# Advanced Mechanism Design for Electric Vehicle Charging Scheduling in the Smart Infrastructure

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# Abstract

Advanced Mechanism Design for Electric Vehicle Charging Scheduling in the Smart Infrastructure

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Electric vehicle (EV) continues to grow rapidly due to low emission and high intelligence. This thesis considers a smart infrastructure (SI) as an EV-centered ecosystem, which is an integrated and connected multi-modal network involving interacting intelligent agents, such as EVs, charging facilities, electric power grids, distributed energy resources, etc. The system modeling paradigm is derived from distributed artificial intelligence and modelled as multi-agent systems (MAS), where the agents are self-interested and reacting strategically to maximize their own benefits.

The integration, interaction, and coordination of EVs with SI components will raise various features and challenges on the transportation efficiency, power system stability, and user satisfaction, as well as opportunities provided by optimization, economics, and control theories, and other advanced technologies to engage more proactively and efficiently in allocating the limited charging resources and collaborative decision-making in a market environment. A core challenge in such an EV ecosystem is to trade-off the two objectives of the smart infrastructure, of system-wide efficiency and at the same time the social welfare and individual well-being against agents' selfishness and collective behaviors. In light of this, scheduling EVs' charging activities is of great importance to ensure an efficient operation of the smart infrastructure and provide economical and satisfactory charging experiences to EV users under the support of two-way flow of information and energy of charging facilities.

In this thesis, we develop an advanced mechanism design framework to optimize the charging resource allocation and automate the interaction process across the overall system. The key innovation is to design specific market-based mechanisms and interaction rules, integrated with concepts and principles of mechanism design, scheduling theory, optimization theory, and reinforcement learning, for charging scheduling and dynamic pricing problem in various market structures.

Specifically, this research incorporates three synergistic areas: (1) Mathematical modelling for EV charging scheduling. We have developed various mixed-integer linear programs for single-charge with single station, single-charge with multiple stations, and multi-charge with multiple stations in urban or highway environments. (2) Market-based mechanism design. Based on the proposed mathematical models, we have developed particular market-based mechanisms from the resource provider's prospective, including iterative bidding auction, incentive-compatible auction, and simultaneous multi-round auction. These proposed auctions contain bids, winner determination models, and bidding procedure, with which the designer can compute high quality schedules and preserve users' privacy by progressively eliciting their preference information as necessary. (3) Reinforcement learning-based mechanism design. We also proposed a reinforcement mechanism design framework for dynamic pricing-based demand response, which determines the optimal charging prices over a sequence of time considering EV users' private utility functions. The learning-based mechanism design has effectively improved the long-term revenue despite highly-uncertain requests and partially-known individual preferences of users.

This Ph.D. dissertation presents a market prospective and unlocks economic opportunities for MAS optimization with applications to EV charging related problems; furthermore, applies AI techniques to facilitate the evolution from manual mechanism design to automated and data-driven mechanism design when gathering, distributing, storing, and mining data and state information in SI. The proposed advanced mechanism design framework will provide various collaboration opportunities with the research expertise of reinforcement learning with innovative collective intelligence and interaction rules in game theory and optimization tools, as well as offers research thrust to more complex interfaces in intelligent transportation system, smart grid, and smart city environments.

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# Chapter 1

# Introduction

Replacing a fossil fuel-powered car with an electric model can halve greenhouse gas emissions over the course of the vehicle's lifetime and reduce the noise pollution [1, 2]. Compared to fossil fuel-powered vehicles, the driving range of electric vehicles[1] (EVs) for a single charge is around one-third of the petrol-equivalent, while the recharging time can be hours, compared to minutes at a gas station [4]. Moreover, EVs must recharge frequently due to the limited driving range allowed by the battery capacities; worse still, each recharge also takes a significant amount of time. Due to the unique feature of EVs, users and manufacturers agree that the ability for convenient and rapid charging is key to persuading drivers to go green. Recently, more charging facilities have been deployed in urban parking lots, residential areas, working places, highway service stations, parks, etc. However, the deep penetration of EVs brings two crucial consequences: they introduce heavy load impact into the power grid by shifting energy demand from gasoline to electricity [5, 6], and the competition for the limited charging resources degrades quality of service and thus can compromise the original intent of advocating electric vehicles [7]. Therefore, it is important to recognize the importance of scheduled or "smart" charging as a key element for the environmentally beneficial and efficient integration of EVs into the smart infrastructure.

As an emerging field, EV-related problems are the focus of many ongoing researches, referred to some surveys in the literature [5, 8, 9, 10]. The development of information technology and the advent of smart devices, precipitate the boom of

[1]Electric vehicle basically includes two types, battery electric vehicle (BEVs), which is powered by only electricity, and plug-in hybrid electric vehicle (PHEV), which is powered by both gasoline and electricity [3].

EV-centered ecosystem. Fig. 1.1 describes the role of EV charging in the smart infrastructure that charging scheduling integrates with – and deeply influence – various issues in transportation, power systems, and smart city management, etc. Among many tracks of researches related to EV charging, we identify that increasing the efficiency of charging scheduling is a very important research issue with the following **motivations**:

*(1) Environmental incentives*: The transport sector alone is currently responsible for 20.5% of the global emissions. Therefore, the transport sector is exploring new technologies and business models to make a transition to EVs [11]. Due to the low emission of EVs, many countries grab an early lead in EV adoption (China, U.S., Canada, Japan, parts of Europe). *(2) EV-charging facility ratio*: Convenient and fast recharging services thus become essential for EV users to alleviate their *range anxiety* and persuade drivers to go green. Up to now, the growth of publicly accessible chargers, especially the fast chargers, still falls behind the increase in the number of EVs on the road [12, 13]. *(3) Integration of public transportation and power system operation*: the efficiency of charging scheduling will influence the waiting time for charging and EV's route planning, especially in highway travels. Moreover, the load induced by EV charging will stress the electricity network that delivers energy to each charging station [9]. The uncontrolled EV charging impacts the local distribution grid in terms of its voltage prole, power loss, grid unbalance, and reduction of transformer life, as well as harmonic distortion [5]. The large load variations in the electrical grid will impact the power quality of the distribution grid and the usual operations of the power system. *(4) Social welfare*: in such a market, the efficiency of charging scheduling is highly dependent on the information provided by EV users who act strategically as independent, rational and self-interested agents. *(5) Autonomous driving*: autonomous vehicles represent the tendency of vehicle-to-Internet, where they and cyber-physical systems should be operated together in a collaborative way to explore the future electrified and intelligent transportation in greater depth [14]. Vehicle-mounted system should integrate the charging, path planning and other tasks in an automate manner.

Motivated by these factors, it is of great importance to efficiently coordinate and schedule different charging requests, such as single charge, deferrable charge or partial

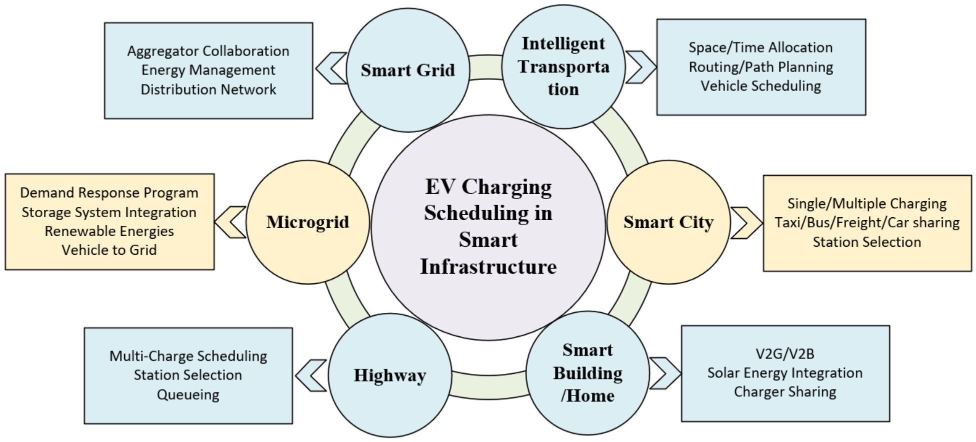



Figure 1.1: An EV-centered ecosystem in the smart infrastructure

charge, in order to maintain charging load stability, improve drivers and consumer experiences, as well as transport efficiency. To achieve these goals, different approaches, e.g., mathematical or stochastic optimization, game theory, and machine learning, are imperative to EV charging scheduling problems in the decentralized and stochastic environment so that the social welfare can be maximized.

However, the existing literature still has crucial gaps: (1) The centralized mathematical models or automated control methods assume that the system has agent's perfect information for decision-making, which is unrealistic in practice. (2) Restricted by the computing ability and accessible data, the classic economic theory, i.e., gamification modelling or mechanism design, is only applicable in very restricted settings under strong assumptions of agent's fully rationality and formulaic utility function. However, agents may have different level of rationality and risk attitudes, and their preferences may also change over time, making these agent-related assumptions of the common mechanisms ineffective in real-world cases [15]. Besides, the equilibrium solutions are not always optimal. (3) The uncertainties, non-statistically known agent utility, and the coordination of these intelligent agents in the smart infrastructure remain extra challenges in a decentralized, dynamic, and data-driven environment. The massive data exchanging between agents requires extensive communication costs, and make market-based mechanisms execute at high frequencies where the designers should flexibly adjust parameters to adapt to the dynamic environments [16].

The management on the smart infrastructure should be associated with information gathering and decision-making through a coordinated, cooperative and distributed manner. It is crucial to understand and formalize the various design dimensions for smart infrastructures, particularly where elements may be optimized for specific application contexts considering their unique constraints. In a market environment, agents have a significant impact on the output of systems with which they interact in the smart grid or intelligent transportation system. They are active participants, having the ability to make decisions that influence market and system operations through Internet of Things (IoT) technology [17]. The system efficiency is highly dependent on the dynamic and stochastic behaviors of agents acting strategically as independent, rational and self-interested individuals in charging scheduling. Therefore, properly and efficient utilization of EVs' charging activities by providing economic incentives for EV users and managing their charging preferences can greatly improve the efficiency of transportation and grid systems and benefit users themselves. The objectives of system efficiency and agent utility maximization can be conflicting with each other since, in many cases, mechanism design-based approaches can strike a balance between the two conflicting objectives in the smart infrastructure management, as natural solutions to allocate the limited charging capacities in a fair and economic way.

Given that effective EV charging scheduling must involve multiple agents in the decision-making process, game theoretic models can help describe the interactions between agents and prescribe the outcomes of marked-based resource allocation models, such as auctions while multi-agent systems models can be used as the system modeling paradigm and interaction framework among agents. Auctions, in general, can be seen as mechanism design for the interaction between the resource providers and consumers such that the desired outcome arises naturally from the rational decision-making process within the framework of the designed auctions [18, 19]. In this thesis, we design an advanced mechanism design framework to efficiently allocate the limited charging capacities to EV users, and determine their payments based on the market demands. We formulate different centralized mathematical models for EV charging scheduling problems in the smart infrastructure, and devise different mechanisms to solve different decentralized problems. The purpose is to present the methodology for mechanism design based on the corresponding features and challenges of various kinds of markets in different parts of smart infrastructure.

To this end, this Ph.D. dissertation aims to develop an advanced mechanism design framework to optimize and automate the overall system and economic processes in the smart infrastructure. The key innovation is to design specific mechanism paradigm and interaction rules, integrated with various optimization and machine learning techniques, for charging scheduling and dynamic pricing problems in single or multiple markets. The objective is to trade-off the scheduling efficiency and the social welfare, improve the charging resource utilization, and maintain the gird stability in the interoperability between the selfish agents.

## 1.1 Problem Definition

We provide a brief introduction to definitions and classification schemes for scheduling problems in this section. We begin with the definition of EV charging scheduling problem in the view of optimization.

**Four-element structure**

As a sub-field of operations research, scheduling aims to find the best way to assign the resources to the activities at specific times such that all of the constraints are satisfied and the best objective measures are produced [20]. In spite of the variety of the definitions and models, most of the scheduling problems can fit in a four-element structure, which consists of resources, jobs, constraints, and objectives [19]. The relationships of these elements can be described as: resources are assigned to jobs over the continuous-time or discrete-time manner[2], and this assignment process is restricted by the constraints and guided by the objectives. The EV charging scheduling diagram is shown in Fig. 1.2. Based on this, we define the EV charging scheduling problems as a resource-constrained allocation problem in terms of the following elements:

*Charging requests*: a set of charging activities that must be executed by electric-based vehicles in order to complete electricity fulfilling jobs;

*Resources*: charging resources refer to the space and power at charging station. The charging space includes the number of installed charging points, and parking

[2] In terms of the time representation in scheduling formulations, continuous-time models are potentially allowed to take place at any point in the continuous domain of time. While the whole optimization process in discrete-time models is split into a series of time slots and allocate energy in each time step. The mathematical programs for continuous-time problems are usually of much smaller sizes and require less computational efforts for their solution than the discrete one.

space. The power resources can be distributed generations (photo-voltaic system, wind power, hydro turbines, bio-gas, etc.) [21], energy storage system (ESS), and EVs' battery (Vehicle-to-Grid (V2G) mode). The battery swap station can also be regarded as a sort of energy resource;

*Constraints*: a set of conditions which must be satisfied in the charging scheduling process, e.g., precedence constraints, release time and deadlines of request, battery capacity, or the resource capacity constraints. To be specific, constraints can be generally classified into three types: power capacity, limited space (parking space and charging points), time and energy constraints from users;

*Objective*: is to judge a schedule's performance, which can be classified into two categories: from grid and charging station prospective and from EV users prospective. Users measure the quality of service, charging costs and their satisfaction. Charging station measures the grid stability and the utilization efficiency of its limited capacity.

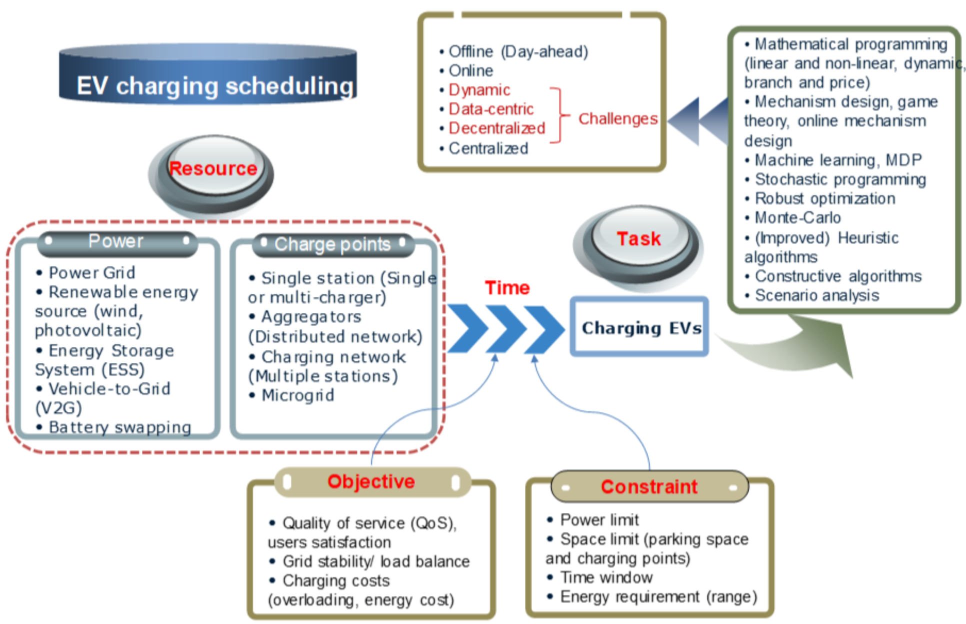



Figure 1.2: Four-element structure for EV charging scheduling problem

From above, we categorize the electric vehicle charging scheduling problems addressed in the smart infrastructure into one classical *resource-constrained allocation* problem. In contrast to the traditional scheduling problems (such as workshop scheduling), EV charging scheduling problem has several unique features as follows:

(1) *Market property*[3]: EV charging is the process by which the prices of charging services are established. And this market facilitates trade and information exchange, moreover, enables the distribution and resource allocation in the transportation and power system community. In a market, EV drivers' objectives and preferences will greatly impact the scheduling efficiency;

(2) *Integration with transportation*: solves the space assignment and routing problem, which decides where and when to activate the charging demand taking into account drivers' predefined deadlines, energy demands, charging station availability, and power limits. The objective is supposed to minimize the waiting time, costs, or travelling distances, by selecting appropriate charging stations and timing;

(3) *Integration with power grid*: solves the energy management problem, which decides the amount of energy can be allocated to each plug-in EV during each time period in distribution networks. Energy management is extremely important for coordinating the transport and recharge of freights or buses in central charging depots. The energy demand for each trip, charge timing as well as the charging station capacity should be considered in charging scheduling to provide high-quality services and, at the same time, maintain the grid stability and reliability. Moreover, the charging facilities can be integrated with intermittent renewable energy sources or Distributed Generation (DG), such as solar or wind energy. However, the distributed energies will pose more uncertainties and challenges to the charging scheduling;

(4) *User's diminishing gain on battery charging*: indicates the *marginal utility* of EV users for obtaining more energy decreases along the time given the lithium battery charging profile (non-linearity of the charging curve of the battery). Sometimes a partial charge could be more economical than a full charge, this characteristic is extremely important for satisfying time and energy constraints of different trips, in order to find the best the trade-off between recharge and transport;

(5) *Battery swapping paradigm*: battery swapping, as a new energy source instead of charging, could be a more efficient and grid-friendly way for the electric trip, especially for the frequent transportation works in logistics. The whole operation could take less than 10 minutes, which is on par with conventional vehicles and much

[3]A market is one of the many varieties of systems, institutions, procedures, social relations and infrastructures whereby parties engage in exchange. It is such complex in economics that we only capture its several important concepts in conducting our research, i.e., competition, individual behaviors, price maker and taker, limited resource allocation, demand and supply, negotiation, social welfare and decision-making.

faster than even some fast recharging stations [22].

