a BP model, which can not only guarantee the EVs' charging demand by reasonably assigning the limited chargers, but also reduce the charging cost by optimal scheduling the charging power. The upper level mainly decides the charger index and available charging period of EVs. The lower level solves the EVs charging power within their available charging period by responding to the TOU electricity price. Then, as the upper level is a mixed nonlinear integer program while the lower level is a linear program, a compound solving algorithm is designed to get the detailed optimal EVs charging scheduling solutions. Through performance verification, the proposed algorithm can find the solution within an acceptable time. Finally, the proposed optimal charging scheduling method is compared with the uncontrolled charging scheduling method and a commonly used charging power scheduling method. According to the results, the proposed method can provide a detailed and efficient EV charging scheme, which can minimize the charging cost while guaranteeing the EVs' charging demand when considering the limited number of chargers.

In Chapter 5, a data-driven intelligent EV charging scheduling (DICS) algorithm is proposed to guarantee different EV users charging requirements and improve the charging station profit. First, an EV charging demand forecasting method based on the neural network algorithm is proposed. For considering the special needs of limited charging facilities, the forecasting process predicts both the numbers of subsequent vehicles and their respective energy requirements, which is called estimated EV information. The established estimated information contains the specific charging demand information of each predicted EV and can be used to guide the scheduling optimization process. Second, the charging scheduling model considering the limited charging facilities is designed. The optimization model contains both real and estimated EV and comprehensively minimizes charging cost, battery degradation, and charging incomplete rate. The total charging cost for the charging operators is reduced while the charging requirements and reducing the battery degradation are assured. Then the corresponding solving technique based on the heuristic algorithm is introduced. And the solved results show how to flexibly use the limited chargers to connect the appropriate EVs and provide corresponding charging power. After that, the real-time charging scheduling system operation process is introduced. Since the traffic flow in the station is changing in time series, the forecasting results of subsequent EVs and the charging scheduling scheme for current EVs will be updated at each time slot, and the current traffic information will be adopted for keep training to improve the prediction accuracy. Finally, the proposed data-driven intelligent EV charging scheduling is compared with the existing methods and the advantages of the proposed method are verified.

In Chapter 6, a collaborative optimal routing and scheduling (CORS) method is proposed. The proposed algorithm arranges specific navigation and charging schemes for each EV in turn according to the order in which the EVs report charging requirements. The proposed CORS method can not only assign and route charging stations for EVs but also optimize the scheduling of charging power based on the assigned charging stations. An optimization model that considers EV driving cost, electricity purchase cost, and battery degradation cost is proposed to find the routing and scheduling scheme with the least comprehensive cost. The charging facilities limitation in a charging station is also considered. To solve this complex optimization mode, we split the optimization model into the upper layer and lower layer optimization. The upper layer mainly decides the charging station assignment process including determining the charging station and planning the driving path. Meanwhile, the lower layer solves the coordinate charging scheduling scheme for the EV with the charging station assignment results from the upper layer. The modified distributed biased min consensus (DBMC) and generalized benders decomposition (GBD) methods are introduced as the solver.

Finally, Chapter 7 summarizes the whole research in the dissertation, points out the remaining problems in the research process, and sorts out and looks forward to the next research content.

2 State of Research and Technology

Extensive research works have been carried out around the optimal planning and operation of EV charging stations. Likewise, the increase in EV usage over the past ten years has generated interest in the topics of construction cost and profit, the convenience of charging, charging economy, user satisfaction, battery energy management, etc. This chapter demonstrates an overview of problems and challenges in the expansion of EV charging stations and highlights the mainstream approaches for charging station applications.

2.1 Review of Charging Station Planning and Routing Approaches

The planning of charging stations is an unavoidable issue for large-scale promotion of EV applications. Lack of charging facilities and unreasonable charging station navigation strategies are [2] main reasons to obstruct the widespread use of EVs. This section introduces two aspects: station planning and routing.

2.1.1 Sizing and Planning Approaches

In the early investigations of EV charging station planning, based on the gas station to integrating public charging infrastructure into a city is one of the major views [15]. Meanwhile, planning methods for gas stations have gradually been moving towards a standardization and legalization direction [16]. However, researchers realized that combining charging infrastructure with the conventional gas stations may not be appropriate as the relatively long charging process will saturate the limited space of the gas stations, and therefore put forward new requirements for the realization of transportation electrification [17]. At present, the main planning methods can be divided into two different ways: planning approaches mainly consider convenience and construction costs, and planning approaches consider the interaction of transportation and distribution grids.

- Planning approaches mainly consider convenience and construction costs

As a mobile energy demand used by people, the EV charging load is influenced by human daily mobility that determines the EV travel distance within a day, EV charging locations, and the time charging starts. The research in [18] and [19] simulated the EV driving patterns according to the data from national driving patterns and demographics. However, these studies did not consider the fundamental principles of transportation systems. As a popular tool, Markov Chain is often used to simulate the EVs' mobility [20] and formulate optimal charging station capacity sizing [21] and location [22] schemes. The development of information technology facilitates the application of OD analysis for analyzing traffic flow characteristics. In [23, 24], A spatio-temporal model (STM) was developed to model the mobility of EVs both spatially and temporally. Based on this spatial information, an EV charging modeling method based on OD analysis was proposed in [25]. For public transportation electrified vehicles, their charging facilities planning principle is choosing suitable locations in their fixed driving route. The EV charging station placement for urban public bus systems is proposed in [26]. Based on the driving path of the bus, a dynamic wireless charging method in a smart city is proposed in [27].

In the process of construction of charging stations, not only the traffic information should be considered, but also the construction difficulty and construction cost of the location should be taken into account. Using real geographic information, [28] compared the information in the city including land rent, charging facility construction and maintenance costs, station electrification component costs, and grid energy loss in detail. And developed a charging station planning method that balances the overall cost of station construction and the convenience of EV users. Meanwhile, the capacity setting of the charging station is also a research direction that cannot be ignored. Since the charging time of EVs is much longer than the energy replenishment speed of fuel vehicles, the charging stations with small capacity will increase the waiting time of EV users. In contrast, an excessively large charging station capacity will increase the idle time of the charger, waste construction costs, and make it difficult for the charging station operators to be profitable. The charging station model based on queuing theory [29] can well reflect the flow of EVs entering and leaving the station, so it is applied to the charging station planning process by researchers [30]. The M/M/s queuing theory is adopted in [16] to simulate the queuing process of EVs in the charging stations on the freeway.

In order to improve the low utilization of charging facilities in EV charging stations, researchers have turned their attention to the construction of charging stations. In [31], a single charger multiple ports (SCMP) charging station planning approach is proposed. In this structure, a charger has multiple cables connected to different parking ports, and by controlling the cable switches, the charger can be selected to serve EVs in different parking ports. Planning charging stations with this structure can effectively reduce the construction cost of charging stations while reducing the idle time of a single charger and improving profitability. In addition, this method can effectively reduce the increased costs caused by the transformation of the power grid. To avoid the charging power of the charging power exceeding the capacity of the transformer when too many chargers work simultaneously, a charging station for electric taxis in Shenzhen, China adopted the SCMP structure [32]. On this basis, [33] proposed the multiple chargers multiple ports MCMP charging station planning method, which further improves the flexibility of the charging station.

- Planning approaches considering the interaction of transportation and distribution grids

To improve the charging speed, chargers with higher charging power are applied to charging stations. With the large-scale construction of charging stations, researchers have started to realize the impact of the charging system on the existing grid. Jiang *et al* [34] evaluate actual EV charging behavior of different brands and models from EV users and charging stations usage at the University of California, Los Angeles for more than one year. In [35], a queuing analysis-based method for modeling the 24-h charging load profile of an EV charging station is presented, and corresponding statistical impact on the distribution system operator is given. The study results illustrate that the large static charging load of EVs significantly changed the peak and valley periods of the grid. Reliability is one of the pivotal operating parameters of the distribution network whose degradation will result in customer dissatisfaction. Thus, the reliability of IEEE 33 bus test system with installed charging stations is discussed in [36]. The power quality impact of charging stations on distribution networks is discussed in [37], results show that suddenly increasing charging load will bring harmonic problems to the grid. Wang *et al* [38] summarize the trends, standards, issues, and mitigation measures of the impact of charging stations on the power grid, and then formulate an overview.

The papers discussed above are from the transportation perspective, which ignores power system constraints. Thus, the planning results may need readjustment according to the practical power system conditions. Existing work usually aims to site charging stations in power systems to satisfy power system economic or security operation constraints, while minimizing the investment costs for the charging stations and corresponding power grid upgrades. A two-step screening method is developed by [39] to locate charging stations in a distribution network and a modified primal-dual interior-point algorithm is proposed to determine sizing. In [40], the optimal sizing and siting of an EV charging station with vehicle-to-grid (V2G) capabilities in distribution networks are studied. However, the transportation constraints and the results may need readjustment according to the practical transportation conditions, which have been ignored by these papers. On this basis, [41] presents an EV fast-charging station siting and sizing approach considering transportation and power networks interaction. The influences of EV population, power system security operation constraints, and EV range are analyzed. Wang *et al* [42] integrate the interests of traffic networks into distribution network and charging station joint planning model to mitigate negative impacts on traffic conditions caused by installing FCSs. The designed multi-objective joint planning model can minimize both the planning costs and unbalanced traffic flows, which can be solved by a new bilayer Benders decomposition algorithm.

The urgent demand for alternative fossil energy has increased the development of renewable energy. Meanwhile, with the improvement of power grid intelligence, there is more integration of renewable energy sources in the form of distributed generations (DGs) as controllable components in the distribution network. The distribution system has a more vulnerable structure compared to the transmission system, it is necessary to combine the intermittent and random characteristics of DGs and the high load power of charging facilities. In [43], a multi-objective optimization problem was developed to obtain the optimal siting and sizing of charging stations and renewable energy sources in distribution networks. In [44], the uncertain output power of the charging station due to its stochastic charging and discharging schedule is considered for optimal siting and sizing of distributed generators in distribution systems. A comprehensive optimization model for the sizing and siting of different renewable resources-based DG units, EV charging stations, and energy storage systems within the distribution system are presented by [45]. The proposed optimization model is formulated as a second-order conic programming problem, considering also the time-varying nature of DG generation and load consumption. The eco-friendly remote hybrid microgrids concept is proposed in [46] and a corresponding joint planning approach of smart EV charging stations and DGs is designed.

2.1.2 Routing and Navigation Approaches

Proper selection of EV paths will be helpful to improving the travel efficiency of EV users and alleviate their difficulties in charging during peak hours. A decentralized policy was studied in [47] to assign EVs to a network of FCSs with the goal of minimizing the queueing time. However, this approach did not consider the personalized needs of users in different aspects, which limits the usefulness and expansion of this strategy. In order to effectively shunt the charging demand at peak hours, a personalized fast-charging navigation strategy based on the mutual effect of dynamic queuing is proposed by [48]. A multi-criterion charging queuing model is established to facilitate personalized navigation that can achieve orderly charging and personal benefit. Moreover, to solve the problem of insufficient computing power caused by excessive traffic flow during peak hours, Liu *et al* propose a simplified algorithm in [49] to relieve the computing burden in the navigation under time-differentiated pricing. As there are randomness and uncertainty in traffic networks, the deviation between the simplified deterministic model and the actual traffic network may lead to over-discharging of batteries or even driving out of power halfway. In order to improve the accuracy of navigation, Liu *et al* extend their previous deterministic charging navigation to an online navigation system based on stochastic traffic network models and online information [50].

From the perspective of individual EVs, Researchers will also formulate navigation strategies to reduce battery consumption. For public transportation systems with fixed routes, their navigation strategies are often centered on minimizing driving costs, improving lifetime life, and driving safety. For example, [51] and [52] have designed dispatch routing approaches for airport shuttles that operate on electric batteries, each having a fixed schedule. Private EV users need to reasonably arrange the navigation path of the charging station, [53] uses heuristic control strategy to optimize energy consumption for given torque and speed. In [54], an optimization problem to enable the driver to select the appropriate drive modes for energy minimization is proposed, the trip information is adopted and optimal path planning is also integrated. The proposed algorithm is evaluated on a real vehicle, which shows significant energy savings.

Since the traffic flow of the transportation network and the operating conditions of the power systems are time-varying, it is important to consider the grid influence when implementing real-time charging navigation for EV drivers. To relieve the traffic and power line congestions, a novel navigation approach is proposed to search the charging station with the lowest overall objective, which consists both of the time consumption and the financial cost [55]. In [56], a dedicated traffic user equilibrium model is proposed to describe the steady-state distribution of traffic flows comprised of gasoline vehicles and EVs. The network equilibrium through iteratively solving the traffic assignment problem and the optimal power flow problem is identified. By simultaneously considering the dynamic user equilibrium of the transportation network and the alternating current dynamic optimal power flow of the distribution network, the traffic-distribution coordination (TDC) TDC model is proposed in [57] to minimize the travel cost of the transportation network and the energy service cost of distribution network.

2.2 Review of Charging Station Operating Schemes

In the foreseeable future, charging stations will be connected to both transportation and power networks on a large scale, and the large charging load characteristics make charging stations a type of load that cannot be ignored. On the one hand, for the fast-charging stations or chargers, such as specific charging stations on the motorways, the charging load is not adjustable, because users who apply fast charging want to complete the charging as quickly as possible. On the other hand, EV users without urgent charging requirements, such as parking EVs, only need to complete the charging within the parking time, which provides an application scenario for charging stations to participate in power scheduling and improve overall flexibility. This section introduces the works from: economic-based scheduling, battery management-based scheduling, and demand uncertainty-based scheduling.

2.2.1 Economic-Based Scheduling Approaches

The economics of charging is one of the most important indicators to measure the pros and cons of charging schemes. As mentioned above, many charging station operators are currently operating with low profits [4]. Appropriate charging scheduling strategies can significantly improve the charging economy and increase the enthusiasm of operators. Centralized charging and decentralized charging are currently the two mainstream scheduling perspectives [58]. In centralized charging control, the optimization of EV charge scheduling is done centrally at the aggregator after collecting information about the power requirement of the EVs. EVs can only communicate their electrical parameters such as maximum battery capacity, SOC, and charge rate to the aggregator. In contrast, in decentralized charging control, each EV is equipped with some computing capability, and the decision to charge or not is taken by each EV in collaboration with the aggregator. Each EV communicates its energy requirements to the aggregator and uses part of this information collected at the aggregator to decide on an optimal schedule. The merits and demerits of centralized and decentralized scheduling methods are shown in Table 2.1.

Table 2.1 Comparison of Centralized and Decentralized Scheduling Approaches

Categories	Merits	Demerits
Centralized scheduling methods	• Able to calculate the optimal schedule as all the information is available to it • Reduced power fluctuations	• At the expense of user privacy • Computationally intractable in general for a large number of EVs
Decentralized scheduling methods	• Good scalability • Protect personal privacy • easy to achieve	• lack of complete information at any EV makes the charge schedule suboptimal

- Centralized charging scheduling

A charging algorithm based on the prediction of the energy prices during the charging period is proposed by [59], where the charging stations are informed about real-time pricing information through wireless communication. During the charging process, the k-nearest neighbor classification algorithm is applied to predict the price signals of the grid. If the predicted price is greater than a threshold, charging is delayed until it determines a suitable time of charging for the vehicle. Quan *et al* [60] proposed serving EV parking lot users by utilizing a centralized charging controller that considered the size of the battery pack. The main goal of the above-mentioned study was to minimize the peak loads on the grid and satisfy driver expectations. Wu *et al* [61] proposed centralized charge scheduling and load dispatch algorithms that aggregators can use to minimize their energy cost. A minimum-cost load scheduling algorithm is designed, which determines the purchase of energy in the day-ahead market based on the forecast electricity price and PEV power demands. The same algorithm is applicable for negotiating bilateral contracts. The impact of a combined PEV load over the distribution grid is also studied.

The above investigations use centralized scheduling approaches while only considering the static situations. To fill the gap, the following works also use centralized control but consider some mobility aspects of the EVs while forming a charge schedule. Sortomme and El-Sharkawi [62] explored the problem of maximizing the profit of the aggregator that bids for ancillary services (regulation and spinning reserves) while facilitating the charging of EV batteries. An optimal bidding strategy is formulated, which selects the optimal charging point and the capacities of each ancillary service to be sold. Mobility aspects considered include EV driving statistics for the whole day, which is used to derive the expected availability times for EVs and travel distances, which, in turn, are used to select the daily charging profile. In [63], the scheduling problem is formulated to maximize the time-averaged expected social welfare, which is a function of the total customer utility, the electricity cost associated with EV charging, and the penalty for not meeting EVs' charging requests. The decision-making problem is formulated as an infinite-horizon dynamic programming problem that considers the stochastic arrival process of the PHEVs that evolves like a Markov chain, the uncertainty in renewable generation, and the inexact forecast of grid loads.

- Decentralized charging scheduling

Ma *et al*. [64] proposed a decentralized charge scheduling algorithm for a large number of EVs using the Nash certainty equivalence methodology. The grid operator broadcasts the expected non-PEV base demand among the PEV agents, and each PEV agent proposes a charging plan based on this initial forecast to minimize its charging cost. Latifi *et al*. [65] present a gametheoretic decentralized EV charging schedule for minimizing the customers' payments, maximizing the grid efficiency, and providing the maximum potential capacity for ancillary services. The proposed mechanism is quite general, takes into account the battery characteristics and degradation costs of the vehicles, provides a real-time dynamic pricing model, and supports the vehicle-to-grid and modulated charging protocols. A time-dependent optimal power flow charging problem is studied [66] that optimizes the operation of the power grid and the charging activity of EVs. The objective is to reduce the charging cost and the total power generation cost. They also consider the uncertainty arising out of the future price-inelastic load, and a near-optimal distributed online algorithm is developed for that. The authors proved that this problem is convex with respect to the total electricity demand, and the solution to the scheduling problem fills the demand valley optimally.

Similarly, investigations considering mobility with decentralized scheduling approaches are carried on. In [67], a decentralized EV charging algorithm in response to TOU price in a regulated market remains constant for a long time. The charger with an embedded TOU price module formulates an optimized charging scheme to minimize the charging cost. By using the relation between the acceptable charging power of the EV battery and the SOC, a heuristic algorithm is presented to reduce the charging cost. To address mobility, the diversity in arrival time of EVs is considered in the multi-EV case. Hutterer *et al.* [68] proposed a multi-agent policy optimization where each EV (agent) acts in response to dynamic conditions in its environment according to a given strategy. Evolutionary computation has been used for optimizing EVs' charging behavior such that EVs' energy demand is satisfied and secure power grid operation is guaranteed using renewable power. The driving profiles of EVs (locations, time of arrival, and stay time at each location) and uncertainties in intermittent supply are considered.

2.2.2 Battery management-based scheduling Approaches

As the core part of the energy storage of electric vehicles, the battery has the characteristics that the energy replenishment time is significantly longer than that of fuel vehicles and the storage efficiency decreases significantly over time. How to effectively improve battery efficiency, improve vehicle endurance, and extend service life has become a problem that cannot be ignored in the charging scheduling process. Li-ion Battery (LIB) has been widely applied as the power supply for EVs.

In order to study the degradation characteristics of the battery, the evaluation methods can be mainly divided into three classes: experimental methods, model-based methods, and data-driven methods [69]. As the name implies, the experimental method is to analyze the aging behavior of the battery through a large number of experiments. Limited by the discharge rate or special experimental equipment, the application scenarios of the experimental method are limited [70]. The model-based methods are introduced to realize online and reliable monitoring of battery degradation. For instance, a LiFePO4 lithium-ion battery degradation model equivalent to money cost is formulated in [71], and the corresponding experimental is implemented to verify the results. The data-driven methods describe battery internal degradation evolution through the abundant pretest data and some machine learning algorithms without expert knowledge on aging mechanisms. Compared to model-based methods, the data-driven approaches show great advantages: 1) they have self-adaptability, model-free nature, and the ability to learn from historical data; 2) Deep reinforcement learning (DRL) can learn a good control policy, even under a very complex environment by using deep neural networks. Cao *et al.* [72] address the modeling by using a model-free (DRL method to optimize the battery energy arbitrage considering an accurate battery degradation model.

The intelligent charging scheduling system capable of estimating and minimizing these effects can potentially extend the battery life and reduce battery degradation. Therefore, to achieve the best operating mode, it is crucial for the system to develop an effective charging scheduling scheme to minimize the battery degradation cost and reduce the system peak power load. In [73], the experimental modeling methods are adopted to analyze the impact on battery degradation of the average state of charge. And the grid power supporting method is proposed based on the controlled scheduling charging. Pelzer *et al.* [74] present a scheduling approach that considers the non-linear dependencies of battery aging from various operation parameters along with TOU prices and price forecasts for computing optimal charging/dispatching schedules. The methodology is applied to price data obtained from four different electricity markets. The investigation partly confirms existing profitability concerns but further shows that explicit consideration of battery degradation can yield profitable outcomes. The EV charging scheduling problem of a park-and-charge system with the objective to minimize the EV battery charging degradation cost while satisfying the battery charging characteristic is studied in [75]. In addition, as a new form of EV energy replenishment, substation swapping has a better flexibility margin than plug-in charging in terms of charging scheduling. An optimal scheduling method of battery charging station serving EVs based on battery swapping is proposed by [76]. The charging rate of each charging bay is controlled while the scheduling problem is formulated as a mixed-integer program with quadratic battery degradation cost. A generalized benders decomposition algorithm is then developed to solve the problem efficiently.

2.2.3 Demand uncertainty-based scheduling Approaches

In addition to the issues discussed above, the uncertainty of future charging demand is also one of the important factors affecting the scheduling effect. In the time dimension, charging scheduling is to allocate the corresponding power to the EV staying in the charging station at different times. However, for charging stations for private EV users without a fixed timetable, the randomness of EV charging demand in the future time will increase the complexity and inefficiency of scheduling strategy formulation. For instance, in order to ensure the completion of charging requirements, a management system was designed in [77] to determine the charging order by considering the departure times. This brings more calculations because of the constantly updated charging strategy, and the margin of EV dwell time is not fully utilized.

In response to the above problems, Akhavan-Rezai *et al*. [78] present an approach that realizes demand response programs by developing an energy management system for incorporating aggregated EVs. The arrival time and energy requirements of EVs are also considered in a stochastic manner. In [79], through the provision of V2G programs during outage events, the role of parking lots in improving the reliability of renewable-based distribution systems is investigated. The random charging habits of EV users in parking lots are simulated based on real data. In [11], an optimal energy management strategy for EV parking, lots considering peak load reduction-based demand response programs is a built-in stochastic programming framework. The uncertain behavior of EVs, such as arrival and departure times, and the stochasticity of the remaining state-of-energy of EVs are taken into account to maximize the load factor during the daily operation of an EV parking lot. Furthermore, Pflaum *et al*. [10] proposed an EV charging station scheduling strategy considering the highly uncertain load characteristic. By using the randomized algorithm and statistic occupancy model of the charging station, the quality of service can be guaranteed and less information of EV users is required.

The demand profile of traffic flow and charging have a strong time sequence, thus, the research works began to discuss the prediction of charging demand and the design of scheduling schemes in stages. Zhang *et al*. [41] designed a two-stage stochastic optimization is developed to minimize the expected annual costs for providing charging services in different scenarios and further verify this two-stage optimization algorithm in [33]. In contrast to the two-stage stochastic model, A charge scheduling model considering multiple possible stages is proposed in [80] The proposed multi-stage model is more consistent with the real situation of a parking lot that the requests are realized at different times. In the finite time horizon, it can divide time into appropriate equal-length time-slots that allow for recourse decisions at multiple stages of the charging schedule. Nevertheless, it takes several hours to obtain a high-quality solution, which is inefficient in practical applications.

The rise of artificial intelligence algorithms helps improve the efficiency of such demand forecasting that cannot be modeled by formulas. A neural network-based approach for forecasting travel behavior to improve the scheduling efficiency is proposed in [81]. In this study, the correlation among arrival time, departure time, and trip length are also considered. The forecasted EV travel behavior is then compared with Monte Carlo Simulation (MCS) which is the main benchmarking method in this field, and results depicted the robustness of the proposed methodology. Based on deep reinforcement learning, Wan *et al*. [13] proposed a real-time EV charging scheduling without establishing the detail optimization model. The proposed approach can adaptively learn the transition probability and does not require any system model information. But the charging demand constraints of EVs, which can make sure the EVs can be fully charged upon departure, have been ignored. Therefore, a constrained Markov Decision Process EV charging scheduling approach based on safe deep reinforcement learning is proposed by [14]. The aim is to find a constrained charging/discharging scheduling strategy to minimize the charging cost as well as guarantee the EV can be fully charged. The proposed approach does not require any domain knowledge about randomness. It directly learns to generate the constrained optimal charging/discharging schedules with a deep neural network. However, the methods mentioned above all use a centralized forecasting method, which regards the power demand of the charged EV as a whole, ignoring the traffic flow information of each individual EV. Therefore, those prediction and scheduling methods cannot be applied to the charging stations with limited chargers that can be flexibly scheduled.

2.3 Review of Scheduling Approaches Considering the Transportation and Distribution Networks Interaction

The charging station of EVs is an integral part of the actual transportation network, and the electrical system also needs to be integrated into the actual distribution network [28]. Therefore, the charging demands of EV users reflect in the transportation and power network are the changes in traffic and power flow. According to this, by formulating reasonable charging strategies, such as allocating idle charging facilities according to traffic conditions, pricing charging prices according to geographic locations, adjusting charging power in response to grid status, and using charging facilities to maintain power quality, etc., the operating efficiency of both transportation and distribution network can be improved. This section introduces the application of V2G technique, coordinated operation of charging stations and renewable energy sources, and scheduling approaches with alleviating traffic congestion.

2.3.1 Application of V2G Technique

Vehicle-to-Grid (V2G) is a power scheduling process that allows the EVs to inject power to or draw power from the grid, which was introduced by W. Kempton in 1997 [82]. This concept utilizes the stored energy of the vehicle to fulfill the demand of the grid during peak hours and enhance the power quality of the grid when needed.

- Energy compensation

Peak-shaving and valley-filling of the distribution network are some of the main application aspects of V2G technology. In [83], a home energy management system integrating vehicle-to-grid (V2G) capability for predetermined scenarios is proposed. The proposed system aims to address the demand response schemes, both real-time pricing and emergency load curtailment, V2G mode of operation. In order to assign real-world randomness to the EVs' availability in the households and their charging requirements, Rassaei *et al*. [84] provide a general demand-shaping problem applicable for limit order bids to a day-ahead energy market. With the proposed distributed demand response algorithm, the peak is reshaped towards 0% penetration of EV without affecting the users' convenience. A similar approach is proposed in [85] to stimulate the potential role of EVs as distributed energy storage units to minimize peak demand in the power distribution system.

EV charging at public places such as large parking complexes, charging stations, offices, and apartment parking can be clustered through an aggregator. It acts as a centralized system operator who controls the charging and scheduling of each EV [86]. The aggregator can cluster a large fleet of EVs to increase their capacity payment, which depends on the capacity of the connected load. During peak hours, the aggregator can maximize the revenue with energy payment for providing the reserve and regulation services. Aggregating large-scale charging stations can help reduce electricity prices during the bidding process in the electricity market. With the objective of minimizing charging costs while satisfying the PEVs' flexible demand, an aggregator bidding approach into the day-ahead electricity market is discussed in [87]. A classification scheme is proposed in [88] to minimize the total cost of energy trading with different energy entities. In this scheme, EVs are classified into different classes with different pricing, charging rates, allotted power, and charging times. Aggregator maximizes its profit by optimally charging each class of EVs based on the strategy suitable for that class while saving on the energy purchased from the power grid.

- Power flow operating

Due to the access of high charging power EV charging stations, the power flow in the distribution network has been greatly changed. Economic dispatch may result in unacceptable flows or voltages in the network. Thus, optimal power flow (OPF) is a good solution for this problem that can minimize the total generation cost. Both equality and inequality constraints are considered in OPF. According to the investigations from [89], the scheduling problem for the EV charging can be augmented into the OPF problem to obtain a joint OPF-charging (dynamic) optimization. A solution to this highly nonconvex problem optimizes the network performance by minimizing the generation and charging costs while satisfying the network, physical and inelastic-load constraints. In [90], a hierarchical system model to jointly optimize power flow routing and V2G scheduling for providing regulation service are proposed. By adopting the semidefinite programming relaxation, the original non-deterministic polynomial-time hard (NP-hard) problem is transformed into a convex problem. The proposed scheduling algorithm can flatten the power fluctuations at the buses with EVs attached, alleviate grid stability issues and reduce the system power loss in a great manner while providing voltage regulation.

The assessment of EV charging scenarios based on demographical data is discussed in [91], and three different charge strategies are designed and the impacts of EVs charging on the distribution system are assessed using standard load flow calculations. Results show that implementation of the loss minimization strategies improves the lifetime and efficiency of distribution system equipment. Considering distribution system constraints such as transformer rating, current rating of lines, voltage drop, and phase unbalance, an optimal scheduling problem is formulated in [92]. Using the proposed optimal charging method, high percentages of EV uptake can be sustained in existing networks without requiring any further network upgrades, leading to more efficient use of existing assets and savings for the consumer.

- Power quality

The introduction of the smart grid concept increases the number of controllable components in the power system, and at the same time brings more complex power quality issues. When connected to charging stations, EVs can be equivalent to energy storage elements, so they can be used to help alleviate power quality problems. Voltage fluctuations are a common problem in distribution networks. Brenna *et al*. [93] aim to provide a possible solution to some common and dangerous power quality problems and voltage sags, considering the large diffusion of electric vehicles. Deep energy and power analysis to evaluate the feasibility of the vehicle-to-grid (V2G) function to compensate for power quality disturbances were presented. Mohamed *et al*. [94] present an attempt to use the V2G connected system to play an effective role in the regulation of the voltage and power of the power system and to demonstrate its positive effect on the system frequency. In [95], presents an optimized bidirectional V2G operation, based on a fleet of EVs connected to a distributed power system, through a network of charging stations. The system is able to perform day-ahead scheduling of EV charging/discharging to reduce EV ownership charging costs through participating in voltage regulation services. By responding to real-time EV usage data, the optimizing method that the use of EVs to support voltage regulation is designed. EV aggregators can integrate the scattered EVs and play the role of VR sources with a high response speed and low cost. To address the challenges of stochastic EV mobility, various distribution network topology, and the competition mechanism, Liu *et al*. [96] proposed a discounted stochastic multiplayer game approach to analyze the competition among EV aggregators. Thus, the impact of distribution network topology on the voltage regulate efficiency is investigated. The randomness of EV numbers is considered when predicting the EV aggregators' available voltage regulate capacity so that the tendency for the EV aggregators to follow the optimal strategies can be modeled accurately.

Frequency adjustment is also a V2G application direction that is currently widely used to enhance power quality. In [97], a decentralized V2G control method is proposed for EVs to participate in primary frequency control considering charging demands from EV customers. When an EV customer wants to maintain the residual state of charge (SOC) of the EV battery, a V2G control strategy is performed to maintain the battery energy around the residual SOC along with adaptive frequency droop control. By using EVs for frequency control in an isolated small smart power system, a load frequency control V2G scheme is presented in [98]. The model predictive control method (MPC) is used as a robust area controller to solve the problems of load change and system uncertainties. A load frequency control method for conventional power plants, battery energy storage systems, EVs, and heat pump water heaters is proposed in [99], which provides an alternative to battery energy storage system with the integration of EVs and heat pump water heaters while suppressing the frequency fluctuation from the integration of renewable energy sources. Chen *et al*. [100] designed a hierarchical game framework, which includes a grid operator, an EV aggregator, and EVs, that can provide V2G regulation services. In this framework, both non-cooperative games and cooperative games are studied to coordinate the aggregator and EVs to provide V2G regulation services. By using the cooperative game approach, the social welfare of EVs and the EV aggregator can be further improved to the global optimum and the V2G regulation services can also obtain near-optimal performance, though with small communication overhead.

2.3.2 Coordinated operation of charging stations and other renewable energy sources

In recent years, the penetration rate of renewable energy sources (RESs) in the power system has increased rapidly [101]. Therefore, when formulating a coordinated charging scheduling strategy, the interaction with RESs has become an issue that cannot be ignored. When RESs are integrated with the power grid, their variable generation could cause frequency fluctuation in the power grid, which destabilizes the power system and gives rise to the power quality and power fluctuation issues [86]. To address this issue, a fuzzy controller is used in [102] for the control of EV charging in order for the frequency control of a deregulated grid. By modeling the RESs part and considering the intermittent characteristics, smart deregulated grid frequency control in presence of renewable energy resources by EVs charging control is designed. An autonomous distributed V2G control scheme can provide a distributed spinning reserve for unexpected frequency fluctuations caused by the RESs. Ota *et al*. [103] proposed an autonomous distributed V2G control scheme. A grid-connected electric vehicle supplies a distributed spinning reserve according to the frequency deviation at the plug-in terminal, which is a signal of supply and demand imbalance in the power grid. An optimization model for V2G dynamic regulation of the EVs connected to the distribution network with RESs is proposed in [104]. The proposed model uses V2G to smooth out the power fluctuation from RES penetration and minimizes the operation cost.

Uncoordinated charging of EVs leads to congestion in distribution feeders when the penetration of EVs is reasonably high. In order to relieve the uncoordinated charging of plug-in EVs, a Congestion management system in a distribution system with RESs is presented in [105]. The large proliferation of PEVs has been significantly creating an impact on the transportation and power sector in recent times. Appropriate stochastic models are introduced in [79] to capture the volatility and intermittency of renewable sources. Several outage management schemes on the basis of bankruptcy problems are proposed to fairly distribute the available resources among different microgrids/sections, once a failure occurs in the system. The results suggest that the realization of V2G programs offered by EV parking lots, accompanied by appropriate outage management schemes, can significantly enhance the reliability of supply in modern distribution networks. Wang *et al*. [106] study an approach to smoothing the fluctuations of large-scale wind power by using vehicle-to-grid systems. Energy management and optimization system are designed and modeled. By using the wavelet packet decomposition method, the target grid-connected wind power, the required electric vehicle (EV) power, and supercapacitor power are determined. The energy management model for EVs is then developed by introducing a knap-sack problem that can evaluate the needs of an EV fleet.

Smart-houses, which contain different generation resources, storage devices, and a controllable load, is going to be the next step in the distributed energy resources framework. Due to the current development of EV technology and its commercialization, the integration of the EV in the optimal management of residential energy systems will become a real need in the medium term. In [107], an optimization model is proposed to manage a residential microgrid including a charging spot with a V2G system and renewable energy sources. The model is executed one day ahead and generates a schedule for all components of the microgrid and the designed managing strategies show daily costs savings of nearly 10%. By considering the advantages that the charging demand of EVs can be fully or at least partially supplied by the local RESs to help reduce their impacts on the power grid, Yang *et al*. [108] investigated the important problem to coordinate EV charging with the locally generated wind power of multiple buildings, which incorporates the random driving requirements of EVs among different buildings. The idea of model predictive control is introduced to tackle the uncertainties of the problem and an iterative EV-based decentralized charging algorithm is developed to improve scalability.

2.3.3 Scheduling Approaches with Alleviating Traffic Congestion

As discussed in the last section, the conservational research for transportation network (TN) operation mainly focused on EVs' route charging navigation. For instance, in [109], rapid-charging navigation of EVs based on real-time power systems and traffic data is proposed. But this investigation only considered the fast-charging stations which are equivalent to uncontrollable load components. The ability to charge stations as controllable components to support grid dispatching is not been taken into account, and the flexibility of charging stations in smart grids is not been fully activated. However, due to the application of charging scheduling technology, people realize that the TN and distribution network (DN) coordinated operation affects both the efficiency of charging station scheduling and TN traffic flow situation. On this basis, Tan *et al*. [110], based on a hierarchical game approach is proposed, presented an integrated EV charging transportation operation framework, which takes into consideration the impacts from both the power system and transportation system. The proposed framework links the power system with the transportation system through the charging navigation of massive EVs. It benefits the two systems by attracting EVs to charge at off-peak hours and saving the time of EV owners with real-time navigation. By considering the differentiated services in an EV public charging station network, Moradipari *et al*. [111] considered a charging network operator that owns a network of EV public charging stations and wishes to offer a menu of differentiated service options for access to its stations. The priority level and energy request amount are listed in a differentiated service menu, and then the charging network operator directly assigns EV to a station with a low traffic path. This allows higher priority users to experience lower wait times at stations and allows the charging network operator to directly manage demand, exerting a higher level of control that can be used to manage the effect of EV on the grid and control station wait times.

The operating methods mentioned above are mainly employed centralized algorithms, which may not be computationally efficient when confronted with large and complex systems. To address this issue, Shi *et al*. [55] proposed a distributed navigation approach to search the charging station with the lowest overall objective, which consists both of the time consumption and the financial charging cost. The operating is performed with real-time data, demonstrating the adaptiveness of the proposed distributed approach to changes of the transportation network topology and power system operating condition. In [112], a decentralized optimization framework was proposed to analyze the impact of wireless charging on TN and DN, and the user equilibrium traffic assignment and the day-ahead electricity market operation were simultaneously considered. The coordination between electricity and transportation networks would help mitigate congestion in the electricity network by routing the traffic flow in the transportation network. The presented formulation leverages decentralized optimization to address the economic dispatch in the electricity network as well as the traffic assignment in the transportation network. Similarly, the equilibrium model integrating the stochastic user equilibrium and direct current optimal power flow was developed in [113] to study the interaction between traffic flow and TOU prices. Sun *et al*. [57] proposed a traffic-distribution coordination model to minimize the travel cost of TN and the energy service cost of DN, which simultaneously considers the economic operation of DN by alternating current dynamic optimal power flow and the traffic flow assignment of TN by EVs dynamic user equilibrium, respectively.

2.4 Summary

This chapter focuses on the research on location planning of charging facilities, charging power scheduling, traffic network congestion mitigation, and coordinated operation with the power grid that researchers have carried out in order to cope with large-scale EV applications. Since large-scale EV applications will profoundly change the existing traffic behavior and power system state, the research on charging facilities is comprehensive work.

Generally speaking, for the planning of charging stations, the investment cost is usually the first consideration, and the convenience of charging for users and the profitability of operators are considered as the main evaluation criteria. In the updated research, the planning of charging facilities will further refer to the impact on the power distribution system and the application of subsequently coordinated scheduling. With the planned charging stations, providing EV users with appropriate charging station routing services can effectively activate the enthusiasm of using EVs, and to a certain extent alleviate the problems of traffic congestion and long queue time caused by EV charging. Therefore, the charging routine investigations are usually assigning charging stations to EVs as even as possible, and avoid congested traffic sections when providing path navigation. In recent years, the routing strategy of charging stations that consider the interaction between the power grid and the transportation network has also gradually become a research hotspot.