## 1.2 Scope and Methodology

EV charging scheduling issues in the smart infrastructure is a multidisciplinary field of operations research, engineering and computer science and has drawn lots of attentions in recent years. Our research focuses on mathematical modelling and scheduling for EV charging, demand response via dynamic pricing, mechanism design and game theoretical analysis of charging markets, and reinforcement learning based mechanism design, with the research topic as advanced mechanism design for market-based EV charging scheduling in the smart infrastructure. And our research considers the smart infrastructure as an EV-centered ecosystem, which is an integrated and connected multi-modal network involving interacting intelligent agents, such as EVs, charging facilities, electric power grids, distributed energy resources (DERs), etc.

Multi-agent systems (MAS) [23] architecture is a suitable modeling and design paradigm for the application of market-based mechanisms in SI. The system modeling paradigm and interaction framework in this dissertation are mainly derived from distributed artificial intelligence and modelled as MAS. When modeling the smart infrastructure, the stakeholders, such as charging stations, distribution network operator, load aggregators, generators, DERs, EVs and regular consumers, even appliances in their homes can be modelled as agents in the system. And it is reasonable to assume the agents are self-interested and reacting rationally. Since multi-agent systems provide a natural modeling of the distributed and dynamic aspects of charging markets, the implementation of market-based mechanisms for the smart infrastructure management in MAS can be intuitive and efficient. In addition, existing agent-based simulation platforms from both academic and commercial sectors will provide invaluable tools for validating market mechanism designs.

In such MAS, we aim to develop advanced mechanisms for different decentralized charging scheduling problems in the smart infrastructure. First of all, we interpret the EV charging scheduling problems using mechanism design framework. Moreover, we also analyze various kinds of markets and their corresponding features and challenges that different part owns in the smart infrastructure. The market mechanisms design fitted in charging scheduling that come to trade-off the optimality of decision making and entities' rationality, such that represent an economy of the smart infrastructure. Our research outline for EV-related charging problems at different market structures can be found in Fig. 1.3.

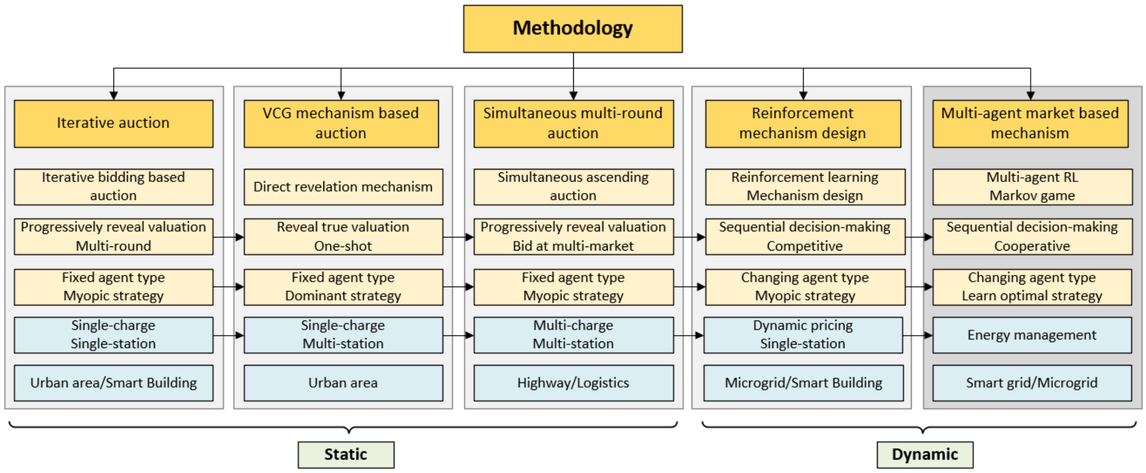


Figure 1.3: Research outline

## 1.3 Challenges

In what follows, we elaborate the research challenges arising from the EV charging scheduling in SI. Basically, charging planning and scheduling in the smart infrastructure arise two level of challenges: from the basic scheduling domain; and from the environment factors.

The scheduling domain complexity involved in solving the most NP-hard optimization problems is the central theme of charging resource allocation, which is related to the computational requirements to generate an outcome given EV users' charging requests and different kinds of constraints.

Aside from the computational complexity, the information availability and information control pose additional challenges on the top of traditional scheduling domain complexity in solving the realistic charging scheduling problems. These challenges will be further amplified when involving and coordinating large number of entities. Follows are the detail analysis on the complexities from environmental factors:

- **Information availability in stochastic and online environment**

The charging activities are operated in highly distributed and dynamic environments, such as traffic congestion, availability of charging stations, arrivals of EVs, request changing, uncertain charging time, uncertain generation and demand, as well as the dynamic energy prices [24, 25, 26, 27, 28, 29]. It is realistic that different type of uncertainties exist in practical scheduling scenario and some data are not precisely known. These uncertainties in real-world applications will influence the decisions made on when, where, and how much to recharge an electric-based vehicle based on the target of optimization procedure. Sometimes more than a single decision; rather, a sequence of decisions need to be made, such as taxis with several partial charges during the day trip. These decisions often depend crucially on the dynamic aspects of the environment.

Moreover, the uncertainties also exist in the power systems, such as the state of the electricity grid, the production of renewable sources, the charging point availability, the congestion at communication and transportation networks, and the number of EVs available to provide V2G services, which are changing quickly while a large number of EVs are either driving or charging [9]. Moreover, maintaining load stability is especially challenging in Microgrid[4] management, due to the uncertainties from renewable energy supplies, and the lower load capacity compared to power grid.

- **Information control in decentralized environment**

In decentralized environment, the information is distributed among stakeholders who are self-interested agents and only aim to advance their own utility. The charging scheduling problems can be viewed as distributed optimization problems, with an objective function that depends on the strategic behaviors and private information of the stakeholders in the system. Typical example of decentralized charging scheduling problem exists in task allocation across multiple self-interested shipping companies; or the decision made by electric drivers on the trade-off between recharge and jobs pickup. The presence of stakeholder inputs is a necessary and sufficient condition to define a charging scheduling as a service process.

Since the stakeholders are self-interested agents who aim to maximize its own utility, the challenges that significantly affect the social welfare of the whole society can be attributed to three factors from agents' standpoint:

[4]Microgrid is a small-scale power production and delivery system comprising distributed generation facilities co-located with the loads they serve.

- Agents may be reluctant to participate in the scheduling process;
- Agents may misrepresent their energy demands and preferences on charging pattern, such as deadlines, charging time, and energy requirements;
- Agents may be stubborn or insensitive to alter their charging or electricity consuming habits to gain greater benefits in response to market signals;
- Agents may be unaware of the precise representation of their valuations or preferences.

In terms of this characteristic, market-based mechanisms can be a natural way to tackle the strategic behaviors and information distribution in decentralized setting. To deal with the strategic behaviors of stakeholders in chargers scheduling, game theory and auction in games is able to capture the conflicting economic interests of the resource providers and resource consumers [30, 31, 32, 33]. Users can interact with each other via information exchange and negotiation, to coordinate their electricity usage, so that maximization of the social welfare is achieved.

In addition to the incentive mechanisms in game-theoretic design, time-of-use, dynamic pricing or float pricing strategies in DR program are quite efficient in providing incentives for users to change their charging habits as their best response relied on the other users' economic rationality, by allowing collectives of EV users to participate in the charging resource allocation [34]. The prices are retained fixed within different pricing periods ahead-of-time, users receive this signal and are motivated to reduce or shift their power demands and energy usage by observing these price signals in a competitive market. However, these pricing schemes do not involve the utility theory and strategic behaviors (such as misreport information) of users in a decentralized environment as the information revealed by users is guaranteed truthful. It is always challenging to elicit users' true preferences over the charging and sensitivity on the changing of time and energy price.

Moreover, DR can also be adopted in cooperation with other mechanisms that target the control of crucial system parameters, such as frequency control, or voltage control [34]. DR is classified in two types, the first case is that users is price-taker, who follow the price signal from the grid and take the utility-maximization action in response to this signal; while the second one allows users to participate in the negotiation for the price set by the resource provider. The participation in the program is motivated by efficient market mechanisms, where consumers calculate their own optimal demand and report it to the utility, and most importantly, have the willingness to change their energy demand in response to the market.

- **Conflicting Objectives**

Conflicting objective between different entities (EV users, charging stations and distribution power network). Moreover, the competition exists among users, or among charging stations. The entities in the decentralized environment with similar or conflicting goals interact directly with each other, in a cooperative or competitive manner. A market employs a multi-layer structure with a coordinator or aggregator entity which coordinates the negotiation across the entities, typically applied in this multi-agent system.

The objectives for the decentralized charging scheduling vary depending on the EV user, the grid, and the charging framework. The list includes (1) increase of stake holder comfort and well-being; (2) energy cost reduction, e.g., minimization of energy consumption; (3) adapting to the variations in power supply from renewable energy sources to reduce power imbalance (smart grid application); and (4) efficient utilization of the charging spaces and time in a charging station.

The agents in decentralized charging scheduling should negotiate and coordinate with each other through an efficient market mechanism, such that the social welfare is achieved and the utility of each entity is maximized. In this mechanism, resource consumers have incentives to change their demand and habit in order to achieve a higher utility.

## 1.4 Outline of the Dissertation

In the following we summarize the five research projects that we accomplished in this dissertation. And all these works are finished under the supervision of Dr. Chun Wang and Dr. Jun Yan.

- **Iterative bidding for single-charge single-station scheduling.** We study an EV charging scheduling setting where vehicle users can reserve charging time in advance at a charging station. In this setting, users are allowed to explicitly express their preferences over different start times and the length of charging periods for charging their vehicles. The goal is to compute optimal charging schedules which maximize the social welfare of all users given their time preferences and the state of charge of their vehicles. We propose an iterative auction which computes high quality schedules and, at the same time, preserve users' privacy by progressively eliciting their preferences as necessary. We conduct a game theoretical analysis on the proposed iterative auction to prove its individual rationality and the best response for agents. Through extensive experiments, we demonstrate that the iterative auction can achieve high-efficiency solutions with a partial value information. Additionally, we explore the relationship between scheduling efficiency and information revelation in the auction.

We present this research in Chapter 3. A paper describing this research has been published in the Proceedings of IEEE Transactions on Intelligent Transportation Systems [35], with the title of "Bidding for Preferred Timing: An Auction Design for Electric Vehicle Charging Station Scheduling".

- **Incentive-compatible auction for single-charge multi-station scheduling**. Charging network scheduling for EVs is a complex research issue on deciding where and when to activate users' charging under the constraints imposed by their time availability and energy demands, as well as the limited available capacities provided by the charging stations. Moreover, users' strategic behaviors and untruthful revelation on their real preferences on charging schedules pose additional challenges to efficiently coordinate their charging in a market setting. To tackle these challenges, we propose an incentive-compatible combinatorial auction for charging network scheduling in a decentralized environment. In such a structured negotiation framework, users can bid for their preferred destination and charging time at different stations, and the scheduling specific problem solving structure is also embedded into the winner determination model to produce feasible schedules. The objective is to maximize the social welfare across all users which is represented by their total values of scheduled finishing time. The Vickrey–Clarke–Groves payment rule is adopted to incentivize users to truthfully disclose their true preferences as a weakly dominant strategy. Moreover, the proposed auction is proved to be individually rational and weakly budget balanced. We also present a case study to demonstrate its applicability to real-world reservation scenarios using the charging network data from Manhattan, New York City.

We present this research in Chapter 4. A paper describing this research has been submitted to Journal of Integrated Design & Process Science, with the title of “An Incentive-Compatible Combinatorial Auction Design for Charging Network Scheduling of Battery Electric Vehicles”.

- **Iterative bidding for multi-station charging scheduling on highways.** An efficient coordinated scheduling of highway charging stations requires EV users’ availability information to improve the utilization of the scarce charging capacities and users’ convenience. However, the self-interested users may report an incomplete availability in order to obtain the prioritized charges at the potential charging stations. In this work, we present a bidding-based mechanism for the multiple charging station scheduling problem at highways, this mechanism allows users to progressively reveal their complete available time window for charging. The objective is to maximize the number of vehicles that highway charging stations can serve, such that limited charging capacities are efficiently utilized and, at the same time, users’ waiting time for charging is minimized. We also carry out a computational study to verify the correlation between charging capacity utilization and users’ waiting time, and evaluate the performance of the proposed bidding mechanism.

  We present this research in Chapter 5. A paper describing this research has been published in 2019 IEEE 23rd International Conference on Computer Supported Cooperative Work in Design (CSCWD) [36], with the title of “Accommodating More Users in Highway Electric Vehicle Charging through Coordinated Booking: A Market-Based Approach”.

- **Simultaneous multi-round auction design for multi-charge multi-station scheduling on highways.** Highway EV charging scheduling faces many challenges depending on the fast charging capacity provided and the information available in coordinating drivers’ multiple charges at charging stations. Moreover, user’s partially-known preferences and potential dynamic events remain extra challenges in maximizing user’s satisfaction, improving the revenue of highway charging stations and efficiently utilizing the limited charging capacities. In such separate and simultaneous markets, users aim to advance their own benefits but negotiable on their charging plans in advance. In this work, we propose a simultaneous multi-round auction to address the highway charging scheduling problem, where users are allowed to bid and compromise on their preferred stops, charging time, and energy simultaneously at separate charging stations. The objective is to maximize the total revenue of these stations. In the course of auction, users can gradually figure out how can their charges fit together by adaptively adjusting their bids placed at different stations. As a result, high-quality solutions are obtained and user's privacy can be preserved by progressively eliciting their private preferences as necessary. In addition, we develop a dynamic scheduling algorithm to deal with the changes of user's reserved charges and unexpected arrivals of other vehicles. We conduct extensive experiments to validate the proposed approach, and the results demonstrate that it can achieve high-quality solutions with a partial private information. Moreover, a simulation study shows the dynamic scheduling can further improve the revenue and resource utilization level in realistic scenarios.

We present this research in Chapter 6. A paper describing this research has been submitted to the Proceedings of IEEE Transactions on Intelligent Transportation Systems, with the title of "An Incentive-Compatible Auction for BEV Charging Scheduling with Private Preferences across Multiple Charging Stations".

- **Reinforcement mechanism design for dynamic pricing in Microgrid charging stations.** Reinforcement learning has become an important scheduling solution with many successes in markets with dynamic pricing options, e.g., electric vehicle charging in a deregulated electricity market. However, the highly-uncertain requests and partially-unknown individual preferences remain major challenges to effective demand responses in the user-centric environment. For charging stations who aim to maximize the long-term revenue in this fast-growing market, an accurate estimate of user's sensitivity, or acceptance, of the prices they offered to the potential customers is the key to the success of dynamic pricing. While most existing pricing schemes assume users will consistently follow stable patterns that are observable or inferrable by the charging service provider, it remains crucial to consider how users may be influenced by historic prices they have observed and react strategically to decide optimal charging demands that can maximize their utilities. To overcome this limitation, we present a new framework based on reinforcement mechanism design to determine the optimal charging price in a mechanism design setting, which can optimize the long-term revenue of charging stations as well as the social welfare of users with private utility functions. Specifically, the strategic interaction between the station and users is modelled as a discrete finite Markov decision process, a Q-learning-based dynamic pricing mechanism is proposed to explore how price affects users' demands over a sequence of time. The experiments demonstrate that our pricing mechanism outperforms the predetermined time-of-use pricing in maximizing the long-term revenue of the charging station.

We present this research in Chapter 7, which was developed in collaboration with Shuai Ma and Jia Yuan Yu, at Concordia Institute for Information Systems Engineering (CIISE), Concordia University. A paper describing this research has been published in The 2020 International Joint Conference on Neural Networks (IJCNN 2020), with the title of "Reinforcement Mechanism Design for Electric Vehicle Demand Response in Microgrid Charging Stations".

## 1.5 Main Contributions

My research focuses on mathematical modelling and scheduling for EV charging, demand response via dynamic pricing, mechanism design and game theoretical analysis of charging markets, and reinforcement learning based mechanism design.

Specifically, my research incorporates three main contributions: (1) mathematical modelling for charging scheduling; (2) market-based mechanism design; and (3) intelligent mechanism design via reinforcement learning.

- **Mathematical modelling for charging scheduling**

A mathematical program is the collection of variables and relationships needed to describe pertinent features of an optimization problem [37]. To mathematically model the charging scheduling problems, we have developed various mixed-integer linear programs for single-charge with single station, single-charge with multiple stations, and multi-charge with multiple station in urban or highway environments. These programs are based on the parallel machine or flexible jobshop shop models, which represents problem choices as decision variables and seeks values that maximize or minimize objective functions of economic benefits subject to constraints on agents' preferences, charging capacity, or grid stability.

- **Market-based mechanism design**

Based on the proposed mathematical models, we have developed particular market based mechanisms from the resource provider's prospective, including iterative bidding auction, incentive-compatible auction, and simultaneous multi-round auction design. The proposed auctions contain bids, winner determination models, and bidding procedure, with which the designer can compute high quality schedules and preserve users' privacy by progressively eliciting their preferences as necessary. We also proposed a simultaneous interaction framework, which enables agents to negotiate and compromise on their preferences at separate markets concurrently. To deal with the changes of agent's reserved bids and unexpected arrivals of other agents, we developed a dynamic scheduling algorithm to further improve the revenue. In addition, we conducted game theoretical analysis to investigate agent's best response and effects on the performance of markets.

- **Intelligent mechanism design via reinforcement learning**

Mechanism design can be integrated with various machine learning techniques to accommodate a variety of dynamic settings across periods and agents' changing preferences. Along this direction, we have proposed a reinforcement mechanism design framework for dynamic pricing-based demand response, which determines the optimal charging prices over a sequence of time considering EV users' private utility functions. The learning-based mechanism design has effectively improved the long-term revenue despite highly-uncertain requests and partially-known individual preferences of users. We model the strategic interaction between the station and users as a discrete finite Markov decision process, and use Q-learning to decide the optimal charging prices given the estimate of user's sensitivity of the prices.

Overall, we have completed five research projects so far. First, we designed an iterative bidding auction to allocate the limited chargers and charging time in a stand-alone charging station. Later, we extended single charging station scheduling to multiple stations, which is solved by an one-shot incentive compatible auction based on VCG principle. We further extended single charge multiple charging stations to multi-charge multiple stations, in which a simultaneous ascending auction based mechanism is developed to coordinate user's multi-charge at highway charging stations. The above three charging scheduling problems are modeled as deterministic mechanism design problems. In an offline mechanism, the auction is run periodically and allocates resources for only one period of time. After that, we proposed a dynamic pricing mechanism for microgrid charging station to deal with users' changing types, their uncertain energy demands and arrivals in a dynamic environment. The energy is allocated to users over a sequence of time and the best pricing set at each time slot can be learned by reinforcement learning in order to maximize the long-term stations revenue. To gain an insight into this auction framework, we also conducted game-theoretical analysis and extensive experiments to validate the proposed mechanisms for EV charging scheduling related problems. We believe our research will encourage implementation of auction-based mechanisms for addressing EV charging scheduling problem in the market environment, and also initiate other researches in this field.

## 1.6 Organization

The rest of the dissertation is organized as follows.

In Chapter 2, we review the related literature and present a taxonomy of the related works and the classification of the approaches.

In Chapter 3, we present our research on designing an iterative bidding-based auction for scheduling user's single charge at a charging station. We develop its auction framework, prove its game theoretical properties, and conduct experimental study to compare it with with the centralized scheduling.

In Chapter 4, we present our research on designing an incentive-compatible combinatorial auction for scheduling user's single charge at multiple charging stations, and we also present an extensive proof on its properties.

In Chapter 5, we present our research on iterative bidding-based auction for scheduling user's multiple charges at highway charging stations, where users can bid on different combinations of entry and exit time while the exact charging time and location is decided by the charging stations.

In Chapter 6, we present our research on designing a simultaneous multi-round auction for highway charging scheduling. As an extension of the work in Chapter 5, we expand the decisions to be made that allows users to decide their charging stops, energy demand and time window at each station. Moreover, users can negotiate with others and flexibly adjust their bids in the course of auction.

In Chapter 7, we present our research on designing a reinforcement mechanism design framework for dynamic pricing in an microgrid charging station, we also analyze the best response of users and properties of this framework.

In Chapter 8, we describe the potential future directions and promising practices of our research.

Finally, we conclude the dissertation in Chapter 9.

# Chapter 2

# Literature Review

As the research and development of mechanism design, optimization and their applications on charging scheduling are evolutionary, we provide a detailed summary and taxonomy of related EV charging scheduling problems in the literature. Moreover, our work complements the existing surveys by presenting the challenges for solving these charging scheduling problems in the literature.

## 2.1 Classification of Charging Scheduling Problems

The current charging scheduling problems addressed in the literature can be subclassified according to the decision variable into two main groups, the first group (a) is charging period and space allocation, which decides where and when to activate the charging demands taking into account the predefined deadlines and energy requirements [38, 39, 40, 41]; and the second group (b) is energy management, which decides the amount of energy units can be allocated to each plug-in EV during each time slot in distribution networks [27, 42, 43, 44]. Some works model the day-ahead dispatching and real-time energy management as a two-stage charging scheduling problem and solve it through stochastic programming [45, 46, 47, 48]. The objective is to minimize the load mismatch between day-ahead and real-time market. The classification of EV charging scheduling problems is summarized in Table 2.1.

According to the aforementioned features of charging scheduling problems, we analyze several important EV-related charging scheduling problems by presenting a broader view on the current literature:

Table 2.1: A brief review on EV charging scheduling problems

| Ref. | Specific Objective | Solving Technique | Scheme | Constraint | Assumption and Gap |
|---|---|---|---|---|---|
| [38, 41, 49, 50] | [a]Determine the places, routes and charging time; reduce congestion and minimize waiting time | Mathematical programming (MILP, MIP, QP) | Offline or dynamic, centralized | User time constraint and energy demand, limited space | Limit charging space; known user's perfect information, continuous-time manner |
| [38, 39, 40] | [a]Dispatch EVs to appropriate charging stations; minimize waiting time, balance the traffic flow | Queuing theory, distributed algorithms | Online, distributed | Number of chargers, length of queue | Poisson arrival process; no market involved, no user preference and time constraint |
| [30, 32, 42, 51] | [b]Model the allocation of power units to a collective of EVs as a (Stackelberg) game; find a Nash equilibrium to maximize social welfare | Game theory, duality in optimization theory, heuristic algorithms | Offline, decentralized | Power capacity, energy demand and power limit | Known strategy (action) space; no space constraint, time and power discretization |
| [33, 43, 43, 52] | [b]Users participate in day- or hour- ahead allocation of power units; to maximize the social welfare | Mechanism design: auctions, VCG mechanism | Online or offline, decentralized | Distribution network capacity, user time and power constraint | Self-interested agent (user) characteristic; no coordination for charging, no space constraint |
| [27, 44, 53, 54] | [b]Reduce the overloads following the price signal, to minimize the total power consumption, or minimize the electricity costs | Demand response program (fixed or real-time price) | Offline, dynamic, distributed | Capacity and energy storage constraint, user energy demands | Long connection time; no users' strategic behaviors, no space constraint, high communication cost |
| [45, 46, 48, 55, 56] | [ab]Two-stage charging scheduling; (joint) maximize social welfare and minimize the operational cost of distribution network | Stochastic programming, Markov decision process, machine learning | Offline and online, decentralized | Power capacity, time constraint, user energy demand | Gaussian arrival process, stable power output; no space constraint, high communication cost, no users' strategic behaviors |

*a*: Charging period and space allocation; *b*: Energy management, classified according to the decision variable.

- **Charging scheduling with limited space**

This traditional scheduling is to assign the charging periods or start times to EVs under the time constraint (arrival, departure and charging) of users and the limited number of chargers. For instance, J. Timpner and L. Wolf proposed a coordinated charging strategy to integrate the reservation and dynamic charging requests into the charging schedule, in order to improve the utilization of the limited charging places [41]. M. Zhu *et al.* [57] models the EV charging scheduling problem as one Parallel Machine Scheduling (PMS) problem, which is to schedule EVs to different charging outlets with the total waiting time minimized. The charging time is modelled as a fuzzy number in [24]. A simple genetic algorithm and a method based on priority rules is proposed in [26] to minimize the total tardiness.

To efficiently utilize the limited charging space, a charging cable sharing strategy is proposed in [58] to efficiently use the limited charging space in the public charging station coordinated charging. The authors solved optimal configuration of charging stations and scheduling of charging power to each EV during each time interval. The objective is to enhance charging station's utilization level and save corresponding investment costs. Similarly, a charging point sharing paradigm is proposed to balance the charging space with energy flow at a charging station. The idea is to use a M (input)-to-N (output) charger, with which the charger output and input is restricted by the limited transformer capacity [59].

- **Vehicle scheduling problem (VSP) with recharge**

The city transportation sector is under intensifying pressure in delivering a better service at an ever-lower cost by electric taxis, freights, or buses. For logistics, both the frequency and the duration of EV charging are concerning. Without careful charging scheduling and management, on-route fast-charging for logistics vehicles may significantly increase fuel costs and reduce the economic attractiveness. In terms of this, VSP models and optimizes tour assignments of EVs with energy constraints [60]. Each customer has a given demand that has to be satisfied without exceeding a maximum vehicle capacity; and the scheduler dispatches a group of EVs to execute jobs with different start and end time and, at the same time, decides when and where to charge EVs for multiple times when executing a set of tasks. The objective is to maximize the number of tasks that are completed [61], to minimize the number of vehicles used and total distance travelled [60, 62], or to minimize the costs through ahead-of-time charging planning [63]. To achieve these goals, it is key to estimate the energy-related costs and restrictions, energy demand and time constraint of each job, and the space and power capacity constraint of charge depot.

A typical application is the scheduling of urban taxis for customers pick-up and drop-off services [64]. Taxis have to get sufficient power for the remaining driving distance of next pickup service. The objective is to maximize the total profit, taking into account the revenues paid by the passengers, vehicle maintenance costs, vehicle depreciation costs, parking space maintenance costs in the train station and parking costs in the service zones. A well-planned charging can provide enough electric taxis for customers at peak hours, which can ease customers' anxiety and improve taxi drivers' income.

- **Routing and charging station selection**

Charging routing problem with energy constraint is to find the most economical route or charging places with the minimum time (waiting or driving time) or energy consumption, taking into consideration of the traffic conditions (path planning) and available charging resources at the charging stations [65, 66]. In addition, the charge station selection problem can be integrated with power allocation [67, 68], which optimizes both transport and charging under the constraint of availability, power capacity and price of charging stations.

- **Demand response and dynamic pricing**

Microgrids are advancing the management efficiency and security of power grids with the ability to integrate distribution renewable energies, energy storage systems and distributed controllers [21]. However, peak power demands at some specific times of the day may bring higher costs to end-users and instabilities to the electricity networks [69]. In terms of this, demand response (DR) programs encourage electricity consumers to change their normal consumption patterns through time-varying prices or incentives at different periods, the aim is to improve the grid stability by shifting on-peak charging demands towards off-peak periods [34]. Typical pricing schemes in the existing literature include time-of-use (TOU), critical-peak and real-time mode [34]. In addition, dynamic pricing also plays an important role in modern intelligent transportation system, by offering appropriate solution to address peak load balancing in charging/discharging of EVs, maximization of profit for charging facilities, minimization of fare/parking/toll prices, vehicle routing, and so on [70].

Dynamic pricing based demand response problems have been extensively studied in recent years [71, 72, 73]. For instance, Muhammad B. rasheed *et al.* investigated a general framework for modelling electricity retail pricing based on load demand and market price information [71]. The goal is to minimize the average system cost and rebound peaks through energy procurement price, load scheduling and renewable energy source integration. A day-ahead price information is utilized to construct individualized price profiles for each user, and the genetic algorithm is adopted to test the applicability of proposed pricing policy. Tao and Gao [73] formulated real-time pricing for smart grid by a non-cooperative game with time-space constraints, and proposed a distributed online algorithm to obtain the best response and further obtain Mash equilibrium.

- **Energy management in smart grids**

In this next-generation power grid, a variety of energy management challenges such as balancing the demand and supply, improving energy efficiency, and maximizing the utility of consumers can be tackled by market-based mechanisms [18]. Scheduling, clustering, and forecasting are widely used strategies to control the penetration of high EV charging [5]. The main objectives of these strategies are to minimize the impact of charging on the electricity distribution. EV charging coordination is intended to maintain the stability of the electricity network by ensuring the balance between the power supply and energy demand of electricity. The power system community pay more attention to the charging scheduling in a particular charging station for a long time while neglecting the mobility of vehicles [74].

We review the application of market-based mechanisms to energy management in smart grids, which includes microgrid management [75, 76, 77], smart home energy management [78, 79, 80], and EV charging related works [33, 42, 81]. For instance, Gerding *et al.* [33] proposed an online model-free mechanism to assign different charging rate units to EVs per time interval based on their demands, the payment policy is based on VCG mechanism. This work shows that the greedy allocation policy (allocating the charging rate units to the user with highest marginal valuation) may cause over-allocation problem, which means unnecessarily allocates uneconomical charging rate to users. Zeng *et al.* [82] proposed an auction-based demand response management approach to reduce the system cost and maintain the load stability in microgrid. In their approach, EVs are financially incentivized to participate in the energy allocation with the feedback dynamic pricing determined by the group-selling-based auction. In addition, a second auction is also conducted among the aggregators in the microgrid to determine the winner aggregators who can sell their surplus electricity to the microgrid. Bhattacharya *et al.* [83] proposed two second price auction mechanisms for electricity allocation in EV charging.

- **Multi-aggregator collaboration**

In power community, dispatching is used to represent scheduling, which coordinates multiple energy demands from EVs to different charging stations in the electric power networks, with objective of alleviating the negative effects of charging activities on electric distribution networks, such as the voltage deviation, transformer saturation, or power loss and voltage deviation [8]. Energy management is an optimal control process for the output power to the plug-in EV during different time intervals

[84, 85]. Energy management usually do not consider the limited spaces in charging stations, but only the limited power capacity in the electric power networks. Vishu Gupta *et al.* [86] addressed a multi-aggregator-based charge scheduling problem that incorporates collaborative charging and realistic situations with variable energy purchase and cancellation charges. The objective is to maximize the number of EVs that are scheduled at public charging stations, along with maximizing the total profit of the aggregators.

• **V2G paradigm**

EVs can play as energy storage units and join the energy management of the local network by returning electricity to the grid or by throttling their charging rate, when they park a long time and charge at parking lots at homes or working places most of the day [87]. This paradigm refers to Vehicle to Grid (V2G). V2G can provide several ancillary services such as extra power for peak load demand, spinning reserves and regulation of the system, as well as storage of renewable energies, which can be erratic, unpredictable and geographically determined [11]. One typical application scenario of energy management is micro-grid, which realizes the emerging potential of distributed renewable energy generation and associated loads (such as EVs) [88]. M. Honarmand *et al.* [89] proposed an energy resources management model to integrates EVs and distributed energy resources into the power system. The stored energy of EVs is aggregated into the compensation of the renewable power forecasting error.

V2G can bring more economic incentives to users by selling the energy to the grid, meanwhile, it can provide a better management of electricity resources. However, the costs over battery performance and degradation, as well as the uncoordinated charging models of EVs should be carefully tackled in V2G [11]. Despite these concerns, vehicle to everything (V2X) paradigm, i.e., vehicle to home (V2H), vehicle to vehicle (V2V), or vehicle to load (V2L), still leads to EV's larger functionalities acting as independent clusters of generation.

• **Scheduling: joint transport and power**

The interdependences between electric power systems and transportation systems are becoming increasingly tight as the penetration of EVs keeps booming [90]. Considering them as an integrated system becomes a critical issue, and we call this novel field as grid-interactive transportation, which concentrates on the systematic interaction of the intelligent transportation system and power systems in charging scheduling, which solves charging planning and scheduling problem, taking into account of the spatial charging demands from users and the limited space and power capacity of the charging facilities [25].

Some planning and scheduling problems consider the benefits of both resource provider (charging facility) and resource consumer (EV users), such as charging capacity, users' demand and time constraint. Y. Luo *et al.* [91] proposed a multi-objective charging scheduling strategy for the EV charging scheduling and path planning, taken transport and grid related system information into account, such as road length, vehicle velocity, waiting time, as well as load deviation and node voltage in distribution network. H. Chen *et al.* [49] studied a charging facility planning problem and built two-stage stochastic programming model to serve more EV users with random behaviors and demands. This charging coordination is restricted by a limited power and parking space in a multiple-charger multiple-port charging environment. Moreover, a double-layer smart EV charging scheduling problem in working place is addressed in [66], where the first level considers the transformer power demand and transformer capacity from the prospective of power grid, and the second level routes the EVs to the most suitable charging point, and controls the charging process cost-effectively and reliably.

Z. Ding *et al.* in [90] optimized the operation strategies of EV charging stations by solving a marginal price based mixed integer linear optimization model. Such coordination optimization consists of the travel-route scheduling for EVs and resource management and pricing problem for charging stations. The objective is to minimize users' charging costs and maximize the operation revenue under the transportation and power constraints. In addition, reference [74] addressed an EV sharing problem where the customers can hire an EV at one parking lot and drive it to another one and pay for the service at a certain price. The EV company should solve a bilevel program, where the lower level simulates the distribution market clearing, and the upper level represents the pricing and charging scheduling problem in order to maximize the profits. The authors developed an equivalent mixed-integer program based on primal-dual optimality condition and integer algebra technique, together with a warm-start strategy which accelerates computation remarkably.

Another sort of problems mainly address the location planning of public charging infrastructure. A charging infrastructure location model is proposed in [92] to determine the volume of EV flows between the sub-regions in the first step, and then develops a simulation model to determine the expected number of EVs that successfully charge at a candidate location. The final step uses a linear integer programming model to determine the location and size of charging stations.

## 2.2 Taxonomy

In view of above related work, we present a taxonomy for the EV charging scheduling problems according to the operational environment, as shown in Table 2.2. The classification standard is based on environmental factors: the **information availability** in offline, stochastic, online environment, as well as the **information control** in centralized, distributed, decentralized environment.

The offline environment assumes all the problem data (e.g., number of jobs, charging times, release dates, due dates, charging facility information, and so on) are known in advance. As for the stochastic environment, distributions of the problem data are known in advance. While in an online environment, scheduler does not know the upcoming jobs or charging requests, including number of jobs to be processed, release dates, processing times, etc. Jobs are presented to the scheduler one after another in a real-time manner.