Looking to the more long-term future, as countries around the world strongly support the EV industry, the coverage rate of charging stations will definitely be as full as the current gasoline stations, or even be higher. The user's demand for the cruising range of EVs will force manufacturers to continuously increase the battery capacity, resulting in huge demand for charging energy. How to reasonably scheduling such a huge energy demand will also be a challenge to the future intelligent power system. The current research can be divided into two directions from the level of a single charging station and the level of coordinated operation of the entire system. From the perspective of a single charging station, profitability, or charging cost, is the most important indicator. Therefore, research works in this area are mainly focused on power scheduling schemes in response to fluctuations in TOU electricity prices. Further research will discuss in depth the previous demand game process between users and operators, so as to provide equilibrium charging schemes.

In contrast, if investigations are carried out from the perspective of the entire system, more non-negligible factors have emerged. State of power gird is taken into account in some existing works Therefore, the impact of charging stations on the power grid is studied, and countermeasures based on reasonable charging and discharging of EV batteries are proposed to support the grid frequency and voltage, or to respond to grid demand including other types of loads. Further research works pointed out that there will be a large number of renewable energy with controllable components in the future intelligent power system. Therefore, the coordinated charging station scheduling strategy based on improving the consumption level and utilization efficiency of new energy are also one of the hot topics of current research. In addition, as the charging station is an important component for the coupling power system and the transportation network, exploring the coordinated operation of the power grid and the transportation network is also a key research direction at present and in the future. It mainly focuses on improving the overall transportation network operation efficiency, reducing the unnecessary loss of electric vehicles, improving the stability and economy of grid operation, ensuring charging demand, and reducing charging costs. What's more, the integrated energy internet coupling more networks, such as the heat network, is also a more complex research field. And the security, economy, and efficiency of the network are topics that cannot be circumvented in the EV charging scheduling.

3 Planning Strategy Considering Multiple Factors for Electric Vehicle Charging Stations along Motorways

One of the main reasons obstructing the widespread use of electric vehicles is the lack of charging facilities. In addition, the rapidly increasing number of charging facilities are equivalent to a load from the grid side, which will change the power flow of the existing power system and bring significant challenges to the power quality as well as overall grid stability. Intensive research has been carried out to study the optimal positioning of charging stations, their impact on the power grid, and corresponding energy management strategies. However, the situation for planning the charging stations on motorways is different. The charging stations on motorways are designed to satisfy the long-distance travel of EVs. Besides the insufficient number of charging stations, another reason that suppresses people's purchasing desire is that the energy replenishment speed of EVs is far more than the traditional fuel vehicles. On the actual motorway, there are already many service areas where drivers are allowed to park their vehicles. Constructing charging stations on existing service areas is more efficient.

Therefore, in this chapter, a charging station planning method based on the existing service areas is proposed. Because this method is based on the existing service area on the real motorways, additional motorway retrofit costs are not required. Comprehensive consideration of the construction cost of charging stations, the waiting time for charging, and the inconvenient driving cost. The proposed planning method can reduce the total cost as much as possible while guarantee the distribution density of charging stations and the number of charging facilities in charging stations that can meet the EV drivers' requirements. Because the established model is a mixed-integer non-linear problem, a corresponding improved solving technique based on the genetic algorithm is designed. Three different planning scenarios: orientation to minimize social cost, orientation to minimize charging station operating, and orientation to minimize charging station construction, are defined to meet the different planning requirements, and the effectiveness of the proposed method is verified by simulation.

3.1 Motorway Service Area Modeling Methodology

Based on publicly available data from Open Street Maps [114], the first step is to obtain location information for all German service stations located near motorways, which represent potential locations for charging infrastructure.

3.1.1 EV Charging Characteristics

Traffic data from the "Bundesanstalt für Straßenwesen" (BASt) [115] will then be assigned to these locations so that it is possible to estimate the temporal pattern of the traffic volume near each service area. Based on the binomial distribution, time series of the charging demand (in vehicles per hour) for each service area are generated, which form the basis for subsequent optimization. The binomial distribution is described as:

$$X \sim B(NVE, p_b) \tag{3.1}$$

To make statements about the charging demand occurring at the potential charging location, it is necessary to know the relevant parameters of the vehicles wanting to charge. These include in particular the (maximum) charging power, the capacity of the battery together with the start and end values of the SOC. Based on the types and quantities of EVs registered in Germany in 2019 [116] and the batteries parameters of the corresponding EVs [117], the relationship among charging power, battery capacity, and travel distance of EVs is generated by exponential fitting and linear fitting.

In most cases, if there is any free charger, the EVs start charging as soon as they arrive at the charging station. The charging time T_c. is calculated by:

$$T_c = \frac{(SOC_e - SOC_s) * Cap}{\eta P_c} \tag{3.2}$$

where η is the charging efficiency; P_c is the charging power which depends on the battery capacity; SOC_s and SOC_e represent the start state of charge (SOC) and end state of charge SOC. It is defined that $SOC_s \in [0.05, 0.25]$ and $SOC_e \in [0.7, 0.9]$ are following the normal distribution. Each vehicle's condition is generated by the Monte Carlo simulation method.

In order to evaluate the overload level, the line overloading can be further defined as follows:

$$\begin{cases} SOC_s \sim N(\mu_2, \sigma_2) \\ SOC_e \sim N(\mu_3, \sigma_3) \end{cases} \tag{3.3}$$

If the generated battery capacity SOC is not within the rated range of SOC_s and SOC_e, the battery SOC_s and SOC_e are regenerated based on normal distribution until they are within [0.05, 0.25] and [0.7, 0.9] respectively.

3.1.2 Clustering of the Candidate Service Areas

The existing service areas on the motorway are the candidate points for placing the charging station. Define the set of all service areas as Ω^{SA}. The information of s-th service area is contained in Ω_s^{SA}, as described:

$$\begin{cases} \Omega^{SA} = \{\Omega_1^{SA}, \ldots \Omega_s^{SA}\} \\ \Omega_s^{SA} = \{lon_s, lat_s, y_s, M_s\} \quad \forall \Omega_s^{SA} \in \Omega^{SA} \end{cases} \tag{3.4}$$

where lon_s and lat_s represent the longitude and latitude of the s-th service area, y_s donate whether the service area installed charging station, M_s is the number of chargers in s-th service area. The purpose of clustering in this chapter is to aggregate the closer service areas into one cluster and select the optimal one or several service areas as the charging station location. The distance matrix $\boldsymbol{D}_{s \times s}^{cand}$ contains the distance between each service area, as described:

$$\boldsymbol{D}_{s \times s}^{cand} = \begin{bmatrix} d_{11}^{cand} & \cdots & d_{1s}^{cand} \\ \vdots & \ddots & \vdots \\ d_{s1}^{cand} & \cdots & d_{ss}^{cand} \end{bmatrix} \tag{3.5}$$

In General, a motorway is long and contains plenty of service areas. However, the current cruising range of electric vehicles is limited, so it is unnecessary to optimize the service area that is too far away. Because the electric vehicle cannot reach far away from the charging station when it has charging demand. Therefore, the cluster boundary is defined to ensure that when the EV has charging demand, it can use the remaining power to reach the charging station:

$$R_c = SOC_s^{\max} \times E_c \times Cap \tag{3.6}$$

where R_c is the cluster boundary; SOC_s^{max} represents the maximum battery start charge SOC; E_c is the energy consumption of electric vehicles.

As illustrated in Figure 3.1, the clustering process starts from the first service area i at the motorway, and then the distance d_{ij}^{cand} between i and the nearest service area j is compared. If d_{ij}^{cand} $\leq R_c$, service area i and j are classed into the same cluster k. Then, continue to search the following nodes until the distance between adjacent service areas is greater than the cluster boundary R_c. Therefore, the output set $\boldsymbol{SA}^{clu}$ contains different clustering, and set $\boldsymbol{D}^{clu}$ contains the distance matrix between service areas in different clusters. Let sk be the number of service areas in cluster k. $\boldsymbol{D}_{sk \times sk}^{clu,k}$ is a matrix that contains the distance between each candidate service area of cluster k. $d_{ij}^{clu,k} \in \boldsymbol{D}_{sk \times sk}^{clu,k}$ is the distance between service area i and j in cluster k.

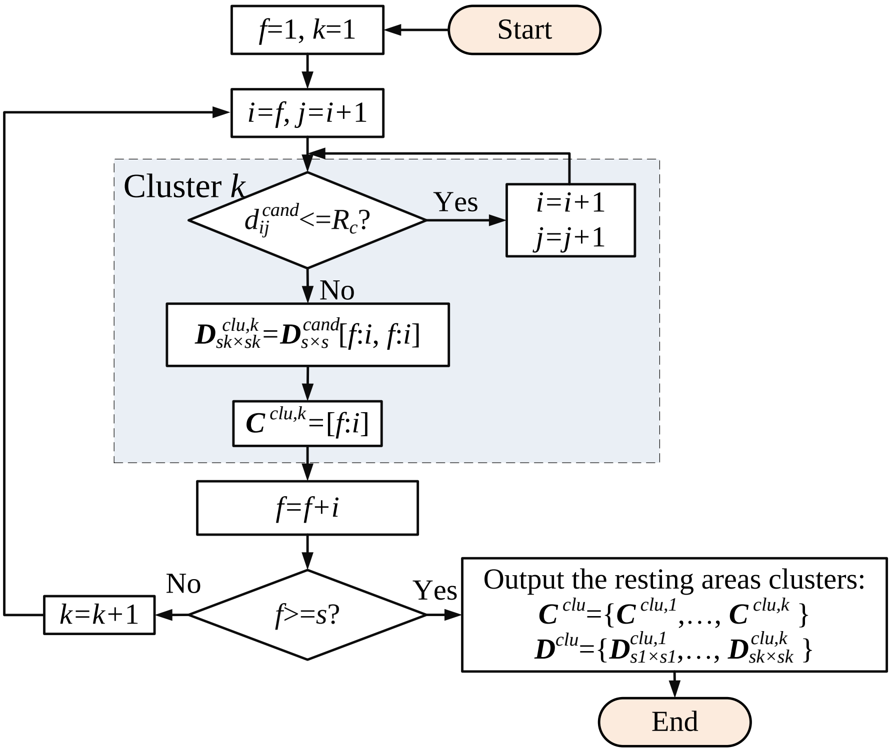


Figure 3.1. Service areas clustering process.

3.2 Charging Station Planning Model

The basic points for planning charging stations are their size and location. The larger size charging stations contain more chargers, which can serve more EVs at the same time but increase the construction cost. Thus, a motorway charging station planning model that considers the construction cost, waiting cost and EVs inconvenient driving cost is proposed. Because a motorway is long and contains plenty of service areas as the candidate points for chargers, it is unnecessary to optimize the service areas that are far away from each other. In addition, optimizing all candidate service areas at the same time increased the calculation time. Therefore, the subsequent optimization is performed in units of one cluster.

3.2.1 Station Cost Components

Station Construction Cost: This cost includes the fixed cost for constructing the fixed one-time construction cost $C_{f,t}$ (including all the cost for constructing a charging station, such as the material costs and land rent) and the cost for extra chargers $C_{s,t}$. It is assumed, that the fixed costs of building new charging stations are the same on every possible location in this chapter. Because the number of EVs having charging demand changes over time, the waiting cost and the inconvenient driving cost are based on time variation. Let g be the index of the candidate service area where can install the charging station. The fixed part of the construction cost is one-time consumption, thus, converter it into hourly values while considering its life-cycle, $C^k_{c,g,t}$ ($g \in \boldsymbol{C}^{clu,k}$) is described as:

$$\begin{aligned} C^k_{c,g,t} &= y^k_g\left(C_{f,t} + m^k_g C_{s,t}\right) \\ &= y^k_g\left(V_f \frac{i_r(1+i_r)^l}{(1+i_r)^l - 1}\Big/ 8760 + m^k_g V_s \frac{i_r(1+i_r)^l}{(1+i_r)^l - 1}\Big/ 8760\right) \end{aligned} \tag{3.7}$$

where V_f and V_s are the cost for the fixed one-time construction for charging stations and chargers; i_r is the cost of capital; l is the life-cycle of the charging station; y^k_g is binary decision variable in cluster k, which is equal to 1 if service area g has charging station, otherwise, zero; m^k_g is integer decision variable in cluster k, means the number of chargers in charging station g.

It is assumed that all charging stations and charging piles are the same types, with the same service life and construction cost. From equation (3.7), it can be found that the one-time charging station construction cost V_f is equivalent to the cost per hour according to the interest rate and chargers' life cycle. Similarly, the one-time charger construction cost is also converter into the cost per hour. Moreover, the more chargers in the charging station the higher the construction cost. In addition, the construction cost is zero when g-th service area installs none charging station (y^k_g is zero).

EVs inconvenient driving Cost: This part is adopted to define the other part of the satisfaction degree of drivers. Driving longer distances to find a charging station will reduce EV drivers' satisfaction, so the inconvenient driving cost is taken into account. The motorway is bi-directional and cannot turn around during driving, therefore, charging station planning in different directions is independent. The optimization results based on these two directions are independent. Define one of the driving directions of the motorway as direction A and the opposite as direction B. Thus if a charging station is installed in the service area in one direction, the service area in another direction will also have charging facilities. The EVs inconvenient driving cost $C^k_{d,g,t}$ ($g \in \boldsymbol{C}^{clu,k}$) of one charging station g in time t is determined by:

$$C^k_{d,g,t} = \left(1 - y^k_g\right) \cdot C_{ep} E_c \left(NVE^{A,k}_{g,t} d^{A,k}_{min,g} + NVE^{B,k}_{g,t} d^{B,k}_{min,g}\right) \tag{3.8}$$

$$NVE^k_{g,t} = NVE^{A,k}_{g,t} + NVE^{B,k}_{g,t} \tag{3.9}$$

From equation (3.8), the inconvenient driving cost includes both direction conditions, $NVE^{A,k}_{g,t}$ and $NVE^{B,k}_{g,t}$ represent the number of vehicles with charging demand at g driving along direction A and B; $d^{A,k}_{min,g}$ and $d^{B,k}_{min,i}$ are the distance from the service area g without charging station to the nearest service area with charging station along with direction A and direction B respectively.

The relationship between the number of vehicles traveling in different directions is expressed by equation (3.9).

It can be found that when no charging facilities are constructed in g-th service area, EVs having charging demand at this service area need to continue driving in directions A and B to reach the nearest service areas with charging facilities. Therefore, the inconvenient driving cost is a part of the cost in service areas where charging equipment is not installed. Meanwhile, the service area with charging facilities will not contain the incontinent driving cost. As illustrated in equation (3.8), the incontinent driving cost is based on the energy required to drive to the nearest charging station, the longer the driving distance, the more inconvenient the driving cost. Similarly, more EVs causes higher inconvenient driving cost.

Assume that when EVs have charging demand, drivers always choose the nearest charging station. The distances from the g-th service area to the nearest service area installed charging equipment along with direction A ($d_{min,g}^{A,k}$) and along direction B ($d_{min,g}^{B,k}$) are computed by:

$$d_{min,g}^{A,k} = \begin{cases} \min(d_{ij}^{clu,k}) & , j \in \boldsymbol{G}^{ins,k}, \ j < i, y_g^k = 0 \\ 0 & , y_g^k = 1 \end{cases} \tag{3.10}$$

$$d_{min,g}^{B,k} = \begin{cases} \min(d_{ij}^{clu,k}) & , j \in \boldsymbol{G}^{ins,k}, \ j > i, y_g^k = 0 \\ 0 & , y_g^k = 1 \end{cases} \tag{3.11}$$

$$\left\{ \begin{array}{ll} y_g^k \in \boldsymbol{G}^{ins,k} & , y_g^k = 1 \\ y_g^k \in \boldsymbol{G}^{noi,k} & , y_g^k = 0 \end{array} \right\} \ , \forall g \in \boldsymbol{SA}^{clu,k} \tag{3.12}$$

$$\begin{cases} \boldsymbol{G}^{ins,k} \bigcup \boldsymbol{G}^{noi,k} = \boldsymbol{SA}^{clu,k} \\ \boldsymbol{G}^{ins,k} \bigcap \boldsymbol{G}^{noi,k} = \varnothing \end{cases} \tag{3.13}$$

where $\boldsymbol{SA}^{clu,k}$ represents the set of the service areas in cluster k; $\boldsymbol{G}^{ins,k}$ and $\boldsymbol{G}^{noi,k}$ is the set of service areas installed charging stations and without charging stations in cluster k;

According to equation (3.10) and (3.11), when the g-th service area already installed charging equipment (y_g^k =1), the minimum distance from two directions are zero. When no charging facilities are installed in the g-th service area (y_g^k =1), search the nearest charging station from the set $\boldsymbol{G}^{ins,k}$ (service areas containing charging facilities). The service areas without charging equipment (belong to set $\boldsymbol{G}^{noi,k}$) are not in the searching process. Considering that vehicles cannot turn around on the motorway, only the service area along the direction A (B) is searched, indicated as node number $j<i$ ($j>i$). Equation (3.12) shows that the division of the set $\boldsymbol{G}^{ins,k}$ and $\boldsymbol{G}^{noi,k}$ is based on whether or not charging facilities are installed, and equation (3.13) expresses the relationship between the set including charging facilities $\boldsymbol{G}^{ins,k}$ and set not including charging facilities $\boldsymbol{G}^{noi,k}$.

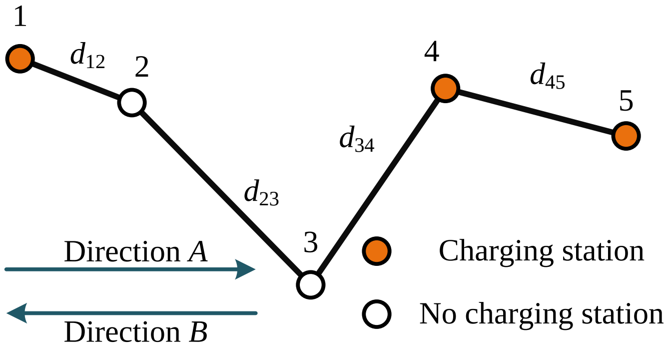


Figure 3.2. Charging selection diagram.

An example of how the drivers select charging stations is shown in Figure 3.2. Points 1, 2, 3, 4, and 5 are the candidate service areas where locations 1, 4, and 5 are chosen for the installation of charging stations. Due to the candidate point 2 has no charging station, the EVs with charging demand at point 2 has to drive to point 1 (direction B) or point 4 (direction A) for charging. Therefore, the number of EVs charging at charging station g in time slot t is computed by:

$$EVC_{g,t}^{k}=y_g^k\left\{NVE_g^k+\sum_{h=1}^{g-1}\left[\left(1-y_j^k\right)\delta_{gh}^{A,k}NEV_h^{A,k}\right]+\sum_{h=g+1}^{sk}\left[\left(1-y_h^k\right)\delta_{gh}^{B,k}NEV_h^{B,k}\right]\right\}\quad \forall g\in \boldsymbol{SA}^{clu,k} \tag{3.14}$$

As expressed in equation (3.14), the number of EVs chosen to charge at charging station g consist of EVs having charging demand at g-th charging station, EVs along direction A indenting to be charged at g-th charging station, and EVs along direction B indenting to be charged at g-th charging station. Where $\delta_{gh}^{A,k}$ and $\delta_{gh}^{B,k}$ are the coefficients that determine whether the cars have charging demand at candidate service area h (driving to direction A and direction B) chose to charge at charging station g in cluster k. $\delta_{gh}^{A,k}$ and $\delta_{gh}^{B,k}$ are calculated as:

$$\begin{cases}\delta_{gh}^{A,k}=1 & ,d_{gh}^{clu,k}=d_{min,g}^{A,k}\\ \delta_{gh}^{A,k}=0 & ,d_{gh}^{clu,k}\neq d_{min,g}^{A,k}\end{cases}\quad \forall g\in \boldsymbol{SA}^{clu,k},\forall h\in \boldsymbol{SA}^{clu,k}$$
$$\begin{cases}\delta_{gh}^{B}=1 & ,d_{gh}^{clu,k}=d_{min,g}^{B,k}\\ \delta_{gh}^{B}=0 & ,d_{gh}^{clu,k}\neq d_{min,g}^{B,k}\end{cases}\quad \forall g\in \boldsymbol{SA}^{clu,k},\forall h\in \boldsymbol{SA}^{clu,k} \tag{3.15}$$

For the equation (3.15), the first term means the number of EVs having charging demand at charging station g; the second term represents all the EVs planning to charge at service area g in direction A; similarly, the third term donates all the EVs planning to charge at service area g

in direction *B*. Equation (3.15) expresses that when the *g*-th service area is the nearest charging station, EVs having charging demand at *h*-th service area, where no charging equipment is installed, select to charge at *g*-th service area.

EVs Waiting Cost: Waiting cost is an indicator of drivers' satisfaction. The number of EVs with charging demand changes over time, so the waiting cost is calculated based on hourly resolution. For calculating the waiting cost of one charging station, the queuing theory model is adopted [29]. It is assumed that each charger that provides the charging service for EVs is working independently. Thus, the charging process at a specific charging station belongs to a standard M/M/C/∞/∞ queuing problem. Define:

$$\lambda = EVC_{g,t}^{k},\ \ \mu_4 = 1/T_c^{mean} \tag{3.16}$$

The number of EVs intent to charge at this charging station ($EVC_{g,t}^{k}$) is calculated by equation (3.14). Thus, the waiting time $C_{w,g,t}^{k}$ ($g \in \boldsymbol{C}^{clu,k}$) is calculated by:

$$\rho_{g,t}^{k} = \lambda / \mu_4 m_g^k \tag{3.17}$$

$$P_0 = \left[\sum_{n=0}^{m_g^k - 1} \frac{1}{n!} \left(\frac{\lambda}{\mu_4} \right)^n + \frac{1}{m_g^k!} \frac{\mu_4}{\mu_4 - \lambda} \left(\frac{\lambda}{\mu_4} \right)^{m_g^k} \right]^{-1} \tag{3.18}$$

$$L_{s,g,t}^{k} = L_{q,g,t}^{k} + \frac{\lambda}{\mu_4} = \frac{\left(m_g^k \rho_{i,t}^k \right) m_g^k}{m_g^k! \left(1 - \rho_{g,t}^k \right)^2} P_0 + \frac{\lambda}{\mu_4} \tag{3.19}$$

$$T_{w,g,t}^{k} = \frac{L_{q,g,t}^{k}}{\lambda} \tag{3.20}$$

$$C_{w,g,t}^{k} = y_g^k L_{s,g,t}^{k} C_h \tag{3.21}$$

Equation (3.18) calculates the probability of charging station idle P_0, while the equation (3.19) computes the queue length $L_{s,g,t}^{k}$ of *g*-th charging station at time slot *t*. Therefore, the theoretical waiting time of *g*-th charging station at time slot *t* is calculated by equation (3.20), which is one of the indicators to judge the satisfaction of EV drivers. Afterward, the satisfaction degree of waiting time is converted to the economic cost, as described in equation (3.21). C_h is the time cost per hour for each EV user in a charging station through the survey [118, 16], therefore, the longer the waiting time, the higher the waiting time cost. Furthermore, as the equation (3.13) described, without charging facilities the total waiting costs of a candidate service area are also zero.

3.2.2 Optimization Model

Because the traffic flow is changing significantly over time, the number of vehicles arriving at each candidate service area per hour is calculated based on hourly resolution one-year traffic data. The objective is to minimize the total cost associated while supplying the charge demand, as illustrated in (3.22).

$$Objective:\ \min C_{total} = \sum_{k=1}^{\Omega^k}\sum_{g=1}^{sk}\sum_{t=1}^{T}\left(C_{c,g,t}^{k} + C_{w,g,t}^{k} + C_{d,g,t}^{k}\right) \tag{3.22}$$

The decision variables are the binary variables y_g^k for the charging station location and the positive integer variables m_g^k for the number of chargers. Decision variables should follow:

$$\begin{cases} y_g^k \in \{0,1\} \\ m_g^k \in \boldsymbol{Z}^+ \end{cases} \tag{3.23}$$

If no charging station is built-in service area g, the number of chargers should be zero. In contrast, the charger number cannot be zero when charging stations are built in this service area.

$$\begin{cases} m_g^k = 0 & , y_g^k = 0 \\ m_g^k \in \boldsymbol{Z}^+ & , y_g^k = 1 \end{cases} \tag{3.24}$$

A cluster covers a wide range, in order to ensure the charging demands, at least one charging station should be placed in one cluster:

$$\sum_{g}^{sk} y_g^k \geq 1 \tag{3.25}$$

The waiting time of charging station g in time t should follow:

$$T_{w,g,t}^{k} \leq T_{w,max} \tag{3.26}$$

In addition, according to the queuing theory, the charging facility utilization of charging station should satisfy:

$$\rho_{g,t}^{k} = T_c^{mean} \cdot EVC_{g,t}^{k} \big/ m_g^k < 1 \tag{3.27}$$

Besides, it should be ensured that when EVs have charging requirements, their remaining electricity can reach the nearest charging station. The distance that the remaining energy can reach is calculated by:

$$R_{\text{lim}} = SOC_s^{\min} \times E_c \times Cap^{mean} \tag{3.28}$$

Therefore, the distance from the service areas without charging station to the closest charging station should follow:

$$\begin{cases} \left(1 - y_g^k\right) \times d_{min,g}^{A,k} \leq R_{lim} \\ \left(1 - y_g^k\right) \times d_{min,g}^{B,k} \leq R_{lim} \end{cases} \tag{3.29}$$

3.2.3 Solution Technique

In order to solve the MINLP optimization model mentioned above, an improved genetic algorithm is proposed. The objective function is composed of three parts: station construction cost, EVs waiting cost, and EVs inconvenient driving cost. It can be found that once the decision variable $\boldsymbol{y}^k$ ($\boldsymbol{y}^k$={y_1^k, y_2^k,… , y_g^k}) in cluster k are determined, the inconvenient driving costs $C_{d,g,t}^k$ will not be affected by the number of chargers in charging station g (m_g^k). Meanwhile, the summation of station construction costs $C_{c,g,t}^k$ and EVs waiting costs $C_{w,g,t}^k$ has a direct relationship with the number of chargers in the charging station g (m_g^k). Increasing the number of m_g^k is proportional to construction costs while inversely proportional to waiting cost. Therefore, the function of $C_{c,g,t}^k$ + $C_{w,g,t}^k$ and m_g^k has a minimum value.

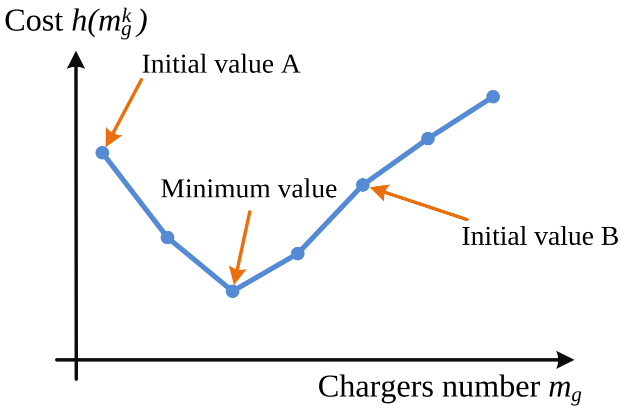


Figure 3.3. Example for searching the optimal chargers number

An example of searching the optimal m_g^k with fixed $\boldsymbol{y}^k$ is shown in Figure 3.3. Set the initial value of the m_g^k to be the minimum value that satisfies the tenable condition of (27) The initial value is defined as $m_{g,0}^k$.

$$s_{g,0}^k = \left\lceil T_c^{mean} \times EVC_{g,t}^k \right\rceil \tag{3.30}$$

where $\lceil T_c^{mean} \times EVC_{g,t}^k \rceil$ represents the smallest integer greater than $T_c^{mean} \times EVC_{g,t}^k$. The relationship between $C_{c,g,t}^k$ + $C_{w,g,t}^k$ and m_g^k is defined as:

$$C_{w,g,t}^k + C_{d,g,t}^k = h\left(m_g^k\right) \tag{3.31}$$

Let $m_{g,1}^k$ = $m_{g,0}^k$+1, compare $h(m_{g,0}^k)$ and $h(m_{g,1}^k)$. If $h(m_{g,0}^k)$>$h(m_{g,1}^k)$, then continue to make $m_{g,2}^k$= $m_{g,1}^k$ +1 and compare the next group of $h(m_{g,1}^k)$ and $h(m_{g,2}^k)$. Until $h(m_{g,n}^k)$< $h(m_{g,n+1}^k)$, $m_{g,n}^k$ is the optimal solution to minimize the summation of construction costs and EVs waiting costs. In another case, when $h(m_{g,0}^k)$< $h(m_{g,1}^k)$, the initial value starts from the initial value B (the right side of the minimum value). However, at this time, the initial value B is the minimum value that ensures the chargers number satisfied the constraint (3.27), thus the initial value B is the optimal solution in this condition. It should be noticed that the constraint (3.26) should be satisfied at the same time. Calculating the waiting time according to (3.12) with the optimal solution $m^k_{g,n}$, if the constraint (3.26) cannot be tenable, the number of chargers needs to be increased to satisfy the waiting time constraint (3.26).

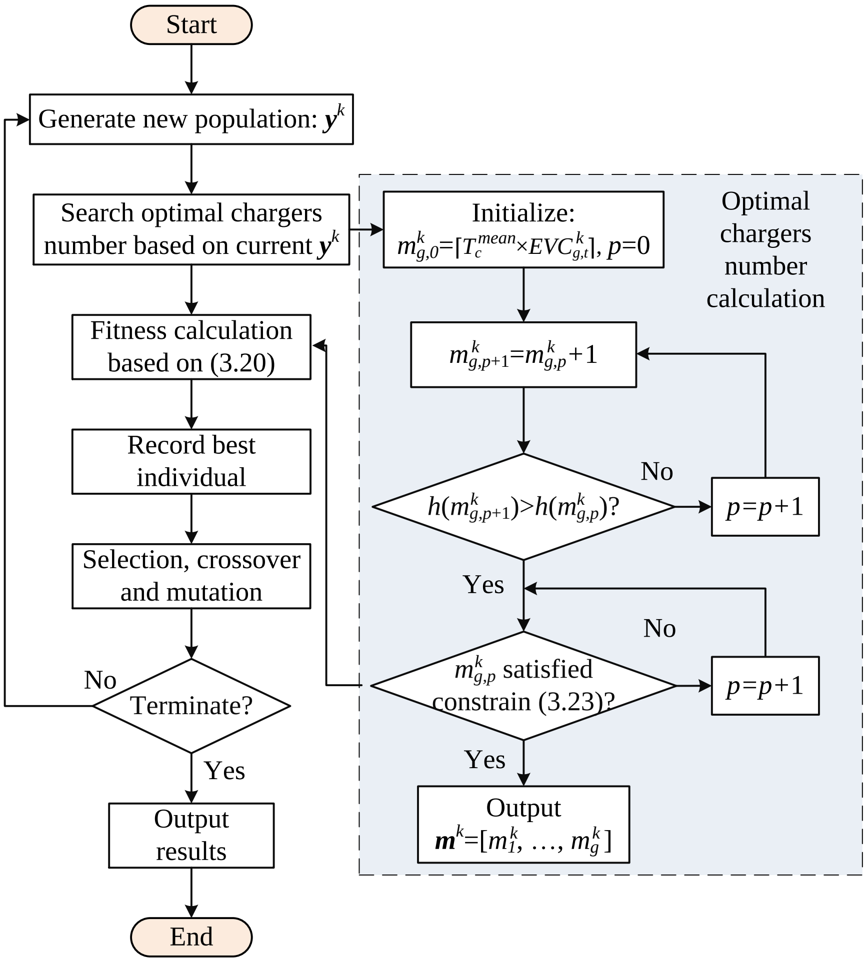


Figure 3.4. The flowchart of the MINLP solution technique.

The genetic algorithm (GA) is adopted to find the optimal location of the charging station y^k_g. The detailed flowchart of the solution process is shown in Figure 3.4. The binary variable y^k_g is the individual inside the population of the GA. Once a new population of y^k_g is created, search the optimal number of chargers m^k_g based on current y^k_g. After that, the fitness values (objective function) of this population are calculated by the obtained y^k_g and m^k_g, and the best individual in this generation is recorded. Then through the selection, crossover, and mutation process, the new generation of $\boldsymbol{y}^k$ is obtained, continue to screen out the best individuals in the new generation. Continue the loop until terminated, select the best individual from all generations as the solution. In this chapter, the service areas in a motorway are clustered into k groups, and the calculation process and results of each group are independent of each other. Thus, the parallel computation can be used to shorten the solving time significantly.

3.3 Case Study of the Charging Station Planning Method

3.3.1 Test System and Simulation Parameters

The test system in this chapter is the German motorway network. The test system includes 163 motorways and 84 of them have candidate service areas. The car flow data based on hourly resolution is collected from [115], and assigned to the nearest resting areas. Figure 3.5 shows the comparison of the number of vehicles passing the service area per hour and the number of vehicles having charging demand at this service area per hour. In addition, the parameters for the EV modeling and charging station planning in this chapter are presented in Table 3.1.

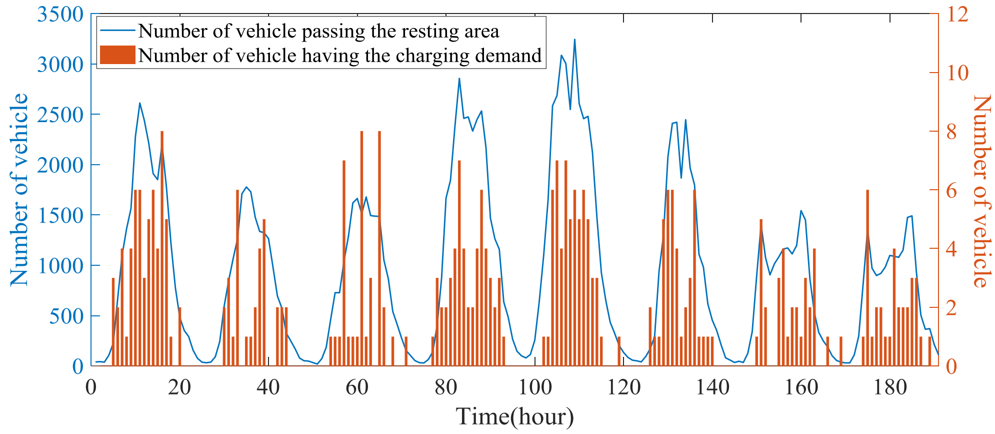


Figure 3.5. Number of vehicles passing through the service area

Table 3.1 Main Parameters

Parameter	Value	Unit	Parameter	Value	Unit
μ_2	0.15	-	$C_{f,t}$	62,000 [28]	€
σ_2	0.15	-	$C_{s,t}$	27,600 [28]	€
μ_3	0.8	-	i_r	0.1	-
σ_3	0.15	-	p	30	years
η	0.9	-	C_h	2 [16]	€/hour
p_b	0.002	-	C_{ep}	0.29	€/hour
$T_{w,max}$	0.5	hour	E_c	7 [28]	km/kWh

In order to meet different development policies and different planning demands, three different charging station planning scenarios are defined in this chapter.

Scenario 1: Minimizing the total social cost. This means considering the optimization of station construction cost, EVs waiting cost, and EVs inconvenient driving cost.

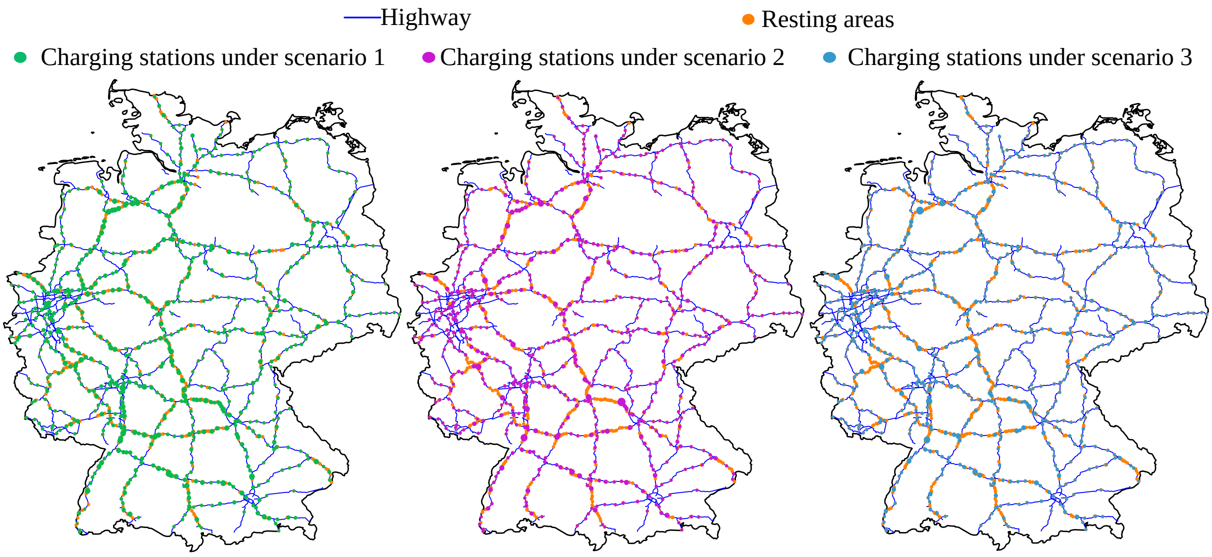
Scenario 2: Minimizing the cost in the charging station. In this scenario, the optimization process only minimizes the summation of construction costs and EVs waiting costs (the left part and middle part of the objective function).

Scenario 3: Only consider the construction costs of charging stations.

The objective function under different scenarios will change, but it should be noticed that constraints should be satisfied in any scenario.

3.3.2 Planning and Sizing Results

The planning results of charging stations under scenarios 1, 2, and 3 are shown in Figure 3.6 (a), (b), and (c), respectively. Larger rounds represent more installed chargers at that charging station. It can be found, that because under scenario 1, the convenience of charging is considered, more charging stations are planned, but the number of chargers per service area is generally lower than in the other two scenarios. In scenario 3, since the objective is to minimize the construction costs, the size of charging stations will be increased. Increasing the size of a charging station will be more economical than building more charging stations, thus the number of charging stations under scenario 3 is the relatively least and the scale of a charging station under scenario 3 is relatively the largest. The number and scale of charging stations in scenario 2 are between scenario 1 and scenario 3.



(a) (b) (c)

Figure 3.6. The charging station planning results under three scenarios (a) scenario 1 (b) scenario 2 (c) scenario 3

To illustrate the detailed planning result, the geographical distribution figure of one specific cluster including 20 service areas is shown in Figure 3.7. The total number of charging stations under scenario 1 is more than under scenarios 2 and 3. Furthermore, the specific cost result of each scenario is shown in Table 3.2. It can be found that the inconvenient driving cost of service areas with charging facilities is zero, while construction cost and waiting cost are the dominant cost. The opposite is true for service areas without a charging station.