Table 2.2: A taxonomy of EV charging problems in the literature

| | | **Information Availability** | | |
|---|---|---|---|---|
| | | Offline/Deterministic | Stochastic/Dynamic | Online |
| | Centralized | [26] [60] [62] [63] [64] [57] [93] [94] [95] | [24] [41] [87] [50] | [61] [96] |
| **Information Control** | Distributed | [45] [46] [55] [56] | | [27] [85] [54] |
| | | **x** | [58] [65] [97] [25] [53] [98] [40] [99] | |
| | Decentralized | [30] [31] [42] [52] [100] | [32] [84] [101] [51] [102] | [28] [33] [103] [104] |

The central controller in centralized environment collects the charging requirements from the relevant entities, and then makes the decision and allocates the available resources as required [52]. The centralized scheme can get the optimum solution, in which each user contributes to the decision-making individually, without requiring the knowledge of the involvement of the other users in the community.

Centralized paradigm aims to solve this problem by communicating information from the relevant entities to a central controller who then tacklers the decision making and allocates the available resources as required [52]. In this paradigm, each user contributes to the decision-making individually, without requiring the knowledge of the involvement of the other users in the community. It is important to study the behavior of individuals and small impacting organizations in making decisions on the allocation of limited resources in a decentralized market environment.

The distributed and decentralized environment does not need the control center and allows each entity to make its own decisions in a distributed environment, where stakeholders are autonomous decision makers who are motivated by their own objectives and not controlled by other entities or a system-wide authority. Moreover, these two schemes both assure scalability, with which scheduling related information is normally located in entities which are scattered across the system, and no entity has a global view of the problem [19]. The difference between the distributed and decentralized scheme is that stakeholders in the decentralized environment may behave strategically who may misreport their private information. Therefore, the decentralized scheme is a good means of user privacy protection, by preventing central authorities from collecting information for decision making [34].

Compared to it, decentralized scheduling allows each entity to make its own decisions and achieve a social welfare. This decentralized paradigm assures scalability, while it is also a means of user privacy protection, by preventing central authorities from collecting information for decision making [34]. And decentralization in charging scheduling problems present two types of challenges attributable to the distribution of scheduling knowledge and the distribution of control. The challenge for a decentralized solution is how to collect information, manage message passing, and determine the solution consisting of independent self-interested agents.

## 2.3 Modelling and Methodology

In this section, we will review the most recent activities relevant to the optimization of charging scheduling problems in the literature. Existing works typically use either mathematical programming or utility-based agent coordination combined with the mechanism design approach, such as auction and game theory, to model the charging scheduling problems in dealing with the complexities of information control and availability. The scheduling approaches in literature can be generally classified into **centralized**, **distributed** and **decentralized** based approach with respect to the challenges. A classification of existing approaches in dealing with the aforementioned challenges is provided in Table 2.3.

Table 2.3: The classification of existing approach

| | Offline/Deterministic | Stochastic/Dynamic | Online/Real-time |
|---|---|---|---|
| Centralized | Mathematical optimization<br>Meta-heuristics | Robust optimization | Meta-heuristics<br>Machine learning |
| Distributed | Mathematical optimization<br>Meta-heuristics | Stochastic optimization (with ML)<br>Distributionally Robust Stochastic<br>Pricing strategy | Online optimization<br>Markov decision process |
| Decentralized | Game theory<br>Combinatorial auction | Auctions & reinforcement learning<br>Stackelberg game | Online mechanism design |

### 2.3.1 Centralized/Deterministic Approach

Theoretically, a centralized approach allows for achieving the best solution as the central authority has access to all information about charging scheduling. However, the difficulty of this approach lies in application bottlenecks such as scalability, computation tractability, data privacy concerns and communication infrastructure [10].

The model parameters (energy demand, arrival times, charging time, etc.) in centralized/deterministic approaches that are known with certainty even though they are truly only estimates of the values that will arise in real application. We can also conclude from Table 2.2 that most of the EV charging scheduling works are solved by heuristics [26, 57, 63, 93, 95].

#### Mathematical programming

Centralized optimization is of great importance, since it constitutes the basis for solving a dynamic and distributed charging scheduling problem. For modelling and solving the vehicle scheduling problem with recharge, charging scheduling with limited space, and routing and charging station selection, extensive works apply linear programming (LP)[87], dynamic programming (DP) [48], mixed integer linear programming (MILP) [25, 64]; decomposition techniques: Lagrangian Relaxation (LR) [29], Lagrangian decomposition (LD) [105], or robust optimization [25, 84] and stochastic programming [45, 46] in developing efficient scheduling strategies.

The above approaches follow a *centralized* scheme under the coordination by a central controller. In this way, each user contributes to the scheduling process individually, without requiring the knowledge of the involvement of the other users in the group. One advantageous aspect for the scheduling results is the optimal solution and highest efficiency is supposed to be obtained with the complete and truthful information from users.

**Heuristic-based approach**

The meta-heuristic algorithms can efficiently explore large search spaces and incorporate heuristic knowledge on the problem domain in NP-hard scheduling problems, such as Genetic Algorithms (GA) [24], Particle Swarm Optimization (PSO) [106], and Artificial Bee Colony Algorithm [107], etc. A meta-heuristic may provide a sufficiently good solution to the charging scheduling problem, especially with incomplete or imperfect information or limited computation capacity.

Although meta-heuristics do not guarantee global optimal solutions compared to the exact algorithms, they are still playing an important role in charging scheduling and routing problems in a centralized environment. For instance, a two-phase heuristic algorithms are also used in routing planning of taxis in [62] to minimize the total travel distance. The nearest-neighbor heuristic adds the closest customer to extend a route in the first phase, and two types of move operations, exchange and relocate, are combined with a tabu search in the improvement (second) phase.

The centralized approaches deliver a straightforward manner for EV charging scheduling, however, it is not applicable for large-scale numbers of EVs, as it requires massive computational power and an advanced communication system [5]. Shortcomings have also been stated concerning the information confidentiality of EV users, as their charging behaviors, preference information and related data would be publicly known, increasing the threat of exposure to the cyber-attacks and the well-being of the whole society.

### 2.3.2 Stochastic/Dynamic Approach

In this part we will review some typical modelling paradigms for EV charging scheduling with uncertainties in stochastic/dynamic environments.

While the distributed and decentralized approach eliminate several disadvantages of a centralized approach at the cost of stability and optimality, however, it is more efficient in addressing the uncertainties in a distributed environment. The parameters of stochastic/dynamic approaches are known only in probability, that is, random variables for which a probability distribution of possible parameter realizations is known but variability of possible values must be modeled to validly choose best values for the decision variables of the optimization.

#### Stochastic optimization

Stochastic models are strong tools to deal with uncertainties in practical scheduling problems, such as Markov Decision Process (MDP), Stochastic Programming (SP) and Robust Optimization (RO).

*Stochastic programming*:

SP is a framework for modeling optimization problems that involve uncertainty, where deterministic optimization problems (e.g., day-ahead) are formulated with known parameters, while the stochastic problems (real-time) almost invariably include some unknown parameters. The uncertainties from the probability distribution will be addressed in the second stage [27, 54]. SP is efficient for modeling and solving two-stage energy management in demand response program, the goal is to improve the efficiency, reliability and safety of the power system, through motivating changes in the customers' power consumption habits [34].

Extensive works model day-ahead demand dispatching and real-time power control as a two-stage optimization process for energy management [54]. For instance, a two-stage model by SP is proposed in [45], where the energy scheduling with the day-ahead power market is solved in the first stage, and the real-time energy scheduling is solved in the second stage. The objective is to find solutions that are feasible for all possible scenarios while minimizing the expected cost at the first stage. Similar works can also be found in [46, 55, 56], and SP can be combined with robust optimization as a Distributionally Robust Stochastic [25, 84], which is presented in the following.

*Robust Optimization (RO) and Distributionally Robust Optimization (DRO)*:

RO is a relatively new approach to model uncertainties in charging scheduling optimization, such as uncertain renewable energy supplies, market prices, and drivers' energy demands. This uncertainty modelling approach is suitable for situations where the range of the uncertainty is known, while the distribution of uncertainty is unknown [84]. Whereas stochastic programming assumes there is a probabilistic description of the uncertainty, robust optimization works with a deterministic, set-based description of the uncertainty, which constructs a solution that is feasible for any realization of the uncertainty in a given set[5].

Moreover, data-driven optimization under uncertainty requires distributionally robust optimization [25, 84], also known as data-driven stochastic program, where the uncertainty is modeled by a set of probability distributions, namely ambiguity set. DRO can obtain prior knowledge of the probability distributions through historical and/or real-time data, in terms of the practical scenarios where the precise information of the ambiguity set is rarely available or known. For instance, the day-ahead energy management model incorporated uncertain market prices using RO, and used stochastic optimization to model the uncertain charging demand (arrival, departure, and charging times of EVs at charging station) [84]. A uncertainty set is constructed for market prices to minimize the mismatch of the realized specific prices and the forecast one, and thus may decrease charging stations' monetary losses. Moreover, a data-driven robust optimization model is developed in [25] to optimize the capacities of renewable generations and energy storage units in each charging station, where the uncertainty on the output of photovoltaic energy and charging demands are formulated via robust chance constraints.

*Queueing theory*:

Queueing theory solves routing and charging station selection problem, in order to find the most appropriate charging sites with minimum waiting time, and balance the traffic flow among different stations [65, 97, 108]. This distributed and cooperative scheduling is designed to assign EVs' multiple charges to different charging stations, which is often applied to the highway scenario. For instance, S. Bae and A. Kwasinski [109] proposed a spatial and temporal model of EV charging demand, which first predicts arriving rate of EVs by the fluid dynamic traffic model, and then forecasts the charging demand by queueing theory.

[5] Robust Optimization: https://neos-guide.org/content/robust-optimization.

*Markov Decision process*:

Some discrete-time stochastic charging scheduling problem can be modelled as a MDP, with the typical time-driven scheduling policy adopted. A MDP model is defined as a 5-tuple: 1) decision epoch; 2) action; 3) state; 4) transition probability; and 5) reward and cost functions. MDP can investigate the constrained stochastic optimization problem in terms of the uncertainty of, for instance, the arrival of EVs, the intermittent renewable energy, or the variation of the energy price [29]. If the probabilities or rewards are unknown, the problem is one of reinforcement learning in practical deployment [110, 111]. Typical work refers to David C. Parkes [28], which modelled the online mechanism design problem as an MDP to solve an energy allocation problem. The optimal policies are implemented in a truth-revealing Bayesian-Nash equilibrium.

### Online Optimization

Some charging scheduling problems adopt model-free online scheme. The time horizon is slotted in equal intervals in time-driven mode and scheduling decisions are made at each time interval. For instance, a distributed offline and online framework is proposed in [85] to collaborate multiple aggregators for scheduling, in order to maximize he total profit of the aggregators and the total number of vehicles charged. Some other online mechanisms for dealing with energy allocation are presented in Game-theoretic/Mechanism Design part. However, F. Kong *et al.* [104] point out that the major dilemma for applying the time-driven scheduling policy to charging network is to determine the length of time slots. Long time slots lead to few charging mode switches but cause under-utilized charging points at the stations, while short time slots improve charging point utilization but cause many mode transitions for EVs. Given this, event-driven could be an efficient solution for online charging scheduling.

### Machine learning

Machine learning is widely applied to analyze data and design autonomous systems to adapt to their environments. Data-driven optimization under a highly stochastic and distributed environment that integrates machine learning and mathematical programming is appealing in the era of big data, which can predict EV mobility, charging demands, load fluctuation, renewable energy generation, as well as other system uncertain parameters in SI. For example, Artificial Neural Network (ANN) is applied in the optimal energy management for a day-ahead price forecasting, so that the error between the actual and predicted electricity prices and the cost of parking lot owner with respect to the time of use can be minimized [48]. Similarly, ANN with sample average approximation is used for predicting the base load power consumption [45].

Some charging scheduling problem are modelled as MDP and solved by reinforcement learning, which controls diverse energy systems in the decentralized charging scheduling problems with user's participation [112]. For instance, the cost-effective day-ahead consumption plan can be learned to better forecast numerous details about each EV behavior (e.g., plug-in times, power limitations, battery size, power curve, etc.) [111].

Ioannis C. *et al.* proposed a gamification approach for smart building infrastructure in [113], with a goal of motivating human occupants to consider personal energy usage and to have positive effects on their environment. The authors first proposed a benchmark utility learning framework via deep learning that employs robust estimations of occupant actions toward energy efficiency, and then incorporates customers in the loop modeling by creating an interface to allow building managers to interact with occupants and potentially incentivize energy efficient behavior. This research shows that the adoption of human-centric building services leads to improvements in the operational efficiency for energy usage.

### 2.3.3 Game-Theoretic Approach

As we mentioned above, the demand information is not centrally collected by the central authorities for decision-making in *decentralized* approach. This decentralized control assures scalability, incentive as well as user privacy protection, by motivating the participation of users and alteration of users' demand profile and charging habits to match the supply in the decentralized scheduling process, as well as preventing central authorities from collecting information for decision making [34].

To deal with EV drivers' strategic behaviors in decentralized environment, general equilibrium theory in game theory [30, 32, 42] and mechanism design based on micro-economic theories [31, 33, 104] incentivize users to participate in the scheduling process, reveal their real private preferences over charging, and alter their charging or electricity consuming habits to gain greater benefits. A key to making these market-based mechanisms efficient in the smart infrastructure is to design proper incentives and pricing policies for selfish agents in optimization and decision-making. These market based mechanisms are widely applied for energy until allocation and aggregator collaboration in either offline [30, 32] or online environment [28, 103, 104].

The equilibrium in game-theoretic models is defined as the condition that each participant acts on its best-response strategy with respect to others' strategy and cannot benefit itself by unilaterally deviating from this current state with an alternative strategy [114]. For instance, the energy exchange process is modelled as a non-cooperative Stackelberg game in [42], in which the smart grid acts as a leader, who needs to decide on its price so as to optimize its revenue; while the EVs act as followers, who need to decide on their charging strategies so as to optimize a trade-off between the benefit from battery charging and the associated cost. A distributed algorithm enables EVs and smart grid to reach a generalized Nash equilibrium. In addition, a cake cutting game is applied in [101] to deal with the selection of EVs and route for transportation demands, in which the limited idle time for the serving EVs should be efficiently utilized for charging. The goal is to balance the transportation and charging demands to guarantee the long-term operation of photovoltaic systems with less charging costs and more profits.

The most important application of mechanism design in market setting is auctions. In a decentralized environment, users are allowed to negotiate on the power allocation at different time intervals with the electricity network, through mechanism design based-approaches [28, 100]. For example, a pricing process for multi-tenancy autonomous vehicle servicing problem is modeled as a combinatorial auction based on Vickrey-Clarke-Groves (VCG)-based charging mechanism in [31], in which the service providers, as bidders, compete for offering transportation services; as a result, the social welfare is maximized. Moreover, a type of Groves mechanisms is proposed in [52] to allocates the available charging capacity (discrete energy unit) under network constraints at the distribution networks, this mechanism is able to obtain a Nash equilibrium and is shown to be efficient and strategy-proof.

## 2.4 Summary

This chapter reviewed related EV charging scheduling problems and existing solution approaches. We presented a taxonomy of current research issues on EV charging in intelligent transportation systems, smart grids, and smart cities by analyzing its unique features with some typical use cases, such as space assignment, routing and energy management. We discussed the challenges, i.e., the information availability and stakeholders' strategic behaviors that arise in stochastic and decentralized environments; and classifies the existing approaches, as centralized, distributed and decentralized ones, that apply to these challenges.

The position taken in this thesis is to develop advanced mechanism design framework based on scheduling theory and model, optimization and machine learning techniques. We expect that, by carefully investigating the nature and features of decentralized EV charging scheduling problems, effective and practical auction-based scheduling approach and interaction rules can be developed, such that an efficient operation of transportation and power systems are ensured and, at the same time, economical and satisfactory charging services are provided for EV users.

# Chapter 3

# Iterative Bidding for Single-Station Charging Scheduling

## 3.1 Background

Compared to internal combustion engine vehicles, the driving range of EVs for a single charge is around one-third of the petrol-equivalent, while the recharging time can be hours, compared to minutes at a gas station [4]. Convenient and fast recharging services thus become essential for EV users to alleviate their *range anxiety* [115]. Public charging networks, such as ChargePoint or The Electric Circuit, can greatly extend EV driving range by providing first-come-first-serve charging services. However, this uncoordinated management may cause congestion and long waiting time at peak hours [38], which in turn negatively impacts charging resources utilization and users' satisfaction. Therefore, it is of great importance to schedule multiple users' requests based on their private preferences in terms of start times and charging duration *in advance*, such that charging network utilization efficiency and user satisfaction can be maximized.

In this work, we address a charging scheduling problem in a decentralized reservation setting, in which users with strict time requirements can express their preferences and reserve their charging time based on their State of Charge ($SoC$). Reservations can be made to achieve two main objectives:

*Improve users' satisfaction*: Reservations can guarantee the availability of charging facility at users' reserved time. A high preference for reservation is expected by the users who have more strict time requirements for their charging, such that they can integrate charging with their daily activities and reduce the traveling time for finding an available charging point. Moreover, reservation is also important for long distance travel, as it enables users to reserve their preferred time at the highway charging stations before departure, such that they can recharge as planned on the road [39]. In such a highway scenario, reservation can reduce waiting time at charging stations and total travelling time to destination [40, 98].

*Improve charging resource utilization*: Reservations can eliminate the conflicts among the multiple charging requests in advance and, at the same time, achieve an efficient utilization of the limited space and power at the charging stations [99, 116]. Up to now, the growth of publicly accessible chargers, especially the fast chargers, still falls behind the increase in the number of EVs on the road. The reason could be attributed to the large costs of charging facility investment and long payback period [117]. In this situation, reservation can be a good solution to accommodate more EVs with the limited charging capacities [49, 118], adjust the expected profit and task declining cost [119], and make more profits for charging stations [120]. Moreover, reservations can also play a key role in alleviating the adverse impacts of charging activities on grid reliability and stability, as discussed in [52, 121, 122]. It can also contribute to charging infrastructure planning and management by reducing the required number of charging points and improving the charging station's profits [53, 123].

The decentralized approach is justified by users' *self-interested* behaviors that may yield negative consequences to the social welfare and the utilization efficiency in the charging network [43]. Decentralized charging scheduling needs significant inputs from the self-interested users, thus the solution quality depends heavily on the charging requests and preferences gathered from them. However, self-interested users may reveal incomplete, or perhaps untruthful information, about their preferences, if that leads to an individually preferable outcome. Such *strategic* and *economical rationality* may jeopardize the quality of solutions and the social welfare.

In this work, we solve an electric vehicle charging scheduling problem as an iterative bidding process in a decentralized day-ahead setting, which can be applied in different scenarios, such as highway, shopping mall, or hospitals, etc. Specifically, we address a charging scheduling problem with the limited charging space, where the energy management issue and charging impacts on the stability of distribution network are neglected. The proposed multilateral bidding framework allows the self-interested users to iteratively negotiate with others on the charging time and the prices. And they are allowed to progressively reveal their preferences over different start times as necessary. Given users' private preferences and assuming all requests are available at the beginning of decision making horizon, the iterative bidding framework computes a social-welfare solution with the minimum preference elicitation.

## 3.2 Related Work

Among the solving techniques, games and auctions are widely applied to address the social welfare issue in decentralized charging scheduling [124]. However, two gaps exist in the current researches: First, most of the existing works tackling space or energy reservation does not consider the decentralized nature of the charging scheduling problem. They focus on the mathematical programming based approaches, instead of on the market based mechanisms, as discussed in [6, 41, 50, 57, 120]. From another aspect, market mechanisms are frequently applied in a discrete time and dynamic charging scheduling environment [42, 76, 118, 125], rather than in the continuous time and reservation environment. Second, more efforts should be put into developing efficient market mechanisms with privacy preservation for decentralized charging scheduling problems. Current works focus on applying Stackelberg game [42] and Vickrey-Clarke-Groves (VCG) auction [43]: Stackelberg game aims to analyze and predict the potential outcomes of the leader-follower interaction, however, we should develop a mechanism for EV charging scheduling with the bidding and payment rule such that the desired outcomes can arise naturally from the strategic interactions among users; moreover, instead of forcing users to truthfully report their private preferences through VCG mechanism, we expect participants to gain greater utility by revealing less privacy through an iterative bidding process [126].

The optimization process in real-time energy management or online auction design of charging scheduling often adopts discrete-time model, which splits the time period into a series of units and allocates the power at each unit [30, 32, 54]. This is more flexible for real-time power control with the potential of accommodating dynamics. However, the mathematical programs for discrete-time problems are usually of much larger sizes and require more computational efforts to solve than the continuous one. Moreover, continuous-time model can take place at any point in the continuous domain of time. In this work, we build a continuous-time, offline model for the charging scheduling problem without considering the dynamic events during optimization process. This research provides the first baseline for deterministic scenarios while robustness against uncertainties and dynamics may be further addressed in our future work.

Most energy management problems assume charging stations have enough service points to accommodate all charging requests [45, 46, 53], which is impractical in real-world scenarios. This work aims to relieve the range anxiety in public charging station by allocating reserved charging space for users with preferences. Moreover, compared to the decision variables and constraints in traditional parallel machine models, we considered users' restricted time window for charging and added a selection decision variable on each constraint. The objective is refined to maximize users' value on the start time, instead of minimizing only the total completion time. This allows us to optimize the valuation, not just the duration, of time for the EV users based on their practical demands and preferences.

## 3.3 Our Contribution

To be specific, our work contributes to the existing literature in two aspects:

(1) We formulate the decentralized charging scheduling as a mixed-integer linear program (MILP) in a stand along charging station system, which resolves the selection issue from the limited charging space and users' available time window. This mathematical formulation introduces novel decision variables and constraints to the parallel machine (Pm) scheduling model while delivering a continuous-time solution to the problem.

(2) We devise an iterative bidding framework based on game theory and mechanism design to solve this charging scheduling problem. We have conducted both game theoretical analysis and extensive simulations to validate its performance. The results have demonstrated (i) the generalized game theoretical properties, including individual rationality and the best response for agents; (ii) the performance on numerical experiments, where iterative bidding achieves on average 85% of efficiency

under a partial information revelation.

The remainder of this work is organized as follows, Section 3.4 describes the charging scheduling problem and presents its mathematical formulation. Section 3.5 illustrates the implementation of the iterative bidding framework for the problem, and presents its game theoretical properties. Section 3.6 presents a computational study to test the performance of the proposed iterative bidding framework. Section 3.7 draws a conclusion and outlooks the future work.

## 3.4 Single Charging Station Scheduling

A market-based charging scheduling problem is considered as a decentralized decision making process in which a charging station interacts with a group of users. Each user has one charging request, which consists of an available time window for charging, a preferred start time and a required charging duration. Users have preferences over different start times, expressed by values. In this decentralized setting, users' values are considered as private information, which is not known by the charging station. The charging station has a limited charging capacity restricted by the number of charging points. The station shall then select a subgroup of the charging requests and allocate charging space and start times to these requests, such that the available time windows of all selected requests are satisfied and the sum of the values across all users is maximized. A nomenclature of problem variables and parameters can be found in Table 3.1.

Table 3.1: Nomenclature of Chapter 3

| | **Index** | | **Function** |
|---|---|---|---|
| $i, j$ | Index of user | $v_i(\cdot)$ | Value function of user $i$ |
| $k$, $k'$ | Index of users' bid | $c_i(\cdot)$ | Cost function of user $i$ |
| $t$ | Index of iterative round | $p_i(\cdot)$ | Price function of user $i$ |
| | **Parameters** | | **Decision Variable** |
| $\overline{at_i}$, $\overline{dt_i}$ | Earliest arriving time, latest departure time of user $i$ | $st_i$ | Start time of user $i$ |
| $pst_i$ | Preferred start time of user $i$ | $X_i$ | Whether user $i$ is selected |
| $cd_i$ | Charging duration of user $i$ | $Y_{i,j}$ | Whether user $i$ and $j$ are adjacent |
| $Q_i$ | Charging request of user $i$ | $Y_{0,i}$ | Whether user $i$ is the first one to charge |
| $lst_{i,k}$ | Latest start time of user $i$'s $k$th bid | $Y_{i,n+1}$ | Whether user $i$ is the last one to charge |
| $\varepsilon$ | Increment of iterative bidding | $X_{i,k}$ | Whether the $k$th bid of user $i$ is selected |

Consider a charging scheduling scenario involving one charging station with $m$

charging points, and a set of $n$ users, denoted as $N$. The charging request of each user $i \in N$ is defined by a 4-tuple $< \overline{at_i}, \overline{dt_i}, pst_i, cd_i >$, where $\overline{at_i}$ is the earliest arriving time of user $i$, and $\overline{dt_i}$ is her latest departure time. $\overline{at_i}$ and $\overline{dt_i}$ indicate the earliest time that user $i$ can start to charge and the latest time by which she has to finish, respectively; they constitute the available time window of user $i$ for charging. $pst_i$ is the preferred start time of user $i$, where $\overline{at_i} \leq pst_i \leq \overline{dt_i} - cd_i$. And $cd_i$ is the charging duration needed for user $i$ to reach her required $SoC$. $cd_i$ can be computed by $E * (SoC' - SoC)/R$, where $E$ is the battery capacity ($kWh$), $SoC'$ and $SoC$ are the required and the initial state of charge, respectively, and $R$ is the constant charging rate ($kW$) delivered at the charging station.

A charging schedule contains the start times allocated to the selected charging requests, and user will have a value for schedule. We follow the *private value model* proposed in [127], where user's value is not dependent on other users' values, and each user knows her own value but not the values of others. Valuation function $v(\cdot)$ measures how user is satisfied with the start time $st$ in the schedule through the monetary value. In our model, we define user $i$'s value as a function of start time $st_i$ in the time window $[\overline{at_i}, \overline{dt_i} - cd_i]$. For the preferred time window $[\overline{at_i}, pst_i]$, $v_i(pst_i)$ is the value that user $i$ assigns to the start time $\overline{at_i} \leq st_i \leq pst_i$. For $st_i$ that is after $pst_i$ and within the time window $(pst_i, \overline{dt_i} - cd_i]$, it is also acceptable but it will incur an extra cost to user $i$. That is, her value $v_i(pst_i)$ will be diminished based on the cost $c_i(st_i)$, which is a non-decreasing function of start time $st_i$. Therefore, for a charging schedule, if user $i$ starts to charge at $st_i$, her value is defined as $v_i(st_i) = v_i(pst_i) - c_i(st_i)$. For her preferred time window $[\overline{at_i}, pst_i]$, $c_i(st_i) = 0$ and $v_i(st_i) = v_i(pst_i)$. User $i$ does not accept any charging schedule if the start time $st_i$ allocated to her is before $\overline{at_i}$ or the finish time $st_i + cd_i$ is after $\overline{dt_i}$, i.e., user's value $v_i(st_i) = 0$.

As charging scheduling involves the charging request selection due to the limited charging capacity, then let $X_i = 1$ if user $i$ is selected in the schedule, otherwise $X_i = 0$. Moreover, let $Y_{j,i} = 1$ if both users $i$ and $j$ ($i, j \in N$, $i \neq j$) are selected in the schedule, and user $i$ charges immediately after $j$ on a charging point, otherwise $Y_{j,i} = 0$. $Y_{j,i}$ is the precedence constraint for users $i$ and $j$ on a charging point, combined with the selection issue. Note that there are two implications for $Y_{j,i} = 0$: First, if any of user $i$ and $j$ is not selected, or neither of them is selected, $Y_{j,i}$ equals zero. At this time, the unselected user should not be adjacent with any other selected users, which indicates the unselected user is removed from the charging scheduling process. Second, if both of $i$ and $j$ are selected, but they are not adjacent, $Y_{j,i} = 0$.

In addition, let $Y_{0,i} = 1$ if user $i$ is selected and the first one to charge on a charging point, otherwise $Y_{0,i} = 0$. Also, let $Y_{i,n+1} = 1$ if user $i$ is selected and the last one to charge on a charging point, otherwise $Y_{i,n+1} = 0$.

A centralized setting is first considered where the values of users are assumed to be known by the charging station for scheduling. The charging scheduling problem is formulated as a mix-integer program, which involves the selection of multiple charging requests such that the scheduling constraints for all selected requests are satisfied and, at the same time, the social welfare, i.e., the sum of the values across all selected users, is maximized.

Mathematically, the centralized scheduling model solves:

$$max \sum_{i=1}^{n} X_i(v_i(pst_i) - c_i(st_i)) \tag{3.1}$$

subject to

$$X_i\overline{at_i} \leq st_i \leq \overline{dt_i} - cd_i + H(1 - X_i) \quad \forall i = 1, ..., n \tag{3.2}$$

$$\sum_{i=1}^{n} X_i Y_{0,i} \leq m \tag{3.3}$$

$$\sum_{j \in \{0\} \cup (N \setminus \{i\})} Y_{j,i} = X_i \quad \forall i = 1, ..., n \tag{3.4}$$

$$\sum_{j \in \{n+1\} \cup (N \setminus \{i\})} Y_{i,j} = X_i \quad \forall i = 1, ..., n \tag{3.5}$$

$$Y_{j,i} + Y_{i,j} + HX_i + HX_j \leq 2H + 1 \quad \forall i, j = 1, ..., n, i \neq j \tag{3.6}$$

$$\begin{aligned} st_j + cd_j + HX_i + HX_j + HY_{j,i} \leq st_i + 3H \\ \forall i, j = 1, ..., n, i \neq j \end{aligned} \tag{3.7}$$

$$\begin{aligned} X_i, Y_{i,j}, Y_{0,i}, Y_{i,n+1} \in \{0, 1\} \\ \forall i, j = 1, ..., n, i \neq j \end{aligned} \tag{3.8}$$

$$st_i \geq 0 \quad \forall i = 1, ..., n \tag{3.9}$$

Constraints (3.2) ensures that the start time $st_i$ of a selected user $i$ should not be earlier than her arriving time $\overline{at_i}$, and the finishing time $st_i + cd_i$ should not be later than her departure time $\overline{dt_i}$. $H$ is a large positive constant for the linearization of the logical constraint "if". Constraint (3.3) ensures that at most $m$ users can be selected as the first one to charge. Constraints (3.4) enforces that a selected user $i$'s charging should either be the first one on a charging point, or after some other users'. Constraints (3.5) enforces that a selected user $i$'s charging should either be the last one on a charging point, or before some other users'. Moreover, constraints (3.4) and (3.5) denote if user $i$ is not selected, all decision variable $Y_{j,i}$, $Y_{0,i}$ and $Y_{i,n+1}$ related to $i$ should be set as zero. Similar usage for constraints (3.4) and (3.5), as well as $Y_{0,i}$ and $Y_{i,n+1}$, can also be found in [57] [128], however, they did not involve the selection issue in their modeling. Constraint (3.6) ensures that if both users $i$ and $j$ are selected and adjacent, they have one determined precedence sequence for charging, which means one should charge either before or after the other one. Constraint (3.7) ensures that if both users $i$ and $j$ are selected and $i$ charges immediately after $j$ on a charging point, user $i$ does not start before $j$ is completed. The domain of decision variables $X_i$, $Y_{i,j}$, $Y_{0,i}$ and $Y_{i,n+1}$, as well as the start time $st_i$, is defined in (3.8) and (3.9).

The centralized modeling allows us to gain a better understanding of this charging scheduling problem and extend it to the decentralized setting for combinatorial optimization. In particular, we had assumed that users' preference values are known by the charging station in the centralized optimization, so it can obtain the same outcome as VCG auction, where each user is incentivized to truthfully report their values. In next section, we will remove this assumption in the decentralized setting and consider users' values as private information. This allows us to focus on the strategic interaction between the charging station and the users, in which users may misreport their values if that can improve their own benefits. In order to reflect this self-interested property of users, we call them *agents* and propose an iterative bidding framework to solve the decentralized problem.

## 3.5 Iterative Bidding Framework

Iterative bidding is an auction-based approach containing three major components: the bids, a winner determination model, and an iterative bidding procedure. The bids allow agents to express their charging requests and prices. The winner determination model takes agents' bids as input to solve the bid selection and charging scheduling to maximize the sum of bidding prices. The iterative bidding procedure is an interactive process for the charging station (auctioneer) and the users to negotiate on the start times and prices in a systematic way, through which the provisional charging schedule evolves towards an optimal one.

The bidding process can be implemented on users' smart phones or other platforms, where users can set up their preferences in advance to participate. After that, bidding is executed automatically, and users need not to wait or bid manually. In real-world applications, iterative bidding also adds the potential of accommodating dynamic changes by running multiple bidding events. If a user has any change of charging requests, she may update her bids and participate in the next bidding event.

We will elaborate on these three components through game theoretical analysis with a worked example in the following.

### 3.5.1 Bids

During the strategic interaction with the auctioneer in iterative bidding, an agent can often express her preferences over different charging schedules through a conditional statement, which involves the charging request, the start time and the price. We use the atomic bid in [129] as a basis to represent agents' preferences in terms of these three elements. The bids are defined as a 3-tuple $< Q, lst, p >$, where $Q$ represents the charging request of one agent that contains her arriving time $\overline{at}$ and the required charging duration $cd$. $lst$ is the latest start time. And $p$ represents the price that one agent is willing to pay for request $Q$ to be started before $lst$, which implies the start time $st$ is within the time window $[\overline{at}, lst]$.

The bids can be connected by *XOR* connective as *XOR* bid [129], which enables agents to express their complete preferences over different start times. *XOR* connective is an operation over bids, enabling each user to submit an arbitrary number of bid $< Q, lst, p >$, where implicitly an user is willing to obtain at most one of these bids. For instance, $< Q_i, lst_{i,1}, p_{i,1} > XOR < Q_i, lst_{i,2}, p_{i,2} >$ indicates agent $i$ will pay $p_{i,1}$ if she can start to charge before $lst_{i,1}$ (the allocated start time $st_i$ is before $lst_{i,1}$), and pay $p_{i,2}$ if she can start to charge before $lst_{i,2}$. Suppose agent $i$ has $w_i$ bids for the charging started after her preferred start time $pst_i$, i.e., $pst_i < st_i \leq \overline{dt_i} - cd_i$, then her full preferences can be represented using the $XOR$ bid: $< Q_i, lst_{i,0}, p_{i,0} > XOR < Q_i, lst_{i,1}, p_{i,1} > XOR, \cdots, XOR < Q_i, lst_{i,w_i}, p_{i,w_i} >$, simplified as $XOR_{0 \leq k \leq w_i} < Q_i, lst_{i,k}, p_{i,k} >$, where $lst_{i,0} = pst_i$, $p_0 = v_i(pst_i)$, and $lst_{i,w_i} = \overline{dt_i} - cd_i$. Each agent wants just one of her $XOR$ bid to be selected in the schedule. If we restrict the values of the start times to integers, $XOR$ bids have full expressiveness in representing agents' values, and we could formulate a linear winner determination model with a finite set of start times. This is reasonable because agents usually define their start times in terms of the number of certain time units, such as hours, from the time when they arrive. Given this, we have $lst_{i,k} = lst_{i,k-1} + 1$, for $k = 1, \ldots, w_i$.