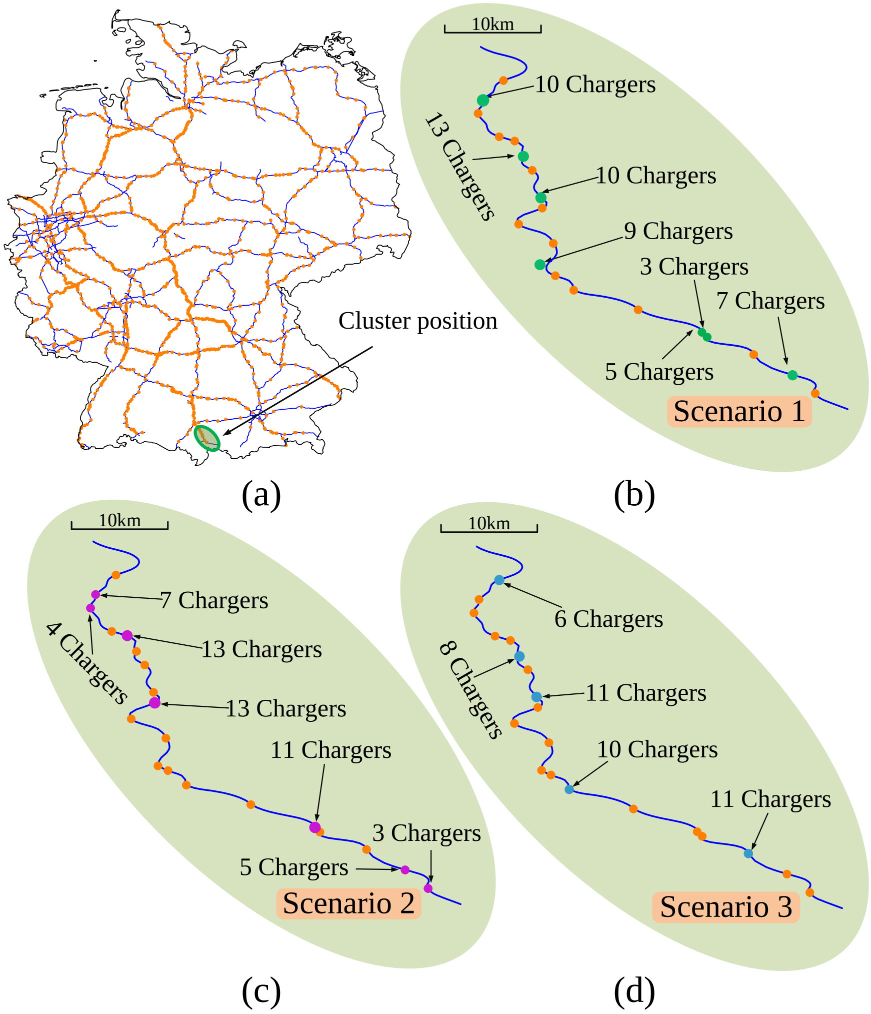


Figure 3.7. The Detailed planning results under three scenarios of a specific service area cluster (a) position of the selected cluster (b) charging stations under scenario 1 (c) charging stations under scenario 2 (d) charging stations under scenario 3

In order to reflect the advantages of the proposed method, a control scenario was added to the discussion. The control scenario adopts the planning method proposed in [119, 16] suggesting that all service areas are considered as charging stations, and the number of chargers of single charging stations is calculated independently. The overall cost distribution diagram of the whole German motorway under three scenarios is shown in Figure 3.8, where the effectiveness of different scenarios optimization is proved. Obviously, the proposed method can reduce not only the construction cost but also the total social cost. That is because the method proposed in this chapter considers the coordination between different charging stations so that one charging station is able to serve EVs in multiple adjacent service areas with charging demand, with no need to install charging stations at every service area. Meanwhile, it is guaranteed that the majority of EV users are able to reach a charging station because the distance between the charging stations remains in the distance constraint. Comparing the cost, the total cost under scenario 1 is the least, which corresponds to the optimization objective of minimizing the total social cost. The total social cost under scenario 2 is relatively smaller than scenario 3 but larger than scenario 1, while the summation of charging station construction cost and EVs waiting cost is the least. Since the objective is set to minimize the construction cost in scenario 3, the construction cost shown in Figure 3.8 under scenario 3 is the least, but the total social cost under this scenario is the largest.

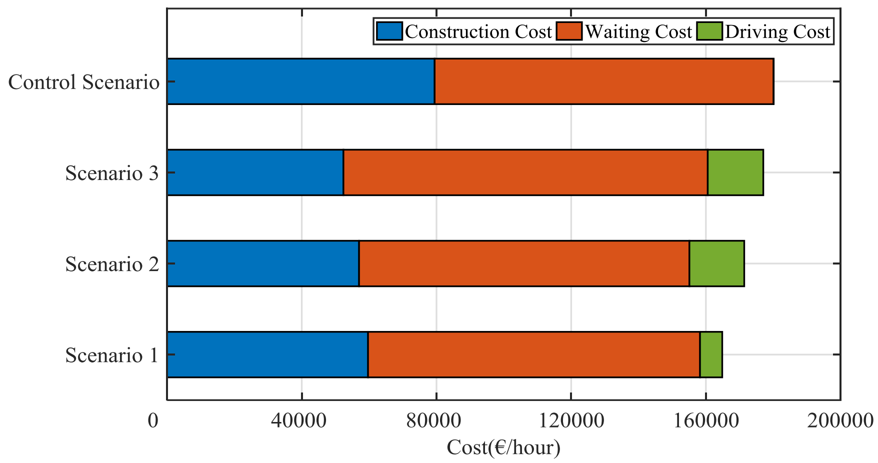


Figure 3.8. The different types of costs under three different scenarios

Table 3.2 Detailed cost of different service areas

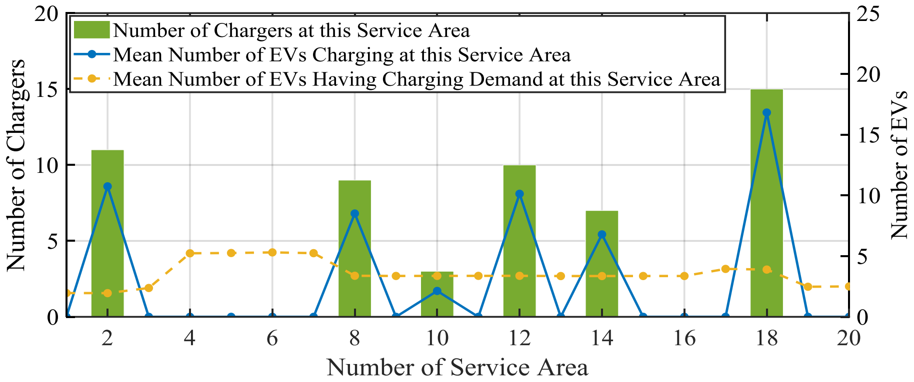
	Scenario 1	Scenario 2	Scenario 3	Control Scenario
Number of Charger	4989	4855	4335	5633
Number of Charging Station	768	696	695	1274
Proportion of charging stations installed	60.28%	54.63%	54.55%	100%
Average number of chargers per charging station	6.49	6.97	6.23	4.42

The total number of service areas participating in the charging station planning algorithm is 1274. Table 3.3 illustrates the installation ratio of charging stations and charging poles in different scenarios. It can be found that because all the mentioned cost factors are comprehensively considered in scenario 1, it has the largest number of charging stations and chargers of the proposed three scenarios. In contrast, in scenario 2, the number of chargers per charging station is the largest, because the main purpose of scenario 2 is to improve EV drivers' satisfaction by reducing the waiting time. In Scenario 3, the main objective is to reduce construction costs while ensuring that the waiting time and the remaining cruise range are within the constraints. Therefore, the number of charging stations and chargers planned in Scenario 3 is the smallest. In the control scenario, although all the service areas are equipped with charging stations, the number of chargers per charging station is smaller than in the other three scenarios, which means the number of EVs served by each charging station and the utilization rate is lower.

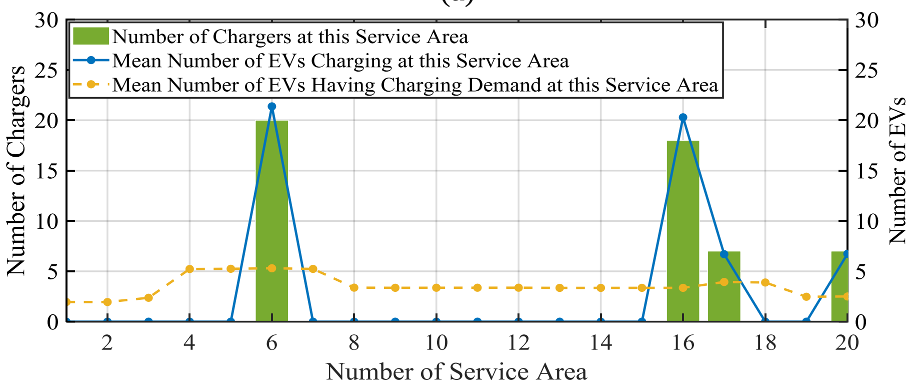
Table 3.3 Detailed cost of different service areas

Service area	Distance (km)	Scenario 1					Scenario 2					Scenario 3					Control Scenario				
		y_g^k	m_g^k	$C_{c,g,t}^k$ (€/h)	$C_{w,g,t}^k$ (€/h)	$C_{d,g,t}^k$ (€/h)	y_g^k	m_g^k	$C_{c,g,t}^k$ (€/h)	$C_{w,g,t}^k$ (€/h)	$C_{d,g,t}^k$ (€/h)	y_g^k	m_g^k	$C_{c,g,t}^k$ (€/h)	$C_{w,g,t}^k$ (€/h)	$C_{d,g,t}^k$ (€/h)	y_g^k	m_g^k	$C_{c,g,t}^k$ (€/h)	$C_{w,g,t}^k$ (€/h)	$C_{d,g,t}^k$ (€/h)
1	0	0	0	0	0	10.79	1	3	46.5	47.3	0	0	0	0	0	34.25	1	3	46.6	42.5	0
2	4.89	1	7	82.1	132.7	0	1	5	64.3	89.7	0	0	0	0	0	23.19	1	3	46.6	42.4	0
3	9.94	0	0	0	0	10.90	0	0	0	0	10.90	0	0	0	0	12.00	1	3	46.6	42.3	0
4	15.51	1	3	46.5	45.9	0	0	0	0	0	2.34	1	11	117.6	288.6	0	1	4	55.4	84.9	0
5	16.60	1	5	64.3	87.8	0	1	11	117.6	211.2	0	0	0	0	0	2.34	1	4	55.4	85.6	0
6	22.96	0	0	0	0	13.49	0	0	0	0	13.49	0	0	0	0	15.80	1	4	55.4	84.7	0
7	29.28	0	0	0	0	10.68	0	0	0	0	27.21	0	0	0	0	7.98	1	4	55.4	85.4	0
8	33.01	0	0	0	0	2.71	0	0	0	0	35.46	1	10	108.7	274.8	0	1	4	55.4	70.7	0
9	34.26	1	9	99.8	171.8	0	0	0	0	0	33.61	0	0	0	0	2.73	1	4	55.4	70.5	0
10	40.73	0	0	0	0	13.95	0	0	0	0	19.39	0	0	0	0	16.66	1	4	55.4	69.9	0
11	45.52	0	0	0	0	23.05	0	0	0	0	14.43	0	0	0	0	42.99	1	4	55.4	71.7	0
12	49.73	0	0	0	0	8.520	1	13	135.41	291.57	0	0	0	0	0	30.95	1	4	55.4	70.1	0
13	52.24	1	10	108.7	202.2	0	0	0	0	0	8.56	0	0	0	0	22.53	1	4	55.4	71.1	0
14	58.84	0	0	0	0	11.05	0	0	0	0	24.96	1	11	117.6	302.3	0	1	4	55.4	71.6	0
15	62.07	1	13	135.4	266.9	0	0	0	0	0	13.95	0	0	0	0	11.09	1	4	55.4	71.8	0
16	66.12	0	0	0	0	13.85	1	13	135.41	266.95	0	1	8	91.0	253.9	0	1	4	55.4	70.1	0
17	67.28	0	0	0	0	17.76	0	0	0	0	3.93	0	0	0	0	3.93	1	4	55.4	71.0	0
18	72.99	0	0	0	0	10.55	1	4	55.47	70.06	0	0	0	0	0	23.14	1	4	55.4	70.0	0
19	76.13	1	10	108.7	200.7	0	1	7	82.12	137.11	0	0	0	0	0	16.90	1	3	46.6	43.83	0
20	81.09	0	0	0	0	16.91	0	0	0	0	16.91	1	6	73.2	154.4	0	1	3	46.6	42.4	0
Total cost		-		645.9	1108.3	164.2	-		637.0	1114	225.2	-		508.3	1274.2	266.5	-		1065.1	1333.5	0
					1918.5					1976.2					2049.1					2398.7	

Notice: Distance means the distance from the first service area to this service area; $C_{c,g,t}^k$, $C_{w,g,t}^k$ and $C_{d,g,t}^k$ represent the average construction cost, EVs waiting cost, and EVs driving cost per hour, respectively.



(a)



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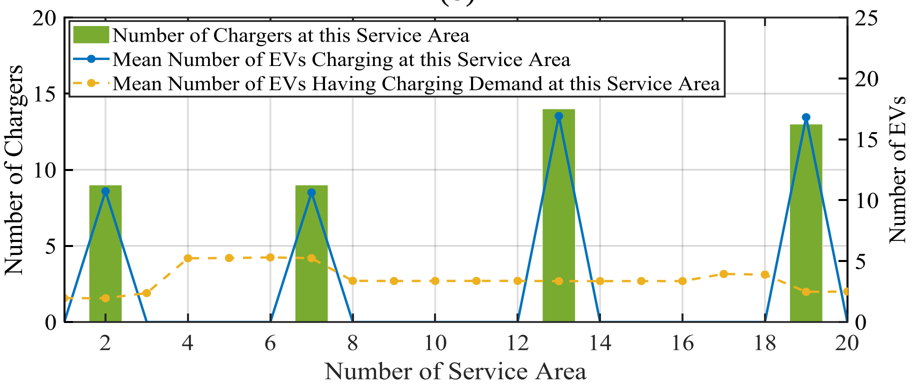
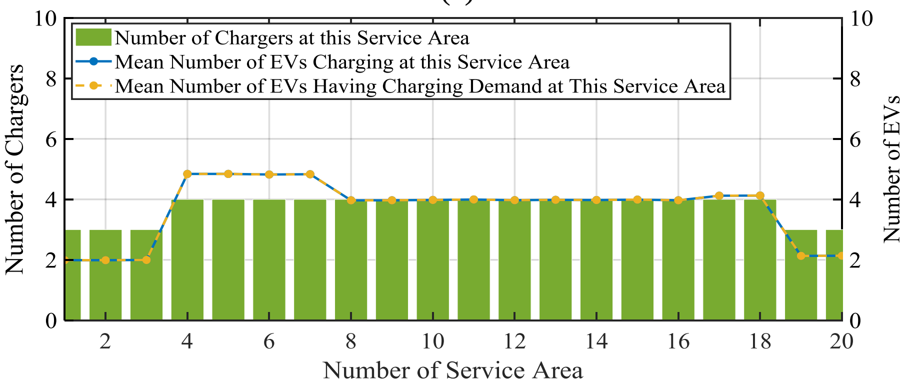


(c)



(d)

Figure 3.9. Relationship between charging demand and number of chargers under (a) scenario 1 (b) scenario 2 (c) scenario 3 (d) control scenario

The relationship between the charging demand and the number of chargers of one specific cluster is shown in Figure 3.9 and the detailed cost of different service areas in Table 3.3. When there is no charging facility in the service area, the number of EVs at nearby charging stations will increase. Charging stations with more EVs tend to have more chargers installed. Thus, compared with the control scenario, the proposed three scenarios can not only reduce the construction cost but also decrease the waiting cost.

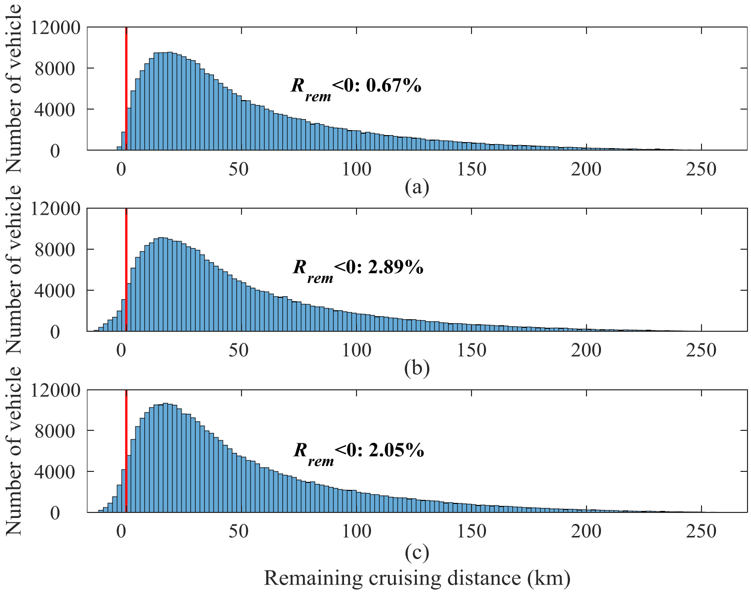


Figure 3.10. Monte Carlo simulation results: The RCD distribution histogram under (a) scenario 1 (b) scenario 2 (c) scenario 3

The Monte Carlo analysis method is adopted to evaluate the satisfactions of EV drivers. The planning results should ensure that EVs with charging demand can reach the nearest charging station, thus, the remaining cruising distance (R_{rem}) with the remaining SOC after EVs arrived at the nearest charging station is defined as:

$$R_{rem} = R_{bat} - d_{\min} \tag{3.322}$$

where d_{min} is the distance to the nearest charging station and R_{bat} is the distance that the remaining battery energy can reach, where:

$$R_{bat} = SOC_s^{min} \cdot E_c \cdot Cap \tag{3.33}$$

Therefore, if the R_{rem} is smaller than 0, the vehicle cannot reach the nearest charging station. The Monte Carlo method is adopted to simulate the vehicle R_{rem} with charging demand in Germany for one year. Randomly generated EV information such as battery capacity, charging time, and remaining battery capacity when having charging demand is used. The results are shown in Figure 3.10. It can be found that most of the EVs with charging demand can reach the charging station under all three scenarios. Since scenario 1 takes into account the driving loss of EVs, the largest number of vehicles can meet their charging requirements.

In addition, the long charging time is one of the main obstacles to the diffusion of electric vehicles. Thus, the Monte Carlo simulation is also adopted to simulate the waiting time of each EV. Similarly, each EV's information is generated based on the EV modeling that was described in Section II. The waiting time of each EV is calculated by subtracting the time of arrival from the time at which the charging process starts. When there are idle chargers, the first arriving vehicle is charged first. The time interval between the previous vehicle finishing charging and the next vehicle starting charging is simplified to 0. Thus, if there are idle chargers when an EV arrives, the waiting time of this EV is 0.

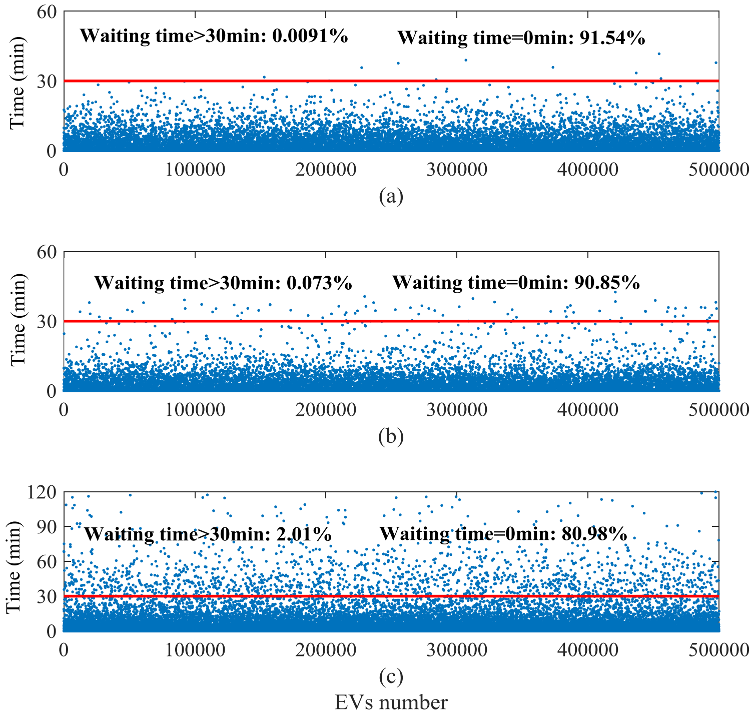


Figure 3.11. Monte Carlo simulation results: The waiting time of each EV in the charging station under (a) scenario 1 (b) scenario 2 (c) scenario 3

The waiting time of each EV under different scenarios is shown in Figure 5.11 respectively. The maximum allowed average waiting time $T_{w,max}$ in this chapter is set to 30 minutes, as shown in Table 3.1. Obviously, most of the EVs under all three scenarios can keep their waiting time below 30 minutes. Comparing Figure 3.10 and Figure 3.11, it can be found that under scenario 1, the majority of EVs can not only reach the nearest charging station with their remaining power when they have charging demand, but they also spend less time waiting in the charging station. For scenario 2, because the planning only considers the construction cost and the waiting cost, fewer charging stations are established, which prevents relatively more vehicles from reaching the nearest charging station with their remaining power. However, the waiting times in this model are still within reasonable limits. On the contrary, more than 97% of vehicles can reach the charging station under scenario 3, but the waiting time for each vehicle is the relatively largest. Therefore, three different scenarios have their own advantages and disadvantages. According to the demand and policy of car charging, different planning schemes can be selected.

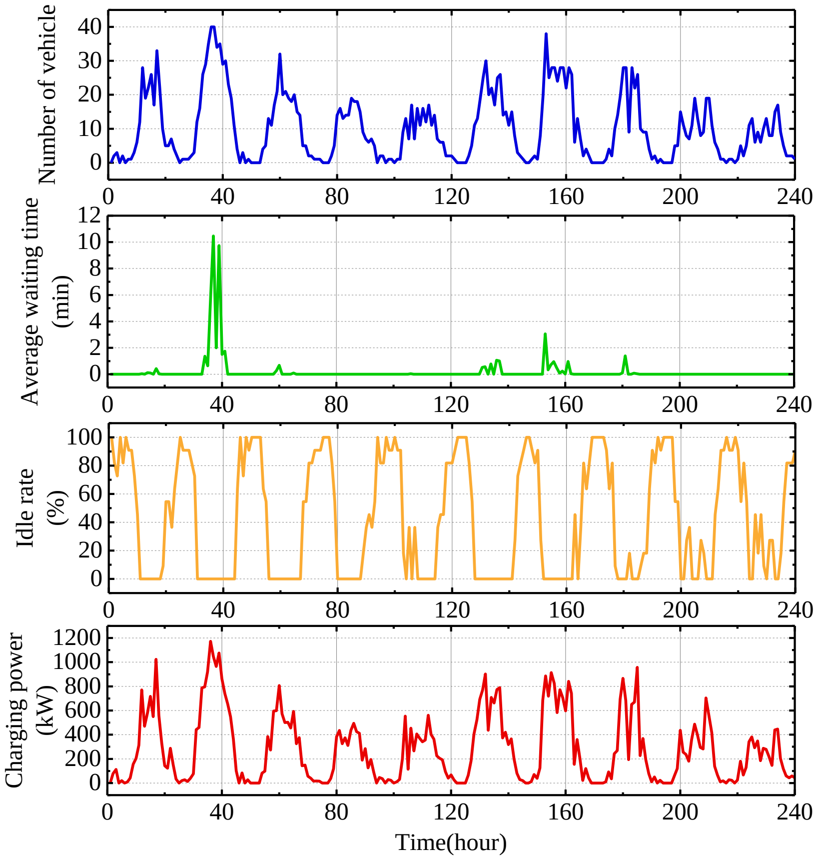


Figure 3.12. The hourly number of vehicles, average waiting time, idle rate of chargers and charging power of a charging station under scenario 1.

Scenario 1:

Advantages: most of the vehicles can reach the nearest charging station and the waiting time is relatively low.

Disadvantage: the construction cost is the highest.

Scenario 2:

Advantages: the waiting time for EVs is low and the construction cost is lower than scenario 1.

Disadvantage: relatively more vehicles could not reach the charging station.

Scenario 3:

Advantages: the construction cost is relatively lowest meanwhile most of the vehicles can reach the nearest charging station.

Disadvantage: the waiting time of the vehicles is significantly higher than in the other two scenarios and is more likely to exceed 30 minutes.

Furthermore, the internal characteristics of charging stations are also discussed in this chapter. One example is shown in Figure 3.12. The selected example has 13 chargers. It can be found that the more vehicles arrive, the more likely the EVs have to wait for charging. At some points, even if a vehicle arrives, the waiting time is still 0. That is because some chargers are idle and the vehicles can be charged directly without waiting. The idle rate reveals the utilization of chargers, in Figure 3.12, the idle rate is often zero while the average waiting time is still very short. Thus, the number of installed chargers is reasonable, meaning that the construction cost is saved while the charging demand is satisfied. In most of the peak hours when many EVs arrive, the chargers are fully utilized while the waiting time EVs is not long. The charging power is calculated based on the EVs battery capacities, charging time, and charging power as described in Section II. The charging power profiles can be superimposed to the MILES model [120] to describe the impact of highway charging stations on the power system.

3.4 Summary

In this chapter, an EV charging station planning strategy for motorways is proposed. The site of the charging stations is selected from the existing service areas on the motorways, and the size of charging stations is computed based on the number of EVs with charging demand. The influence of multiple factors on placing charging stations on the motorway are considered comprehensively. The proposed method can reduce the social cost as much as possible while satisfying the charging demand of the majority of EVs. In addition, an improved genetic algorithm is proposed to solve the established MINLP model. Because the candidate placing points in this chapter are divided into many clusters, the parallel computation can be used, which greatly improves the speed of the solution. Furthermore, in order to satisfy the different planning requirements, three different scenarios are proposed. Considering the advantages and disadvantages of different scenarios, suitable scenarios for planning can be selected according to existing policies and development needs.

4 Optimal EV Charging Scheduling strategy with a Limited Number of Charging facilities

Lack of charging facilities is still a significant barrier to the electrification of the logistic system. However, a contradictory fact is that the high vacancy rate of the charger is also one of the main problems at present. This is because the charging demand characteristics of EVs have obvious timing characteristics, so there is insufficient charging equipment during the peak period of the traffic flow, and the phenomenon of idleness during the low traffic flow period. How to effectively schedule the electric vehicle (EV) charging power to reduce the charging station operating cost when the number of chargers was limited becomes an important issue.

Considering the limited number of chargers, an optimal charging power scheduling method based on TOU electricity price is proposed. Firstly, the uncontrolled charging scheduling model is designed for fully charging EVs as fast as possible. There is no coordination among charging EVs, and no charging power optimization scheduling is implemented. Then, considering the limited chargers assignment scheme, an EV optimal charging scheduling model to minimize the total charging cost is proposed. The established model is a bilevel programming (BP) model, which can not only guarantee the EVs' charging demand by reasonably assigning the limited chargers, but also reduce the charging cost by optimal scheduling the charging power. The upper level mainly decides the charger index and available charging period of EVs. The lower level solves the EVs charging power within their available charging period by responding to the TOU electricity price. Then, as the upper level is a mixed nonlinear integer program while the lower level is a linear program, a compound solving algorithm is designed to get the detailed optimal EVs charging scheduling solutions. Through performance verification, the proposed algorithm can find the solution within an acceptable time. Finally, the proposed optimal charging scheduling method is compared with the uncontrolled charging scheduling method and a commonly used charging power scheduling method. According to the results, the proposed method can provide a detailed and efficient EV charging scheme, which can minimize the charging cost while guaranteeing the EVs' charging demand when considering the limited number of chargers.

4.1 Overall System Model

The proposed optimal charging scheduling strategy is for logistics transportation with EVs. Therefore, in order to meet the requirement of logistics transportation, the requested energy, arrival time, and departure time of EVs are needed to know. When an EV arrives at the charging station, it is required to fill up all the required power before its departure time. Due to the limited number of charging facilities, when there are large among of EVs having charging requirements at the same time, the subsequent EV cannot start charging until the previous EVs finish.

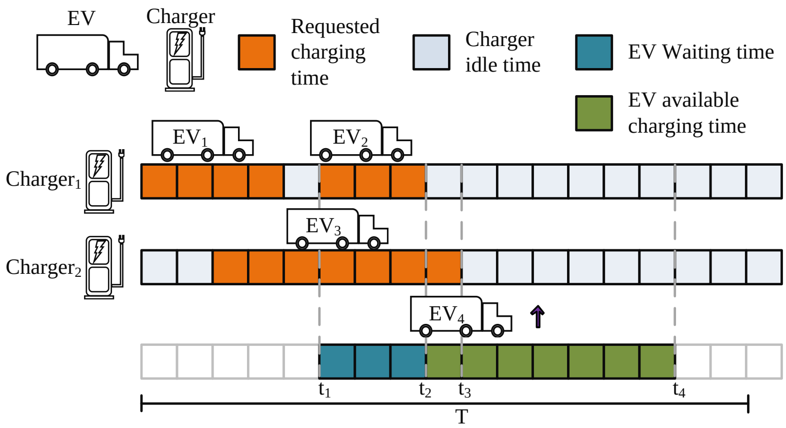


Figure 4.1. Charging station operating model

As shown in Figure 4.1, while EV_4 arrives at the charging station at t_1, both $charger_1$ and $charger_2$ are utilized and will finish their work at t_2 and t_3, respectively. Thus, its available charging time is from t_2 to t_4 at $charger_1$, and the available charging time is from t_3 to t_4 at $charger_2$. Moreover, the TOU electricity price in each hour is also different. Therefore, how to schedule the EVs charging power to reduce the charging cost and meet their energy requirements is the optimization problem to be solved.

4.1.1 Electric Vehicle Model

Considering the realistic scenarios, the arrival rate and departure rate are the time-dependent data that the EVs distribute goods in the daytime and back to the charging station at night. Thus, we set one whole day (24 hours, from the first day 12:00 to the next day 12:00) as one period. Then divide it into T time slots equally and let t (t= 1, 2, …, T) donate t-th time slots (an hour is one time slot). The arrival time, departure time, and required energy of each EV are required information for optimal scheduling, which is:

$$\Omega_n^E = \left\{ t_n^a, t_n^d, E_n^{req} \right\} \tag{4.34}$$

where t_n^a and t_n^d represent the arrival and departure time of EV n; E_n^{req} means the required energy of EV n. Each arrival EV is sequentially indexed. Considering the realistic logistic transmission scenarios, the number of charging EVs per hour and the required power to each EV are different. The arrival time follows Poisson distribution [121, 122] with the average rate of λ_t. The probability for N EVs arriving at the charging station during time slot t is given by:

$$P\{N\} = \frac{e^{\lambda_t}(\lambda_t)^N}{N!} \tag{4.2}$$

Meanwhile, the departure time follows the truncated normal distribution [123, 7] $N(\lambda_1,\mu_1)$, where λ_1 is the mean of the departure time and μ_1 is the standard deviation. The required charging energy is determined by the initial battery state of charge (SOC) S^{ini} and the requested SOC S^{req}. According to the realistic transportation, the initial SOC and requested SOC are following the normal distribution [123] $N(\lambda_2,\mu_2)$ and $N(\lambda_3,\mu_3)$ respectively. Where λ_1 and λ_2 are the mean of the S^{ini} and S^{req}, μ_2 and μ_3 are the deviations. Consequently, the required energy for each EV is computed by:

$$E_n^{req} = (S_n^{req} - S_n^{ini}) \cdot Cap \tag{4.3}$$

Considering the fact that the vehicle type of a logistics company is uniform, it is supposed that all the types of EVs and chargers are the same and each charger provides the same amount of energy in a certain time slot.

The maximum power that a charger can provide within one time slot is defined as P_{max}, Δt is the time interval. When an EV charging with P_{max}, the charging time for this EV is the shortest. Thus, the minimum required time to fully charge is described as:

$$t_n^{full} = \left\lceil \frac{E_n^{req}}{P_{max}} \right\rceil \cdot \Delta t \tag{4.4}$$

Remark 1: considering the realistic operation of the charging station, it is assumed that when EVs need not queue for charging, all EVs can complete charging within their dwell time at the charging station. Thus, the charging information of n-th EV should satisfy: $t_n^d - t_n^a \geq t_n^{full}$.

Remark 2: the index of EV will be sorted according to the time of arrival. EVs arriving earlier will be charged first. When serval EVs have the same arrival time t_n^a, the EV with earlier departure time t_n^d has more urgent charging demand, thus, has higher charging priority. In addition, for EVs with the same arrival time t_n^a and departure time t_n^d, EVs with more energy requirement E_n^{req} will be charged first. The sorted set of EVs according to the above rules is defined as:

$$\Omega^E = \{\Omega_1^E, \ldots, \Omega_n^E, \ldots, \Omega_N^E\} \tag{4.5}$$

4.1.2 Uncontrolled Charging Station Operation Model

In this chapter, each single time slot t is an hour. In realistic uncontrolled scenarios, EVs tend to finish charging as fast as possible. So, an EV will immediately start charging with the maximum charging power once a charger was idle.

According to *Remark 2*, the index order in $\mathbf{\Omega}^E$ is the sequence of EVs into the charging station, the charging process is shown in algorithm 1. Defined the output of Algorithm 4.1 is the charger power matrix $\boldsymbol{P}_{ch}$ and the EV power matrix $\boldsymbol{P}_{ev}$, as described in:

$$\boldsymbol{P}_{ch} = \begin{bmatrix} P_{ch(1,1)} & \cdots & P_{ch(1,T)} \\ \vdots & \ddots & \vdots \\ P_{ch(M,1)} & \cdots & P_{ch(M,T)} \end{bmatrix} \tag{4.6}$$

$$\boldsymbol{P}_{ev} = \begin{bmatrix} P_{ev(1,1)} & \cdots & P_{ev(1,T)} \\ \vdots & \ddots & \vdots \\ P_{ev(N,1)} & \cdots & P_{ev(N,T)} \end{bmatrix} \tag{4.7}$$

$\boldsymbol{P}_{ch}$ ($M\times T$) is the charger charging power matrix where $P_{ch(m,t)}$ means the charging power provided by the m-th charger at time slot t. Similarly, $\boldsymbol{P}_{ev}$ ($N\times T$) is the EV charging power matrix where $P_{ev(n,t)}$ means the charging power of the n-th EV at time slot t.

Algorithm 4.1: Uncontrolled charging model

1: **Start Algorithm**
2: **Input:** ***VEC***, M, N, T, P_{max}
3: **Initialization:** $\boldsymbol{P}_{ch}$=zeros[M,T] ($M\times T$ null matrix); $\boldsymbol{P}_{ev}$=zeros[N,T] ($N\times T$ null matrix)
4: **Procedure** EPS($\boldsymbol{P}_{ev}$, $\boldsymbol{P}_{ch}$, M, T, P_{max})
5:   **for** every EV n=1:N
6:     (T_{ear}, λ)= ICS($\boldsymbol{P}_{ch}$, M, T)
7:     **while** δ is not empty **and** $E_n^{req} > 0$ **and** $T_{ear} \le t_n^d$
8:       **if** $P_{\max} - P_{ch(\lambda,T_{ear})} \le E_n^{req} / \Delta t$ **then**
9:         $P_{ch(\lambda,T_{ear})} = P_{\max}$
10:         $P_{ev(n,T_{ear})} = P_{\max} - P_{ch(\lambda,T_{ear})} + P_{ev(n,T_{ear})}$
11:         $E_n^{req} = E_n^{req} - \left(P_{\max} - P_{ch(\lambda,T_{ear})}\right)\Delta t$
12:       **else**
13:         $P_{ch(\lambda,T_{ear})} = P_{ch(\lambda,T_{ear})} + E_n^{req} / \Delta t$
14:         $P_{ev(n,T_{ear})} = E_n^{req} / \Delta t + P_{ev(n,T_{ear})}$
15:         $E_n^{req} = 0$
16:       **end if**
17:       $T_{ear} = T_{ear} + 1$
18:     **end while**
19:   **end for**
20:   **return:** $\boldsymbol{P}_{ch}$, $\boldsymbol{P}_{ev}$
21: **end Procedure**
22: **Procedure** ICS($\boldsymbol{P}_{ch}$, M, T)
23:   Initialize: T_{ear}=T
24:   **for** every charger m=1:M
25:     **for** every time slot t=1:T
26:       **if** $P_{ch(m,t)} < P_{\max}$ **then**
27:         When the m-th charger is idle CT_n=t
28:         **jump to 31**
29:       **end if**
30:     **end for**
31:     **if** T_{ear}>CT_n **then**
32:       T_{ear}=CT_n
33:       Record the earliest idle charger λ=m
34:     **end if**
35:   **end for**
36:   **return:** T_{ear}, λ
37: **end Procedure**
38: **Output:** $\boldsymbol{P}_{ch}$, $\boldsymbol{P}_{ev}$
39: **End Algorithm**

In the uncontrolled charging model, EVs always select the earliest idle charger to charge. For example, an EV arrives at the charging station while one charger is idle and the others are utilized; this EV will select the idle one. In another case, as shown in Figure 4.1, the last EV_4 arrives while all the two chargers are not idle. Because $charger_1$ finishes the charging earlier, EV_4 will queue in $charger_1$.

Remark 3: If the EV n has completed charging at charger m at time slot t, and the charging power provided by the charger m at this time slot is $P_{ch(m,t)}=P_{ev(n,t)}$, the maximum allowed charging power for the next EV j who charged at the same charger m at the same time slot t is: $\widetilde{P}_{ev(j,t)}=P_{max}-P_{ev(n,t)}$.

Remark 4: The under charging EVs will not stop charging until their energy requirements are satisfied or their departure time is reached.

The uncontrolled charging model includes two procedures: idle chargers searching (ICS) procedure and EV power supplement (EPS) procedure. The ICS finds the earliest idle charger λ and its idle time T_{ear} according to the current charging station status $\boldsymbol{P}_{ch}$. The EPS procedure supplies energy to each EV. For each EV, it will queue at the earliest idle charger λ and start charging after T_{ear}. The output of algorithm 1 is the EVs charging power matrix $\boldsymbol{P}_{ev}$ and chargers charging power matrix $\boldsymbol{P}_{ch}$. Thus, the charging characteristics of one charging station under the uncontrolled charging model can be obtained.

4.2 Optimal Charging Scheduling with Limited Charging Facilities

Minimizing the charging cost by optimal charging scheduling can effectively reduce the cost of logistics transportation with EVs. By considering the TOU electricity price, shifting the charging peak into the valley TOU price can reduce the charging cost significantly.

Limited by the number of chargers, the optimal charging process needs to assign chargers to each EV, arrange feasible charging durations for each EV and determine the charging power of each EV. Therefore, this chapter decomposes the optimization problem into a BP model. In the upper level, according to EVs' dwell time and requested power, each EV is assigned to a specific charger, and then its start charging time and end charging time are determined. In the lower level, with the fixed start charging time and end charging time, the charging power of each EV is optimized to minimize the charging cost by responding to the TOU price.

4.2.1 Lower Level Model

The lower level model is designed to optimize the charging power based on the TOU electricity price when the charging duration of each EV is determined. Define the *n*-th EV start charging time as t_n^s and the end charging time as t_n^e.

The lower level model is designed as:

$$\min_{P_{ev(n,t)}} \sum_{n=1}^{N} \sum_{t=1}^{T} P_{ev(n,t)} e_{price}(t) \tag{4.8}$$

subject to

$$\sum_{t=t_n^s}^{t_n^e} \Delta t P_{ev(n,t)} = E_n^{req} \ , \forall n \in N \tag{4.9a}$$

$$P_{ev(n,t)} = 0, \ \forall t \notin \left[t_n^s, t_n^e\right], \forall n \in N \tag{4.9b}$$

$$P_{ev(n,t)} \le P_{\max}, \ \forall t \in T, \forall n \in N \tag{4.9c}$$

$$P_{ev(n,t_n^s)} + P_{ev(j,t_j^e)} \le P_{\max} \ \ ,\text{if } t_n^s = t_j^e \tag{4.9d}$$

In the objective function (4.8), $e_{price}(t)$ donates the electricity price at time slot t. $P_{ev(n,t)}$ is the decision variable that represents the charging power of EV n at time slot t. Constraint (4.9a) expresses that each EV should be fully charged with the required energy E_n^{req} within its start charging time t_n^s and end charging time t_n^e(*Remark 4*). Constraint (4.9b) represents that the *n*-th EV cannot be charged while the time is early than its start charging time t_n^s or later than its end charging time t_n^e. Constraint (4.9c) means the power provided per time slot cannot exceed the maximum allowed charging power P_{max}. In constraint (4.9d), in a certain time slot, subsequent EVs can be charged with the remaining energy if the charging power of the previous EV at the same time slot has not reached the maximum allowed charging power P_{max}(*Remark 3*). It can be found that once the charging duration t_n^s and t_n^e are fixed, the lower level model becomes a linear optimization problem.

4.2.2 Upper Level Model

Due to the limited number of chargers, the charger assignment process needs to take into account. Define the chargers assignment matrix δ ($M \times N$), and its inside elements are described as:

$$\delta_{(m,n)} = \begin{cases} 1 & \text{if EV } n \text{ charging in charger } m \\ 0 & \text{otherwise} \end{cases}, \forall \delta_{(m,n)} \in \boldsymbol{\delta} \tag{4.10}$$

Define C_n as the index of charger selected for n-th EV, L_n as the position in the charging queue of n-th EV, as described:

$$\begin{cases} C_n = m & \text{, if } \delta_{(m,n)} = 1 \\ L_n = \sum_{j=1}^{n} \delta_{(m,j)} & \text{, if } \delta_{(m,n)} = 1 \end{cases} \tag{4.11}$$

Therefore, it is necessary to assign each EV to reasonably choose the charger to achieve the purpose of reducing costs. In addition, the start and end charging time should be optimized when the charger assignment is determined.

As shown in Figure 4.2, suppose three EVs are assigned to charge at one specific charger, and they have their own arrival and departure times. The first vehicle EV_n is still in the charging station when the second vehicle EV_j arrives, thus there is an overlap time between the two EVs. Because one charger can only serve a single EV at once, the switch time $t_{n,j}^{switch}$ between EV_n and EV_j should be set. Switch time is the time when the previous EV_i finished charging and the next EV_j started charging, where $t_{n,j}^{switch} = t_n^e = t_j^s$. The end charging time of EV_n is set as t_n^e and this EV can charge during [t_n^a, t_n^e]. Similarly, EV_j needs to wait for EV_n to complete charging before starting charging, and the available charging duration of EV_j is [t_j^s, t_j^d]. The end charging time of vehicle n is equal to the start charging time of EV_j. For the third arriving EV_r, it has no overlapping dwell time with the previous vehicle, so the available charging duration is [t_r^a, t_r^d].

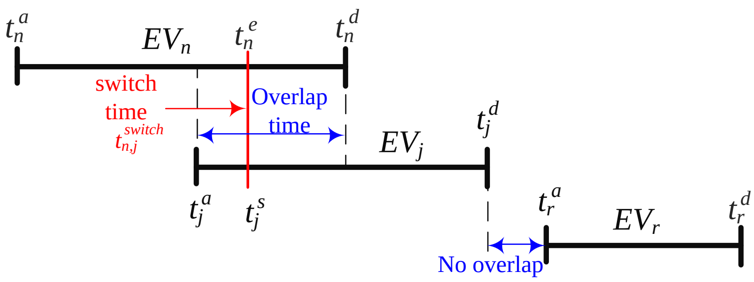


Figure 4.2. Example of the time limit

Selecting a reasonable charger and deciding the suitable start charging and end charging time is to reduce the charging cost as much as possible. The mathematical program of the upper level model is:

$$\min_{\delta_{(m,n)}, t_n^s, t_n^e} \sum_{n=1}^{N} \sum_{t=t_n^s}^{t_n^e} \sum_{m=1}^{M} \delta_{(m,n)} P_{ev(n,t)} e_{price}(t) \tag{4.12}$$

subject to

$$\sum_{m=1}^{M}\delta_{(m,n)} \equiv 1 \quad ,\forall n \in N \tag{4.13a}$$

$$\begin{cases} t_n^s \ge t_n^a \\ t_n^e \le t_n^d \end{cases}, \ \forall n \in N \tag{4.13b}$$

$$t_n^s \le t_n^e \quad ,\forall n \in N \tag{4.13c}$$

$$\begin{cases} t_j^a \le t_j^s \le t_n^e \le t_n^d & ,\text{if } C_n = C_j \ \& \ L_n + 1 = L_j \ \& \ t_j^a \le t_n^d \\ \begin{cases} t_n^s = t_n^a \\ t_n^e = t_n^d \end{cases} & ,\text{otherwise} \end{cases} \tag{4.13d}$$

$$t_n^e - t_n^s \ge t_n^{full} \quad ,\forall n \in N \tag{4.13e}$$

In order to reduce the total charging cost, the objective (4.12) is to set the charger selection element $\delta_{(m,n)}$, start charging time t_n^s, and end charging time t_n^e as the decision variable. Constraint (4.13a) expresses that all the vehicles should be assigned to one and only one charger for charging. Thus, in each column of matrix δ, at least and only one element is 1. Considering the realistic situation of the charging process, EVs can only be charged while dwelling in the charging station. Therefore, the start charging time and end charging time should satisfy the constraint (4.13b). Constraint (4.13c) means the end charging time is later than the start charging time. The start charging time of the subsequent *j*-th EV cannot be earlier than the end charging time of the previous *n*-th EV if both *n*-th EV and *j*-th EV charged are at the same charger. Thus, constraint (4.13d) expresses the time restriction setting when two EVs had overlap dwell time in the charging station. In one case, the start charging time of the subsequent *j*-th EV is equal to the end charging time of the previous *n*-th EV when satisfied: 1) both *n*-th EV and *j*-th EV charge at the same charger (C_n=C_j); 2) the *j*-th EV queues just behind the *n*-th EV (L_n+1=L_j); 3) the departure time of the previous *n*-th EV is later than the arrival time of the subsequent *j*-th EV ($t_j^a < t_n^d$). Otherwise, the start and end charging times of an EV are set as its arrival and departure times respectively. The sufficiency charging time is the necessary condition for the fulfill charging, as described in constraint (4.13e).

4.2.3 Solving Algorithm for the Established Bilevel problem

Since the decision variables in the upper level model are discontinuous integers, and the decision variables t_n^s and t_n^e are even the variable index of the lower level model, which makes the BP problem very difficult to solve. The definition of t_n^s and t_n^e is to make the charging power in the lower model satisfy the constraints (4.9a). In fact, it is negligible to first know when an EV starts and finished charging. We only need to ensure that each EV meets the corresponding charging demand within its dwell time and will not replenish energy during the non-dwell time. Then according to *Remark 3*, compute the start and end charging time of EVs. Thus, we convert the problem from solving $P_{ev(n,t)}$ into solving $P_{ch(m,t)}$. The converted lower level model is:

$$\min_{P_{ch(m,t)}} G = \sum_{m=1}^{M}\sum_{t=1}^{T} P_{ch(m,t)} e_{price}(t) \tag{4.14}$$

subject to

$$P_{ch(m,t)} \le P_{\max} \quad ,\forall t \in T, \forall m \in M \tag{4.15a}$$

$$\delta_{(m,n)} P_{ch(m,t)} = 0 \ \ , \forall t \notin [t_n^a, t_n^d], \forall n \in N, \forall m \in M \tag{4.15b}$$

$$\sum_{t=t_n^a}^{t_n^d} \Delta t P_{ch(m,t)} = E_n^{req} \ \ , \text{if } \delta_{(m,n)} = 1, \forall n \in N, \forall m \in M \tag{4.15c}$$

$$\begin{cases} \sum_{t=t_n^a}^{t_j^a} P_{ch(m,t)} \le P_n^{req} \\ \sum_{t=t_n^d}^{t_j^d} P_{ch(m,t)} \le P_j^{req} \end{cases} , \text{ if } \delta_{(m,n)} = \delta_{(m,j)} = 1 \,\&\, L_n + 1 = L_j, \forall m \in M \tag{4.15d}$$

In the converted lower level, decision variables are transferred from the charging power of EV $P_{ev(n,t)}$ to the charging power of charger $P_{ch(m,t)}$, where satisfy $P_{ch(m,t)} = \sum_n^N (\delta_{(m,n)} P_{(n,t)})$. The real meaning is the charging power of one charger is the summation of all the EV power charged in this charger. Constraint (4.15a) is the charging power limited, constraint (4.15b) represents EVs cannot be charged when not in the dwell time, and constraint (4.15c) expresses EVs should finish charging during their dwell time. Constraint (4.15d) determines the charging duration of EVs with overlapping dwell time. The charging power cannot exceed the required energy of the previous *n*-th EV when the arrival time of the subsequent *j*-th EV t_j^a has not reached. Similarly, the charging power cannot exceed the required energy of the subsequent *j*-th EV when the departure time of the previous *n*-th EV t_n^d is already reached.

As decision variables in the lower level model are converted, the converted upper level model only needs to consider the chargers assignment matrix δ as decision variables:

$$\min_{\delta_{(m,n)}} F = \sum_{i=n}^{N}\sum_{t=1}^{T}\sum_{m=1}^{M} \delta_{(m,n)} P_{ch(m,t)} e_{price}(t) \tag{4.16}$$

subject to

$$\sum_{m=1}^{M} \delta_{(m,n)} \equiv 1 \quad , \forall n \in N, \forall m \in M \tag{4.17}$$

By the above modification, the decision variables in the upper level problem are reduced from t_n^s, t_n^e, and $\delta_{(m,n)}$ to only $\delta_{(m,n)}$. Meanwhile, the lower level problem is a linear problem once the decision variables in the upper level problem are fixed. Although this BP problem is still an NP-hard problem, the converted model has greatly reduced the search range compared to the previous model. Currently, the heuristic algorithm is one of the mainstream methods for solving such NP-hard problems [124, 7]. Since the decision variables $\delta_{(m,n)}$ are in binary, we don't need to proceed with the encoding and decoding steps when using genetic algorithms. Thus, the genetic algorithm with specific improvements is used to solve this problem. Since the generated matrix $\boldsymbol{\delta}$ may conduct to one charger serving for too many EVs, which makes the lower level model unsolvable, we need to quickly determine whether the lower level model can be solved with the generated $\boldsymbol{\delta}$ matrix.

Theorem 1: define that the dwell time of *K* EVs overlaps when charging at the same charger *m*. Suppose the index of *K* EVs is *n*=1, 2, …, *K*. The dwell time overlap means: ($t_1^d < t_2^a$) *&* ...*&* ($t_K^d < t_{K-1}^a$). Define condition:

$$\mathcal{P}: \left\{ \left(t_K^d - t_1^a\right) \Delta t P_{\max} < \sum_{n=1}^{K} E_n^{req} \middle| \exists \left(t_1^d < t_2^d\right) \wedge \cdots \wedge \left(t_K^d < t_{K-1}^d\right) \right\} \tag{4.18}$$

$\mathcal{Q}$: problem (4.14)-(4.15) is **not** solvable.

$\mathcal{P}$ is necessary and sufficient condition for $\mathcal{Q}$, which is $\mathcal{P} \Leftrightarrow \mathcal{Q}$. The condition $\mathcal{P}$ can be used to quickly judge whether the lower level model is severable.

Proof 1: Firstly, the proof $\mathcal{P} \Rightarrow \mathcal{Q}$ is true. According to condition $\mathcal{P}$, due to the dwell time of the previous EVs and subsequent EVs overlap, we can get:

$$\sum_{t=t_1^a}^{t_1^d} P_{ch(m,t)} + \cdots + \sum_{t=t_K^a}^{t_K^d} P_{ch(m,t)} = \sum_{t=t_1^a}^{t_K^d} P_{ch(m,t)} \tag{4.19}$$

According to constraint (4.16c) and $\mathcal{P}$, we have:

$$\sum_{t=t_1^a}^{t_K^d} \Delta t P_{ch(m,t)} \le \left(t_K^d - t_1^a\right) P_{\max} < \sum_{n=1}^{K} E_n^{req} \tag{4.20}$$

To make the problem solvable, all constraints must be satisfied. But combining (4.19) and

(4.20), constraint (4.15d) cannot be established, which means the problem is not solvable, $\mathcal{P}\Rightarrow\mathcal{Q}$ is true.

Then, the proof $\mathcal{Q}\Rightarrow\mathcal{P}$ is true. We can prove $\neg\mathcal{P}\Rightarrow\neg\mathcal{Q}$ is true. Thus, according to $\neg\mathcal{P}$, we have:

$$\left\{\left(t_K^d - t_1^a\right)P_{\max} \geq \sum_{n=1}^{K} E_n^{req} \middle| \forall\left(t_1^d < t_2^d\right) \wedge \cdots \wedge \left(t_K^d < t_{K-1}^d\right)\right\} \tag{4.21}$$

Combining (4.16b), (4.20), and (4.22), we have:

$$\sum_{t=t_1^a}^{t_K^d} P_{ch(m,t)} \leq \sum_{n=1}^{K} E_n^{req} \leq \left(t_K^d - t_1^a\right)P_{\max} \tag{4.22}$$

Therefore, $\exists P_{ch(m,t)}$ to make the constraint (4.15d) established. Then, since we have $t_K^d < t_{K-1}^a$, the relationship can be obtained by combining constraint (4.15d):

$$\begin{cases} \sum\limits_{t=t_i^a}^{t_{n+1}^a} P_{ch(m,t)} \leq \sum\limits_{t=t_n^a}^{t_n^d} P_{ch(m,t)} = E_n^{req} \\ \sum\limits_{t=t_n^d}^{t_{n+1}^d} P_{ch(m,t)} \leq \sum\limits_{t=t_{n+1}^a}^{t_{n+1}^d} P_{ch(m,t)} = E_{n+1}^{req} \end{cases}, \forall n \in K \tag{4.23}$$

where the (4.23) means EV i is charged less power in [t_n^a, t_{n+1}^a] than in [t_n^a, t_n^d] and EV $n+1$ is charged less power in [t_n^d, t_{n+1}^d] than in [t_{n+1}^a, t_{n+1}^d]. Both EV n and EV $n+1$ are charged at the same charger and EV $n+1$ is subsequent to EV n. Therefore, constraint (4.15d) is satisfied. Obviously, constraint (4.15c) is easy to establish, so all constraints of the problem (4.14)-(4.15) are satisfied, which means $\neg\mathcal{Q}$ is true when $\neg\mathcal{P}$. Therefore, the statement $\mathcal{P}\Leftrightarrow\mathcal{Q}$ is true.

The solving algorithm flow chart of the proposed BP problem is described in Figure 4.3. Following constraint (4.17) to generate δ as the individual and input it into the lower level model. Then verify whether the problem (4.14)-(4.15) is solvable under each fixed δ following *Theorem 1*. The solvable problem will take δ as a known parameter and solve the linear problem with decision variables $P_{ch(m,t)}$. The unsolvable situation will return "break" information to the upper level. If there are solvable individuals, the minimum charging cost G of each individual, outputted from the lower level, will be their fitness values, and the individuals with smaller G values are more likely to reproduce offspring. Record the individual with the smallest G value at this generation. Then individuals who are able to produce offspring, generate a new population through crossover and mutation, and then repeat the above steps. Until the predetermined generation is reached, stop the calculation and output the best individual as the result. Then output the best chargers assignment matrix $\boldsymbol{\delta}$ and its corresponding charging power matrix $\boldsymbol{P}_{ch}$.

If all individuals in the population are unsolvable, output the best solution recorded before. If no best solution been recorded, then the number of EVs exceeds the service ability of the charging station.

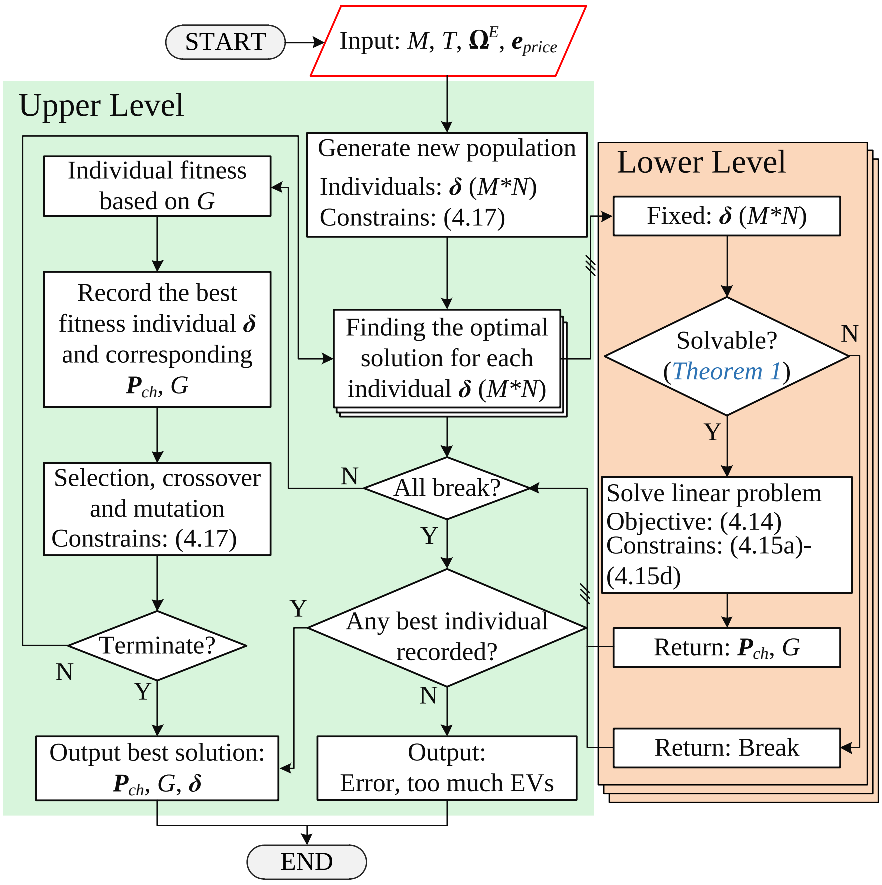


Figure 4.3. Algorithm flow chart

Algorithm 4.2: EV charging power calculating algorithm

Start Algorithm
Input: $\boldsymbol{P}_{ch}$, $\boldsymbol{\delta}$, $\boldsymbol{VEC}$, M, N, T, P_{max}
Initialization: $\boldsymbol{P}_{ev}$=zeros[N,T] ($N\times T$ null matrix), $\boldsymbol{ICV}_m$=[ ]
Procedure $\boldsymbol{ICV}_m$ calculation
  for every charger m=1:M
    for every EV n=1:N
      if $\delta_{(m,n)}$=1 **then**
        $\boldsymbol{ICV}_m$=[$\boldsymbol{ICV}_m$, n]
      end if
    end for
  end for
  return: $\boldsymbol{ICV}_m$
end Procedure
Procedure $\boldsymbol{P}_{ev}$ calculation
  for every charger m=1:M
    n=1
    for every time slot t=1:T
      j= $\boldsymbol{ICV}_{m(n)}$
      if $E_j^{req}>0$ **then**
          $P_{ev(j,t)}=E_{rem}/\Delta t$
          $E_j^{req}=E_j^{req}-E_{rem}$
        else
          $P_{ev(j,t)}=P_{ch(m,t)}$
          $E_j^{req}=E_j^{req}-\Delta t P_{ch(m,t)}$
        end if
      else
        $P_{ev(j,t)}=E_j^{req}/\Delta t$
        $E_{rem}=\Delta t P_{ch(m,t)}-E_j^{req}$
        n=n+1
      end if
    end for
  end for
  return: $\boldsymbol{P}_{ev}$
end Procedure
Output: $\boldsymbol{P}_{ev}$
End Algorithm

20:	**if** $E_{rem} > 0$ **then**	

Combining the optimal charger assignment matrix $\boldsymbol{\delta}$ and charger power matrix $\boldsymbol{P}_{ch}$, the EV power matrix $\boldsymbol{P}_{ev}$, which shows the specific charging power of each EV at each time slot, can be obtained. The detailed procedure for calculating $\boldsymbol{P}_{ev}$ is given in Algorithm 4.2. Define $\boldsymbol{ICV}_m$ as the vector that contains the index of charging EV at charger m. $\boldsymbol{ICV}_{m(f)}$ represents the f-th element in vector $\boldsymbol{ICV}_m$. According to *Remark 4*, one charger can only serve the subsequent EV when the previous EV finished charging, so the charging power of one charger will be allocated in accordance with the charging sequence and required power of EVs. By combining chargers assignment matrix $\boldsymbol{\delta}$ and EV power matrix $\boldsymbol{P}_{ev}$, The specific charging scheme, such as each individual EV charging at which charger and the specific charging power at each time slot, can be obtained.

4.3 Performance Evaluation of the Proposed Optimal Charging Scheduling Method

Since the genetic algorithm is adopted in the proposed optimal charging scheduling algorithm, the performance of the proposed algorithm is discussed. As described above, by establishing the BP model, we can greatly reduce the search range of the genetic algorithm. As shown in Figure 4.4, directly using the normal genetic algorithm to find the results need to search both $\boldsymbol{\delta}$ and $\boldsymbol{P}_{ch}$ at the same time, where $\boldsymbol{P}_{ch}$ belongs to positive natural numbers. That means the calculation time will be long and the results will be far away from the optimal solution. By adopting the solving method proposed by this chapter, the searching range is reduced to only search $\boldsymbol{\delta}$. The value range of $\boldsymbol{P}_{ch}$ is a real number greater than 0, and the range of $\boldsymbol{\delta}$ is only selected between 0 and 1, so the actual possible types of chromosomes are reduced from infinity to a finite number. On this basis, when considering constraint (4.17), the possible types of chromosomes will be much fewer. Because the searching range is been reduced significantly, the computing speed and accuracy will be increased.

Monte Carlo analysis is adopted to find the average generation for getting the best fitness value and the average calculating time under a different number of chargers M and a different number of EVs N. Set the N to a fixed value 15, calculate the average required generation to obtain the optimal solution and the average calculation time under different M. Similarly, Set the M to a fixed value 6, calculate the average required generation to obtain the optimal solution and the average calculation time under different N. The results and parameters of the genetic algorithm are shown in Table 4.1. It can be seen that when the number of chargers increases, the calculation time will also increase. This is caused by the increase in chromosome length (Increase the number of rows of δ). Similarly, when the number of EVs increases, the calculation time will increase. But when the number of EVs exceeds the serving capacity, the calculation time will decrease. This is because according to *Theorem* 1, we can quickly determine whether the lower level model has a solution, which can reduce the calculating time. According to the performance test, we can consider that the parameters setting of the genetic algorithm is reasonable, and it can find the optimal solution in an acceptable time.

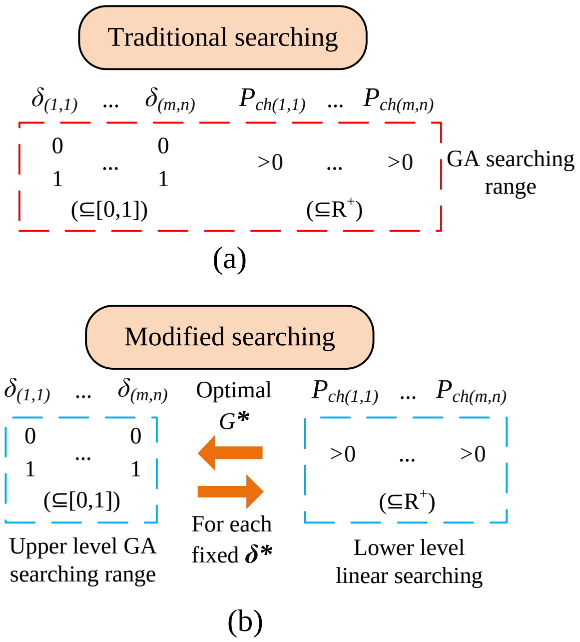


Figure 4.4. Searching range of (a) traditional genetic algorithm (b) modified genetic algorithm

Table 4.1 Performance of the POCS

M/N	Average generation of best fitness value	Average calculating time
4/15	2.5	0.081s
6/15	3.8	0.088s
8/15	4.1	0.102s
10/15	4.5	0.110s
N/M	Average generation of best fitness value	Average calculating time
15/6	3.1	0.084s
20/6	3.9	0.088s
25/6	4.7	0.105s
30/6	4.4	0.095s

Population size: 50, Generations: 20,
Crossover rate: 50%, Mutation rate: 5%

In order to demonstrate the performance of our proposed optimal charging scheduling algorithm (POCS), the uncontrolled charging scheduling (UCS), and the most widely adopted optimal charging without chargers assignment scheduling (WCAS) are taken for comparisons, one charging station for the logistics EVs is considered as a case study. The WCAS method is the most common scheduling method when considering the charging station capacity limitations. However, this method ignores the specific assignment of chargers for each individual EV, which means it cannot figure out the chargers assignment matrix δ. Thus, in this chapter, we call it without chargers assignment scheduling (WCAS). The objective function of WCAS in this chapter for comparison is (4.8) in our chapter and the constraints are based on the model in [125]. In addition, in order to prove the universality of the proposed method, Monte Carlo simulation is adopted to verify the efficiency. The serviceability under different charging methods is compared, the impact of the number of EVs on the charging cost under different charging methods is analyzed, and the economized charging cost rate of the POCS method is compared with the UCS method.

4.3.1 Case Study

The number of chargers is M=6, all EVs and chargers are the same types and the maximum charging power per hour provided by each charger is P_{max}=20kW/h. The battery capacity of the EV is set as Cap=100kWh. The optimization time slot t is set as one hour while the total time slot number T in an optimization duration is set as 24 hours. Because EVs usually transport cargo during the daytime and return to the logistic center at night, the optimization duration starts from one day 12:00 to the next day 12:00. In total 100 EVs were charged in five days. The time of used electricity price is following the Germany electricity spot prices [126]. Both the number of EVs staying in the charging station at each time slot and the TOU price are shown in Figure 4.5.

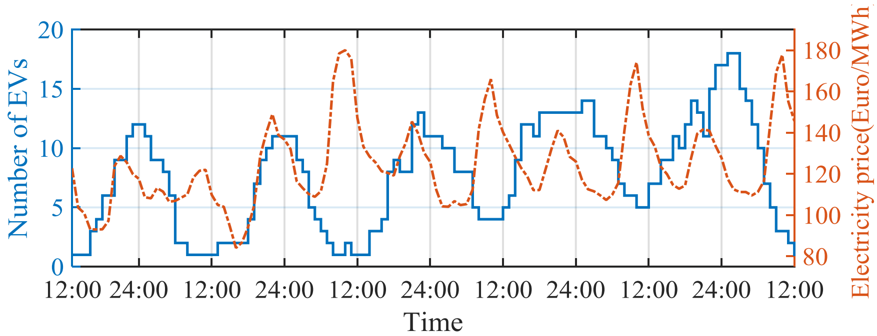


Figure 4.5. TOU electricity price and number of EVs dwelling at charging station

The heatmap of power provided by each charger at different times is shown in Figure 4.6. It can be found that the detailed charging process about how each charger provides energy to each EV is been established by the proposed algorithm. The charging power under POCS is more dispersed in the heatmap. In the POCS method, the chargers are always avoiding to supply energy when the electricity price was at a peak value. In contrast, by adopting the UCS, EVs start charging as soon as they find the idle charger, thus, the economics of EVs energy supply, in this case, is much lower than after scheduling optimization. In addition, the POCS can find out the exact charger index of each specific EV, Figure 4.7 shows the charger selection of each EV in a topical day where the deep color means this EV was charging at the specific charger.

Figure 4.6. Heatmap of the energy provided by each charger at different times.

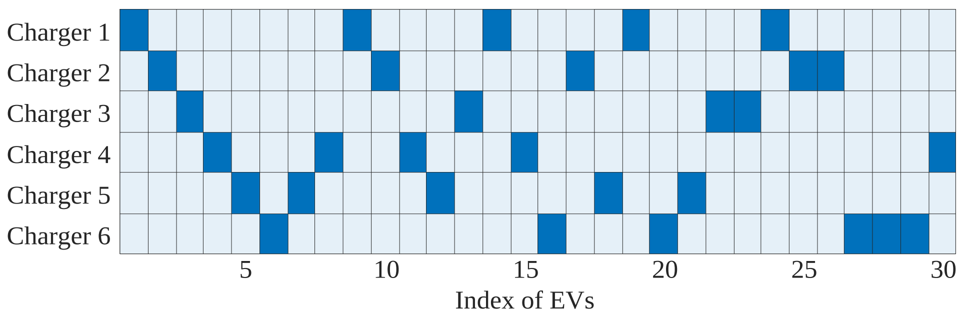


Figure 4.7. Selection of chargers in a topical day.

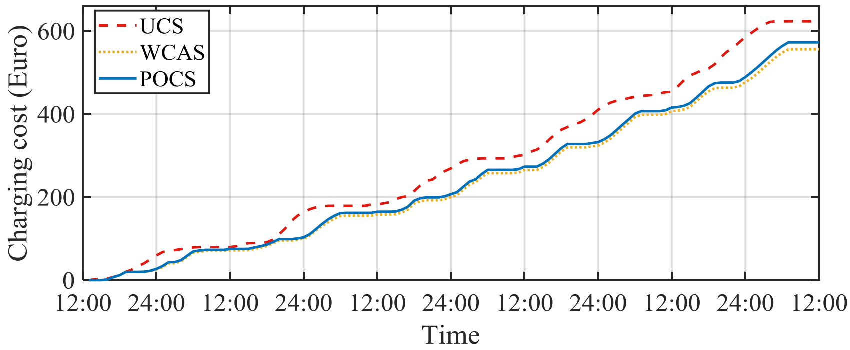


Figure 4.8. The cumulative charging cost under different charging methods.

Figure 4.8 expresses the cumulative charging cost under three different charging methods. It can be found from Figure 4.7 that the cost of adopting WCAS is the least because it simulates an ideal scene and ignores the specific charger assignment scheme for each individual EV. With the help of the POCS, the charging cost is reduced significantly compared with the UCS, and the result is very close to the ideal WCAS condition. Meanwhile, a specific chargers assignment matrix δ cannot be given in the ideal WCAS scenario, so we believe that the POCS can not only reduce charging cost but also provide a more realistic charging operation scheme.

4.3.2 Monte Carlo Analysis on Service Ability of the Charging Station under Different Scheduling Approach

In the realistic operation of the charging station, it is necessary to ensure all EVs are fully charged. However, the number of chargers is limited and each EV requires a specific time for charging, so the ability to provide charging services per day of a charging station is limited by the number of chargers. Because the power requirement is stochastic, the serviceability of the charging station is discussed by the Monte Carlo analysis. The optimization duration T is set as 24 hours from 12:00 to the next day 12:00. Generate one set of $\mathbf{\Omega}^E$ with a certain number of EV N by following normal distribution, as described in Section II. And then, input the generated EVs set $\mathbf{\Omega}^E$ to the optimal charging scheduling model and the uncontrolled charging model. If all EVs are fully charged, increase the number of N, and then generate another set $\mathbf{\Omega}^E$ and repeat the above steps continuously. Once not all EVs are fully charged, record current N as the serviceability. By repeating the above process 500 times, the boxplot of the serviceability under different charger numbers is shown in Figure 4.9.

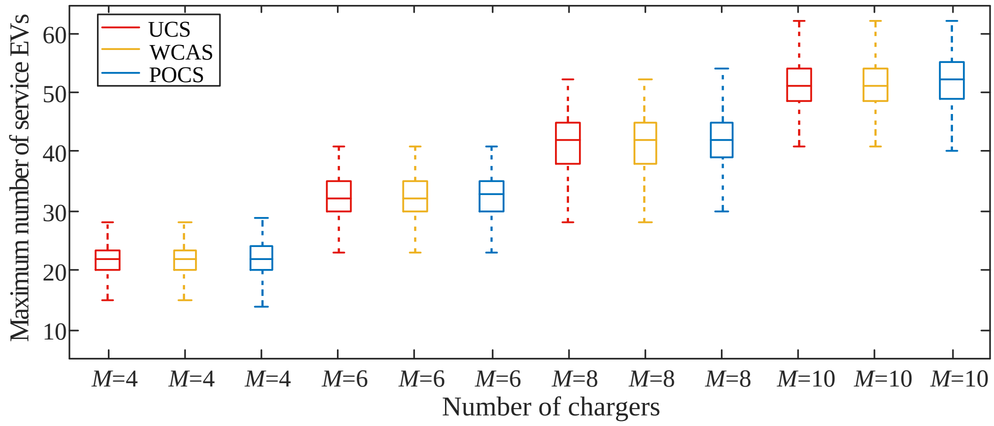


Figure 4.9. The distribution of serviceability after Monte Carlo analysis

Obviously, as the number of chargers increases, the number of EVs that can be charged per day also increases. In addition, the serviceability under the POCS is very close to the serviceability under the UCS and WCAS, which means the proposed charging scheduling method can guarantee the maximum number of EVs to complete charging.

4.3.3 Monte Carlo Analysis on Charging Cost under Different Scheduling Approach

The charging cost under two charging methods with the increase of charging EVs is also analyzed by Monte Carlo simulation. For a certain number of N, generate a set of $\mathbf{\Omega}^{E}$, then input it to the optimized charging scheduling and the uncontrolled charging model to calculate the different charging costs. Repeat this process 500 times, then the charging costs of the current number of N under these two different charging methods are computed.

The simulation results are shown in Figure 4.10. The yellow dotted line and green dotted line represent the price range of POCS and UCS, respectively. Meanwhile, the blue line and point mark the mean charging cost under POCS, and the red line and point mark the mean charging cost under UCS. The mean cost under WCAS is drawn with the black dotted line. Four scenarios with a different number of chargers are simulated. Evidently, regardless of the number of chargers, charging with the POCS can reduce the charging cost significantly than the UCS method. Similar to the result in Figure 4.8, the cost under POCS is very close to the result under the ideal WCAS conditions.

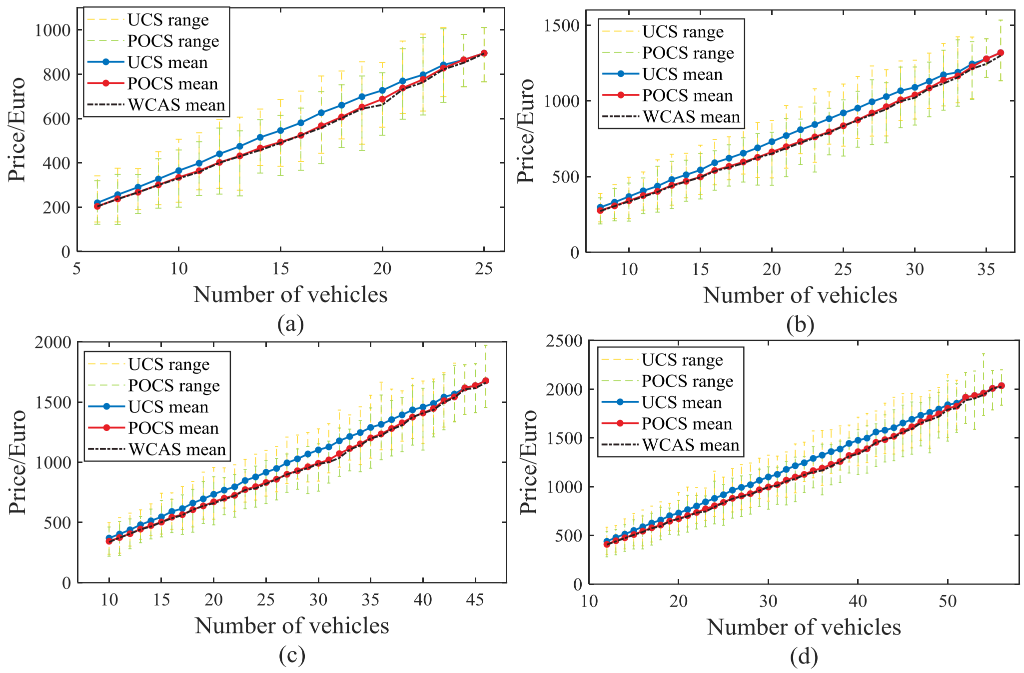


Figure 4.10. Charging cost under different charging methods with the increase of charging vehicles (a) charger number M=4 (b) charger number M=6 (c) charger number M=8 (d) charger number M=10

4.3.4 Efficiency of the proposed optimal charging scheduling algorithm

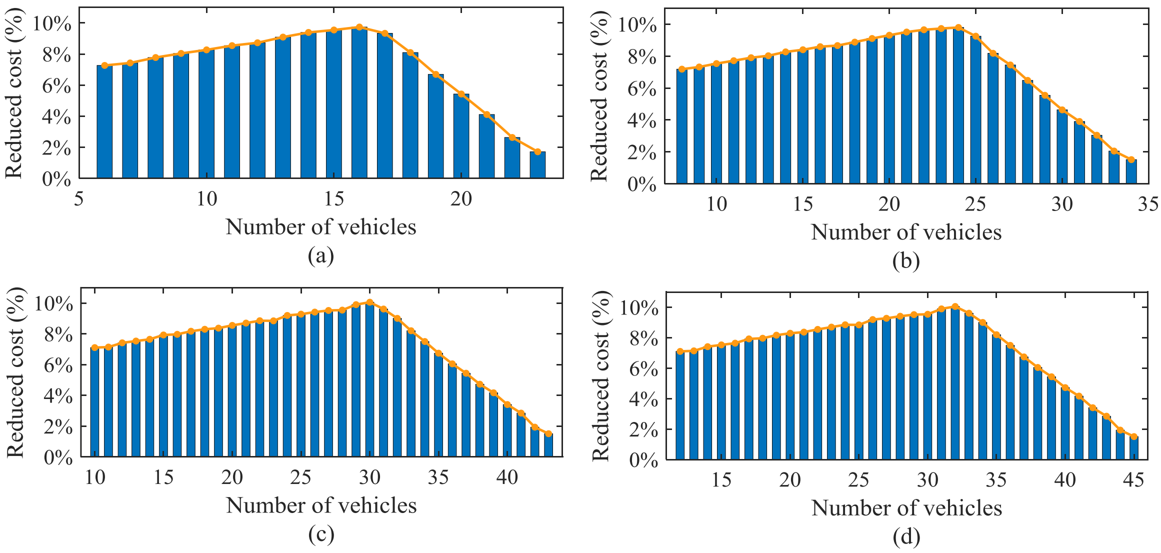


Figure 4.11. Reduced charging cost when adopting POCS compared to UCS (a) charger number M=4 (b) charger number M=6 (c) charger number M=8 (d) charger number M=10

By adopting the POCS, the reduced charging cost compared with the UCS cost is shown in Figure 4.11. It can be found that when the number of EVs is not large, the optimal charging cost is close to the UCS cost because the number of charging EVs that can be rescheduled is small. In contrast, when the number of EVs arrives at a certain number, the optimization is more obvious. However, when the number of charging EVs continues to increase, the optimized charging cost and uncontrolled charging cost will become closer. This is because the number of EVs is close to the charging station's serviceability, in order to ensure that each EV is fully charged before departure, there is a few extra margins for charging scheduling optimization. Through the analysis of the efficiency of the proposed charging scheduling method, the number of chargers in the charging station can be installed according to the actual number of EVs operating every day.