In $XOR$ bid, agents are assumed to be indifferent to the start times within a certain time period, which indicates agents have an equivalent value for the start time that is before one latest start time. For instance, they may claim they would pay \$5 if they can start to charge before 10 a.m., and would only pay \$3 if before 12 a.m.. In this way we turn the continuous cost function of the centralized model into a step-wise price function in the format of $XOR$ bid, such that agents can express their preferences on the limited, discretized time periods, and bid with different latest start times. Using the value on the latest start time to represent the preference over a period of time, we are able to construct the linear winner determination model taking the $XOR$ bids as input.

### 3.5.2 Winner Determination Model

The winner determination task selects a subset of agents' $XOR$ bids such that its constraints are satisfied and, at the same time, the sum of the bidding prices is maximized. Although agents use the bidding prices to express their values over different time windows, they will not necessarily reveal the true values of their bids. The reason is that iterative bidding is essentially a price system, rather than a direct revelation mechanism, i.e., it does not require agents to reveal their complete values, such that agents' privacy is preserved. In such system, rational and self-interested agents tend to partially reveal their values in order to maximize their utility, thus bidding prices do not necessarily correspond to agents' values. In agent $i$'s bids, the bidding price $p_i(lst_{i,k})$ for $lst_{i,k}$ is lower than her value $v_i(lst_{i,k})$ over the $k$th bid. The utility $u_i(lst_{i,k})$ of agent $i$ is the difference of her value and the bidding price, i.e., $u_i(lst_{i,k}) = v_i(lst_{i,k}) - p_i(lst_{i,k})$. We assume that agents prefer an earlier start time, thus they have a higher value and a higher bidding price for it. It can be seen that the bidding price slopes downwards, i.e., $p_{i,k-1} \geq p_{i,k}$, for $k = 1, \ldots, w_i$.

In the winner determination model, we turn $X_i$ (centralized charging scheduling model) into the two-dimensional decision variable $X_{i,k}$, where $k = 0, \ldots, w_i, i = 1, \ldots, n$; and let $X_{i,k} = 1$ if the $k$th bid of agent $i$ is selected in the provisional schedule $s^t$, otherwise $X_{i,k} = 0$. In other words, $X_{i,k} = 1$ indicates the charging for agent $i$ starts before the latest start time $lst_{i,k}$ in her $k$th bid. Taken the *XOR* bids as input, winner determination maximizes the sum of the bidding prices across all selected agents, which solves:

$$max \sum_{i=1}^{n} \sum_{k=0}^{w_i} X_{i,k} p_i(lst_{i,k}) \tag{3.10}$$

subject to

$$\sum_{k=0}^{w_i} X_{i,k} \leq 1 \quad \forall i = 1, ..., n \tag{3.11}$$

$$\begin{aligned} X_{i,k}\overline{at_i} \leq st_i \leq lst_{i,k} + H(1 - X_{i,k}) \\ \forall k = 0, ..., w_i; \quad i = 1, ..., n \end{aligned} \tag{3.12}$$

$$\sum_{i=1}^{n} \sum_{k=0}^{w_i} X_{i,k} Y_{0,i} \leq m \tag{3.13}$$

$$\sum_{j \in \{0\} \cup (N \setminus \{i\})} Y_{j,i} = \sum_{k=0}^{w_i} X_{i,k} \quad \forall i = 1, ..., n \tag{3.14}$$

$$\sum_{j \in \{n+1\} \cup (N \setminus \{i\})} Y_{i,j} = \sum_{k=0}^{w_i} X_{i,k} \quad \forall i = 1, ..., n \tag{3.15}$$

$$\begin{aligned} Y_{j,i} + Y_{i,j} + H \sum_{k=0}^{w_i} X_{i,k} + H \sum_{k'=0}^{w_j} X_{j,k'} \leq 2H + 1 \\ \forall i, j = 1, ..., n, i \neq j \end{aligned} \tag{3.16}$$

$$st_j + cd_j + HX_{i,k} + HX_{j,k'} + HY_{j,i} \leq st_i + 3H$$
$$\forall k = 0, ..., w_i, k' = 0, ..., w_j; \quad i, j = 1, ..., n, i \neq j \tag{3.17}$$

$$X_{i,k}, Y_{i,j}, Y_{0,i}, Y_{i,n+1} \in \{0, 1\}$$
$$\forall k = 0, ..., w_i; \quad i, j = 1, ..., n, i \neq j \tag{3.18}$$

$$st_i \geq 0 \quad \forall i = 1, ..., n. \tag{3.19}$$

Unlike the centralized model, the winner determination objective function is linear. Constraints (3.11) enforces that each agent has at most one of its *XOR* bid selected in the provisional schedule. Constraints (3.12) - (3.19) have a similar format and the same purpose as constraints (3.2) - (3.9) in the centralized model, except that $X_{i,k}$ becomes a two-dimensional decision variable.

### 3.5.3 Iterative Bidding Procedure

The iterative bidding procedure is shown as pseudo-code in Algorithm 1. Each agent $i$ first receives a reserve price for charging before the preferred start time $lst_{i,0}$ and any other start times $lst_{i,k}$, $k = 1, \ldots, w_i$. The reserve price is a reference value reflecting the basic cost for the charging, which includes the construction cost of charging stations, the operational costs, and electricity fees. Any prices lower than such reference are deemed invalid and will be rejected by the auctioneer.

After setting up the reserve prices, agents use them as the first-round bidding prices. At the beginning of round $t-1$ ($t > 1$), agents compute the utility-maximizing bids among all their bids. In order to do this, agent $i$ solves the maximization problem $max_{k\in\{0,1,\ldots,w_i\}}[v_i(lst_{i,k}) - p_i^{t-1}(lst_{i,k})]$ for each of her bids, where $p_i^{t-1}(lst_{i,k})$ is the bidding price for $lst_{i,k}$ at round $t-1$. Note that these bids equally maximize agents' utility. That is, for any two bids $k$ and $k'$ in the utility-maximizing bids, they have $v_i(lst_{i,k}) - p_i^{t-1}(lst_{i,k}) = v_i(lst_{i,k'}) - p_i^{t-1}(lst_{i,k'})$. After that, the agents join these bids together as *XOR* bid and submit it to the auctioneer. The auctioneer solves the winner determination using these *XOR* bids as input at round $t-1$, and sends the schedule $s^{t-1}$ of round $t-1$ back to the agents. At the beginning of round $t$, agents need to update the bidding prices for each of their start times based on the schedule at round $t-1$. If one agent is not included in $s^{t-1}$, she has three price-updating options:

**Algorithm 1** Iterative Bidding Framework

**Require:** $N$, $XOR$ bids of all agents, $\varepsilon$
**Ensure:** $s^{final}$; // The final schedule
$t \leftarrow 1$; // $t$: round index
$isTerminated \leftarrow false$; // termination index
*Agent* $i \in N$ *sets her initial bidding price*;
**while** ($\neg isTerminated$ ) **do** // iterative bidding starts
  **for** $i = 1 \rightarrow N$ **do**
    **if** ($t > 1$ && ($i$ *is not selected in* $s^{t-1}$)) **then**
      For each of bids at round $t - 1$ ;
      **do** $p_i^t(lst_{i,k}) \leftarrow p_i^{t-1}(lst_{i,k}) + \varepsilon$;
    **end if**
    Solve $max_{k \in \{0,\ldots,w_i\}}[v_i(lst_{i,k}) - p_i^t(lst_{i,k})]$;
    Update final state and join round $t$;
  **end for**
  *Auctioneer : update isTerminated and do round* $t$;
  **if** ($isTerminated$) **then** break;
  **end if**
  *Solve* $s^t \leftarrow \max_{s^t \in S^t} \sum_{lst_{i,k} \in s^t} p_i^t(lst_{i,k})$;
  *Send bidding result* $s^t$ *back to each* $i \in N$;
  $t \leftarrow t + 1$;
**end while**
*Bidding ends and winners pay their bidding prices.*

- She can increase the bidding prices that she bidded at round $t-1$ or before by $\varepsilon$, where $\varepsilon$ is the minimum increment imposed by the auctioneer. Since the agents are assumed to be rational, in general they do not bid with an increment greater than $\varepsilon$;

- She can keep her bidding prices unchanged. In this case, the auctioneer considers she has entered into the final bid status, where she is forbidden from increasing the bidding prices at any of her latest start times in future rounds;

- She can, of course, withdraw from the bidding process.

If one agent is included in the provisional schedule $s^{t-1}$, she can maintain her bidding prices unchanged at round $t$, which means she is allowed to repeat her bids. After updating the bidding prices, agents recompute their utility-maximizing bids based on their values and the updated bidding prices, and then join them as *XOR* bid for round $t$. The auctioneer allows the agents to repeat their bids in the final round (bid repetition), with the purpose of boosting the auctioneer's revenue. During the bidding process, some bids can be temporarily "excluded" from the provisional schedule due to a particular combination of scheduling constraints and charging requirements of other bids with higher bidding prices. In the latter rounds, however, the schedule may accommodate the previously excluded bids.

Once the bids are received from the agents, the auctioneer first removes the invalid and final-status bids at the current round, and then checks the termination condition against the valid bids. The bidding terminates if there are no price updates for all valid bids in this round, i.e., all agents that bid in the last round have repeated their bids. If the termination condition is satisfied, the auctioneer implements the final schedule and the agents pay their bidding prices. Otherwise the auctioneer takes the set of valid bids as input and solves the winner determination for another round.

In winner determination, the auctioneer computes a new provisional schedule at the current round as long as the bidding is not terminated. At round $t$, the provisional schedule $s^t$ solves:

$$\max_{s^t \in S^t} \sum_{lst_{i,k} \in s^t} p_i^t(lst_{i,k}), \tag{3.20}$$

where $S^t$ is the set of all feasible schedules, given the valid bids submitted at round $t$. The affiliation $lst_{i,k} \in s^t$ indicates the start time $st_i$ allocated to agent $i$ is before the latest start time $lst_{i,k}$ in the provisional schedule $s^t$. And $p_i^t(lst_{i,k})$ is the bidding price that the agent wants to pay for the charging started before $lst_{i,k}$.

Although agents are not required to reveal their values during the bidding process, the winner determination process in each round and price updating policy prompt agents to progressively reveal their complete value information and extend their latest start times if they are not included in the provisional schedule. At first round, agents always submit the bids with their preferred start time $lst_{i,0}$ due to its highest utility. Note that agents have higher values and the corresponding higher bidding prices on the earlier start times, and the utility decreases as the start time delays, i.e., $v_i(lst_{i,k-1}) - p_i(lst_{i,k-1}) > v_i(lst_{i,k}) - p_i(lst_{i,k})$, for $k = 1, \ldots, w_i$. If the submitted bid with higher utility is not selected in this round, agent has to increase its bidding price under the price updating policy, in this case, the utility of this bid will decrease. Therefore, the utility difference of the bid between preferred start time $lst_{i,0}$ and the later start times becomes smaller as the bidding proceeds, as a result, the utility of the earlier and later start time may become equivalent in latter rounds. It can be inferred by computing utility-maximizing bids that, the price updating policy prompts agent to provide more bids if she is not selected in the provisional round. This value revelation process will, to some extent, increase agents' opportunity to be selected in future rounds, however, it will cause a privacy loss to the agents as well.

### 3.5.4 A Worked Example

We take a test case from the numerical experiment (ten agents and three charging points) as an example to illustrate the iterative bidding process. Table 3.2 presents the charging requests, bids, reserve prices and values of these 10 agents. The detailed bidding process and result are shown in Table 3.3 and Table 3.4, respectively. Table 3.3 presents the bids sent to the charging station, the provisional winner bids and the objective value in each round.

As the bidding proceeds, the temporarily excluded agents tend to extend their acceptable start times and submit more bids to the auctioneer. For instance, agent No. 3 in Table 3.3 is not selected in the first two rounds, thus she has to keep increasing her bidding prices and submit more bids in next round. At round #3, she sends five bids and is finally included. Additionally, even though agent No. 5 sends her complete bids at round #3 and #4, but she is not able to be selected in the final schedule. Table 3.3 also reveals that some agents, such as No. 4, 7, and 8, do not bid their complete values but are always selected in schedule. The final schedule includes nine (out of ten) agents with a total revenue of $64.

### 3.5.5 Game-Theoretical Properties

As rational players, agents would like to be selected in the final schedule and maximize their utilities. They behave strategically and progressively reveal their values as the bidding proceeds. In an auction setting, the strategy reflects how each agent take actions to increase her own utility in response to the strategies of other agents. In what follows, we will prove two key properties held in the iterative bidding framework.

**Proposition 3.1** *Iterative bidding is individually rational.*

**Proof** Individual rationality holds if the agents can always achieve as much expected utility from participation as without participation, regardless of other agents' strategies [130]. In other words, the expected utility accrued from participation is non-negative. We prove by cases.

Table 3.2: Bids for test case: Set 5 of Group 3 (10 agents and 3 CPS)

| **Agent** | $\overline{at_i}$ | $\overline{dt_i}$ | $pst_i$ | $cd_i$ | **Charging Requests** | **Initial Price for each bid** | **value ($)** |
|---|---|---|---|---|---|---|---|
| 1 | 9 | 17 | 10 | 3h | $< Q_1, 10, 13 >< Q_1, 11, 10 >< Q_1, 12, 8 >< Q_1, 13, 5 >< Q_1, 14, 4 >$ | 10,8,5,3,2 | 14 |
| 2 | 9 | 16 | 10 | 2h | $< Q_2, 10, 10 >< Q_2, 11, 8 >< Q_2, 12, 6 >< Q_2, 13, 4 >< Q_2, 14, 3 >$ | 7,6,4,2,1 | 9 |
| 3 | 9 | 15 | 10 | 3h | $< Q_3, 10, 11 >< Q_3, 11, 8 >< Q_3, 12, 6 >< Q_3, 14, 4 >< Q_3, 15, 2 >$ | 8,6,4,3,1 | 11 |
| 4 | 9 | 16 | 11 | 2h | $< Q_4, 11, 12 >< Q_4, 12, 9 >< Q_4, 13, 8 >< Q_4, 14, 5 >< Q_4, 15, 4 >$ | 9,7,6,3,2 | 12 |
| 5 | 10 | 16 | 11 | 4h | $< Q_5, 11, 9 >< Q_5, 12, 7 >< Q_5, 13, 5 >< Q_5, 14, 3 >< Q_5, 15, 2 >$ | 6,5,3,2,1 | 9 |
| 6 | 10 | 16 | 12 | 1h | $< Q_6, 12, 8 >< Q_6, 13, 6 >< Q_6, 14, 4 >< Q_6, 15, 2 >$ | 5,4,2,1 | 8 |
| 7 | 10 | 17 | 11 | 2h | $< Q_7, 11, 11 >< Q_7, 12, 9 >< Q_7, 13, 7 >< Q_7, 14, 5 >< Q_7, 15, 3 >$ | 8,7,5,3,1 | 8 |
| 8 | 10 | 18 | 11 | 2h | $< Q_8, 11, 10 >< Q_8, 12, 9 >< Q_8, 13, 5 >< Q_8, 14, 3 >< Q_8, 15, 2 >$ | 8,7,5,3,1 | 10 |
| 9 | 11 | 17 | 12 | 2h | $< Q_9, 12, 9 >< Q_9, 13, 6 >< Q_9, 14, 5 >< Q_9, 15, 4 >< Q_9, 16, 3 >$ | 7,4,3,2,1 | 9 |
| 10 | 11 | 18 | 12 | 3h | $< Q_{10}, 12, 15 >< Q_{10}, 13, 12 >< Q_{10}, 14, 10 >< Q_{10}, 15, 6 >< Q_{10}, 16, 5 >$ | 12,10,8,4,3 | 10 |

Notes: $\overline{at_i}$: earliest arriving time; $\overline{dt_i}$: latest departure time;$pst_i$: preferred start time; $cd_i$: charging duration; Charging Requests of Agents: $< Q_i, lst_{i,k}, p_{i,k} >$.

*Case #1*: If agent $i$ is not selected in the schedule $s^{t-1}$ at round $t-1$ ($t-1 \geq 1$), she has three options: First, she increases the price $p_i^{t-1}(lst_{i,k})$ by $\varepsilon$ on the bids submitted in round $t-1$. Note that increasing the bidding price results in utility loss. If one agent is not included in the schedule, she will keep increasing her bidding prices in future rounds until she is included or reaches her value. A rational agent does not accept a negative utility, which means $p_i^{final}(lst_{i,k}) \leq v_i(lst_{i,k})$, for $0 \leq k \leq w_i$. Second, she claims a final bid status and quits all future rounds except the final one. As a result, she may either be included in the final round with a non-negative utility, or not be included with a zero utility. Third, she withdraws from the bidding with a zero utility.