4.4 Summary

Considering the limited number of chargers, the charging process of a charging station is modeled. An uncontrolled charging scheduling process is designed to reflect the working way of each charger when no extra optimization method is implemented. Then, an optimal charging scheduling method is proposed by reasonably arranging the charging time and chargers for each EV. By scheduling the charging power within EVs' available charging time by responding to the TOU electricity price, the proposed method can reduce the charging cost as much as possible while ensuring that all EVs are fully charged. Besides, we analyzed the serviceability of the charging station with the limited chargers and compared the economized charging cost under a different number of charging vehicles and a different number of chargers. The POCS method is compared with the UCS method and the WCAS method. Through extensive simulations, it has been shown that with the proposed optimal charging scheduling algorithm, the charging station can not only schedule the charging process more efficient but also provide a more detailed optimal charging scheme.

5 Data-driven Intelligent EV Charging Operating Considering the Charging Demand Forecasting

In the last chapter, the scheduling schemes of limited charging facilities are discussed. Coordinated charging scheduling can improve the operating economics of charging stations, promote the utilization rate of charging facilities and reduce the required amount of chargers. However, the limitation of the proposed scheduling method in the last chapter is obvious. To apply the scheduling method in the last chapter, the future charging demand of each EV is required, which means it is only suitable for a parking lot with a fixed charging timetable, such as electric bus charging and electric logistics truck charging. Besides that, the battery degradation characteristics that affect user satisfaction are also not considered.

To tackle this issue, a data-driven intelligent EV charging scheduling algorithm is proposed in this chapter, by scheduling in response to the time-of-use (TOU) electricity price, the limitation of charging facilities, and detailed charger operating process is also considered. The EV charging demand forecasting process is proposed in this more versatile chapter. An EV charging demand forecasting method based on a neural network algorithm is proposed. The forecasting process predicts the subsequent set of charging EVs including the number of subsequent EVs and their respective dwell period and energy requirements. The charging scheduling optimization model considering the limited charging facilities is proposed. The object of the optimization model is to minimize the overall cost. The equilibrium between station operators and EV users is obtained. The total charging cost for the charging operators is reduced while the charging requirements and reducing the battery degradation are assured. Combining the charging demand forecasting method and the scheduling optimization model, the real-time charging scheduling system operation process is introduced. By considering the real and estimated EVs in the optimization model, the more accurate guidance for the charger power allocation at the current moment can be obtained. Detailed power scheduling and charger operating processes for each individual EV are provided. The proposed DICS approach can provide the scheme of how to flexible use the limited chargers to connect the appropriate EVs and provide corresponding charging power.

5.1 The Charging Station Model and the Necessarily of Forecasting

As discussed above, coordinating charging stations for EVs can help improve the overall charging economy and reduce the construction cost of charging stations. Therefore, the multiple-to-multiple charging station type designed in [33] is applied for charging scheduling designing. The proposed DICS method in this chapter is mainly for operating a single charging station and can be applied to places suitable for optimized charging scheduling, such as work locations, commercial centers, and residential areas. The data-based intelligent charging scheduling system model is shown in Figure 5.1. When an EV intends to charge at the charging station, the system will report its required charging information, including arrival time, departure time, and energy requirement. Since the performance of the power scheduling is time-dependent and the information of the subsequent EVs is unknown, we apply the information of historical arrived EVs to predict the future charging demand. With the reported and predicted EVs' information, the intelligent charging scheduling procedure is controlled by the charging scheduling system (CSS). Each EV parks in the charging area and connects to the charging network. The charging network is the multiple-charger multiple-port charging system, each charger is allowed to serve multiple parking spaces and each EV is allowed to be charged by multiple chargers, but one charger can only charge one EV at a time [33]. By considering the TOU price, battery degradation characteristics, and users' satisfaction, the CSS coordinates the service objects of each charger and adjusts the power dispatch from each charger. All the charging activities are automatically switched.

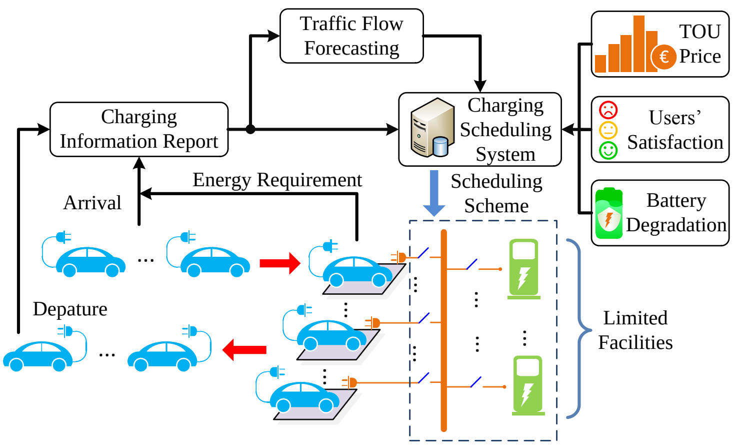


Figure 5.1. Model of the data-based intelligent charging scheduling system

Figure 5.2 gives a toy example about the advantage of scheduling considering the EV information forecasting in the case of limited charging facilities. Assume that the maximum power that a charger can provide in a time slot is P_{max}=4, and only one charger is available in the charging station that can only serve one EV at the same time. In Figure 5.2 (a), the current time slot is 1, the EV $\boldsymbol{\Omega}_1^E$ with 10 units of energy demand arrives at time slot 1 and will leave at time slot 5. When no subsequent EVs are considered for scheduling the optimal charging scheme is to charge 2, 4, 4 units of power at time slots 1, 4, 5 for $\boldsymbol{\Omega}_1^E$. Because this charging scheme can ensure user $\boldsymbol{\Omega}_1^E$ completes its charging demand before leaving, and the TOU price at time slots 1, 4, 5 are lower than other times. From time slots 1 to 2, the scheduling process in total provides 2 units of energy to $\boldsymbol{\Omega}_1^E$ to avoid the high TOU price. However, when the time slot comes to 3, an actual EV $\boldsymbol{\Omega}_2^E$ with 6 units of energy demand arrived and will leave at time slot 5, shown in Figure 5.2 (b). From time slots 3 to 5, it can only provide a maximum of 12 units of energy, while $\boldsymbol{\Omega}_1^E$ and $\boldsymbol{\Omega}_2^E$ have a total of 14 units of energy demand at this time, so the charging demand cannot be fully guaranteed. In addition, the charging station has to provide charging power at time slot 3 when the TOU price is the highest, which further reduces the charging economy.

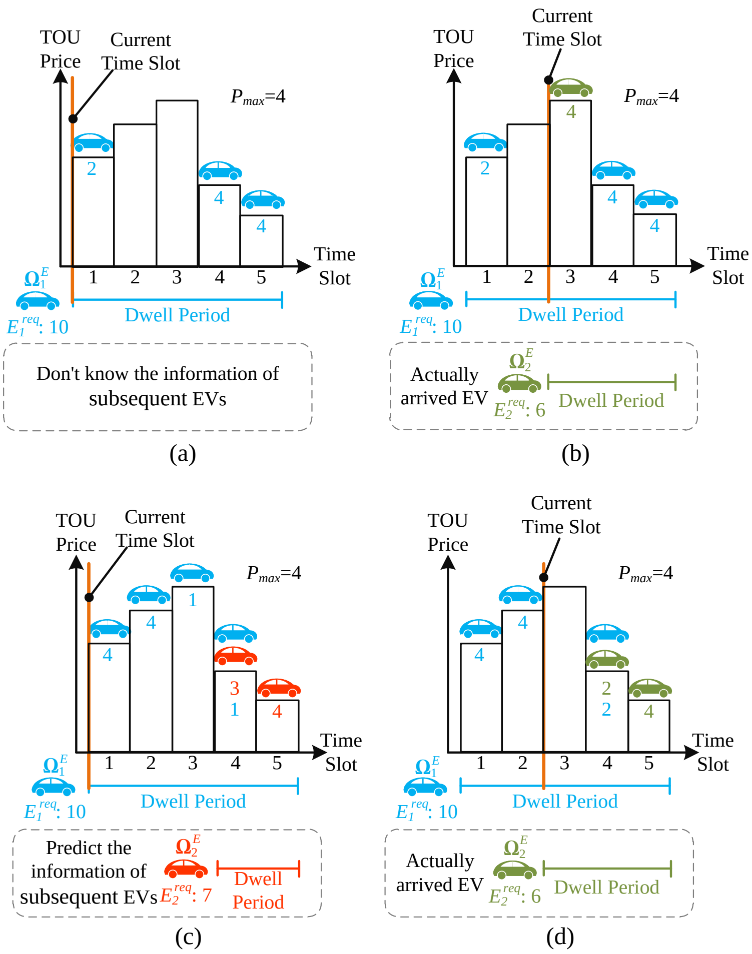


Figure 5.2. Toy example for the scheduling (a) without EV information forecasting at time slot 1 (b) without EV information forecasting at time slot 3 (c) with EV information forecasting at time slot 1 (d) with EV information forecasting at time slot 3

In other cases, illustrated in Figure 5.2 (c), assume at time slot 1, it is predicted that EV $\mathbf{\Omega}_2^E$ with 7 units of energy demand will arrive at time slot 4 and leave at time slot 5. Then the optimal charging scheme is to charge $\mathbf{\Omega}_1^E$ 4, 4, 1, 1 unit of energy at time slots 1, 2, 3, 4 and charge the predicated $\mathbf{\Omega}_2^E$ 3, 4 units of energy at time slots 4, 5. Similarly, when the time slot comes to 3, the actual EV $\mathbf{\Omega}_2^E$ with 6 units of energy demand arrived, shown in Figure 5.2 (d). Since the charging margin has been taken into account by forecasting, 8 units of energy had been charged to $\mathbf{\Omega}_1^E$ in advance at times 1 and 2. Therefore, after the actual $\mathbf{\Omega}_2^E$ arrived, both $\mathbf{\Omega}_1^E$ and $\mathbf{\Omega}_2^E$ can get sufficient energy supply at the lower TOU price period, time slots 4 and 5.

In the case of limited charging facilities, we not only need to predict the amount of energy demand in the subsequent moments but also need to predict the number of EVs and allocate the energy demand to them. Even if the forecasting process cannot provide the completely accurate follow-up EV data, the scheduling with subsequent can still provide a certain margin for the charger and bring a significant improvement in the economy and user satisfaction. Of course, the more accurate the forecast is, the more efficiency would be improved.

5.1.1 Electric Vehicle Charging Demand Information

In a realistic situation, the charging demand in a charging station is time-depended, which that means at different times, the number of EVs in the charging station is different. The arrival time and departure time of the n-th EV are t_n^a and t_n^d, where $t_n^a < t_n^d$. E_n^{req} represents the required energy of n-th EV. The required charging energy is determined by the initial battery state of charge (SOC) S_n^{ini} and the requested SOC S_n^{req} where both of them are following the Gaussian distribution [123]. Consequently, the required energy for each EV is computed by:

$$E_n^{req} = \left(S_n^{req} - S_n^{ini}\right)Cap_n \tag{5.1}$$

where Cap_n is the battery capacity of n-th EV. P_{max} is the maximum power that a charger can provide within one time slot. It is assumed that the charging demand of all cars will not exceed the maximum power that can be obtained during the dwell time, which means $t_n^d - t_n^a \geq E_n^{req}/P_{max}$. The arrival time, departure time, and required energy of each EV are required information for optimal scheduling, which can be regarded as a *User*, defined as:

$$\Omega_n^E = \left\{t_n^a, t_n^d, E_n^{req}\right\} \tag{5.2}$$

EVs staying in the charging station for a certain period can be regarded as a charging *Task* of the charging station. Define the *Task* set: $\mathbf{\Omega}^E = \{\mathbf{\Omega}_1^E, \ldots, \mathbf{\Omega}_2^E, \ldots, \mathbf{\Omega}_N^E\}$, where N denotes the number of users in one task, n is the index of the user.

The TOU electricity price at different time slots is defined as $e_{price}(t)$, where t is the index of time slot. Therefore, the electricity purchase cost for the charging operator is:

$$G(P_{n,t}) = e_{price}(t)P_{n,t} \tag{5.3}$$

where $P_{n,t}$ denotes the charged power of EV n at time slot t.

5.1.2 Battery degradation characteristic

From the perspective of users, EV users expect to complete the charging requirements within the dwell time while increasing the battery life. Thus, the battery degradation model is established. The LiFePO4 lithium-ion battery, which has more thermal and chemical stability, has been widely used in a variety of EVs [76]. A degradation cost model for LiFePO4 battery cells is developed in [71], which can be expressed as:

$$\Phi(P_{n,t}) = a_t (P_{n,t}/Cap_n)^2 + b_t P_{n,t}/Cap_n + c_t \tag{5.4}$$

where parameters a_t, b_t and c_t are related to the battery characteristics:

$$\begin{aligned} a_t &= 10^6 tC_{cell}\beta_4 /(DV_{nom}) \\ b_t &= 10^3 tC_{cell} /(\beta_2 - \beta_6 V_{nom}) \\ c_t &= tDC_{cell}V_{nom} /(\beta_1 + \beta_3 V_{nom} + \beta_5 V_{vom}^2 + \beta_7 V_{vom}^3) \end{aligned} \tag{5.5}$$

where C_{cell} is the price (\$/Wh) of battery cell capacity; V_{nom} denotes the cell voltage; D is the number of composed identical cells; β_i, i= 1,…,7 are the parameters specified in [127].

5.2 Data-Driven EV Charging Demand Forecasting based on LSTM

In the actual scene, the charging demand information of EVs that will arrive in the future is unknown. However, the information of the subsequent EVs will affect the scheduling efficiency. Thus, it is essential to forecast the subsequent charging demand for improving scheduling efficiency, reducing charging costs, and increasing users' satisfaction.

5.2.1 Long short-term memory (LSTM) network Application

Data Preprocessing: In order to improve the performance of intelligent charging scheduling, detailed EV information (including arrival time, departure time, and required energy) is required to be predicted. From the perspective of the charging station operator, it is easy to record the number of vehicles arriving and departing at different times, as well as the energy demand data of the respective EVs. Define N_t^a and N_t^d are the number of EVs arriving and departing at time slot t. N_t^s denotes the number of EVs dwelling at the charging station at time slot t. Let ψ_t denotes the expected total energy demand at time slot t, which is computed as:

$$\begin{cases} E_n^{av} = \Delta t \dfrac{E_n^{req}}{\left(t_n^d - t_n^a\right)} \\ \psi_t = \sum_{n=1}^{N} E_n^{av} \quad , \text{where } \forall t_n^a \le t \le t_n^d \end{cases} \tag{5.6}$$

where Δt represents one time slot; E_n^{av} means the average energy demand of EV n at one time slot, which is evenly distributed according to its dwell time. The ψ_t represents the sum of the E_n^{av} of all EVs staying in the station at time slot t (The EV n must stay in the charging station at time slot t, that is $t \in [t_n^a, t_n^d]$).

Recurrent neural network layer: Recurrent neural networks (RNN) have a powerful capability of forecasting the time series problem. The long short-term memory (LSTM) network is a variant of the RNN, which can learn the long-term dependencies, and alleviate the problems caused by gradient disappearance and gradient explosion [128]. Therefore, it can be well adapted to the forecast of traffic flows on special dates, such as weekends and holidays. N_t^a, N_t^d, $N_{t,}^s$ and ψ_t show the strong time-series correlate, therefore, based on past data, LSTM can be adopted to predict future EV charging demand information. Figure 5.3 shows the architecture of the LSTM unit. The compact forms of the equations for the forward pass of an LSTM unit are [128, 129]:

$$f_t = \sigma(W_f \cdot [h_{t-\Delta t}, X_t] + b_f) \tag{5.7}$$

$$i_t = \sigma(W_i \cdot [h_{t-\Delta t}, X_t] + b_i) \tag{5.8}$$

$$C_t = f_t * C_{t-\Delta t} + i_t * \tanh(W_C \cdot [h_{t-\Delta t}, X_t] + b_c) \tag{5.9}$$

$$o_t = \sigma(W_o \cdot [h_{t-\Delta t}, X_t] + b_o) \tag{5.10}$$

$$h_t = o_t * \tanh(C_t) \tag{5.11}$$

In the above equations, the forget gate's activation vector is f_t, the input gate's activation vector is i_t and the output gate's activation vector is o_t; C_t represents the cell state vector; σ is the sigmoid function; W and b are weight matrices and bias vector parameters which need to be learned during training. The symbol $*$ is the Hadamard multiplication. X_t and h_t denote the input and output vectors of the LSTM unit. In the operation process of the proposed DICS algorithm, new data will be recorded to update the LSTM module at each executing time slot. This can further improve the accuracy of the forecast, and make the forecasting more adaptable to the rapid changes in the market share of EVs.

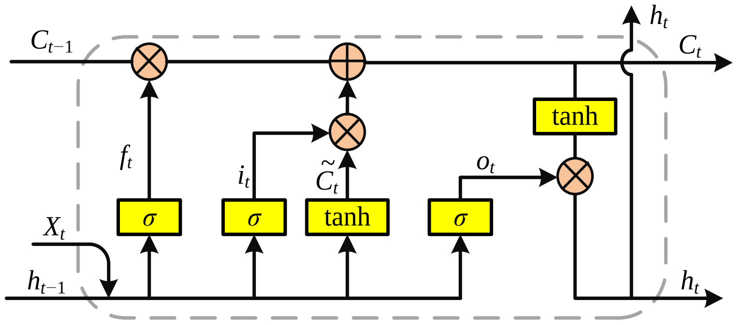


Figure 5.3. LSTM unit

5.2.2 Establishment of the Predicted Charging Demands

Overall charging demand: Define τ as a current time slot, information about EVs arrived earlier than current time slot ($t_n^a \le \tau$) is known, and some of their departure time later than current time slot ($t_n^d > \tau$). In order to better schedule the charging scheme within the EVs' dwell time, the information of EVs arrived after the current time slot ($t_n^a > \tau$) needs to be predicted. Let $\mathbf{\Omega}_\tau^E$ be the overall charging *Task* at time slot τ. This includes the EVs currently staying in the station and the EVs that will arrive in the station in the future. For the EVs that stay in the station with charging requirements at the current moment τ, their charging demand information is known. Thus, we define this part of EVs as *Real* EVs. Define the set of real EVs tasks at the current time slot τ is:

$$\Omega_\tau^{E,re} = \left\{ \Omega_{1,\tau}^{E,re}, \ldots, \Omega_{N_\tau^{re},\tau}^{E,re} \middle| \forall t_{n,\tau}^{a,re} \le \tau \le t_{n,\tau}^{d,re} \right\} \tag{5.12}$$

where $\mathbf{\Omega}_\tau^{E,re}$ represent the *Real Task* at current time slot τ; $\mathbf{\Omega}_{n,\tau}^{E,re}$ represent the *Real User n* at current time slot τ; N_τ^{re} denotes the number of EVs in $\mathbf{\Omega}_\tau^{E,re}$. Real EVs tasks at the current time slot are composed of uncompleted charging tasks at the last time slot $\mathbf{\Omega}_{\tau\text{-}\Delta t}^{E,re,un}$ and EVs arriving at the station at current time slot $\mathbf{\Omega}_\tau^{E,re,a}$, which is $\mathbf{\Omega}_\tau^{E,re} = \mathbf{\Omega}_{\tau\text{-}\Delta t}^{E,re,un} \cup \mathbf{\Omega}_\tau^{E,re,a}$.

Since we need to formulate a charging scheduling strategy for the EVs currently staying in the station, the optimized time period is from the current time slot τ to the time when the last EV. Define the interval to be predicted as [τ, T_τ], where T_τ indicates the latest departure time of the EVs in $\mathbf{\Omega}_\tau^{E,re}$, computed by:

$$T_\tau = \left\{ \max\left(t_n^d\right) \middle| n \in \Omega_\tau^{E,re} \right\} \tag{5.13}$$

Let the previous information N_t^a, N_t^d, N_t^s, and ψ_t ($\forall t \le \tau$) be the input of the LSTM layer, the output of the LSTM layer is:

$$h_t = \left\{ N_t^{a,pred}, N_t^{d,pred}, N_t^{s,pred}, \psi_t^{pred} \middle| \forall t \in [\tau, T_\tau] \right\} \tag{5.14}$$

where $N_t^{a,pred}$, $N_t^{d,pred}$, and $N_t^{s,pred}$ represent the predicted number of arrived, departed, and stayed EVs at future time slot ($t \in [\tau+\Delta t, T_\tau]$, $\tau+\Delta t$ means the next time slot after τ), respectively; ψ_t^{pred} is the predicted total energy demand at future time slot ($t \in [\tau+\Delta t, T_\tau]$).

Algorithm 5.1: Overall charging demand task establishment

Start Algorithm
Input: $\boldsymbol{\Omega}_\tau^E$, $\boldsymbol{\Omega}_{\tau-1}^E$, $N_t^{a,re}$, $N_t^{d,re}$, $N_t^{s,re}$, ψ_t^{re}, τ, T_τ, h_t
Initialization: $n_1=1$, $n_2=1$
for each $t \in \{\tau+1, \tau+2, \ldots, T_\tau\}$
  while $n_1 \le N_t^{a,pred}$ **do**
    The arrival time of n_1-th EV is set as $t_{n_1}^{a,es} = t$
    n_1++
  end while
  Number of estimated EVs leaving at t: $N_t^{d,es} = N_t^{d,pred} - N_t^{d,re}$
  if $N_t^{d,es} > n_1 - N_t^{d,es}$
    $N_t^{d,es} = n_1 - N_t^{d,es}$
  end if
  while $n_2 \le N_t^{d,es}$ **do**
    The arrival time of n_1-th EV is set as $t_{n_2}^{d,es} = t$
    n_2++
  end while
  Average power of estimated EVs at t: $P_t^{av,es} = \left(\psi_t^{pred} - \psi_t^{re}\right) / N_t^{s,es}$
end for
for all the estimated EVs: $n \in \{1, 2, \ldots, n_1\}$
  Power required by each estimated EV is $E_n^{req,es} = \sum_{t=t_n^{a,es}}^{t=t_n^{d,es}} \Delta t P_t^{av,es}$
end for
Create the estimated EV users and the estimated charging task at the current time slot $\tau : \Omega_{n,\tau}^{E,es} = \left\{ t_{n,\tau}^{a,es}, t_{n,\tau}^{d,es}, E_{n,\tau}^{req,es} \right\}$ and $\Omega_\tau^{E,es} = \left\{ \Omega_{1,\tau}^{E,es}, \ldots, \Omega_{N_\tau^{es},\tau}^{E,es} \right\}$
The overall charging task is: $\Omega_\tau^E = \Omega_\tau^{E,re} \bigcup \Omega_\tau^{E,es}$ where the users in task are: $\Omega_{n,\tau}^E \in \Omega_\tau^E$
Output: $\boldsymbol{\Omega}_\tau^E$
End Algorithm

Let $N_t^{a,re}$, $N_t^{d,re}$, and $N_t^{s,re}$ represent the number of real arrived, departed and stayed EVs at future time slot ($t \in [\tau+\Delta t, T_\tau]$); ψ_t^{re} denotes the total power of the real EVs at future time slot ($t \in [\tau+\Delta t, T_\tau]$). Since the subsequent traffic is uncertain, the number of real arrived EV $N_t^{a,re}$ at future time slot ($t \in [\tau+\Delta t, T_\tau]$) is 0, and the other information $N_t^{d,re}$, $N_t^{s,re}$, and ψ_t^{re} are determined by the current real charging task $\boldsymbol{\Omega}_\tau^{E,re}$. Therefore, at each time slot, the subsequent EVs information need to predict, and the established information set at time slot τ is called *Estimated* task $\boldsymbol{\Omega}_\tau^{E,es}$. $N_t^{a,es}$, $N_t^{d,es}$, $N_t^{s,es}$, and ψ_t^{es} represent the number of estimated arrived EVs, number of estimated departed EVs, number of estimated stayed EVs, and total power of the estimated EVs at future time slot

($t\in[\tau+\Delta t,T_\tau]$). Therefore, by subtracting the real EVs data from the predicted data, the estimated EVs, can be obtained. Figure 5.4 illustrates the relationship between the real and estimated EVs. Algorithm 5.1 shows the establishment of the overall charging demand task $\boldsymbol{VEC}_\tau$ at time slot τ, which is composed by $\boldsymbol{\Omega}_\tau^{E,re}$ and $\boldsymbol{\Omega}_\tau^{E,es}$. $N_\tau=N_\tau^{re}+N_\tau^{es}$ denotes the number of EVs in $\boldsymbol{VEC}_\tau$. The arrival time of estimated EVs in $\boldsymbol{\Omega}_\tau^{E,es}$ will not be early than $\tau+\Delta t$, as described $\forall t_{n,\tau}^{a,es}\geq\tau+\Delta t$.

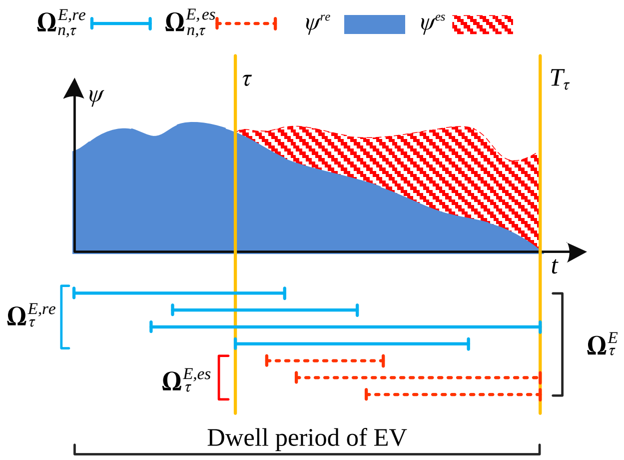


Figure 5.4. Relationship between the real and estimated EVs

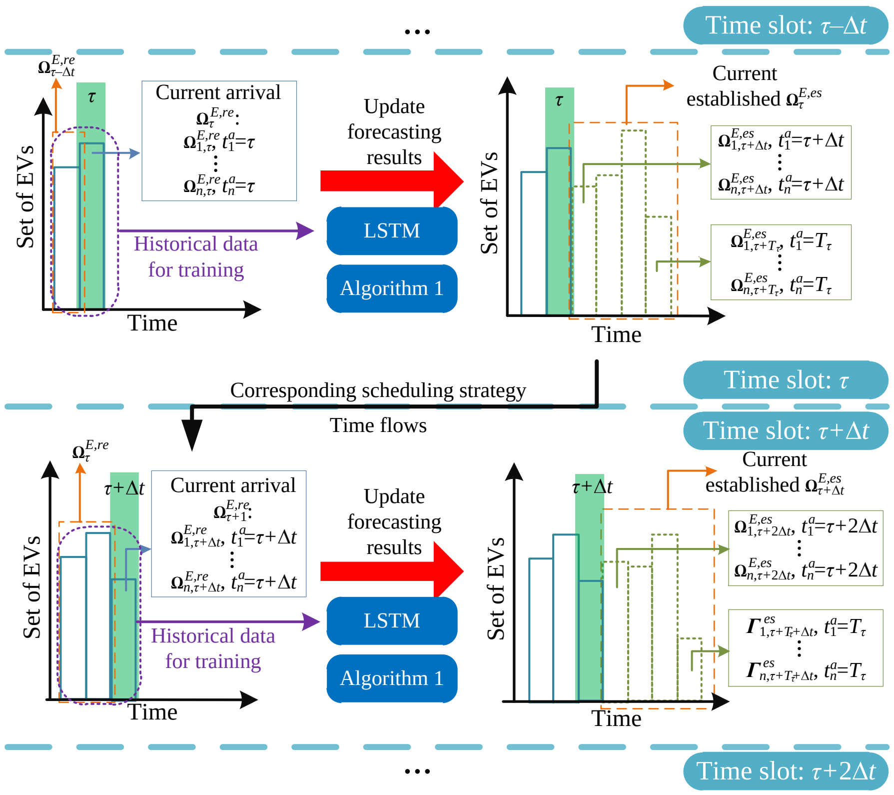


Figure 5.5. Time-varying data prediction and charging task establishment process

Figure 5.5 shows the relationship between the established real and estimated charging tasks at different time slots. As the new time slot τ arrives, the information of the EV entering the charging station at the current time slot can be obtained, which is $\mathbf{\Omega}_{\tau}^{E,re}$. By adopting the proposed Data-Driven EV Charging Demand Forecasting algorithm, we can obtain the subsequent prediction results at the current moment and establish the *Estimated* task $\mathbf{\Omega}_{\tau}^{E,es}$. At the same time, the LSTM module will be upgraded as new data $\mathbf{\Omega}_{\tau}^{E,re}$ becomes available, thus improving the accuracy of subsequent predictions. Then the corresponding charging scheduling optimization calculation is performed based on the unfinished charging task at the last time slot $\mathbf{\Omega}_{\tau-\Delta t}^{E,re}$, new arrival task $\mathbf{\Omega}_{\tau}^{E,re}$ and predicted estimated task $\mathbf{\Omega}_{\tau}^{E,es}$. Then, at the next time slot $\tau+\Delta t$, new EVs with charging task $\mathbf{\Omega}_{\tau+\Delta t}^{E,re}$ will also enter the station. By repeating the above steps, the estimated task at time slot $\tau+\Delta t$ can be predicated, and the optimal scheduling strategy for this time slot can be obtained.

5.3 Optimization Model Establishment and System Scheduling Process

The main target of the proposed charging scheduling scheme is to reduce charging costs and increase users' satisfaction. By introducing both real and estimated tasks into optimization, the charger operating and charging power scheduling at the current time slot is more efficient and economical.

5.3.1 Design of the Optimization Model with the Predicted Information

Considering the charging network service capability, the charging status of each EV should be denoted. Therefore, the binary decision variable $\zeta_{n,t}$ that indicates the connecting between chargers and EVs is be defined as:

$$\zeta_{n,t} = \{0,1\} \quad ,\forall n \in N, \forall t \in [\tau, T_{\tau}] \tag{5.15}$$

Specifically, when $\zeta_{n,t}=1$, the EV n is connected to a charger and can be charged at the time slot t; otherwise when $\zeta_{n,t}=0$, the EV n is not connected to any charger at time t, so it cannot get energy supply.

By considering the charging cost, battery degradation cost, the comprehensive charging cost of the n-th EV at time t can be established as:

$$F(P_{n,t}, \zeta_{n,t}) = \zeta_{n,t}\left(e_t P_{n,t} + \Phi(P_{n,t})\right) \tag{5.16}$$

In order to ensure user satisfaction, EVs need to be fully charged before departure. The following constraint is:

$$\sum_{t=t_n^a}^{t_n^d} \Delta t P_{n,t} = E_n^{req} \quad ,\forall n \tag{5.17}$$

However, in practice, due to the time series of traffic flows, it cannot guarantee that all EVs can be fully charged with limited chargers. From the user's perspective, EVs are expected to complete the charging requirement as much as possible before departure. Thus, the penalty function method is introduced to evaluate user satisfaction. The penalty function of *n*-th EV is:

$$G(P_{n,t}) = \omega \left(E_n^{req} - \sum_{t=t_n^a}^{t_n^d} \Delta t P_{n,t} \right)^2 \tag{5.18}$$

where ω is the penalty factor which is much larger enough. The larger difference between the obtained power and the required power, the greater the penalty function. Thus, the mathematical program of the proposed model is:

$$B(P_{n,t}, \zeta_{n,t}) = \min_{P_{n,t}, \zeta_{m,t}} \sum_{n=1}^{N_\tau} \left[\sum_{t=\tau}^{T_\tau} F(P_{n,t}, \zeta_{n,t}) + \zeta_{n,t} G(P_{n,t}) \right] \tag{5.19}$$

subject to:

(5.4), (5.16), (5.18)

$$\sum_{n=1}^{N_\tau} \zeta_{n,t} \le M \quad ,\forall t \in [\tau, T_\tau] \tag{5.20a}$$

$$\zeta_{n,t} = 0 \quad ,\text{if } \forall t \notin [t_n^a, t_n^d], \forall n \in N \tag{5.20b}$$

$$P_{n,t} \le P_{\max} \quad ,\forall n \in N, \forall t \in [\tau, T_\tau] \tag{5.20c}$$

$$P_{n,t} = 0 \quad ,\text{if } \zeta_{n,t} = 0, \forall n \in N, \forall t \in [\tau, T_\tau] \tag{5.20d}$$

$$\sum_{t=t_n^a}^{t_n^d} \Delta t P_{n,t} \le E_n^{req} \quad ,\forall n \in N \tag{5.20e}$$

In the established optimization model (5.19)-(5.20), the object is to minimize the overall charging cost including the cost of TOU electricity price, the cost of battery degradation, and the penalty part for not meeting the user's charging demand. The decision variable is set as the charging status $\zeta_{n,t}$ and the charging power $P_{n,t}$. Constraint (5.20a) means the maximum M chargers allowed to work at the same time, M represents the number of chargers in the charging station. Constraint (5.20b) means EVs cannot be charged when they were not at the charging station. The power provided by each charger at a time slot has an upper limit, which is represented by constraint (5.20c). Constraint (5.20d) indicates that when the charging state $\zeta_{n,t}$ is 0, the charging power $P_{n,t}$ is also 0. Since we have introduced the penalty function (5.18) to indicate the negative impact of incomplete EV charging, the constrain (5.17) is converted into the constraint (5.20e). Constraint (5.20e) means the obtained energy of an EV cannot exceed its required power.

5.3.2 Solving Technique

Since the established model is based on data prediction, there is no exact optimal solution. And the optimization model is mixed-integer nonlinear programming (MINLP) that includes binary variable $\zeta_{n,t}$ and natural number variable $P_{n,t}$. Since we cannot, in general, construct causal optimal scheduling policies [7, 130], the corresponding sub-optimal heuristic solving algorithm is developed in this chapter. According to convex optimization theory we have:

Theorem 1: when the binary variable $\zeta_{n,t}$ is fixed, the optimization model with only natural number variables is convex.

Proof 1: Let $\zeta_{n,t}$ be the fixed constants, compute the partial derivative of the function (5.19) with respect to variable $P_{n,t}$, we can get:

$$\begin{aligned}\frac{\partial B}{\partial P_{n,t}} &= \zeta_{n,t}e_t + \frac{2a_t}{Cap_n}P_{n,t} + \frac{b_t}{Cap_n} \\ &\underbrace{-2\omega\left[P_n^{req} - \sum_{t=t_n^a}^{t_n^d} P_{n,t}\right] - \cdots - 2\omega\left[P_n^{req} - \sum_{t=t_n^a}^{t_n^d} P_{n,t}\right]}_{\text{number depends on:} t_n^d - t_n^a + 1}\end{aligned} \tag{5.21}$$

Continue to find the second partial derivative with respect to variable $P_{n,t}$, we have:

$$\frac{\partial B^2}{\partial P_{n,t}^2} = \frac{2a_t}{Cap_n} + 2\omega(t_n^d - t_n^a + 1) \tag{5.22}$$

Then find the partial derivative based on (5.21) with respect to variable $P_{n,t'}$($t' \neq t$), we have:

$$\frac{\partial B^2}{\partial P_{n,t}\partial P_{n,t'}} = \begin{cases} 2\omega & \text{,if } t' \in [t_n^a, t_n^d] \\ 0 & \text{,if } t' \notin [t_n^a, t_n^d] \end{cases} \quad ,t' \neq t \tag{5.23}$$

Therefore, the Hessian Matrix of the objective function is obtained:

$$\boldsymbol{H} = \begin{bmatrix} \frac{\partial B^2}{\partial P_{1,1}^2} & \cdots & & \frac{\partial B^2}{\partial P_{1,1}\partial P_{n,t}} \\ \vdots & \ddots & & \vdots \\ \frac{\partial B^2}{\partial P_{1,1}\partial P_{1,t}} & & \frac{\partial B^2}{\partial P_{1,t}^2} & \frac{\partial B^2}{\partial P_{1,1}\partial P_{1,t}} \\ \vdots & & \ddots & \vdots \\ \frac{\partial B^2}{\partial P_{1,1}\partial P_{n,t}} & \cdots & & \frac{\partial B^2}{\partial P_{n,t}^2} \end{bmatrix} \tag{5.24}$$

It can be found that ω is the penalty factor which is positive and much larger enough, the departure time of an EV is always larger than its arrival time, a_t and Cap_n are also positive value.

Thus all items of the Hesse matrix are equal or larger than zero and for all vector $\boldsymbol{x}$ in $\mathbb{R}^n$, we have: $\boldsymbol{H}$ positive semi-definite $\Leftrightarrow$ $\boldsymbol{x}^T\boldsymbol{H}\boldsymbol{x} \geqslant 0$. Constraints (5.20c)-(5.20e) are also linear constraints. Thus, the objective function is convex when the binary variable $\zeta_{n,t}$ is fixed.

Algorithm 5.2: Heuristic algorithm

Set: Generation number g, Population size μ, Crossover probability λ, Mutation probability δ.
Input: $\boldsymbol{VEC}_\tau$
Initialization: Randomly create μ different individuals $\boldsymbol{\zeta}_\mu$ under constraints (5.20a)-(5.20b), where $\boldsymbol{\zeta}^\mu=\{\zeta_{1,\tau},\ldots,\zeta_{n,t}\}$.
while termination criteria, $g>g_{\max}$, not fulfilled, **do**
  Fitness value: with the fixed $\boldsymbol{\zeta}_\mu$, use a convex optimization method to find the solution of lower model (objective (5.19) constraints (5.20c)-(5.20e)) for μ different individuals, record the solved decision variable $\boldsymbol{P}^\mu=\{P_{1,\tau},\ldots,P_{n,t}\}$. $B^\mu(\boldsymbol{P}^\mu,\boldsymbol{\zeta}^\mu)$ is the fitness value.
  Best individual record: record the individual with the smallest B^μ.
  if $B^\mu<B^{best}$
    $B^{best}=B^\mu$, $\boldsymbol{P}^{best}=\boldsymbol{P}^\mu$, $\boldsymbol{\zeta}^{best}=\boldsymbol{\zeta}^\mu$
  end if
  Select: select individuals to produce offspring while individuals with smaller B values are easier to be selected.
  Offspring produce: the selected adjacent individuals have λ rate to exchange chromosomes, and the exchange position is random. Produce the offspring individual $\boldsymbol{\zeta}_\mu$.
  Mutation: the offspring individual $\boldsymbol{\zeta}_\mu$ has δ rate to mutate.
end while
Output: $B_\tau=B^{best}$, $\boldsymbol{P}_\tau=\boldsymbol{P}^{best}$, $\boldsymbol{\zeta}_\tau=\boldsymbol{\zeta}^{best}$

Therefore, by dividing the optimization model into two layers, the search range of the heuristic algorithm is reduced significantly, the computational efficiency is improved and more feasible solutions are obtained. The upper model is for solving binary variables $\zeta_{n,t}$, where the objective function is (5.19) and constraints are (5.20a)-(5.20b). The lower model is set $\zeta_{n,t}$ as a fixed value and takes an objective function as (5.19) and constraints as (5.20c)-(5.20e) to solve charging power $P_{n,t}$. Algorithm 5.2 shows the solving method of the charging scheduling model based on the genetic algorithm [131].

5.3.3 Operation of the Charging Scheduling System with Charging Demand Forecasting

Because the real and estimated EV tasks, $\boldsymbol{\Omega}_\tau^{E,re}$ and $\boldsymbol{\Omega}_\tau^{E,es}$, change in time series, the overall charging task $\boldsymbol{VEC}_\tau$ and corresponding results from Algorithm 5.2 should be updated at the different time τ. In the optimization model (5.19)-(5.20), the $t\in[\tau,T_\tau]$, but the results $P_{n,t}$ and $\zeta_{n,t}$, when $t\geq\tau+\Delta t$, will not be adopted as the scheduling scheme. Because the estimated EVs are included at $t\in[\tau+\Delta t,T_\tau]$, which does not actually exist in the reality. Therefore, we only keep $P_{n,\tau}$ and $\zeta_{n,\tau}$

$(n \in N_\tau)$ as the charging scheme at the current time slot τ.

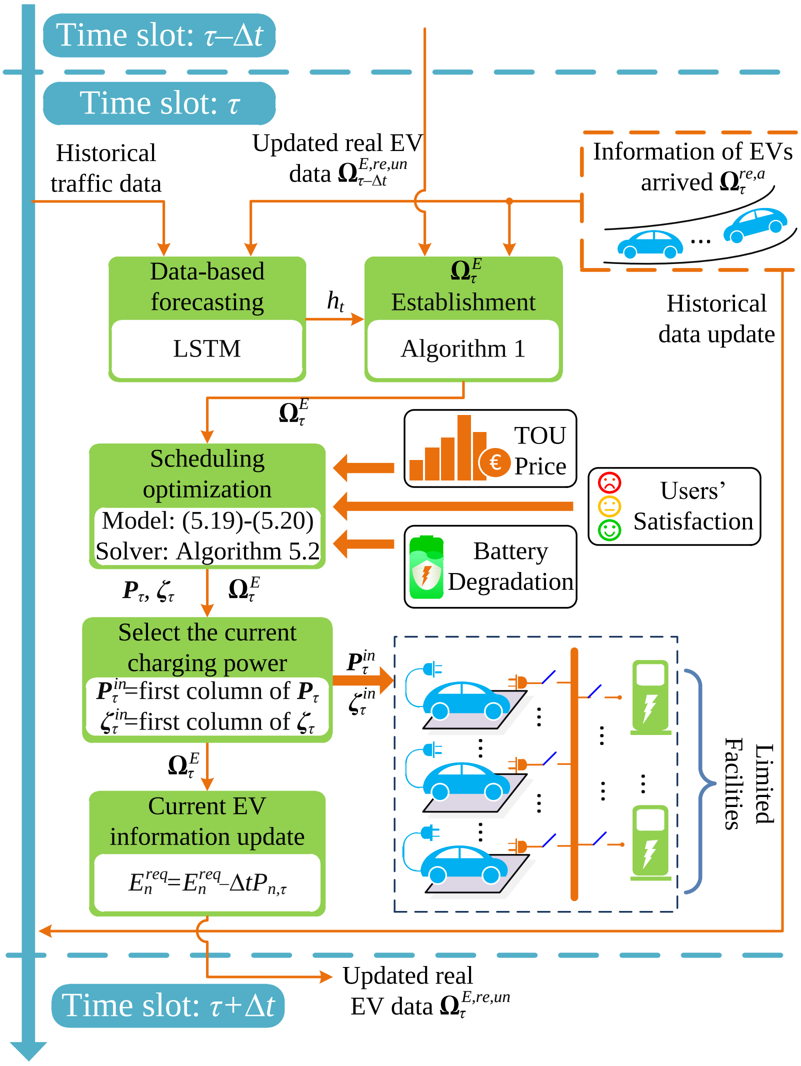


Figure 5.6. Charging scheduling system operation process

The complete charging scheduling system operation process is shown in Figure 5.6. Based on the traffic data, the LSTM algorithm is applied to predict the subsequent traffic data. Combining with the current EV data $\boldsymbol{\Omega}^{E,re}_{\tau}$, the forecasted EV flow data h_t, and the unfinished task $\boldsymbol{\Omega}^{E,re}_{\tau-\Delta t}$, the overall charging task at current time slot $\boldsymbol{\Omega}^{E}_{\tau}$ is established by adopting Algorithm 1. Then, with the overall charging task $\boldsymbol{\Omega}^{E}_{\tau}$, the optimization model (5.19)-(5.20) is formed and Algorithm 5.2 is introduced as the solving technique. By considering TOU price, battery degradation, and user's satisfaction, with the proposed Algorithm 5.2, the model which takes $P_{n,t}$ and $\zeta_{n,t}$ as the decision variables to minimize the overall charging cost is computed. The solved results are matrixes $\boldsymbol{P}_\tau[N_\tau \times (T_\tau - \tau+1)]$ and $\zeta_\tau[N_\tau \times (T_\tau - \tau+1)]$ including the charging scheme of N_τ EVs from time τ to T_τ. All the EVs that receive energy replenishment at the current time slot τ are *Real* EVs. Thereby, the first column of charging status ζ^{in}_{τ} and charging power $\boldsymbol{P}^{in}_{\tau}$ are taken as the input signal, where $\boldsymbol{\zeta}_{\tau}^{in}=\{\zeta_{1,\tau},\ldots,\zeta_{n,\tau}\}$ and $\boldsymbol{P}_{\tau}^{in}=\{P_{1,\tau},\ldots,P_{n,\tau}\}$. $\boldsymbol{\zeta}_{\tau}^{in}$ and $\boldsymbol{P}_{\tau}^{in}$ are regarded as the control signal at time slot τ to guide the charging station operation. Then, the current charging task $\boldsymbol{\Omega}_{\tau}^{E}$ is updated, that is, the user's charging demand is updated, and users who have completed the charging demand will be removed from the charging task set (Algorithm 5.3). After that, the updated charging task at τ is retained until the next time slot $\tau+\Delta t$ for establishing the new charging task $\boldsymbol{\Omega}_{\tau+\Delta t}^{E}$. Repeat the above steps continuously to realize the sequential operation of the charging station.

Algorithm 5.3: Charging task update
Input: $\boldsymbol{\Omega}_{\tau}^{E}$
For each $n\in\{1, 2,\ldots,N_{\tau}\}$
$E_{n}^{req}=E_{n}^{req}-\Delta t P_{n,t}$
If $E_{n}^{req}\leq 0$
Remove $\boldsymbol{\Omega}_{n,\tau}^{E}$ from $\boldsymbol{\Omega}_{\tau}^{E}$.
end if
end for
Output: $\boldsymbol{\Omega}_{\tau}^{E}$

5.4 Performance Evaluation of the Proposed Data-Based Intelligent Charging Scheduling Method

In the case study, the number of chargers in a charging station is M=20, all EVs and chargers are the same types and the maximum charging power per hour provided by each charger is P_{max}=45kW/h. The time slot duration Δt is set as one hour. The TOU price is following the German electricity spot prices [132]. The traffic flow is the topical scenario of workplace that higher on work days and lower on weekends. The initial SOC and required energy value are generated by following the probability density function. In the case study, the average number of EVs charging in a workday and a rest day are set as 100 and 20 respectively.

5.4.1 Verification of Forecasting Results

Figure 5.7 illustrates the comparison of forecasted data under LSTM and real data, including the number of dwell EVs, number of arriving EVs, and expected power at each time slot. According to the introduced Algorithm 5.1, the set of estimated charging tasks can be obtained. The estimated charging task $\boldsymbol{\Omega}_{\tau}^{E,es}$ will be established at every operating time slot based on historical data and current station information. So the estimated charging task established from the perspective of the different time slots is different.

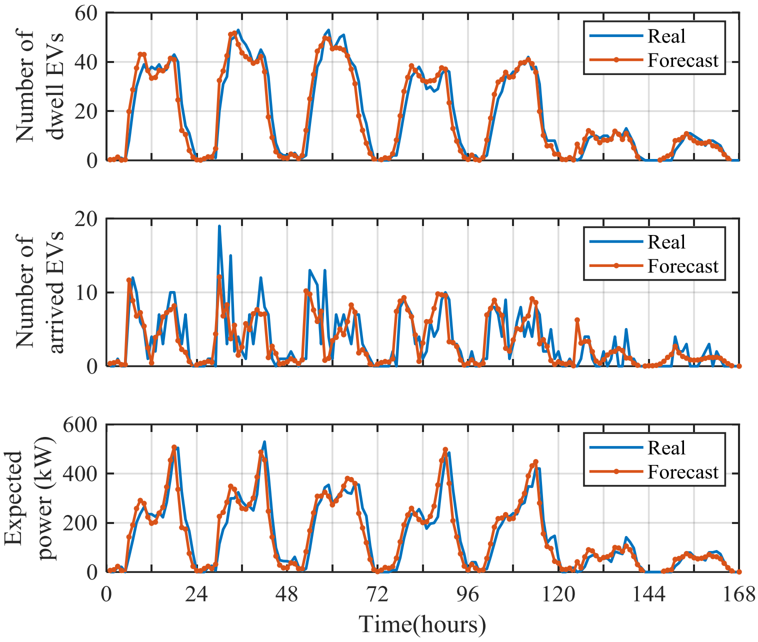


Figure 5.7. Traffic flow forecast.

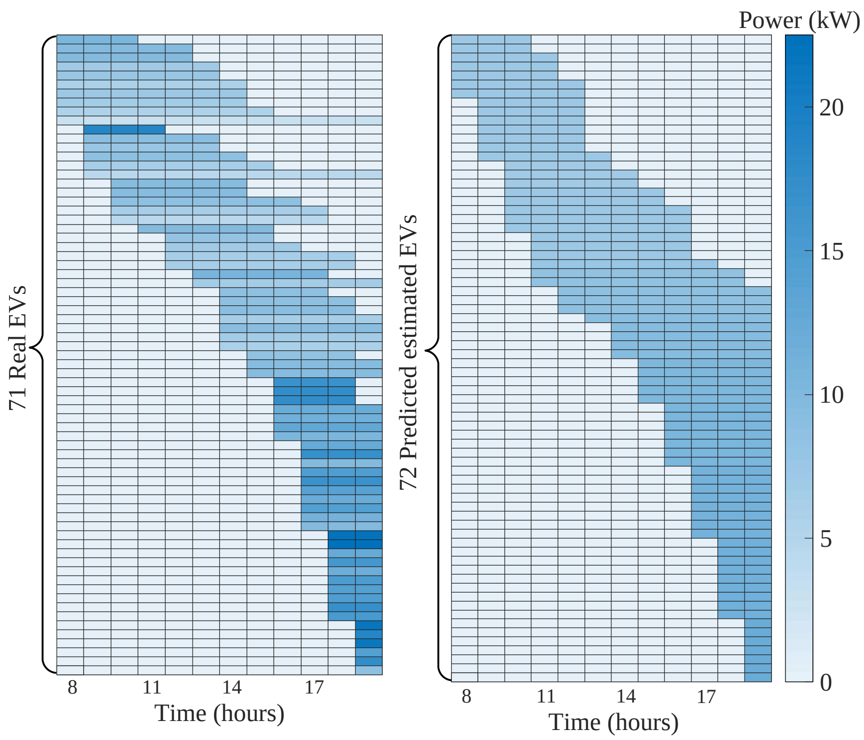


Figure 5.8. Forecast the charging demand of the subsequent EV from the perspective of 7:00.

Thereby, an example that the established subsequent estimated charging task from the perspective of 7:00 ($\mathbf{\Omega}_7^{E,es}$) is presented in Figure 5.8. Because the latest real EV plans to leave at 19:00 (which means in $\mathbf{\Omega}_7^{E,es}$, max(t_n^d)=19:00). So the estimated EVs task $\mathbf{\Omega}_7^{E,es}$ we need to predict is from 8:00 to 19:00. Each square represents the state of an EV at one time slot, where the row represents the index of EV and the column denotes the time slot. The blue color represents the

EV staying in the charging station, and the deeper the blue the greater the charging power required. It can be seen that the number of estimated EVs is close to the real EVs, and overall, the trend of demand energy and dwell time is also similar. The establishment of the future estimated task is only to guide the scheduling at the current time and leave a certain margin for the subsequent vehicles. Therefore, it is not essential to know the accurate charging demand information of each specific subsequent EV, and certain differences are allowed.

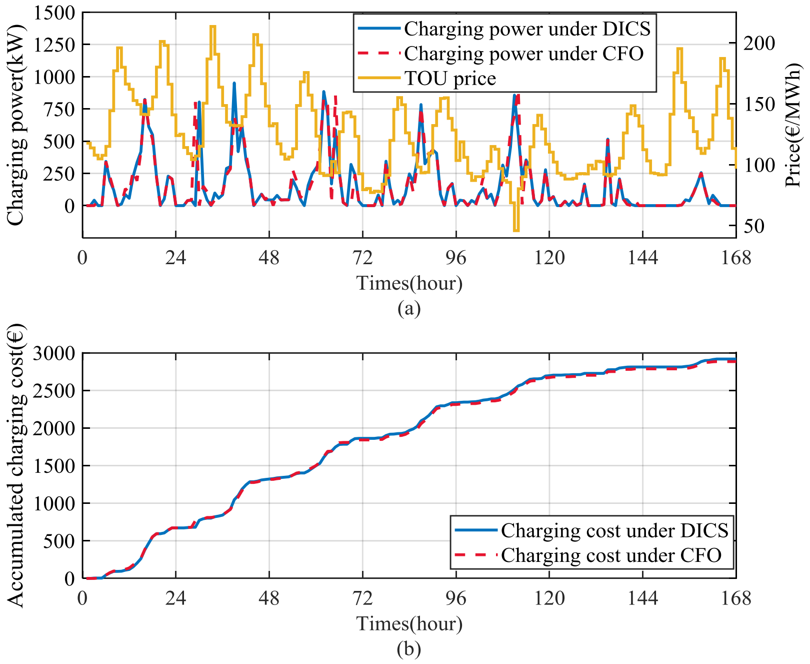


Figure 5.9. Comparisons between the proposed DICS and CFO (a) charging power (b) accumulated charging cost

Compared with the existing scheduling methods that consider charging demand forecasting, the proposed data-based intelligent charging scheduling (DICS) method can provide a detailed charger operating scheme and track the charging demands of each individual EV. The Convectional forecasting optimization (CFO) scheduling method is taken as the comparison. The CFO method only considers the scheduling strategy in a centralized manner. The specific energy demands and battery health of each EV, and the specific operating scheme of each charger is ignored. Therefore, CFO has fewer constraints and can provide better scheduling results from the perspective of the charging station. Figure 5.9 shows the overall charging power and the accumulated charging cost of one charging station under DICS and CFO. It can be found in Figure 5.9 (a), even though more individual factors are taken into consideration, the proposed DICS method is the same as the CFO method, which avoids high-power charging when the TOU price is high and charging as much as possible when the TOU price is low. According to Figure 5.9 (b), the accumulated charging cost under the proposed DICS is also very close to the ideal CFO situation. Meanwhile, the DICS method can also provide a detailed operating scheme with limited charging facilities, which cannot be provided by the CFO.

5.4.2 Case Study of the Optimization Results

At every time slot, the proposed DICS approach will perform the optimization process. The results of the optimization process at each time slot can not only provide the charging scheme for the EVs staying in the station at the current time slot but also predict the scheduling scheme of subsequent EVs from the perspective of the current. In order to better show the optimal results of the proposed DICS algorithm at each time slot, the detailed power scheduling and charger operating heatmap of each individual EV at 7:00 and 8:00 are shown in Figure 5.10. The gray box indicates that the EV is not in the station at this time and cannot be charged. The other boxes indicate that the EV right now stays in the charging station. The white to red gradient color represents the amount of provided charging power. Meanwhile, the box with a green dot denotes this EV is connecting to a charger. The limitation of chargers is considered, the maximum number of chargers that can be activated at each time slot is M, which is set to 20 in the simulation, so each column has a maximum of 20 green dots. In Figure 5.10 (a), the EVs that stay in the charging station at 7:00 are all real EVs, and the established estimated EVs will "arrive" at the charging station after 7:00. So the leftmost column represents the real charged energy at 7:00. The second to last columns represent the predicted charging energy of both real EVs and estimated EVs. The last column represents the time when the last real EV left. The marked Leave represents EVs that completed charging or departure at this time slot and the marked Arrive represents EVs arriving at this time slot. Similarly, Figure 5.10 (b) shows the results at 8:00.

Comparing Figure 5.10 (a) and Figure 5.10 (b), EVs that completed their charging task at 7:00 will not continue to occupy the charging resources at 8:00, while EVs that has not completed charging will perform charging scheduling optimization together with newly arrived EVs at 8:00. If the information of subsequent EVs is ignored (scheduling only considers the real EV part), from the perspective of current time slot, the number of EVs in the station will become less and less in the future, resulting in the wrong judgment that there will be enough chargers in the future, and then formulating unreasonable charging strategies. As new EVs continue to enter the station at subsequent moments, the charging incomplete rate will increase. With the introduction of predicated estimated EVs task, the charging scheduling is more reasonable. In addition, the "arrival" time of the estimated task also ensures that there will be no invalid result output at the current time (send the operating scheme to an estimated EV). Notice that the prediction for the estimated EVs only plays a role in assisting the charging optimization for the real EVs at the current time slot. The current estimated EVs will be cleared and the new estimated task will be created at the next moment. At each time slot, we can get the detailed scheduling heatmap results as in Figure 5.10 (a) or Figure 5.10 (b). The leftmost column of the obtained heatmap is used as the current charging station scheduling plan, and the remaining columns are used as the prediction.

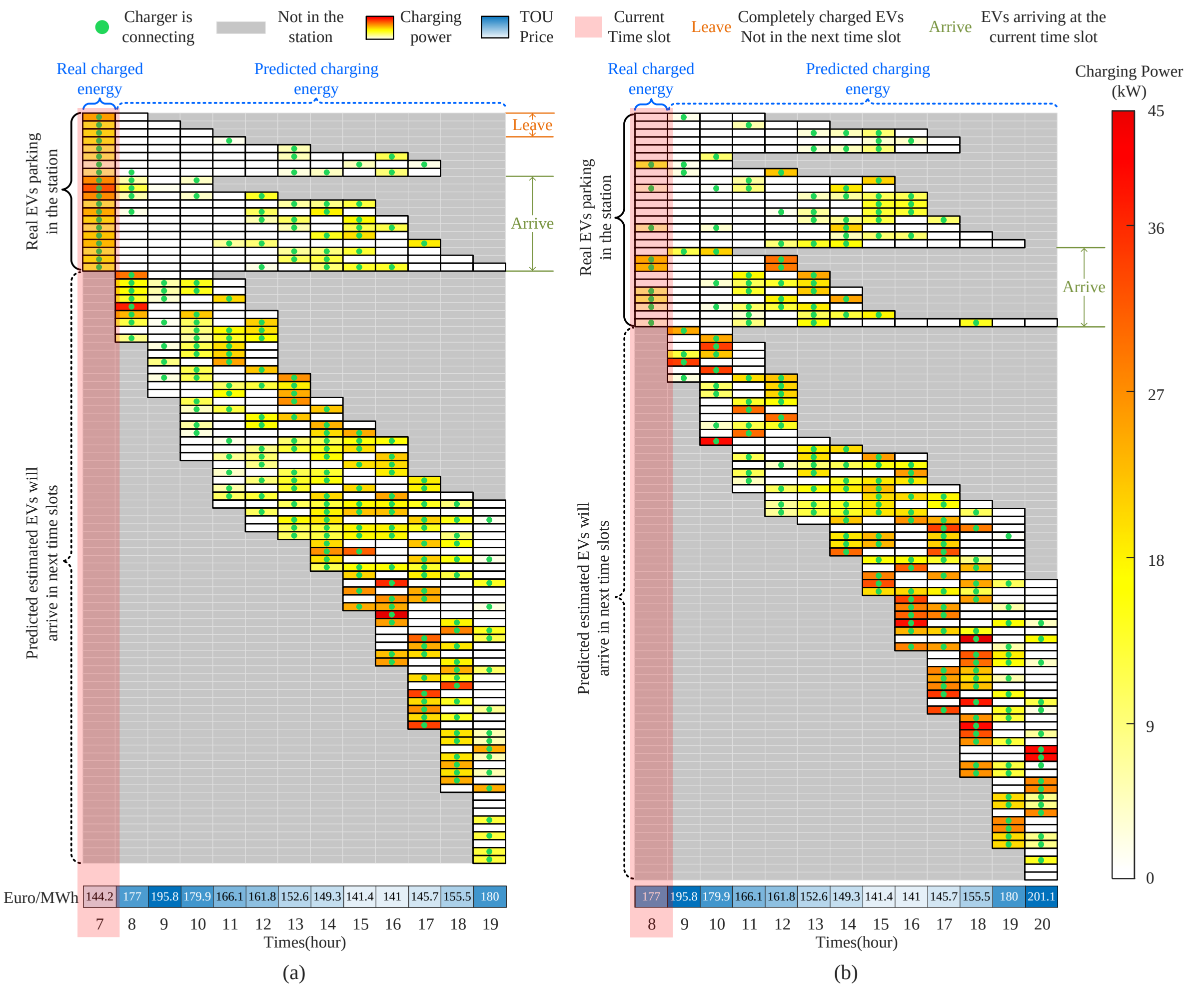


Figure 5.10. Detailed power scheduling and charger operating scheme heatmap of each individual EV at (a) 7:00 (b) 8:00

At every time slot when an EV dwells in the charging station, the DICS will formulate the specific scheduling scheme and predict the subsequent scheduling scheme for the EV, by considering factors such as TOU price, battery degradation, and charger assignment. Figure 5.11 shows in detail the process of obtaining charging energy for a specific EV. This EV arrived at 7 and left at 16, with 47 kWh energy requirement. Each sub-picture in Figure 5.11 represents a different time slot, and only the time slot when the EV is connected to a charger is given here.

By the DICS approach, this EV was connected to a charger at 7:00, 13:00, 14:00, and 15:00 with charged power 14.9 kW, 8kW, 9.9kW, and 14.2kW respectively. When at a certain time slot, the DICS will charge specific energy to this EV and then provide the predicted charging scheme for subsequent moments. However, as the real arrival EV data differs slightly from the predicted EV data, the real charging power at this time slot will be readjusted. For example, shown in Figure 5.11 (a), from the perspective of 7:00, the charging station provided 14.7kWh energy to this EV and predicted the future charging power of this EV. Figure 5.11 (b) shows the charging power and predicted power at time slot 13:00. It can be seen that the charged power at this time is different from the predicted from the perspective of 7:00. This is because the algorithm adjusts the charging power according to the actual arrival of the vehicle. Similarly, Figure 5.11 (c) shows the power charged at 14:00 and the subsequent charging prediction. Figure 5.11 (d) shows the power charged at 15:00. Since the charging of the EV is just completed at this time, there is no need to charge at the next moment. Chargers responsible for this EV can be deployed to serve other EVs when they are not connected to this EV, thereby, the charging efficiency is improved along with the charger utilization rate.

Because the CFO method is a centralized scheduling method and ignores the operating of specific chargers and EVs, it does not have the conditions for direct comparison with DICS considering specific limited charging facilities. In order to demonstrate the performance of our proposed DICS, first come first serve scheduling (FCFS), scheduling without prediction (SWP) and scheduling with real data (SWR) are taken for comparisons. Among them, SWP only considers the current EV data for optimization and does not establish the estimated EV task. SWR is the ideal condition that real EV data is used to replace the predicted estimated EV task. In the FCFS, EVs tend to finish charging as fast as possible, directly charging with the maximum power and disconnecting the charger immediately after the charging is completed.

Table 5.1 Key Performance Indexes Under Different Scheduling Methods

	DICS	FCFS	SWP	SWR
Provided total energy (kW)	24707	24741	24244	24642
Total charging cost (€)	7638	8847	7951	7615
Number of dissatisfied users	3	0	28	4
Average dissatisfaction degree (%)	19.4	0	34.3	21.1

To evaluate the satisfaction of individual EV users, the EV users who have not completed their charging requirements are dissatisfied users, which is $\sum_{t_n^a}^{t_n^d} \Delta t P_{n,t} \leq E_n^{req}$. For the dissatisfied users, the rate of incomplete charging indicates the dissatisfaction degree, which is $(E_n^{req} - \sum_{t_n^a}^{t_n^d} \Delta t P_{n,t}) / E_n^{req}$. To illustrate the performance of the proposed algorithm, the key performance indexes, including provided total energy, total charging cost, number of dissatisfied users, and average dissatisfaction degree, under different scheduling methods are demonstrated in Table 5.1. Obviously, in the designed case, the FCFS guarantees all EVs complete their charging requirements. However, because the FCFS does not perform charging power scheduling based on TOU price, the economy is the lowest. By adopting SWP, the total charging cost is reduced, but due to the lack of subsequent EV information, the number of not fully charged EVs is the most, and the charge rate of these EVs is also low. SWR is the ideal situation, thereby, it can ensure that most EVs can complete the charging requirements while improving the charging economy. Considering the realistic scheduling, the results of performance indexes under DICS are as good as the ideal situation. Therefore, by applying the proposed DICS, with practical feasibility, the charging economy is improved and user satisfaction is also guaranteed.

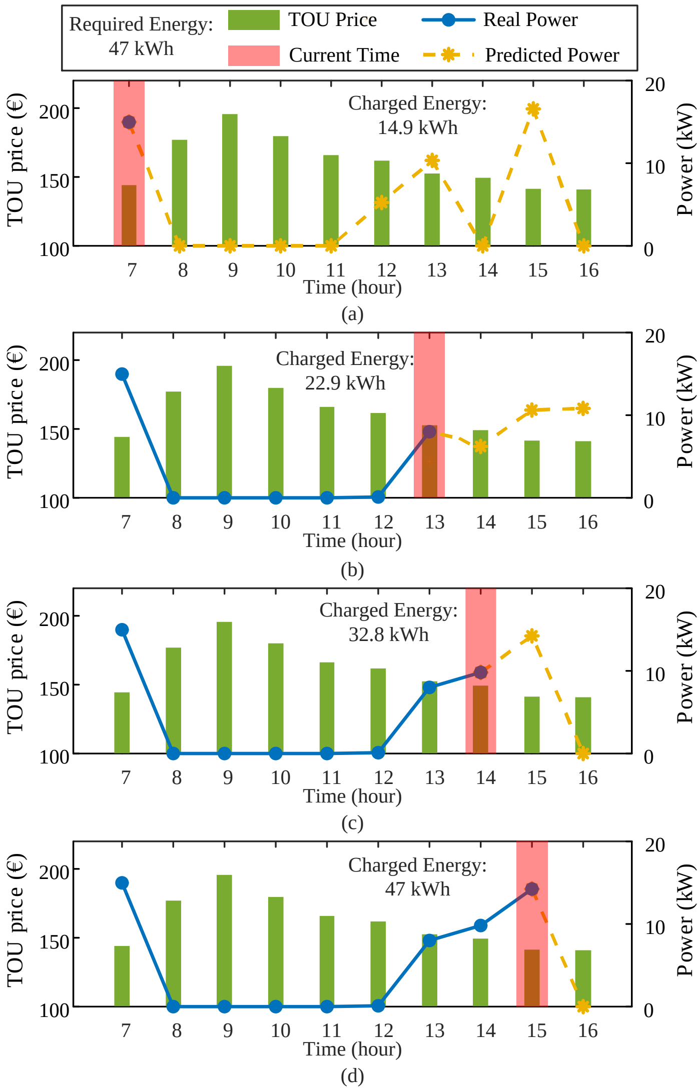


Figure 5.11. The actual charging power and the predicted charging power at different times of one EV (a) 7:00 (b) 13:00 (c) 14:00 (d) 15:00

5.4.3 Monte Carlo Analysis

The service capacity is restricted by the number of chargers, thus the Monte Carlo simulation is taken for further evaluation. Set the daily traffic volume to 100 and change the number of chargers. After 1000 times Monte Carlo simulations, the key performance indexes are shown in Figure 5.12. From Figure 5.12 (a), the smaller number of chargers provides lower total charging power. The total energy that the charging station can provide under SWP is the least. The DICS and SWR can provide as much power as FCFS. From the perspective of charging costs, shown in Figure 5.12 (b), FCFS is the uneconomic way to operate charging stations. The proposed DICS method greatly reduces the charging cost, which is as good as the ideal state SWR. According to Figure 5.12 (c) and (d), SWP is more economical when the charger number is small, because it completes less charging demand and leads to a higher dissatisfaction degree. However, when the charger number increases, SWP costs more than the proposed DICS. FCFS is the best scheduling method to ensure user satisfaction, but it is also the most expensive to charge. In comparison, the proposed DICS, which is remarkably close to the ideal state SWR, not only reduces charging costs but also keeps users' dissatisfaction within an acceptable range.

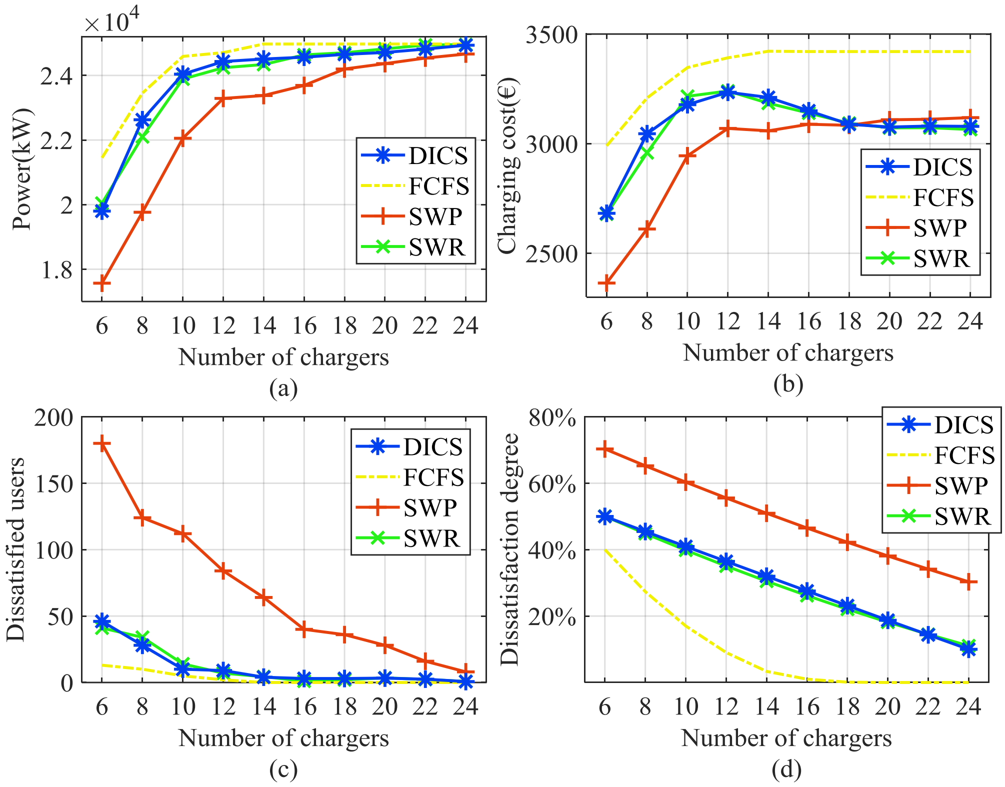


Figure 5.12. Mean value of the key performance indexes under different number of chargers (a) Total provided charging power (b) Total charging cots (c) Number of dissatisfied users (d) Dissatisfaction degree

Figure 5.13 shows the boxplot of different indexes under different numbers of chargers according to the Monte Carlo simulation when DICS is adopted. It can be seen that as the number of chargers increases, the results of charging power, charging cost, and dissatisfied users become more concentrated. Because the greater number of chargers brings greater scheduling flexibility, which improves the economy while making the results more concentrated. By contrast, also the average dissatisfaction degree reduced as the chargers increased, the Monte Carlo simulation results were still scattered. Because when the number of chargers is large, the number of dissatisfied users is small and arrived EVs are random, so the Monte Carlo results are often determined by a few special EVs (such as only one EV in the entire system that does not complete 80% of its charging requirement, so the dissatisfaction degree in this time is 80%). Therefore, we believe these results are acceptable.

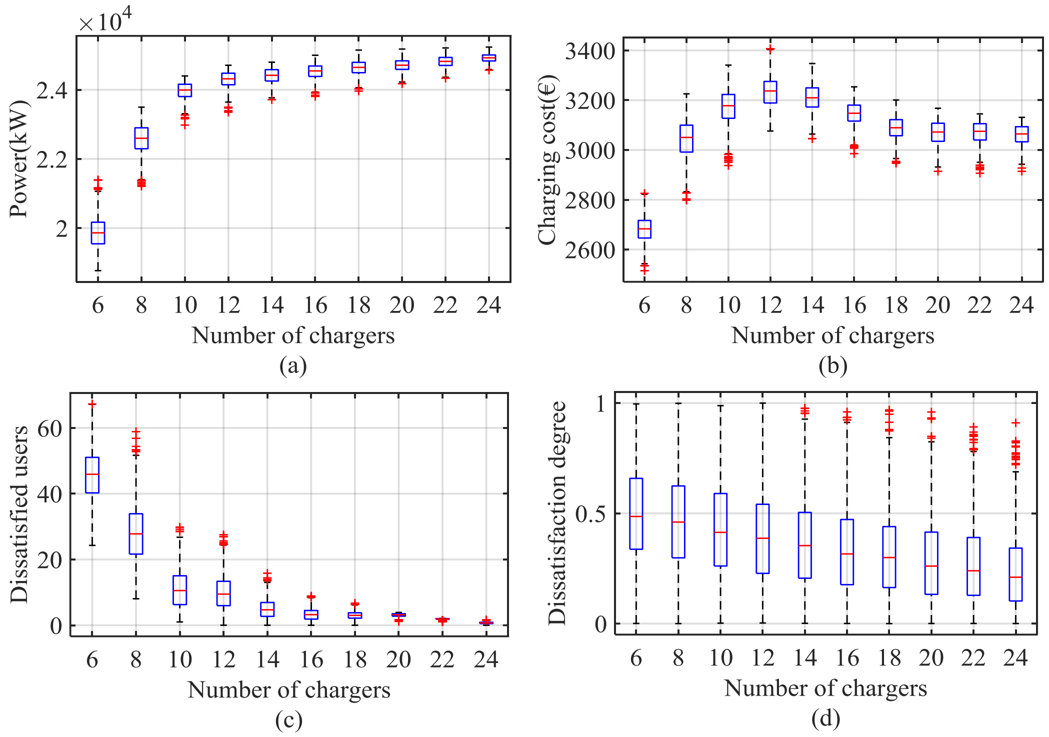


Figure 5.13. Monte Carlo simulation results of different indexes under different numbers of chargers when adopted DICS (a) Total provided charging power (b) Total charging cots (c) Number of dissatisfied users (d) Dissatisfaction degree

Since the battery degradation factor is taken into account in the proposed algorithm, the battery life performance improvement under Monte Carlo simulation is discussed. The scheduling without battery degradation (SWBD) method has been discussed in some previous works [133, 121]. Thus, the battery cost-saving rate of SWBD and DICS compared to FCFS is shown in Figure 5.14, together with the charging cost-saving rate. Obviously, with the number of chargers increasing, both two methods are more economical than FCFS. The charging cost under the SWBD is slightly less than that under the DICS, but there is nearly no positive impact on the EV's battery life. Because SWBD charges as much energy as possible when the TOU price is the lowest, which is not beneficial to the battery. In contrast, the DICS method can balance battery degradation and charging cost, and make a positive contribution to both battery performance and charging economy.