*Case #2*: If agent $i$ is included in the schedule $s^{t-1}$ at round $t-1$, she does not need to update her bids for next round. As a rational agent, she will maintain her

Table 3.3: Iterative bidding example: submitted bids, provisional allocation and schedule of each round

| Round | Submitted Bids (Agent ID, Bid ID) | Provisional Scheduling (Agent ID, Bid ID) | Revenue |
|---|---|---|---|
| 1 | Bid (1,1), Bid (1,3), Bid (2,1), Bid (3,1), Bid (4,1), Bid (5,1), Bid (6,1), Bid (7,1), Bid (8,1), Bid (9,1), Bid (9,2), Bid (9,3), Bid (9,4), Bid (9,5), Bid (10,1) | Bid (1,1), Bid (2,1), Bid (4,1), Bid (6,1), Bid (7,1), Bid (8,2), Bid (9,1) | \$58 |
| 2 | Bid (1,1), Bid (1,3), Bid (2,1), Bid (3,1), Bid (3,2), Bid (3,3), Bid (4,1),Bid (5,1), Bid (5,2), Bid (5,3), Bid (6,1), Bid (6,2), Bid (6,3), Bid (7,1), Bid (8,1), Bid (9,1), Bid (9,2), Bid (9,3), Bid (9,4), Bid (9,5), Bid (10,1) | Bid (1,1), Bid (2,1), Bid (4,1), Bid (6,2), Bid (7,1), Bid (8,1), Bid (9,2), Bid (10,1) | \$62 |
| 3 | Bid (1,1), Bid (1,3), Bid (2,1), Bid (3,1), Bid (3,2), Bid (3,3), Bid (3,4), Bid (3,5), Bid (4,1), Bid (5,1), Bid (5,2), Bid (5,3), Bid (5,4), Bid (5,5), Bid (6,1), Bid (6,2), Bid (6,3), Bid (7,1), Bid (8,1), Bid (9,1), Bid (9,2), Bid (9,3), Bid (9,4), Bid (9,5), Bid (10,1) | Bid (1,1), Bid (2,1), Bid (3,1), Bid (4,1), Bid (6,2), Bid (7,1), Bid (8,1), Bid (9,2), Bid (10,1) | \$62 |
| 4 | Bid (1,1), Bid (1,2), Bid (1,3), Bid (1,4), Bid (1,5), Bid (2,1), Bid (3,1), Bid (3,2), Bid (3,3), Bid (3,4), Bid (3,5), Bid (4,1), Bid (5,1), Bid (5,2), Bid (5,3), Bid (5,4), Bid (5,5), Bid (6,1), Bid (6,2), Bid (6,3), Bid (7,1), Bid (8,1), Bid (9,1), Bid (9,2), Bid (9,3), Bid (9,4), Bid (9,5), Bid (10,1) | Bid (1,5), Bid (2,1), Bid (3,1), Bid (4,1), Bid (6,2), Bid (7,1), Bid (8,1), Bid (9,2), Bid (10,1) | **\$64** |

bidding prices unchanged and repeat her bids at round $t$ for greater utility.

Agents repeat their previous bids in the final round, and those who have room to increase their bidding prices are included in the final schedule $s^{final}$. As a consequence, they gain a positive utility in $s^{final}$, because $max_{k\in\{0,1,\ldots,w_i\}}[v_i(lst_{i,k})-p_i^{final}(lst_{i,k})] \geq 0$. Agents who are not included in the previous rounds have to bid their values, i.e., $p_i^{final}(lst_{i,k}) = v_i(lst_{i,k})$. Then by solving $max_{k\in\{0,1,\ldots,w_i\}}[v_i(lst_{i,k}) - p_i^{final}(lst_{i,k})]$, the agents are able to send all their utility-maximizing *XOR* bids with zero utility at the final round.

Table 3.4: Results of the iterative bidding framework and the centralized model optimization. Test case: Set 5 of Group 3 (10 Agents and 3 CPS)

| | **Iterative Bidding** | | **Centralized Model Optimization** |
|---|---|---|---|
| | Increment $\varepsilon = 1$ | Increment $\varepsilon = 2$ | |
| **Agent ID** | start time | start time | start time |
| 1 | 9 | 14 | 13 |
| 2 | 9 | 9 | 9 |
| 3 | Not Assigned | 9 | 9 |
| 4 | 9 | 9 | 9 |
| 5 | 12 | Not Assigned | Not Assigned |
| 6 | 11 | 13 | 12 |
| 7 | 13 | 11 | 11 |
| 8 | 11 | 11 | 11 |
| 9 | 15 | 13 | 13 |
| 10 | 12 | 12 | 13 |
| Revenue | \$69 | \$64 | \$89 |

Add it all up, the mechanism ensures that each agent has a non-negative utility from participation whatever the final schedule is. Therefore, individual rationality holds.

**Proposition 3.2** *The best response of each agent is to submit her utility-maximizing XOR bids at each round.*

**Proof** The best response refers to an agent's utility-maximizing strategy across a restricted set of all possible strategies [130]. In our case, the best-response strategy for each agent in each round is to send the utility-maximizing *XOR* bids after the price updating policy. We prove by cases.

*Case #1*: If agent $i$ is not selected in the schedule $s^{t-1}$ at round $t-1$ ($t-1 \geq 1$), she has three strategies for round $t$: First, she can update her current bids following the price updating policy and send the utility-maximizing *XOR* bids by solving $max_{k \in \{0,1,\ldots,w_i\}}[v_i(lst_{i,k}) - p_i^{t-1}(lst_{i,k})]$. Second, she can aggressively increase her bidding prices by a higher increment $\varepsilon'$ than the specified $\varepsilon$ ($\varepsilon' > \varepsilon$). This may happen when an agent believes that the competition is fierce, thus bidding with minimum increment $\varepsilon$ could not ensure she is included in the future schedules. However, by doing this, she will lose utility due to higher bidding prices and this aggressive strategy will not guarantee she is included in the schedule. Third, she claims the final bid status. By doing this, it is ensured that she will not lose her utility in all future rounds, i.e., her utility is fixed as $v_i(lst_{i,k}) - p_i^{t-1}(lst_{i,k})$ until the bidding terminates. However, there is no guarantee that she would be selected in the final round. From above, the best response strategy for the excluded agents at round $t-1$ is to send their utility-maximizing *XOR* bids to the auctioneer.

*Case #2*: If agent $i$ is included in the schedule $s^{t-1}$ at round $t-1$, she is allowed to repeat her bids at round $t$. Her utility will not decrease in attending the next round. She, of course, can aggressively increase her bidding prices, however, she would lose utility. Therefore, a rational selected agent will repeat her *XOR* bids of round $t-1$.

To sum up, since the iterative bidding is individually rational, the best response for each agent for the next round is to submit her utility-maximizing *XOR* bids, regardless of the strategies of other agents.

## 3.6 Experimental Study

This section evaluates the performance of iterative bidding in terms of the efficiency, information revelation, computational time and accommodation level through extensive computational studies. As previously mentioned, the partial value revelation on the agents' side is the main benefit of iterative bidding compared to the direct revelation mechanism (such as VCG mechanism). It is notable that this privacy benefit is obtained at a scheduling efficiency cost. The iterative bidding framework maximizes the sum of the bidding prices, and it often terminates before agents have completely revealed their values. Due to this, the efficiency of iterative bidding cannot be guaranteed with the *XOR* bids compared to the solutions obtained by VCG, in which user's complete values are revealed. This section will further explore the relationship between computation efficiency and information revelation for the proposed iterative bidding framework.

### 3.6.1 Experiment Setting

We start with defining the evaluation metrics:

(1) Efficiency $e(s)$ is measured as the ratio of the value of the final schedule $s^{final}$ in iterative bidding to the value of the optimal schedule $s^*$ by solving the centralized model

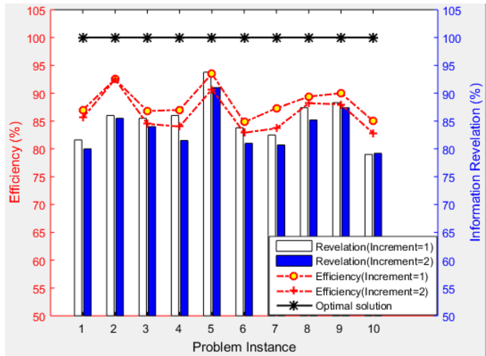
$$e(s) = \frac{\sum_{lst_{i,k} \in s^{final}} v_i(lst_{i,k})}{\sum_{s^*} v_i(s^*)}. \tag{3.21}$$

(2) Information revelation $info(s)$ is measured as the ratio between the sum of the final prices bid by the agents for all latest start times in the final schedule $s^{final}$ and the true values on start time

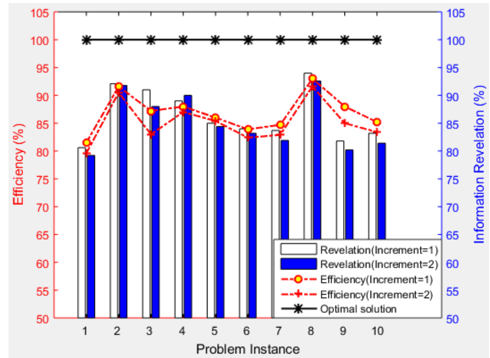
$$info(s) = \frac{\sum_{lst_{i,k} \in s^{final}} p_i(lst_{i,k})}{\sum_{lst_{i,k} \in s^{final}} v_i(lst_{i,k})}. \tag{3.22}$$

$info(s)$ measures the extent to which an agent has revealed her value for each start time during the iterative bidding, which is computed as the average information revelation over all agents.

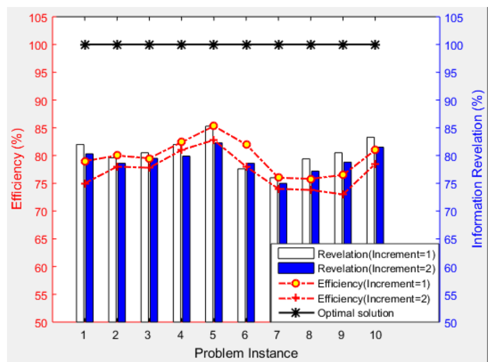
(3) Running time is measured by the computing time needed to terminate the iterative bidding and the centralized model optimization on one problem instance.




(a)




(b)




(c)

Figure 3.1: Efficiency and information revelation between the iterative bidding framework and the optimal solution: (a) Group 1; (b) Group 2; and (c) Group 3.

(4) Accommodation level $ac(s)$ is measured by the number of agents included in the final schedule $s^{final}$

$$ac(s) = \sum_{i=1}^{n} \sum_{k=0}^{w_i} X_{i,k}. \tag{3.23}$$

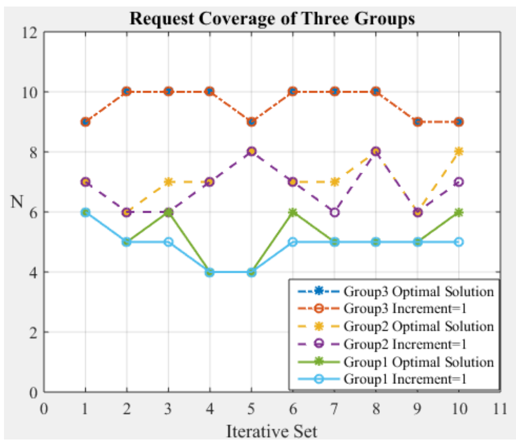
Three groups of problem instances are generated, where the number of agents and charging points (CPs) in each group is configured as 6 agents with 2 CPs (Group 1), 8 agents with 2 CPs (Group 2), and 10 agents with 3 CPs (Group 3), respectively. The reason is that a single AC Level 2 charging station charges averagely four EVs during a day, with around 5.6 hours connected to a vehicle per charging event [131]. The EV/CP ratio we designed for these two groups conforms to the charging station workload in realistic scenarios. And each group has ten random-generated test cases, including the charging request $(\overline{at_i}, \overline{dt_i}, pst_i, cd_i)$, value $v_i(lst_{i,k})$ and initial bidding prices $p_i(lst_{i,k})$ for the $k$th bid of agent $i$'s bids.

The earliest arriving time $\overline{at_i}$ is drawn from a uniform distribution $U(9, 11)$ between 9 and 11 (*a.m.*). The preferred start time $pst_i$ is set as $\overline{at_i} + U(1, 2)$. We assume each agent has at most five bids in *XOR* bid ($w_i \leq 5$), and the time interval between each two adjacent latest start times $lst_{i,k-1}$ and $lst_{i,k}$ is one hour. Therefore, the latest departure time $\overline{dt_i}$ should be $pst_i + cd_i + (w_i - 1)$. The charging duration $cd_i$ (hour, $h$) is drawn from a uniform distribution $\alpha * U(0.3, 1)$. $\alpha = 4$ is an estimate of the maximum charging duration, which is determined by the average charging duration. Here we consider Level 2 charge (AC, 240 Volts/40 Amps) and take the average charging duration over 3 hours according to the battery capacity, the level of charge and the temperature.

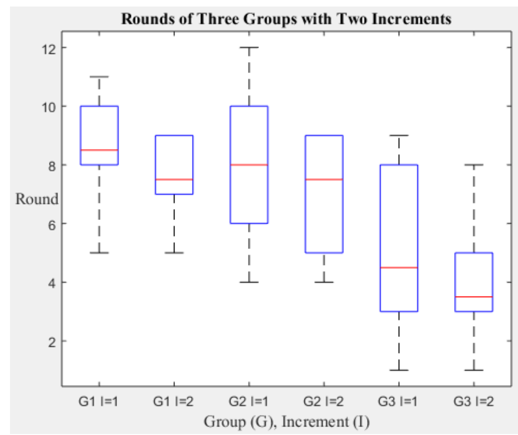
In centralized model, the cost function is defined as a pairwise function of the start time $st_i$, that is, $c_i(st_i) = \beta * (st_i - pst_i)$, for $st_i \in (pst_i, \overline{dt_i} - cd_i]$ and $c_i(st_i) = 0$, for $st_i \in [\overline{at_i}, pst_i]$, where $\beta = 2$. The value for the bids is linear with the charging duration. $v_i(lst_{i,0})$ (dollar, \$) for the preferred start time $pst_i$ is set as $\gamma * cd_i$, where $\gamma$ is drawn from a uniform distribution $U(2, 3)$. The value for the $k$th bid is $v_i(lst_{i,k}) = v_i(lst_{i,k-1}) - U(2, 3)$, for $k = 1, ..., w_i$. As for bidding price of the latest start time $lst_{i,k}$ in the $k$th bid, it is smaller than the value by $U(2, 4)$, i.e., $p_i(lst_{i,k}) = v_i(lst_{i,k}) - U(2, 4)$. For instance, an *XOR* bid could be $< Q_1, 10, \$10 >$*XOR*$< Q_1, 11, \$8 >$*XOR*$< Q_1, 12, \$6 >$, where the \$10, \$8 and \$6 indicate the bidding prices for the $lst_{i,k}$ 10 *a.m.*, 11 *a.m.* and 12 *a.m.* in each bid, respectively. In order to test the effect of $\varepsilon$ on the efficiency $e(s)$ and the number of bidding rounds, we set the increment $\varepsilon$ as 1 and 2 in these three groups.

### 3.6.2 Results and Analysis

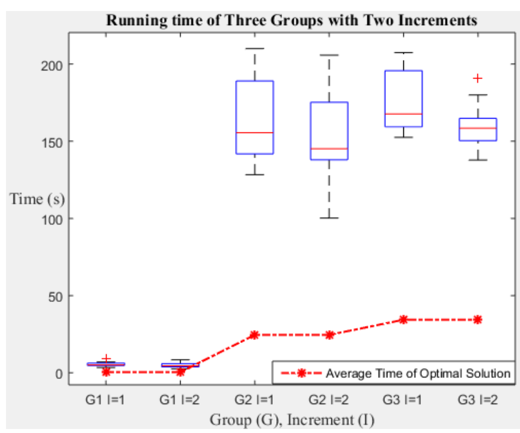
The results of the iterative bidding are compared with the centralized model optimization (the optimal schedule that maximizes the sum of values across all agents). The efficiency, information revelation, running time and accommodation level of these two approaches are tested for three different groups of problem instances and two different increments. To guarantee the optimality of the solutions, the centralized model and the iterative bidding framework are coded in ILOG Optimization Programming Language (OPL), and solved the charging scheduling problems with ILOG CPLEX 12.6.3, as the optimization engine. All experiments are carried out in a PC with a processor of Intel (R) Core (TM) i5-7200U CPU @2.50GHz, 8GB memory.




(a)




(b)




(c)

Figure 3.2: (a) Accommodation level, (b) rounds and (c) running time of the iterative bidding framework and the optimal solution.

The computational results of the three groups of the iterative bidding framework and the centralized model are shown in Fig. 3.1, including the efficiency, information revelation, respectively. We compared the results of the optimal solution and the iterative bidding framework in terms of $\varepsilon = 1$ and 2. Moreover, Fig. 3.2 (a), (b), and (c) present the accommodation level, number of iterative rounds, and running time of iterative bidding under different $\varepsilon$, respectively.