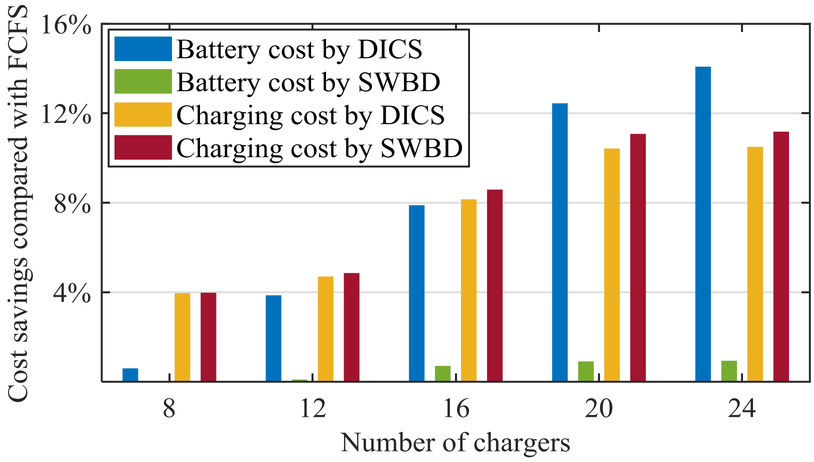


Figure 5.14. Battery and charging cost-saving rate of the proposed DICS and the SWB, N=100

5.5 Summary

To improve the scheduling operation economy of charging stations with limited charging facilities under the uncertainty of charging demand, a data-based intelligent charging scheduling method is proposed in this chapter. Based on historical traffic data, a neural network-based algorithm is adopted to predict the follow-up traffic flow and establish the estimated charging demand task. Through comprehensive consideration of estimated and real tasks, the optimization model considering charging cost, battery degradation, users' satisfaction, and limitation of charging facilities is established. With the introduced solving algorithm, the charging scheme is optimized for guiding chargers' operating. Real-time scheduling of charging stations is achieved by updating the neural network and charging task status. The CFO scheduling method is taken as the comparison to verify the forecasting effectiveness. Furthermore, four key performance indexes are introduced and compared among the proposed DICS method, FCFS, SWP, and SWR methods. In addition, the battery performance improvement compared with the SWBD is also illustrated. According to Monte Carlo simulation results, with the proposed DICS method the charging operators can not only achieve better economic performance as much as possible but also improve service completion rate through predictive algorithms and user satisfaction, which is better than other existing algorithms. The proposed DICS method is the scheduling approach for a single charging station. Therefore, in the future, the study on coordinated charging scheduling of multiple charging stations in the transportation and distribution network interaction system will be carried on. EV charging path planning based on traffic flow data will be considered, and the scheduling method that can reduce the impact of EV charging on the power grid will be formulated.

6 Collaborative EV Routing and Charging Scheduling Considering Power Distribution and Traffic Networks Interaction

Charging stations are often connected to the distribution network. As a large load with typical aging characteristics, the fluctuation of charging power of the charging station will bring a great impact to the distribution network. The increasing of electric vehicles (EVs) alleviates the faced environmental problems but brings challenges to the optimal operation of transportation network (TN) and distribution network (DN). However, most of the existing research works consider EV charging station assignment and navigation services in the TN separately from charging station power scheduling services in the DN. To overcome this research gap, this chapter proposes a collaborative optimal routing and scheduling (CORS) method, providing optimal routes to charging stations and designing optimized charging scheduling schemes for each EV.

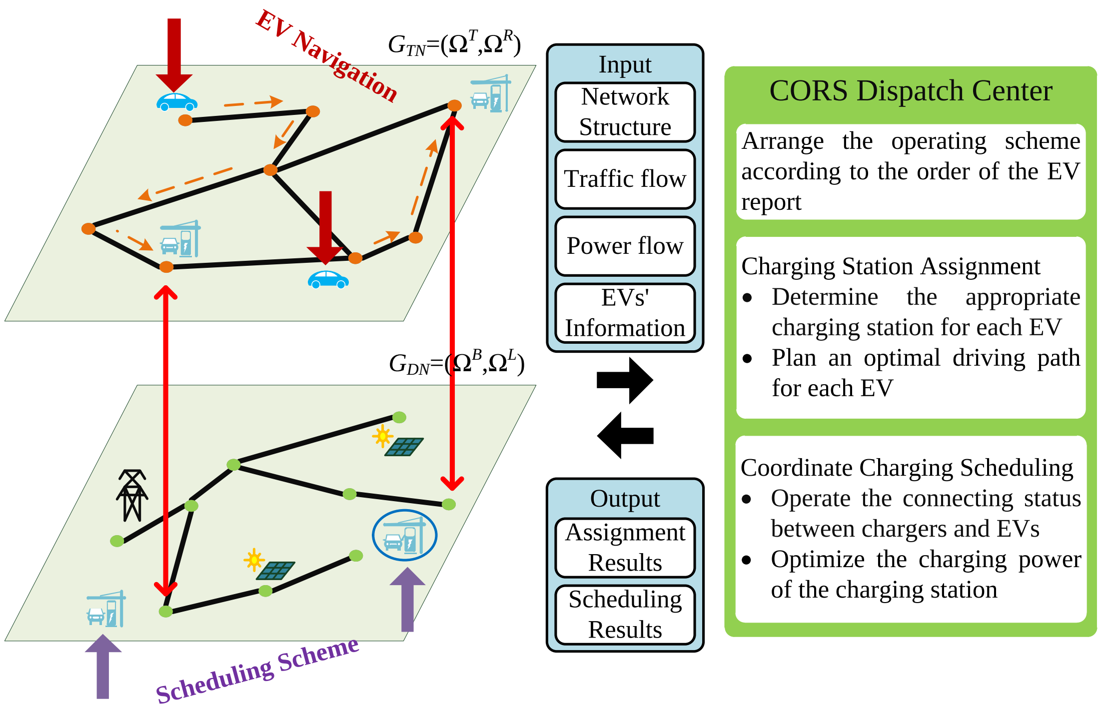


Figure 6.1. The framework of the proposed CORS approach

This chapter proposes a collaborative optimal routing and scheduling (CORS) method. The framework is shown in Figure 6.1. To which the EVs report charging requirements, the proposed algorithm arranges specific navigation and charging schemes for each EV in turn. The proposed CORS method can not only assign and route charging stations for EVs but also optimize the charging power based on the assigned charging stations. An optimization model that considers EV driving cost, electricity purchase cost, and battery degradation cost is proposed to find the routing and scheduling scheme with the least comprehensive cost. The charging facilities limitation in a charging station is also considered. In order to solve this complex optimization mode, we split the optimization model into the upper layer and lower layer optimization. The upper layer mainly decides the charging station assignment process including determining the charging station and planning the driving path. Meanwhile, the lower layer solves the coordinate charging scheduling scheme for the EV with the charging station assignment results from the upper layer. The modified distributed biased min consensus (DBMC) and generalized benders decomposition (GBD) methods are introduced as the solver.

6.1 Modeling of the Integrated Transportation-Distribution System

In the proposed CORS approach, the optimization objective is to minimize the overall operating costs, including the driving time consumption, electricity purchase cost, and battery degradation cost. When an EV has charging demand, the driver can report instructions to the dispatch center through the mobile devices. After that, the dispatch center plans the optimal route to the charging station and then performs power dispatch for the EV according to the actual traffic and power grid status.

In order to provide charging service for EV users, corresponding charging demand information of each EV is required. When the *n*-th EV user has a charging demand and reports to the dispatch center, record the report time as t_n^r. The departure time t_n^d, initial and required battery state of charge (SOC) value S_n^{ini} and S_n^{req}, and battery capacity Cap_n also need to be provided. Let $\Omega_n^{E'}$ be the set of unprocessed charging information of EV *n*, which is reported by the EVs with charging demands in the transportation network:

$$\Omega_n^{E'} = \left\{ t_n^r, t_n^d, S_n^{ini}, S_n^{req}, Cap_n \right\} \tag{6.1}$$

Thus, the required energy of *n*-th EV can be obtained:

$$E_n^{req} = \left(S_n^{req} - S_n^{ini} \right) Cap_n \tag{6.2}$$

The following charging station assignment process will distribute appropriate charging stations *k* and calculate corresponding arrival time t_n^a for each individual EV.

In addition, the expected charging time t_n^e set by users cannot be shorter than the minimum charging time, which is:

$$t_n^e \geq E_n^{req} \big/ P_{\max}^{ch} \tag{6.3}$$

The following section will describe the charging station assignment process of how to distribute appropriate charging stations k and calculate corresponding arrival time t_n^a for each individual EV. Thus, the departure time of EV n can be obtained:

$$t_n^d = t_n^a + t_n^e \tag{6.4}$$

Let Ω_n^E be the set of processed charging information of EV n that needed to participate in scheduling, which can be expressed as the union between the unprocessed set and results of the station assignment process: $\Omega_n^E=\{\Omega_n^{E'}, E_n^{req}, t_n^a, t_n^d, k\}$. Ω^E represents the set of EV charging *Task* that $\Omega^E=\{\Omega_1^E, \Omega_2^E,\ldots, \Omega_n^E\}$. For each reported EV, formulate the corresponding charging station allocation and scheduling plan according to the order of the report, let T_n be the optimal interval of EV n, which is from t_n^r to t_n^d. Notice that users can achieve different demands of charging services through the setting of the charging information. For example, users with urgent charging requirements can set their excepted charging time t_n^e to a smaller value (the minimum value should satisfy (4)), so the dispatch center will finish their charging as soon as possible. In contrast, users with economic charging needs can set the relatively longer excepted charging time t_n^e. A longer scheduling period brings more flexibility that can benefit both charging cost and battery degradation cost.

6.1.1 Driving Consumption Model

The graph theory is adopted to represent the TN, $G_{TN}=(\Omega^T, \Omega^R)$, where Ω^T denotes the set of intersections and Ω^R is the set of roads. The origin-destination matrix is established to indicate the relationship between the intersections of the TN, where r and s denote the origin and destination intersections respectively. A_{uv} denotes the road between intersection u and v. For an EV intended to charge, the driver starts from one origin intersection r to the destination intersection s, and the EV will be charged during the travel. In the TN, the traffic flow varies in different time periods of one day. Dynamic road congestion situations can change the optimal path to reach the destination for each driver[55]. The travel time of different roads can be modeled by the latency function:

$$t_{uv}(\eta_{uv}(t)) = t_{uv}^0 \left[1 + 0.15 \left(\frac{\eta_{uv}(t)}{c_{uv}} \right) \right], \quad u,v \in \Omega^T, A_{uv} \in \Omega^R \tag{6.5}$$

where u and v represent two connected intersections in TN; t_{uv}^{0} denotes the free flow traffic time on the road A_{uv}; $\eta_{uv}(t)$ is the traffic flow at time t and c_{uv} is the capacity of road A_{uv}. Thus, the latency times for roads are also related to the traffic flow at different time slots. When driving from the start traffic node u to the end traffic node v, there will also be a time difference. Therefore, in this chapter, when calculating the real-time traffic flow, the time when an EV at the start node u is used as the benchmark.

Let Ω_{rs}^{T} denotes one path from origin s to destination r, where Ω_{rs}^{T} ={ A_{ru}, A_{uv},…, A_{vs}}. $\Omega^{T}(k)$ represents the traffic node installed with charging station k; Let k_n be the charging station assigned for EV n, $g\in\Omega^{T}(k_n)$ be the traffic node installed with charging station k_n. Thus, the driving cost CT_n for EV n from intersection s to charging station at r can be obtained as:

$$CT_n = \sum_{A_{uv}\in\Omega_{rg}^{R}} \mu t_{uv}(\eta_{uv}) + \sum_{A_{uv}\in\Omega_{gv}^{R}} \mu t_{uv}(\eta_{uv}), \quad u,v\in\Omega^{T}, g\in\Omega^{T}(k_n) \tag{6.6}$$

where μ is the monetary price of time, which is set as 10\$/h. When the EV user intends to charge and sends the charging information to the dispatch center, the arranged charging station should be within the driving range of its remaining power. Assume the energy consumption is a linearly decreasing function [42], the charging station assignment should satisfy:

$$S_n^{ini} E_c Cap_n \geq d_{rg} \quad , r\in\Omega^{T}, u\in\Omega^{T}(k_n) \tag{6.7}$$

where r is the departure node of EV n; g is the destination node with charging station; d_{rg} denotes the distance between node r and g; E_c means the electricity consumption per km, which is set as 7 km/kWh [28].

6.1.2 Driving Consumption Model

Similarly, the DN could also be represented by graph theory, $G_{DN}=(\Omega^{B}, \Omega^{L})$, where Ω^{B} and Ω^{L} denote the set of buses and the set of lines. Let L_{ij} denote the power line connecting bus i and j, $\pi^{B}(i)$ represents the collection of buses stemming from bus i. The constraints of the AC optimal power flow is given [134]:

$$P_{ij,t} + P_{j,t}^{gen} - r_{ij} I_{ij,t}^{2} = \sum_{z\in\pi^{B}(j)} P_{jz,t} + P_{j,t}^{load} + P_{j,t}^{cs}, \quad \forall L_{ij}\in\Omega^{L} \tag{6.8}$$

$$Q_{ij,t} + Q_{j,t}^{gen} - x_{ij} I_{ij,t}^{2} = \sum_{z\in\pi^{B}(j)} Q_{jz,t} + Q_{j,t}^{load}, \quad \forall L_{ij}\in\Omega^{L} \tag{6.9}$$

$$V_{i,t}^{2} - V_{j,t}^{2} = 2\left(r_{ij}P_{ij,t} + x_{ij}Q_{ij,t}\right) - \left(r_{ij}^{2} + x_{ij}^{2}\right) I_{ij,t}^{2}, \quad \forall L_{ij}\in\Omega^{L} \tag{6.10}$$

$$V_{i,t}^{2} I_{ij,t}^{2} = P_{ij,t}^{2} + Q_{ij,t}^{2}, \quad \forall L_{ij}\in\Omega^{L} \tag{6.11}$$

$$\underline{P}_j^{gen} \le P_j^{gen} \le \overline{P}_j^{gen}, \quad \forall j \in \Omega^B \tag{6.12}$$

$$\underline{Q}_j^{gen} \le Q_j^{gen} \le \overline{Q}_j^{gen}, \quad \forall j \in \Omega^B \tag{6.13}$$

$$\underline{V}_j \le V_j \le \overline{V}_j, \quad \forall j \in \Omega^B \tag{6.14}$$

$$\sqrt{P_{ij,t}^2 + Q_{ij,t}^2} \le S_{ij,t}, \quad \forall L_{ij} \in \Omega^L \tag{6.15}$$

The equations (6.8)-(6.11) describe the nodal power balance, where the subscript t represents the value at time t. r_{ij} and x_{ij} mean the impedance and reactance of line L_{ij}. $V_{j,t}$ is the voltage at bus j and $I_{ij,t}$ is the current on line L_{ij}. $P_{ij,t}$ and $Q_{ij,t}$ denote the active and reactive power on line L_{ij}. $P_{j,t}^{gen}$ and $Q_{j,t}^{gen}$ are the active and reactive power output of generation at bus j. $P_{j,t}^{load}$ and $Q_{j,t}^{load}$ represent the active and reactive power load at bus j. $P_{j,t}^{cs}$ is the total charging power of a charging station located at bus j at time slot t. Constraints (6.12)-(6.15) represent the active and reactive power bounds of generations, as well as the voltage magnitude bounds at bus j. (6.15) is the apparent power flow constraint on power line L_{ij}.

The charging of EVs affects the state of the distribution network, which is the controllable variable in the proposed method. After the charging stations assignment process is finished, the arrival information of the EVs will be allocated to different charging stations, then the coordinate charging scheduling algorithm will be implemented. The flexibility of existing charging facilities is fully tapped and a detailed charger operating scheme can be provided. Let $\Omega^E(k)$ be the set of EVs allocated to charging station k for charging, the charging power of charging station k located at bus j at time slot t is:

$$P_{j,t}^{cs} = \begin{cases} \sum\limits_{n \in \Omega^E(k)} a_{n,t} P_{n,t} & \forall j \in \Omega^B(k) \\ 0 & \forall j \notin \Omega^B(k) \end{cases} \tag{6.16}$$

where $a_{n,t}$ is the binary variable that represents the connecting status of each EV by considering the limitation of chargers, which is:

$$a_{n,t} = \begin{cases} 1 & \text{if } \; n \in \Omega^E(k_n) \text{ connected to a charger at } t \\ 0 & \text{otherwise} \end{cases} \tag{6.17}$$

Let $M(k_n)$ be the number of chargers in charging station k_n, due to the charging station service capability, only $M(k_n)$ EVs can be charged at the same time:

$$\sum_{n \in \Omega^E(k_n)} a_{n,t} \le M_k(k_n) \quad \forall k \in \Omega^C \tag{6.18}$$

Since EVs cannot connect to chargers when they were not at the charging station, the following constraint should be satisfied:

$$a_{n,t} = 0 \quad ,\text{if } \forall t \notin \left[t_n^a, t_n^d\right],\ \forall n \in \Omega^E\left(k_n\right) \tag{6.19}$$

The charging power cannot exceed the maximum charging power $P_{\max}$:

$$P_{n,t} \le P_{\max} \quad ,\forall n \in \Omega^E \tag{6.20}$$

The EV cannot be charged when not connected to a charger:

$$P_{n,t} = 0 \quad ,\text{if } a_{n,t} = 0, \forall n \in \Omega^E \tag{6.21}$$

The energy requirement of each EV should be satisfied:

$$\sum_{t=t_n^a}^{t_n^d} \Delta t P_{n,t} = E_n^{req} \quad ,\forall n \in \Omega^E \tag{6.22}$$

Since the maximum charging power that each charger can provide is limited, set to P_{max}^{ch}, the number of chargers in the charging station k is M_k, so the total charging power should follow $P_{j,t}^{cs} \le M_k P_{max}^{ch}$. Therefore, in the charging station assignment model, the capacity limit should also be considered. Due to the flexibility of scheduling, the remaining charging margin of the station should satisfy the EVs' energy demand during their dwell time. Assuming that the expected charging power is superimposed by $n \in \Omega^E(k)$ EVs staying in the station k. For the newly arrived EV n+1, the charging station assignment must follow:

$$E_{n+1}^{req} + \Delta t \sum_{t=t_{n+1}^a}^{t_{n+1}^d} P_{j,t}^{cs} \le \Delta t\left(t_{n+1}^d - t_{n+1}^a + 1\right) M_k P_{\max}^{ch} \tag{6.23}$$

The objective function of the AC optimal power flow (OPF) problem is formulated [57]:

$$CD_n = \min \sum_{t \in T_n} \left[\sum_{j \in \Omega^B} \left[a_j \left(P_{j,t}^{gen}\right)^2 + b_j P_{j,t}^{gen} \right] + \lambda_t \sum_{j \in \Omega^B(1)} P_{1j,t} \right] \tag{6.24}$$

The energy cost in the distribution grid CD_i includes two parts. The first part is the generation cost and the second part is the purchasing cost for buying electricity from the main grid. This chapter focuses on the impact of charging power on the grid, so the controllable components in the distribution network only consider the charging power of EVs. The generators in the distribution network are set as photovoltaic (PV) sources, so the operating cost can be ignored. λ_t is the electricity price at time t. $P_{1j,t}$ is the purchasing power derived from bus 1, which can be modeled as a dummy generator at bus 1. After assigning a charging station to this user, the charging demand $P_{j,t}^{cs}$ of the charging station will be updated by (6.16).

Notice that when power scheduling is performed on the n-th EV, the EV reported before it has completed the charging station assignment and optimal power scheduling process, which means $\{a_{1,t},\cdots,a_{n-1,t}\}$ and $\{P_{1,t},\cdots,P_{n-1,t}\}$ are fixed.

6.1.3 Battery degradation model

An appropriate charging method can reduce battery degradation and improve battery life. The LiFePO4 lithium-ion is a topical and widely used battery material in automobile industries, with more thermal and chemical stability physical characteristics [76]. A degradation cost model for LiFePO4 battery cells is developed in [71], which is related to the EVs' charging power $P_{n,t}$ at time slot t and its battery capacity Cap_n:

$$\Phi_n\left(P_{n,t}\right) = \alpha_1 (P_{n,t}/Cap_n)^2 + \alpha_2\, P_{n,t}/Cap_n + \alpha_3 \tag{6.25}$$

where α_1, α_2 andα_3 are parameters. Specifically, based on the price of the battery cell ($/kWh) and the battery's internal parameters such as voltage, current, and SoC, all of these three parameters can be determined. The calculating of the parameters is given in [127, 71]. Thus, the battery degradation cost can be calculated:

$$CB_n = \min \sum_{t \in T_n} a_{n,t} \Phi_n\left(P_{n,t}\right) \tag{6.26}$$

An appropriate charging method can reduce battery degradation and improve battery life. Setting longer excepted charging time t_n^e allows EVs to avoid high-power charging in a short period of time, which will bring higher degradation to the battery. Users can set it according to their own charging requirements.

6.1.4 Collaborative optimal routing and scheduling model

The spatial and temporal characteristics of the TN and the DN impact the assignment and scheduling efficiency of the EV. Therefore, for every EV with charging requirement, we orderly establish the comprehensive optimization model that considers driving cost, charging cost, and battery degradation cost.

$$f\left(k_n, \boldsymbol{P}_n, \boldsymbol{a}_n\right) = \min_{k_n, a_{n,t}, P_{n,t}} \sum_{t \in T_n} \left(CT_n + CD_n + CB_n\right) \tag{6.27}$$

subject to:

Constraints of charging station assignment (6.7), (6.23)

Constraints of power grid (6.8)-(6.15)

Constraints of provided charging power (6.16)-(6.22)

6.2 CORS Solving Algorithm and Specific Implementing Process

It can be found that the established model is a very complex problem, including shortest path planning and optimal power flow solution containing integer decision variable k_n, binary decision variables $a_{n,t}$, and decision variable $P_{n,t}$. Let $\boldsymbol{a}_n=\{a_{n,t}|t\in T_n\}$ be the vector of binary decision variables and $\boldsymbol{P}_n=\{P_{n,t}|t\in T_n\}$ be the vector of decision variables. By deconstructing the optimization model, we can find that the diving consumption CT_n is only affected by k_n. Meanwhile, the different assignment results k_n correspond to their respective charging station scheduling results $\boldsymbol{a}_n$ and $\boldsymbol{P}_n$. In contrast, when the value of k_n is fixed, the optimization model (6.27) becomes a mixed-integer nonlinear programming (MINLP) $h(\boldsymbol{P}_n,\boldsymbol{a}_n)$ (deformation of $f(k_n,\boldsymbol{P}_n,\boldsymbol{a}_n)$ when CT_n is regarded as a constant), which usually solved by the generalized benders decomposition (GBD) [135] algorithm.

Therefore, when only k_n is considered, we can equate it to the shortest path planning problem, and then find the shortest path to each different charging station and corresponding arrival time. Then, by solving the problem model $h(\boldsymbol{P}_n,\boldsymbol{a}_n)$, we can obtain the optimal scheduling method under all different charging station assignment k_n, and then find out the optimal charging station assignment plan k_n with its corresponding power scheduling scheme $\boldsymbol{a}_n$ and $\boldsymbol{P}_n$.

Therefore, the solving algorithm is divided into two layers. The upper layer solves the charging station assignment problem that regards k_n as the decision variable. The lower layer considers the k_n as a fixed value and solves the $\boldsymbol{a}_n$ and $\boldsymbol{P}_n$. The solving technique of these two levels are introduced separately in the next chapters, and the combined solving approach is comprehensively introduced. In addition, the detailed application process of the proposed CORS in the real situation is also introduced.

6.2.1 Charging station assignment upper layer solver based on distributed biased min consensus

Assigning and navigating an appropriate charging station for EVs is the shortest path optimization problem. Each EV has an individual optimal path and charging station selections, which are determined not only by the time-series traffic flow but also by the charging station status. Therefore, inspired by [136, 55], the distributed biased min-consensus (DBMC) algorithm that can achieve the navigation results in a short time period is adopted and corresponding adjustments are made to the characteristics of our model. For the case that EV n is assigned to k_n, the weight of each edge of the graph G_{TN} can be obtained by:

$$b_{uv}^{n}=\begin{cases}\mu t_{uv}(\eta_{uv}) & ,u\notin\Omega^{T}(k_n),v\in\pi^{T}(u)\\ \mu t_{uv}(\eta_{uv})+\gamma_{uv}^{n} & ,u\in\Omega^{T}(k_n),v\in\pi^{T}(u)\end{cases} \tag{6.28}$$

$$\gamma_{uv}^{n}=\begin{cases}\inf & ,\Omega_n^E\notin \text{constriant }(5),(21)\\ 0 & ,\Omega_n^E\in \text{constriant }(5),(21)\end{cases} \tag{6.29}$$

where $\Omega^T(k)$ is the set of traffic nodes installed with charging station $k\in\Omega^C$. $\pi^T(u)$ is the set of neighboring nodes of traffic node u. γ_{uv}^{n} is the auxiliary parameter, indicating whether the planned path for EV n meets the remaining battery capacity constraint (6.7) and charging station margin constraint (6.23).

For each EV user n, the distributed biased min consensus algorithm is implemented to find the optimal driving path with the minimum driving time:

$$\begin{cases}C_u(q+1)=C_u(0) & ,u\in\Omega^{T}(k)\\ C_u(q+1)=\min_{v\in\pi^{T}(u)}\{C_v(q)+b_{uv}^{n}\} & ,u\notin\Omega^{T}(k)\end{cases} \tag{6.30}$$

where $C_u(q)$ is the state value of node u and k means the number of iterations. The traffic nodes with charging stations are the leader nodes while the others are follower nodes.

Then, all nodes of the graph globally and asymptotically converge to the equilibrium point C_u^*, which satisfies the following equation:

$$C_u^{*}=\begin{cases}C_u(0) & ,u\in\Omega^{T}(k)\\ \min_{v\in\pi^{T}(u)}\{C_v^{*}+b_{uv}^{n}\} & ,u\notin\Omega^{T}(k)\end{cases} \tag{6.31}$$

The proofs of the optimality of (6.30) and the convergence of (6.31) are described in [136, 137, 55]. Then, after the equilibrium point of each traffic node is found, the parent nodes can be obtained:

$$\mathcal{P}(u)=\begin{cases}\varnothing & ,u\in\Omega^{T}(k)\\ \arg\min_{v\in\pi^{T}(u)}\{C_v+b_{uv}^{n}\} & ,u\notin\Omega^{T}(k)\end{cases} \tag{6.32}$$

Then, the optimal navigation path to the determined charging station is discovered by finding the parent nodes in a recursive manner. Let $\Omega_{rs}^{T}(n)=\{r\rightarrow u\rightarrow\cdots g\rightarrow\cdots v\rightarrow s\}$ be the optimal route for EV n form origin r to the destination s while charging at $g\in\Omega^T(k_n)$, thus the driving cost under this k_n can be obtained:

$$CT_n=\sum_{u,v\in\Omega_{rs}^{T}(n)}\mu t_{uv}(\eta_{uv}) \tag{6.33}$$

As mentioned above, the time when an EV at the start node u is used as the benchmark when calculating the real-time traffic flow $\eta_{uv}(t)$. However, the calculated driving time by (6.3) can be any value, but the traffic flow data provided in this chapter is based on the time slot's resolution. Therefore, the real-time traffic flow used when calculating from u to v depends on the traffic flow of the closest time slot when the vehicle is at node u, which can be formulated as:

$$\eta_{uv}(t)=\begin{cases}\eta_{uv}(t_{slot}^{bef}) & if\left|t-t_{slot}^{bef}\right|\le\left|t-t_{slot}^{aft}\right|\\ \eta_{uv}(t_{slot}^{aft}) & if\left|t-t_{slot}^{bef}\right|\ge\left|t-t_{slot}^{aft}\right|\end{cases} \tag{6.34}$$

where t_{slot}^{bef} means the nearest time slot before t, t_{slot}^{aft} means the nearest time slot after t, and t right here represents the time when EV at traffic start node u.

Let $\Omega_{rg}^{T}(n)=\{r\rightarrow u\rightarrow\cdots g\}$ be the optimal route for EV n from origin r to the node of charging station $g\in\Omega^{T}(k_n)$, thus the arrival time can be computed:

$$t_n^a=\left\lceil t_n^r+\sum_{u,v\in\Omega_{rg}^{T}(n)}t_{uv}\left(\eta_{uv}\right)\right\rceil_{slot} \tag{6.35}$$

where $\lceil * \rceil_{slot}$ means the function to find the nearest time slot after *.

The power scheduling part is also based on each time slot ($P_{n,t}$ is the charging power of EV n at time slot t), but the actual calculated arrival time could be at any time. By considering the energy requirement constraint (6.22), the energy requirement can be satisfied during the power scheduling period from t_n^a to t_n^d. However, if the actual stay time of the EV is shorter than the power scheduling period, it may cause incomplete charging. In contrast, if we postpone the arrival time t_n^a to the next time slot, the power scheduling period from t_n^a to t_n^d will be at least shorter than the actual stay time of the EV, which will also satisfy the energy requirement during the actual stay time of the EV. Therefore, this chapter postpones the arrival time t_n^a to the next time slot, which can leave a margin for EV scheduling. Equation (6.35) indicates that the arrival time t_n^a for power scheduling will be the nearest time slot after the actual calculated arrival time.

6.2.2 Coordinate charging scheduling Lower layer solver based on generalized benders decomposition

According to the previous discussion, each fixed k_n value corresponds to an MINLP problem $h(\boldsymbol{P}_n,\boldsymbol{a}_n)$ which can be solved by the GBD algorithm. Here, define the variable $\boldsymbol{z}=[\boldsymbol{P}_n,\boldsymbol{a}_n]$.

To adopt GBD, the optimization problem $h(\boldsymbol{P}_n,\hat{\boldsymbol{a}}_n)$ should be a convex optimization problem with variable $\boldsymbol{P}$, where $\hat{\boldsymbol{a}}$ denotes the vector of fixed $a_{n,t}$ to any feasible region. The object is convex if the Hessian matrix of $h(\boldsymbol{P}_n,\hat{\boldsymbol{a}}_n)$ was positive. Equation (6.36) and (6.37) describes the first-order and second-order partial derivatives of $h(\boldsymbol{P}_n,\hat{\boldsymbol{a}}_n)$.

$$
\begin{aligned}
\frac{\partial h\left(P_{n,t},\hat{a}_{n,t}\right)}{\partial P_{n,t}} &= \frac{\partial}{\partial P_{n,t}}\sum_{t\in T_n}\left[\hat{a}_{n,t}\Phi_n\left(P_{n,t}\right)+CD_n+CT_n\right] \\
&= \hat{a}_{n,t}\left(\frac{2\alpha_1}{Cap_n}P_{n,t}+\frac{\alpha_2}{Cap_n}\right)
\end{aligned}
\tag{6.36}
$$

$$
\begin{aligned}
\frac{\partial h^2\left(P_{n,t},\hat{a}_{n,t}\right)}{\partial P_{n,t}^2} &= \frac{\partial}{\partial P_{n,t}}\left[\hat{a}_{n,t}\left(\frac{2\alpha_1}{Cap_n}P_{n,t}+\frac{\alpha_2}{Cap_n}\right)\right] \\
&= \begin{cases} \hat{a}_{n,t}\dfrac{2\alpha_1}{Cap_n} & \text{, diagonal elements} \\ 0 & \text{, off-diagonal elements} \end{cases}
\end{aligned}
\tag{6.37}
$$

It can be found that the Hessian matrix is a diagonal matrix. For the values on the left side of the diagonal elements: α_1 is a constant related to the battery, which is larger than 0 according to [71]; $\hat{a}_{n,t}$ is the fixed binary value; Cap_n is the battery capacity that can only be a positive value. Therefore, the values of the second-order partial derivatives of $h(\boldsymbol{P}_n,\hat{\boldsymbol{a}}_n)$ are always greater than or equal to zero, so the Hessian matrix is positive semi-definite.

Algorithm 6.1: GBD solving process for the optimal scheduling model

---

Start Algorithm
Input: Ω^E, G_{TN}, G_{DN}, Ω^C, $P_{\max}$
Step 1: Number of iterations: $q\leftarrow 0$; Lower boundary: $LB_0\leftarrow -\infty$; Upper boundary: $UB_0\leftarrow +\infty$; $\hat{\boldsymbol{a}}_0\in$(24)-(25) is the arbitrary but fixed vector
Step 2: $LB_q < UB_q$ **do**
Step 2: Primal problem:
  min $h(\boldsymbol{P}, \hat{\boldsymbol{a}}_q)$
  s.t. $g(\boldsymbol{P}, \hat{\boldsymbol{a}}_q)\leq 0$
 if *Primal* is *feasible*
  Solve the relaxed problem:
   min $L(\boldsymbol{P},\hat{\boldsymbol{a}}_q,\boldsymbol{u})= h(\boldsymbol{P},\hat{\boldsymbol{a}}_q)+\boldsymbol{u}^{\mathrm{T}}g(\boldsymbol{P},\hat{\boldsymbol{a}}_q)$
  Obtain: $\{\boldsymbol{P}_q, \boldsymbol{u}_q\}\leftarrow\{\boldsymbol{P}^*, \boldsymbol{u}^*\}$
  Update: $UB_q\leftarrow\min\{UB_q, h(\boldsymbol{P}_q,\hat{\boldsymbol{a}}_q)\}$
  Add cut: $h \geq L(\boldsymbol{P}_q,\hat{\boldsymbol{a}}_q,\boldsymbol{u}_q)+\nabla_a{}^T L(\boldsymbol{P}_q,\hat{\boldsymbol{a}}_q,\boldsymbol{u}_q)\,(\boldsymbol{a}- \hat{\boldsymbol{a}}_q)$
 else
  Solve the new primal problem:
   min s
   s.t. $g(\boldsymbol{P}, \boldsymbol{a}) - s\leq 0$; $s\geq 0$
  Obtain: $\{\boldsymbol{P}_q, \boldsymbol{u}_q\}\leftarrow\{\boldsymbol{P}^*, \boldsymbol{u}^*\}$
  Update: $UB_q \leftarrow UB_{q-1}$
  Add cut: $0 \geq \boldsymbol{u}_q{}^T\,[g(\boldsymbol{P}_q, \hat{\boldsymbol{a}}_q)+ \nabla_a{}^T g(\boldsymbol{P}_q, \hat{\boldsymbol{a}}_q)\,(\boldsymbol{a}- \hat{\boldsymbol{a}}_q)]$
 end if
Step 3: Solve master problem:
  min $h(\boldsymbol{P}_q,\boldsymbol{a})$
  s.t. cuts
 Obtain: $\{h_q,\hat{\boldsymbol{a}}_{q+1}\}\leftarrow\{h^*,\boldsymbol{a}^*\}$
 Update: $LB_q \leftarrow f_q$
Step 4: **if** $LB_q < UB_q$
  $q\leftarrow q+1$
  jump to **Step 2**
 else
  Problem convergence
  Output: $\{\boldsymbol{P}_q, \boldsymbol{u}_q, h_q\}$
 end if
End Algorithm

In constraints, since the k_n is fixed, the constraints, (6.7) and (6.23), of charging station assignment can be ignored. Among the remaining constraints, the nonconvex situation is caused by (6.11), which can be relaxed as [138]:

$$V_{i,t}^2 I_{ij,t}^2 \geq P_{ij,t}^2 + Q_{ij,t}^2,\quad \forall L_{ij}\in\Omega^L \tag{6.38}$$

Accordingly, the formulated convex optimization problem when charging station assignment k_n is fixed can be obtained:

$$\min h(\boldsymbol{a}_n, \boldsymbol{P}_n) = \min_{a_{n,t}, P_{n,t}} \sum_{t \in T_n} (CT_n + CD_n + CB_n) \tag{6.39}$$

s.t. (6.8)-(6.10), (6.12)-(6.22), (6.38)

Let $g(\boldsymbol{P},\boldsymbol{a}) \leq 0$ be the set of constraints of the optimization model (6.39), the detailed solving process is shown in Algorithm 6.1, where $\boldsymbol{u}$ is the vector of Lagrange multiplier and s is the introduced relaxation variable. Combining the charging station assignment results in the previous chapter and the charging scheduling method in this chapter, the collaborative operation of TN and DN are obtained.

6.2.3 Comprehensive solving algorithm and real-time operation mode

To better illustrate the implementation of the proposed CORS, the detailed solving and operating process is shown in Figure 6.2. The state of the system is updated as a cycle is executed. According to the order of EVs report, the specific routing and charging schemes for each EV are designed in turn in every cycle. First, the algorithm will update the status of the TN and DN based on the CORS results of the previous EV $n-1$. When an EV n reported its charging demand $\Omega_n^{E'}$, the travel distance constraint (6.7) and the remaining capacity constraint (6.23) can be obtained, then the corresponding weight of each edge of the graph G_{TN} can be computed by (6.28) and (6.29). Next, compare the optimal result (6.27) under all the different charging station selection conditions. By activating the DBMC algorithm, to get the optimal route to the charging station k_n for EV n and the corresponding driving cost CT_n can be found. Then the time t_n^a when EV n arrived at the charging station k_n is found by (6.35), with its corresponding power scheduling period from t_n^a to t_n^d. Thereby, solve the coordinate charging scheduling scheme under this k_n condition by Algorithm 1, and obtain the time-series connecting status $\boldsymbol{a}_n$ and charging power $\boldsymbol{P}_n$ of EV n. Meanwhile, the electricity purchase cost and battery degradation cost are also computed. By comparing the driving, electricity purchase, and battery degradation costs under all different k_n conditions, the k_n with the lowest cost is selected as the assigned charging station for EV n, and the corresponding scheduling scheme $\boldsymbol{a}_n$ and $\boldsymbol{P}_n$ are adopted for optimal charging after it arrives at the corresponding charging station. Finally, update the TN and DN situation according to the CORS results of EV n for the next execution cycle.

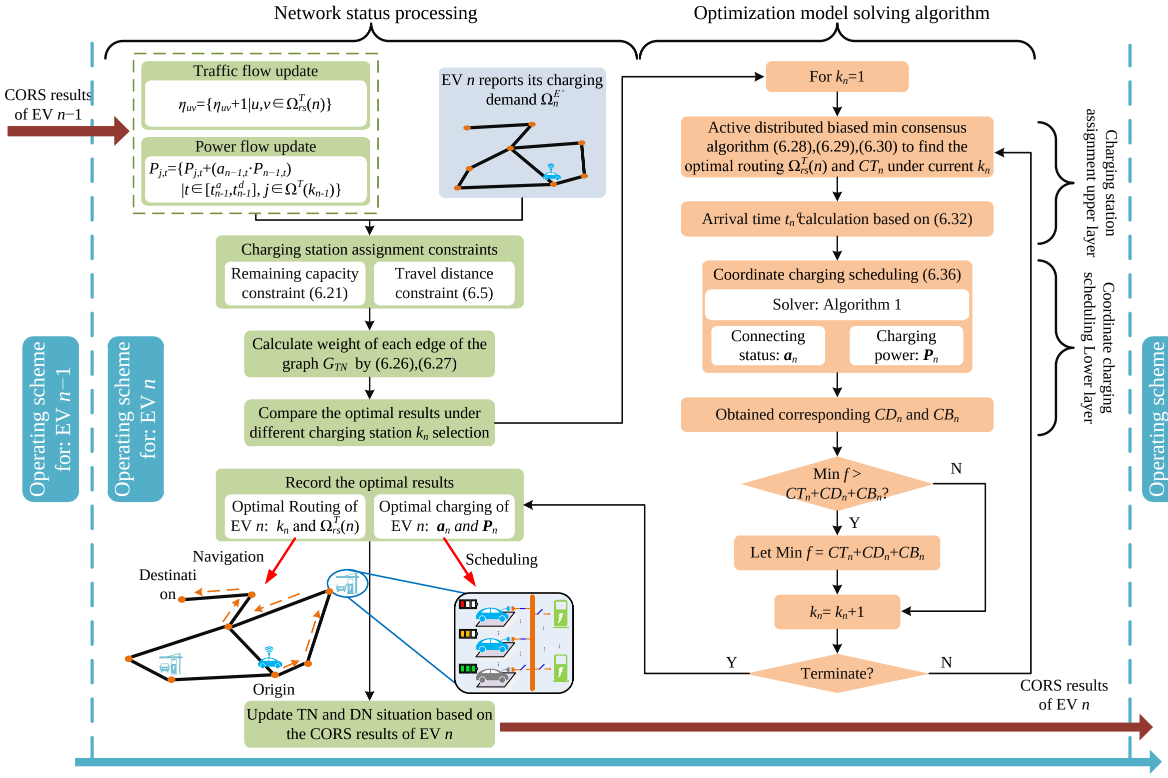


Figure 6.2 The flow chart of the proposed collaborative EV routing and charging scheduling process

This method will arrange the specific routing and charging scheduling method for each EV that uploads its charging demand, and continuously update the grid status with the CORS results of finished EVs to adjust the operation plan of the subsequent EVs. Therefore, it not only avoids the overcrowding of EVs in some charging stations to reduce the insufficient scheduling margins, which leads to an increase in charging costs but also increases the utilization rate of charging facilities.

6.3 Case Study

6.3.1 Case Overview and Basic Settings

In this chapter, we consider the Nguyen–Dupuis TN interaction with IEEE 33-bus DN to illustrate the proposed routing and scheduling method. Nguyen–Dupuis network is a traffic network model developed by [139] and is widely used in various studies related to transportation. The parameters and traffic flow of TN are adopted in [57] and appropriate adjustments are made. The top half of Figure 6.3 displays the topology of the TN with the installation location of the charging station. The basic data of the original IEEE 33-bus network can be found in [140], with extra distributed generations (DGs) and charging stations, the topology of the DN is shown in the bottom half of Figure 6.3. In total there are 5 charging stations in the case study and let the number of in charging stations be the same: M_k=6, the maximum charging power provided by each charger is P_{max}=45kW. The time slot duration is set as 15 minutes.

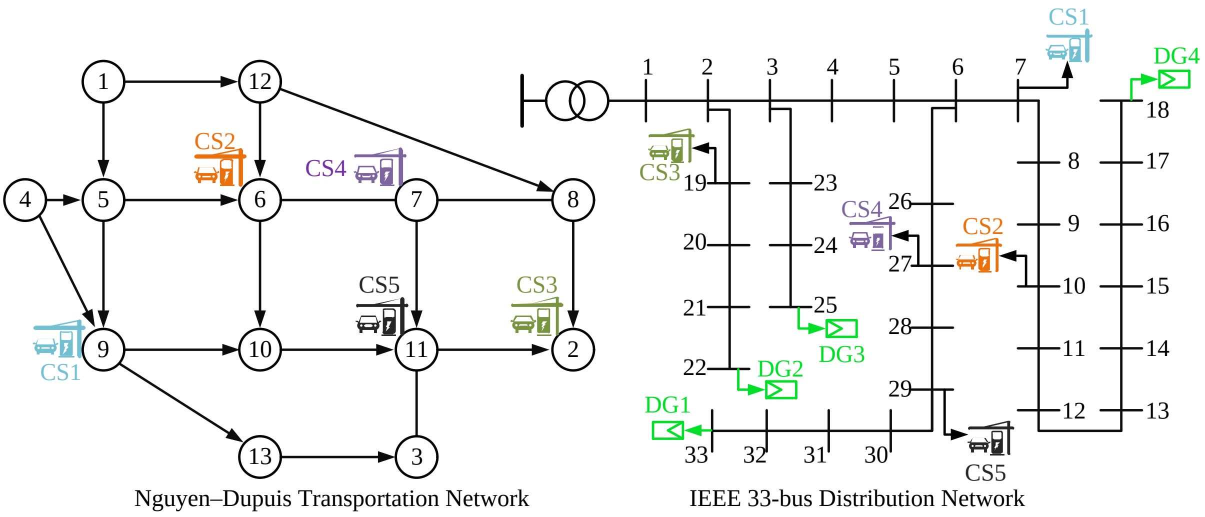


Figure 6.3. Topology of the interacted TN and DN system

Since time series are taken into account in this chapter, the overall traffic flow variation in one day is shown in Figure 6.4, along with TOU electricity price [132] purchase from the main grid. The vehicles depart from starting point 1 or 4, then navigate appropriate charging stations for EVs with charging demands. After EVs finish charging, the algorithm will navigate from the corresponding charging stations to the ending point 2 or 3. The number of EVs with charging demand in the traffic flow is set to 0.1%. Figure 6.5 shows the DGs and loads variation in DN.

In order to demonstrate the effect of the proposed Collaborative Optimal Routing and Scheduling (CORS) method, we consider the Nearby Routing with Optimal Scheduling (NROS), Optimal Routing with Uncontrolled Scheduling (ORUS), and the Nearby Routing with Uncontrolled Scheduling (NRUS) as the comparisons. In the NROS approach, there is no unified dispatching center to arrange and navigate the charging station for EVs, EVs will only the nearest charging station by themselves. Then the charging stations will independently optimize the charging power scheduling to reduce the overall costs. The ORUS can assign the charging station for each EV according to the state of the power grid and traffic network. After the EVs arrive at the charging station, the first come first charge mode is adopted to charge the EV with the fixed maximum charging power [55, 57]. In contrast, the NRUS approach represents a disordered state that EVs find the nearest charging station by themselves and charge in the station without any optimal scheduling technic.

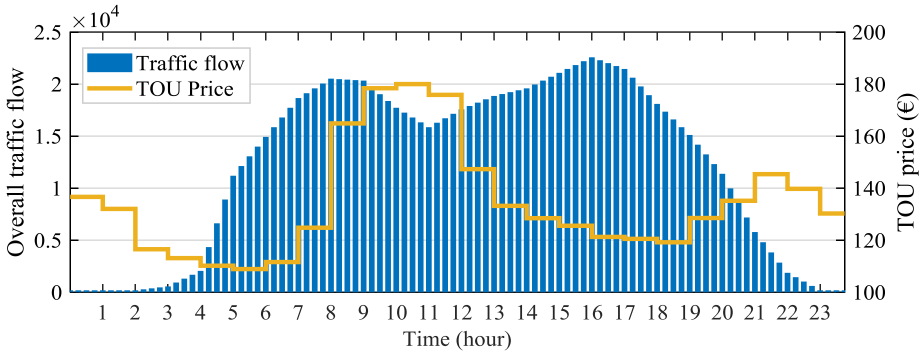


Figure 6.4. Overall Traffic flow and TOU electricity price.

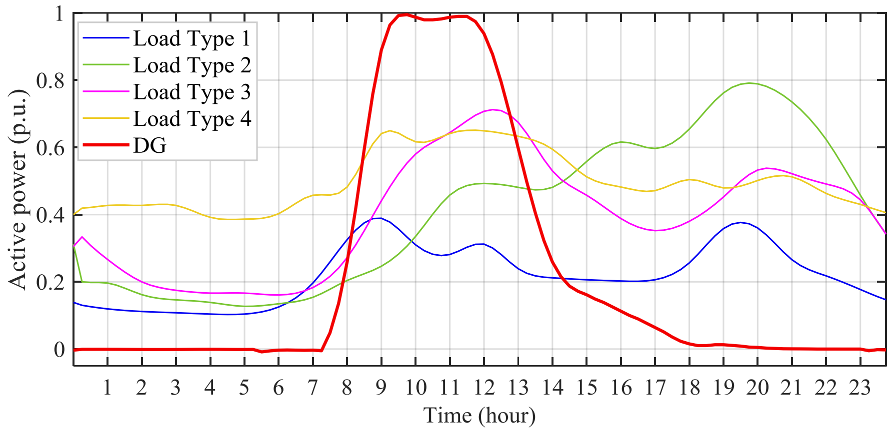


Figure 6.5. Profile of the DGs and different types of loads.

6.3.2 Simulation Results

The simulation results of the designed case are shown in Table 6.1. Obviously, under the proposed CORS method, the charging cost of the entire system and the total driving cost of the EVs are the smallest. Voltage means square error represents the square error to which the voltage of all nodes deviates from the rated voltage at different times, where the rated voltage is set as 1 p.u. Due to the high ratio of *R/X* of the distribution network, the larger voltage deviation will lead to higher grid loss, which is also reflected in Table 6.1. It can be found that by CORS, less voltage means the square error is obtained, along with the smallest grid loss. NROS method ignores the routing planning process, thus the driving cost is significantly higher than CORS and ORUS. Because the scheduling process is implemented independently at each charging station, the overall charging cost of NROS is relatively lower than ORUS and NRUS. Adopting ORUS brings less driving cost but higher charging cost. This is because the optimal routing process reduces the driving cost while EVs adopt the first-come first-charge after arriving at the station method. Therefore, the flexibility of the charging station is not fully utilized. Similarly, the voltage means square error and grid loss are also higher due to the neglecting of charging power scheduling. CORS as the comparison without route and power optimization, all indicators under this method are better. The battery-saving indicator represents the ability of the algorithms to cope with battery degradation. The battery-saving indicator shown in Table 6.1 means the battery cost-saving rate of different algorithms compared with the uncontrolled scheduling situation. It can be found that for algorithms with optimal power scheduling (CORS and NROS), the battery saving rate is significantly higher than that with uncontrolled scheduling (ORUS and NRUS). This means the battery life with CORS and NROS will be longer.

Table 6.1 Simulation results under different algorithms

	Total charging cost (€)	Total driving cost (€)	Voltage mean square error (p.u.)	Grid loss (%)	Battery Saving (%)
CORS	2077	3454.8	0.0014	4.05%	7.03%
NROS	2133	4289.7	0.0014	4.06%	7.11%
ORUS	2349	3454.8	0.0016	4.10%	0%
NRUS	2388	4289.7	0.0018	4.13%	0%

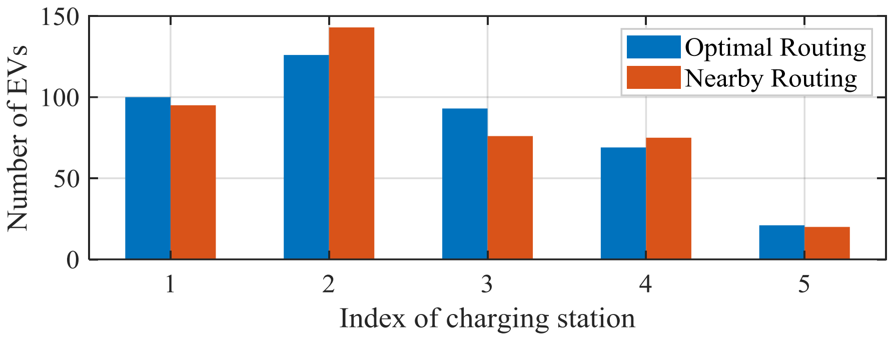


Figure 6.6. The number of EVs assigned to each charging station with and without optimal routing.

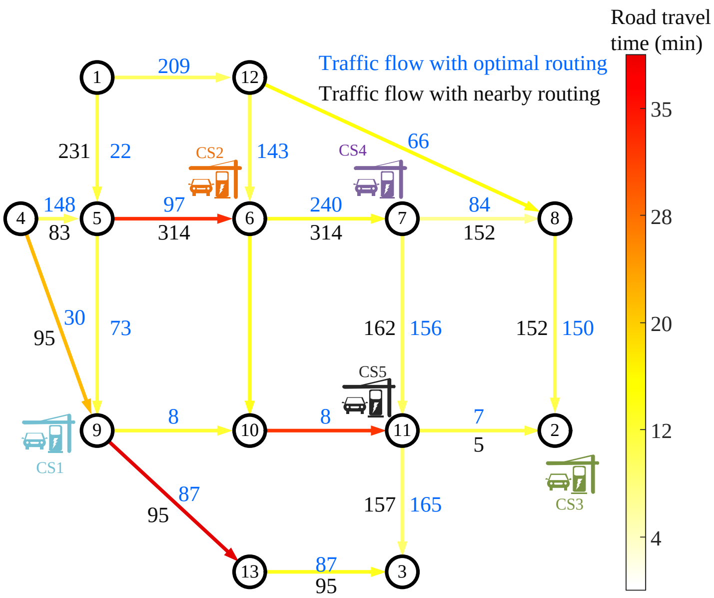


Figure 6.7. Status of the TN and the flow of EVs with charging demand under different routing methods at 10 a.m.

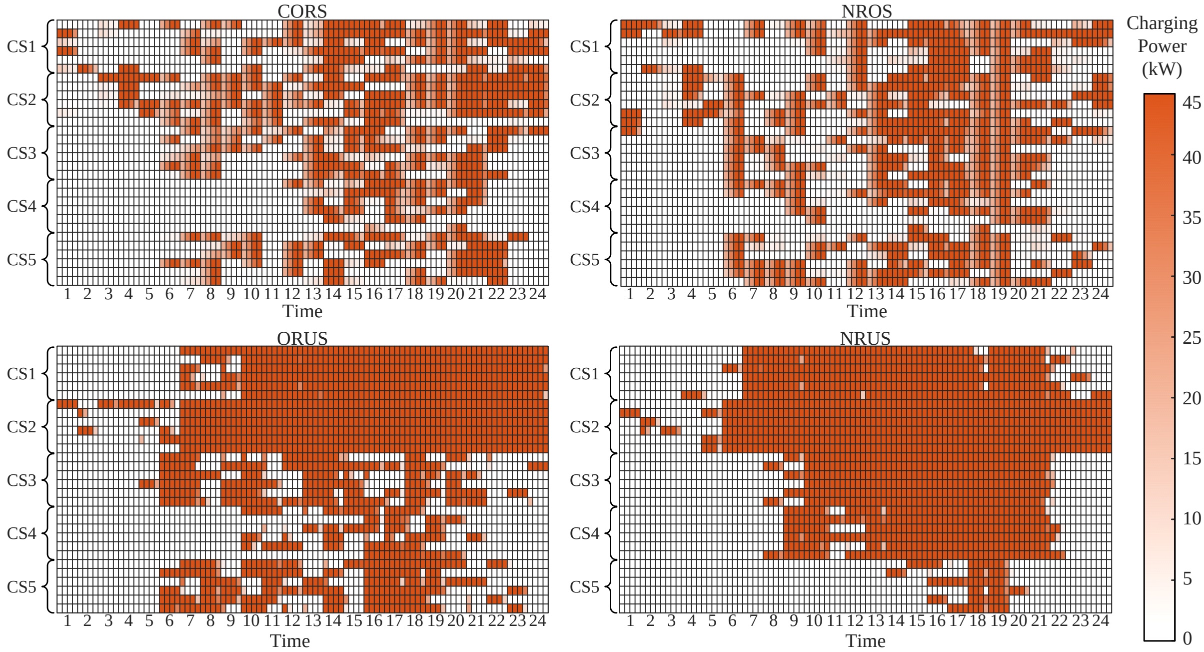


Figure 6.8. Heat-map of the provided energy at different times

To verify the effect of the route optimization, the charging station assignment results are shown in Figure 6.6. The optimal routing is considered in ORUS and our proposed CORS while nearby routing is adopted in NROS and NRUS. Compared with nearby routing, the optimal routing method can divert the overcrowded charging stations to ensure the flexibility margin for power scheduling. For instance, according to Figure 6.3, the CS2 is closer to the starting node at the TN. Thus, unless the capacity limit of CS2 is reached, the EVs with nearby routing will intend to charge at this charging station. CS3 is at the end node of TN while at the upstream node 19 in the DN. Therefore, with the same charging power, the power loss when charged at CS3 is smaller. Thereby, in the optimal routing mode, CS3 is assigned to more charging EVs, while CS2 is assigned fewer EVs compared with nearby routing. The flow of EVs with charging demand under different routing methods at 10 a.m. is illustrated in Figure 6.7. When implementing the nearby routing, each independent EV ignores the current traffic status and will only choose the route with the shortest distance, thus ignoring the traffic congestion. By optimal routing, traffic jams can be avoided. For instance, roads 4-9, 5-6, 9-13 take more driving time, so the optimal routing method reduces the number of EVs on these roads, thereby reducing the overall driving cost. Through the above discussion, it can be seen that the optimal routing process comprehensively considers the operation status of the DN and the TN, which not only reduces the voltage fluctuation of the power grid but also improves transportation efficiency.

The heat-map of power provided by each charger of each charging station at different times is shown in Fig 8. Because the power scheduling process is included in CORS and NROS, the charging power distribution throughout the day is more extensive. By contrast, the ORUS and NRUS methods are executed with first come first charge mode, which leads to a relatively concentrated charging power distribution in the heat-map. The working status of the charging station is closely related to the traffic flow, and the high charging power cannot avoid periods of high electricity prices. Therefore, by CORS and NROS methods, the flexibility brought by the dwell time of electric vehicles has been fully exploited, and the charger utilization rate of each charging station has also been improved.

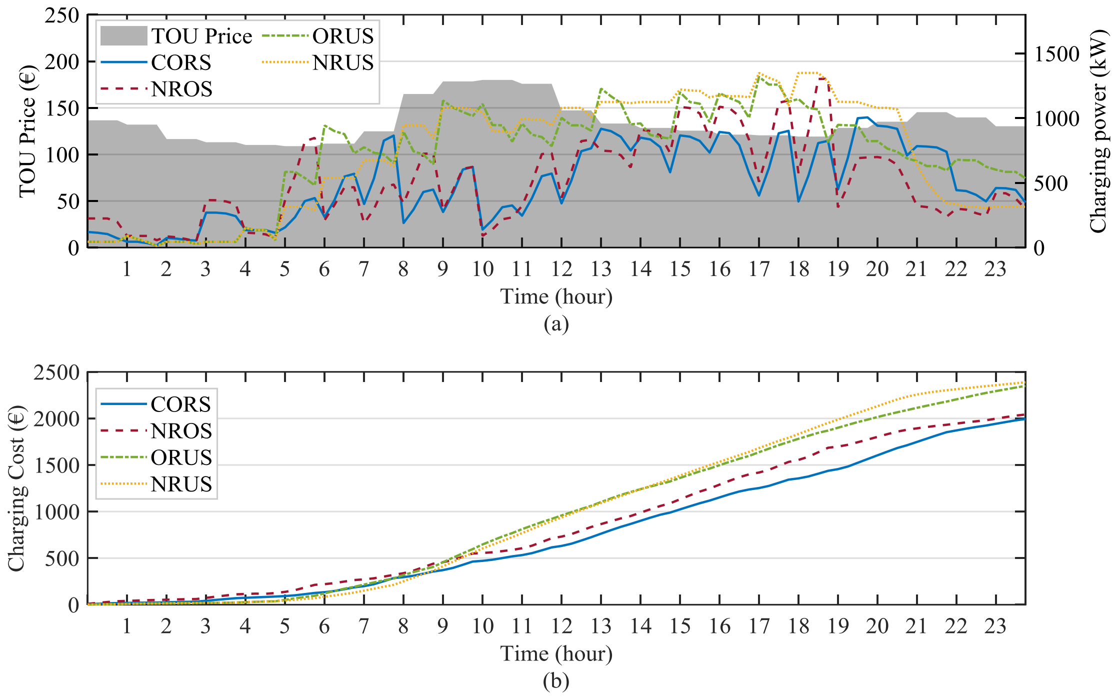


Figure 6.9. Charging power comparisons under different charging methods (a) overall charging power at different time slots and the TOU price (b) cumulative charging cost

Figure 6.9 shows the charging power comparisons under different charging methods. From Figure 6.9 (a), the charging methods CORS and NROS reduce the charging power when the TOU price is relatively higher, such as from 9:00-12:00. And can dispatch peak charging power to the time slot when the TOU price is lower. The cumulative charging cost at different time slots is shown in Figure 6.9 (b). Obviously, the charging costs of charging methods with scheduling processes (CORS and NROS) are lower than with uncontrolled charging processes (ORUS and NRUS). Due to the consideration of optimal routing process, the assignment of charging stations selection is more appropriate, so the cumulative charging cost under CORS is lower than NROS while charging cost under ORUS is lower than NRUS.

The voltage profiles of the DN at different charging methods are illustrated in Figure 6.10. It can be seen that the grid voltages are mainly affected by the operation status of the power grid.

In the daytime, the output of the PV power supply increases, which is the main reason for the voltage to rise. PV cannot supply energy at night while the residential electricity load increases, which causes the voltage to decrease. Even so, the voltages are staying within the regular limits under all operating methods. The maximum and minimum voltage under the proposed CORS in one day is also marked in this figure. In comparison, the proposed CORS algorithm effectively reduces the range of voltage fluctuations, so it has a positive effect on maintaining the stability of the power grid and reducing grid losses.

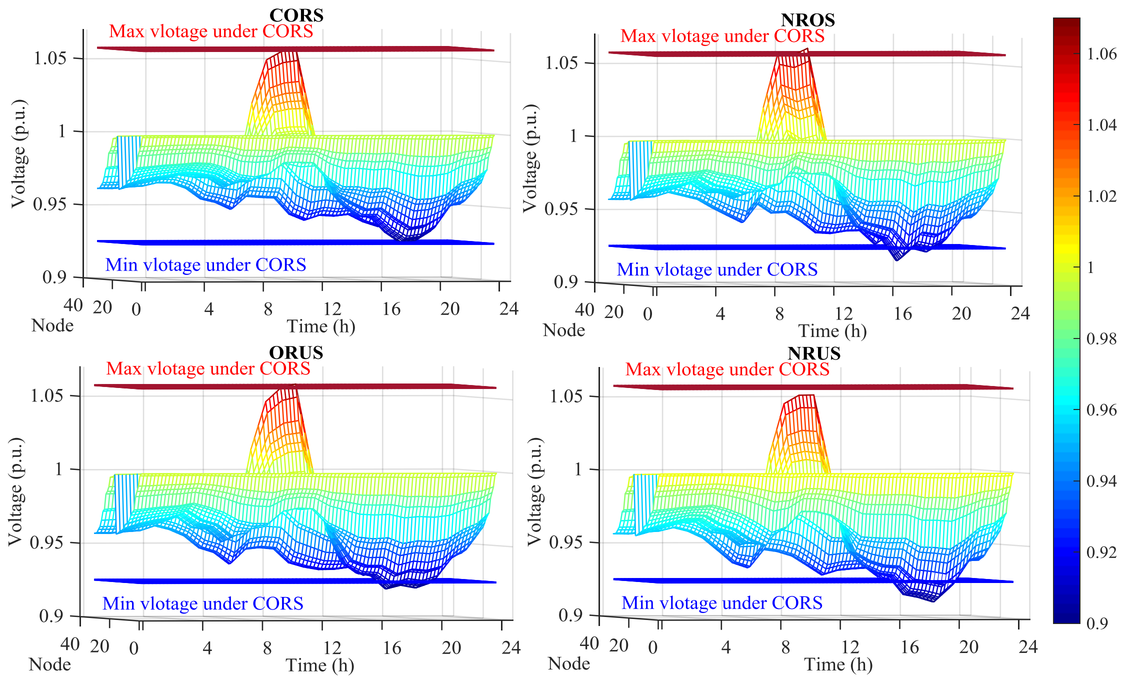


Figure 6.10. Voltage profiles of the DN at different charging methods

6.3.3 Scene analysis based on Monte Carlo algorithm

The above part mainly discusses various technical indicators in a specific case. To verify the universality of the proposed algorithm, set up different scenarios to conduct Monte Carlo analysis on cost indicators. Traffic flow status has a significant impact on path planning. Therefore, let the overall charging demand unchanged (the number of EVs charged in a day and their required power is fixed), set the traffic flow to 20%, 40%, 60%, 80%, and 100% of the total traffic flow in Figure 6.4 as different scenarios. For each scenario, repeat the simulation 1000 times, and record the driving and charging cost of each time. The boxplot reveals the cost and battery-saving rate distribution of different methods under different scenarios, which is shown in Figure 6.11 (a)-(c). It can be seen that with the increase in traffic flow, driving costs have increased significantly. When the number of traffic is small, the effect of optimal routing (CORS and ORUS) on driving cost reduction is not obvious, and the greater the overall traffic flow, the stronger the superiority of optimal routing. In contrast, the impact of traffic flow on charging costs is small, and the proposed CORS method is still optimal. Similarly, traffic flow affects less influence on the battery saving rate, this is because the number of charged EVs and their required energy is fixed. The battery-saving rate is the ratio of battery degradation that can be saved compared with uncontrolled charging, because the ORUS and NRUS are adopted the uncontrolled charging strategy, their battery-saving rate, in any case, is zero. The optimization scheduling is executed in CORS and NROS, so the battery saving rate is higher.

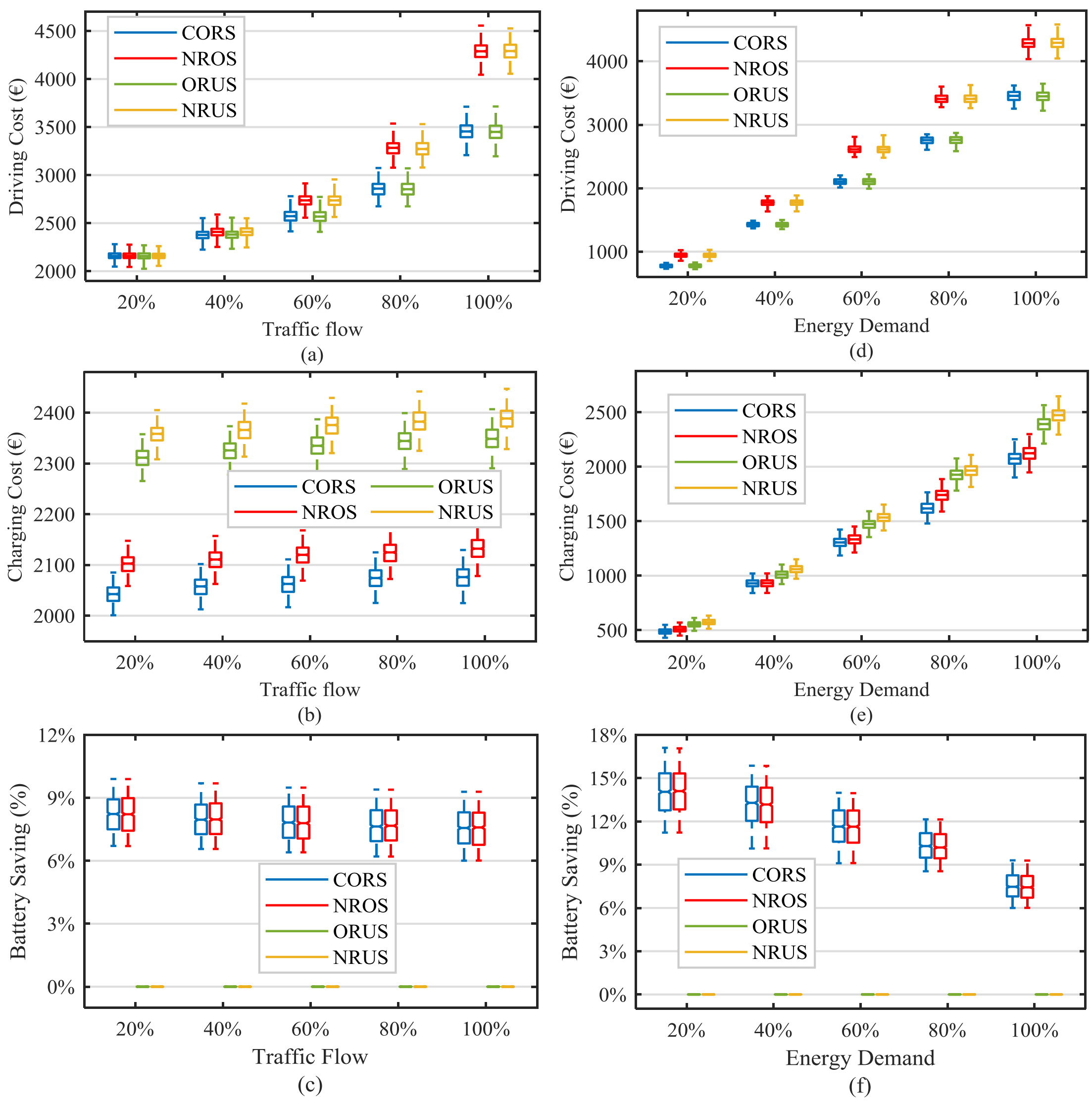


Figure 6.11. Boxplot of (a) driving cost with different traffic scenarios (b) charging cost with different traffic scenarios (c) battery saving rate with different traffic scenarios (d) driving cost with different energy demand scenarios (e) charging cost with different energy demand scenarios (f) battery saving rate with different energy demand scenarios

Figure 6.11 (d)-(f) illustrated the boxplot of driving cost, charging cost, and battery-saving under different methods with different energy demand scenarios. Similarly, let the overall traffic flow unchanged, set the energy demand to 20%, 40%, 60%, 80%, and 100% of the energy demand in the previous case study as different scenarios. It can be seen that the driving cost also increases with the increase in charging demand. This is because the overall number of EVs with charging demand has increased. The driving cost of the proposed CORS is relatively lower than NROS and NRUS. And the charging cost undoubtedly increase with the energy demand increased. But with the CORS method, the cost increase rate is smaller than other methods. As mentioned before, the battery saving rate of ORUS and NRUS with uncontrolled control is zero. CORS and NROS have similar battery savings rates, and they both decrease as energy demand increases. This is because the number of charging EVs increased, and more chargers have to be occupied, resulting in the reduction of the scheduling flexibility. Combining the Monte Carlo analysis of the two situations, the proposed CROS method is in an advantageous position in terms of reducing driving and charging costs and increasing the battery life.

6.4 Summary

Considering the coupling mechanism of the transportation network and distribution network, the CORS method to improve the economic operation of EV charging is proposed in this chapter. By considering the driving cost, electricity purchase cost, and battery degradation cost, the optimal charging station assignment and navigation plan and coordinate charging scheduling scheme are calculated for each EV in turn. The multiple chargers for multiple EVs charging station, which can tap the scheduling flexibility, is applied, and corresponding power scheduling and charger operating process are provided. By introducing the proposed modified combination of DBMC and GBD algorithm, the established complex nonlinear optimization problem is solved, and a real-time implementing process is provided. By introducing the NROS, ORUS, and NRUS methods as comparisons, the advantages of the proposed CORS method are that can reduce the driving and charging cost, improve the utilization rate of chargers, mitigate voltage violations, and decrease the grid loss are demonstrated.

7 Conclusions and Future Works

7.1 Conclusions

This article focuses on the planning and operation of electric vehicle charging stations. It aims to propose an efficient charging station planning plan and formulate a charging scheduling plan that takes into account the economy and user needs.

(i) An EV charging station planning model for motorways, which is based on the existing service area and does not require additional motorway retrofit costs, is proposed. Comprehensive consideration of the construction cost of charging stations, the waiting time for charging, and the inconvenient driving cost. With the proposed planning method, the appropriate distribution density of charging stations and the number of charging facilities in charging stations can be planned. Thus, the total cost can be reduced as much as possible while EVs' requirements can be satisfied. Furthermore, an improved genetic algorithm is designed to solve the established MINLP optimization problem. Because the candidate placing points in this dissertation are divided into many clusters, parallel computation can be used, which greatly improves the speed of the solution. Three different planning scenarios: orientation to minimize social cost, orientation to minimize charging station operating, and orientation to minimize charging station construction, are defined to meet the different planning requirements. Considering the advantages and disadvantages of different scenarios, suitable scenarios for planning can be selected according to existing policies and development needs.

(ii) Considering the limited number of chargers, an optimal charging power scheduling method POCS based on TOU electricity price is proposed. Firstly, the uncontrolled charging scheduling model is designed for fully charging EVs as fast as possible. Then, considering the limited chargers assignment scheme, an EV optimal charging scheduling model to minimize the total charging cost is proposed. The established model is a BP model, which can not only guarantee the EVs' charging demand by appropriately assigning the limited chargers, but also reduce the charging cost by optimal scheduling the charging power. The upper level mainly decides the charger index and available charging period of EVs. The lower level solves the EVs charging power within their available charging period by responding to the TOU electricity price. Then, as the upper level is a mixed nonlinear integer program while the lower level is a linear program, a compound solving algorithm is designed to get the detailed optimal EVs charging scheduling solutions. Through performance verification, the proposed algorithm can find the solution within an acceptable time. Finally, the proposed optimal charging scheduling method is compared with the uncontrolled charging scheduling method and a commonly used charging power scheduling method. Besides, the serviceability of the charging station with the limited chargers is analyzed and the economized charging cost under the different number of charging EVs and the different number of chargers are compared. The POCS method is compared with the UCS method and the WCAS method. Through extensive simulations, it has been shown that with the proposed optimal charging scheduling algorithm, the charging station can not only schedule the charging process more efficient but also provide a more detailed optimal charging scheme.

(iii) A data-driven intelligent EV charging scheduling (DICS) algorithm is proposed. First, an EV charging demand forecasting method based on the neural network algorithm is proposed. For considering the special needs of limited charging facilities, the forecasting process predicts both the number of subsequent EVs and their respective energy requirements, which is called estimated EV information. The established estimated information contains the specific charging demand information of each predicted EV and can be used to guide the scheduling optimization process. Second, the charging scheduling model considering the limited charging facilities is designed. The total charging cost for the charging operators is reduced while the charging requirements and reducing the battery degradation are assured. Then the corresponding solving technique based on the heuristic algorithm is introduced. And the solved results show how to flexibly use the limited chargers to connect the appropriate EVs and provide corresponding charging power. After that, the real-time charging scheduling system operation process is introduced. Finally, the proposed DICS are compared with the existing methods and the advantages of the proposed method are verified. With the introduced solving algorithm, the charging scheme is optimized for guiding chargers' operating. Real-time scheduling of charging stations is achieved by updating the neural network and charging task status. The CFO scheduling method is taken as the comparison to verify the forecasting effectiveness. Furthermore, four key performance indexes are introduced and compared among the proposed DICS method, FCFS, SWP, and SWR methods. In addition, the battery performance improvement compared with the SWBD is also illustrated. According to Monte Carlo simulation results, with the proposed DICS method the charging operators can not only achieve better economic performance as much as possible but also improve service completion rate through predictive algorithms and user satisfaction, which is better than other existing algorithms.

(iv) By considering the interaction of transportation and distribution networks, a collaborative optimal routing and scheduling (CORS) method is proposed. The proposed algorithm arranges specific navigation and charging schemes for each EV in turn according to the order in which the EVs report charging requirements. The proposed CORS method can not only assign and route charging stations for EVs but also optimize the scheduling of charging power based on the assigned charging stations. An optimization model that considers EV driving cost, electricity purchase cost, and battery degradation cost is proposed to find the routing and scheduling scheme with the least comprehensive cost. The charging facilities limitation in a charging station is also considered. In order to solve this complex optimization mode, we split the optimization model into the upper layer and lower layer optimization. The upper layer mainly decides the charging station assignment process including determining the charging station and planning the driving path. Meanwhile, the lower layer solves the coordinate charging scheduling scheme for the EV with the charging station assignment results from the upper layer. By introducing the proposed modified combination of DBMC and GBD algorithm, the established complex nonlinear optimization problem is solved, and a real-time implementing process is provided. By introducing the NROS, ORUS, and NRUS methods as comparisons, the advantages of the proposed CORS method can reduce the driving and charging cost, improve the utilization rate of chargers, mitigate voltage violations, and decrease the grid loss are demonstrated.

7.2 Future Works

On the basis of this dissertation, there are many aspects worthy of expansion a lot of work worth further investigation in the follow-up research:

(i) In the charging station planning, the planning scheme proposed in this dissertation is mainly for the application scenario of motorways. However, when planning charging stations on other types of roads, the factors that need to be considered will be different. For example, on motorways, the energy consumption of EVs is fast. The main purpose of the charging station is to ensure the charging demand of EV owners and alleviate endurance anxiety. Therefore, it is necessary to ensure the density of the charging station. In contrast, in cities, the degree of congestion is different in different regions. How to appropriately arrange the number of chargers to alleviate the long waiting time and provide charger utilization is an important problem worthy of consideration.

Furthermore, with the continuous application of intelligent charging scheduling technology, the planning strategies considering the corresponding scheduling algorithms can be the further step. Planning the charging stations at the nodes with high power-sensitive in the power grid through an appropriate planning scheme can improve the supportability of V2G technology to the power grid in the scheduling process, but it will have a larger impact on the stability of the power grid due to the timing fluctuation of EV charging power, and vice versa. The layout of the charging station in the traffic network will change the traffic flow distribution to a certain extent. Therefore, in future work, by comprehensively considering the impact of charging station planning on the V2G effect and the change of traffic flow, we can formulate charging station planning schemes that can be more suitable for future EV charging applications.

(ii) In the charging scheduling process, it is possible to use the EV batteries as energy storage elements to further support the voltage of the grid or perform load peak-shaving and valley-filling. Therefore, in future research, the corresponding charging power scheduling strategy can be formulated to activate the flexibility of the battery to compensate for the grid to comply with fluctuations. In the future power system, renewable energy will occupy a large proportion like charging facilities for EVs, and intermittent and randomness are also characteristics of renewable energy. Therefore, it has great research value to formulate optimized strategies for the coordination of renewable energy grid-connected inverters and charging stations to improve the economy and stable operating of the power system. In addition, with the large-scale application of energy storage components, their charge and discharge characteristics can be used to coordinate the problem of mismatch between the peaks and valleys of EV charging power and renewable energy output.

As a load with higher electric power, EV charging will become an unignorable part of the power grid after reaching a certain penetration rate. Therefore, EV charging will bring major changes to the future power flow characteristics of the grid. Therefore, corresponding grid expanding methods are required to adapt to the use of large-scale EV scenarios. In addition, a good electricity market model guides the behavior of energy participants and improves the overall energy consumption economy, which can also be one of the future research topics. The developed power market model that adapts to high-penetration EVs and renewable energy will encourage EV users to "shift charging". So the efficiency of charging facilities will be improved while “too many EVs charging at the same time” can be avoided.

In summary, in future work, we will combine past research foundations, comprehensively consider the impact and challenges brought by the large-scale application of electric vehicles and renewable energy to the grid, deeply tap the potential of controllable flexibility of energy consumption participants and provide new solutions for efficient and stable operation of future power grids.

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