It can be seen from Fig. 3.1 that iterative bidding can reach a high efficiency (on average 85%) against the results obtained by the centralized model (regarded as 100% efficiency) among these three groups. As shown in (a) and (b) of Fig. 3.1, with the same charging capacity (2 CPs), iterative bidding achieves a similar efficiency level (around 88% out of 100%) in addressing Group 1 (6 agents) and Group 2 (8 agents). We observe that the performance of iterative bidding is stable when dealing with different size of charging requests. In addition, iterative bidding with $\varepsilon = 1$ usually achieves a higher efficiency compared to $\varepsilon = 2$ among these test cases in three groups. With $\varepsilon = 1$, iterative bidding needs more rounds to terminate with more bids submitted, given this, price updating policy will reveal more value information of agents in each round. Therefore, a smaller increment, theoretically, has a higher efficiency. Furthermore, we can see that the efficiency has a positive correlation with the information revelation level by observing (a), (b), and (c) in Fig. 3.1, the high efficiency of iterative bidding is always accompanied by a high level of information revelation. Thus, information privacy preservation is obtained at an efficiency cost in iterative bidding. Similarly, iterative bidding with $\varepsilon = 1$ has a higher value revelation compared to $\varepsilon = 2$ among these three groups.

Fig. 3.2 (a) reveals the accommodation level of three groups by both approaches ($\varepsilon = 1$ in the iterative bidding). In some cases the charging station is not able to accommodate all users to charge with both approaches. The reason is the limited charging capacity cannot accommodate all charging requests in the final schedule. For instance, only 4 of 8 agents are selected in set 2 of group 2, as they all require a longer charge. Fig. 3.2 (b) presents the number of rounds among these three groups, in which we can see the small increment leads to more rounds and longer time before termination. Fig. 3.2 (c) indicates that the running time increases with the number of agents and the charging duration for both approaches. We can see the iterative bidding takes more time to terminate than the centralized model. And iterative

Table 3.5: Performance of test case with 100 EVs

| Performance | Centralized Optimization | Iterative Bidding ($\varepsilon = 1$) | Iterative Bidding ($\varepsilon = 2$) |
|---|---|---|---|
| Efficiency | 100% | 81.2% | 74.6% |
| Information Revelation | 100% | 79.8% | 70.4% |
| Running Time | 826.57s | 4950.39s | 3764.50s |
| Request Coverage | 100/100 | 99/100 | 98/100 |
| Iterations | None | 9.5 | 5.6 |

bidding with $\varepsilon = 1$ spends slightly more time to terminate than with $\varepsilon = 2$, as the smaller increment leads to more rounds.

### 3.6.3 Scalability of Iterative Bidding

A larger size problem with 5 problem instances is designed to test the scalability of iterative bidding: each with 100 agents and 20 charging points (CPs). And the earliest arriving time $\overline{at_i}$ is drawn from a uniform distribution $U(6, 12)$. The $\alpha$ in charging duration $cd_i$'s distribution $\alpha * U(0.3, 1)$ is set as $\alpha = 2$. The rest is the same as the above setting. We run these 5 instances and take the average value of each metrics, shown in Table 3.5.

Since this charging scheduling problem is NP-hard, the computational time by CPLEX increases dramatically as the problem size (number of users and charging points) becomes larger, as we can see above. Finding the optimal solutions takes averagely 826.57s. And iterative bidding ($\varepsilon = 1$) runs averagely 4950s when dealing with this large test case, and obtains averagely 80% efficiency compared to the optimal solution. Moreover, we observe that the performance of iterative bidding with $\varepsilon = 2$ from Table 3.5. is in line with the results of smaller problem test cases.

## 3.7 Summary

This work studied a decentralized EV charging scheduling problem in a charging station setting. We proposed an iterative bidding framework as a decentralized solution approach to the problem. This framework includes bids, a winner determination model and an iterative bidding procedure. The iterative bidding procedure allows users to progressively reveal their values on various charging start times. Overall charging schedules are achieved through the negotiation between the charging station and EV users. The winner determination model selects a subset of the submitted charging requests that maximizes the charging station's revenue. We present two game theoretical properties of the iterative bidding framework, we also conduct a computational study to validate its effectiveness. Our experiment results show that iterative bidding achieves on average 85% efficiency compared with that of the optimal solution (revealing users' complete values). Moreover, we observe a positive correlation between the scheduling efficiency and value revelation during the iterative bidding process. Experiment results also show that a smaller bidding price increment can achieve higher efficiency, although it always leads to more rounds of bidding.

The proposed iterative bidding provides a potential reservation-based charging solution for a portion of users who have strict time requirements and private preferences in a decentralized setting, but the acceptance and practicality of the bidding methodology is not the focus of this work and waits to be verified in real-world markets. We aim to derive and validate the bidding solutions to deterministic single bidding event, which provides the baseline for dynamic scenarios. The robustness against uncertainties and dynamics, such as the changes of user preferences, or uncertain EV arrivals, is our future work on agenda. Moreover, we will extend this single charging station environment to multiple charging stations where the coordination therein should be carefully addressed with efficient mechanism design.

# Chapter 4

# Incentive-Compatible Auction Design for Charging Network Scheduling

## 4.1 Background

Modern transportation system is embracing an increasing adoption of battery electric vehicles (BEVs) due to its environmental incentives and economic efficiency [132]. Along this trend, charging facilities are becoming indispensable in boosting the share of BEVs and alleviate the range anxiety of drivers. However, the growth of publicly accessible chargers still falls behind the increase of on-road BEVs, as most of the installed chargers are private [133]. The limited charging capacity can be exceeded at busy hours when a high volume of vehicles unexpectedly drive to and charge at a station [7, 134]. It is not longer enough to only have dots on the map and provide charging services by first-come-first-serve manner. Users need to feel secure not just in their ability to find a charger, but also to access it easily when they arrive at a charging station. In a charging market, BEV users, such as company staffs, taxi drivers, highway travellers, or park tourists, tend to reserve a desirable place and charging time beforehand, especially for those who requires frequent charging. Such reservation-based charging scheduling can accommodate more demands and efficiently utilize the parking space by eliminating the time conflicts of different users in advance [50], and meanwhile can alleviate the pressure on grid due to the heavy and intermittent charging loads [33, 124]. Delivering on a satisfied and reliable charging service is the key to accelerate BEV adoption, and charging scheduling can boost user's satisfaction and improve the system efficiency.

The BEV-related research issues have been extensively investigated in intelligent transportation system and smart grid environments [26, 41, 95, 116]. The intuitive way to optimize the charging scheduling is *mathematical optimization*, such as mixed-integer programming [57, 63], and *heuristic algorithms* [26, 41]. However, it is no more applicable to assume that a central authority has a global and perfect knowledge about users' private information and control their behaviors. The centralized approaches are not sufficient to deal with charging scheduling problems which is very restricted in real-world scenarios. The integration of different charging stations in a network is associated with information gathering and decision-making, rendering scheduling essentially a negotiation process between stations and users. The Nobel Economic Sciences Prizes winners Paul R. Milgrom and Robert B. Wilson[6] pointed out that a market analysis is difficult, because agents behave strategically and act on their best response based on the available information they have, their preferences, and their beliefs about the outcomes of their actions. The incomplete or untruthful revelation on their private preferences may degrade the quality of solutions, especially in considerably complicated scheduling objectives [135]. In terms of this, mechanism design is a deliberate choice to capture the strategic interactions among selfish agents and study the setting where agent's preference is unknown [28, 52]. By offering sufficient incentives to agents, the desired outcome can arise naturally during interaction [18].

In terms of this, we propose an incentive-compatible combinatorial auction (ICCA) to solve this reservation-based charging scheduling across multiple stations in a decentralized environment, where users compete for their preferred charging destinations and time periods given their private preferences through bidding.

[6]The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2020, NobelPrize.org. Nobel Media AB 2020. Wed. 28 Oct 2020. https://www.nobelprize.org/prizes/economic-sciences/2020/prize-announcement/.

## 4.2 Related Work

To solve the optimization problems for charging scheduling, extensive works have adopted *mathematical optimization*, such as linear programming [49, 86], mixed-integer programming [57, 63], *queueing theory* [39, 65], and *heuristic algorithms* [26, 41]. Our mathematical model belongs to a mixed-integer programming and is similar with [26, 57, 136]. Our work differs from the above works in two aspects: (1) we extend the single station scheduling model by [57] to multiple stations, in which charging station selection and charging timing allocation are jointly solved, instead of solving only one of them; (2) different from the meta-heuristic solutions in the above works, we consider an auction-based scheduling problem, where the user's value information is distributed and private. Users are deemed as self-interested agents who only advance their own utilities regardless of the social welfare.

However, the above centralized scheduling only considers the benefits to the controller or system, while the individual willingness and private information of users have been largely ignored [137]. A concern inherited from the market characteristic for reservation-based charging scheduling is that users may manipulate the outcome of the limited charging capacity allocation by strategically revealing incomplete or untruthful information about their private preferences over charging time or energy demands. They aim to obtain individually preferable charging services in a market, such as an earlier start time or a closer charging destination. Such strategic behaviors will lead to non-optimal outcomes and jeopardize the social welfare. Typical approaches addressing user's selfishness and incentives for solving charging scheduling in a decentralized environment can be generally classified into three categories: (1) *mechanism design* [28, 52]; (2) *game modelling* [30, 32, 76]; and (3) *Incentive-based demand response program* [47, 82]. Various works applied game theory to analyze and predict the potential outcomes of a mechanism, the most common modelling is the Stackelberg game [30, 32, 42]. Specifically, retailers determine their electricity prices, and customers respond accordingly with their electricity consumption levels. The interaction between retailers and customers is a leader-follower paradigm as both attempt to maximize their own utilities. Differently, we adopt *auction*-based mechanisms to obtain high-quality schedules against users' economic rationality [130]. Contrary to game theory, auctions aim to define the rules of interaction such that the desired outcomes can arise naturally from the strategic interactions among agents.

Auctions have gained successful applications on EV charging scheduling, with some of them adopting VCG mechanism [31, 52, 130, 138]. For instance, Emmanouil S. Rigas *et al.* [139] proposed two pricing mechanisms for allocating EVs to charging stations and scheduling their charging, including fixed-price scheme and VCG mechanism. Users report their preferences on energy and arrival time a day ahead and the system selects to charging requests with the higher valuations given the station and network constraints. Julian de Hoog *et al.* [52] proposed a efficient and strategy-proof mechanism to allocate available charging capacity in a way that ensures network stability considering network-specific constraints that include total network load, voltage drop and phase unbalance. The mechanism maximizes total welfare while ensuring that all bids are honest. Moreover, a VCG-based mechanism is proposed in [31] to model the pricing of multi-tenant autonomous vehicle public transportation system as a combinatorial auction, where service providers compete for offering transportation services as bidders. However, some auction design only allows users to bid on discrete energy items or time slots, which is not intuitive and convenient for users to express their charging requests and preferences in our problem setting. Moreover, it is usually of large sizes and incur heavy computational costs. To address this inadequateness, we extend the classic VCG auction to our charging scheduling problem by allowing users to bid on the continuous time window. Moreover, the scheduling constraints (e.g., space, precedence, non-overlap) are integrated into the winner determination model of the proposed auction.

## 4.3 Our Contribution

Our main contributions are specified as follows:

(1) we build a mixed-integer linear program to mathematically formulate this charging scheduling problem, which jointly allocates the charging destination and time periods to users in a charging network. The objective is to maximize user's values on the finish time for charging, restricted by the constraints imposed by the limited number of charging points in the charging network and user's availability.

(2) we propose an ICCA framework to solve this decentralized charging scheduling problem. In this auction framework, a charging-domain specific bidding language is

developed to allow users to bid on their preferred finish time; moreover, a winner determination model that integrates the charging scheduling constraints is constructed to assign BEVs to different destinations and determine their charging time in a one-shot manner. To guarantee the efficient outcomes, Vickrey–Clarke–Groves (VCG) payment [140] is adopted to incentivize users to truthfully reveal their value information as a weakly dominant strategy.

(3) we also conduct extensive game-theoretical analysis to demonstrate the elegant properties of ICCA, which is individually rational, incentive-compatible and weakly budget balanced.

The remainder of this work is organized as follows: Section 4.4 formulates this decentralized charging scheduling problem. Section 4.5 implements the ICCA design for solving the problem in a decentralized environment. Section 4.6 analyzes its three important game-theoretical properties. Section 4.7 conducts a case study in a real-world scenario. Section 4.8 draws a conclusion.

## 4.4 Problem Formulation and Mathematical Model

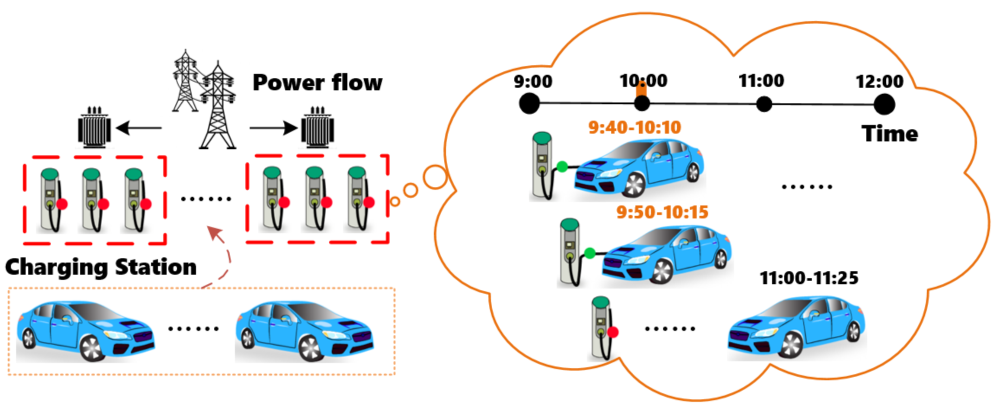



Figure 4.1: Charging scheduling scenario across multiple stations: each EV user requests a single charge at a charging station and each station has several charging points to provide charging services.

In this section, we build a mathematical model the charging network scheduling problem and assume users' value is known by for the optimization. As shown in Fig. 4.1, we consider a BEV charging scheduling problem in multiple charging stations environment. A group of BEV users need to charge their vehicles given their

Table 4.1: Nomenclature of Chapter 4

| | Index and Set | | Function |
|---|---|---|---|
| $i(j)$, $N$ | Index and set of users | $v_i(\cdot)$ | Valuation function of user $i$ |
| $k$, $M$ | Index and set of charging stations | $p_i(\cdot)$ | Price function of user $i$ |
| | **Parameters** | | **Decision Variables** |
| $\overline{dt}_i$, $\overline{ct}_i$ | Earliest time for departure and latest completion time of user $i$ | $st_i$ | User $i$'s actual start time for charging |
| $E_i$, $\eta_i$, $\rho_i$ | Battery capacity, energy consumption per kilometer and average driving speed of user $i$ | $ft_i$ | User $i$'s actual finish time for charging |
| $D_{i,k}$, $T_{i,k}$ | Distance and driving time from current location of user $i$ to charging station $k$ | $Y_{i,j}^k$ | Binary variable - 1 if user $i$ and $j$ are adjacent at charging station $k$, else 0 |
| $R_k$, $CP_k$ | Charging rate and number of charging points of charging station $k$ | $Y_{0,i}^k$ | Binary variable - 1 if user $i$ is the first one at charging station $k$, else 0 |
| $SoC_i$, $SoC_i'$ | Initial and final $SoC$ of user $i$ | $Y_{i,n+1}^k$ | Binary variable - 1 if user $i$ is the last one at charging station $k$, else 0 |
| $SoC_i^k$, $AC_{i,k}$ | Required $SoC$ to drive to charging station $k$, and the available charging stations of user $i$ | $Z_i^k$ | Binary variable - 1 if user $i$ is selected at charging station $k$, else 0 |

current State of Charge ($SoC$) and reserve a charging space at one station. Users are allocated with the appropriate charging destination and time with the best distance-time trade-off, such that they can charge the battery to a certain $SoC$ at their earliest convenience. These charging stations are managed by a charging network who is responsible for collecting the charging requests from users, and decide where and when to charge each selected request based on the preferences of users, restricted by the limited charging number of charging points and the time availability of users. The objective is to maximize the total values revealed by users. To model this charging scheduling problem in real-world scenarios, we make the following assumptions: the reservations do not take into account the traffic jams or accidents, thus we can estimate the expected driving time to each charging station. And any user's charge cannot be suspended or interrupted by others once started.

The nomenclature for mathematical model is summarized in Table 4.1. BEV charging scheduling problem considers a set of $n$ BEV users denoted as $N$ and a set of charging stations denoted as $M$. Each charging station $k \in M$ owns $CP_k$ identical charging points, which share a fixed and identical charging rate $R_k$. Each user $i \in N$ has a charging request to be processed by the charging network, defined as a 7-tuple: $Q_i = \left\langle \overline{dt}_i, \overline{ct}_i, EVt_i, SoC_i, SoC_i', E_i, GIS_i \right\rangle$, where $\overline{dt}_i$ and $\overline{ct}_i$ is user $i$'s earliest time for driving to charging station and latest completion time for charging, respectively.

She has to drive to the assigned charging station and complete charging within her available time window $[\overline{dt}_i, \overline{ct}_i]$. If a user has no stringent deadline, she can set $\overline{ct}_i$ as infinity. $EVt_i$ is user $i$'s vehicle model, with which the charging network can identify the energy consumption per kilometer $\eta_i$ and the charging stations $AC_{i,k}$ that support the vehicle's charging. $SoC_i$ and $SoC_i'$ are user $i$'s initial $SoC$ before departure and the final $SoC$ after charging, respectively. $E_i$ is the battery capacity of user $i$'s vehicle. $GIS_i$ is the initial location of user $i$ before departure, by which the distance $D_{i,k}$ to a charging station $k \in M$ can be calculated. The driving time $T_{i,k}$ from $GIS_i$ to station $k$ can be estimated by $T_{i,k} = \frac{D_{i,k}}{\rho_i}$ based on the average driving speed $\rho_i$ under urban road conditions. Moreover, the charging time for users $i$ at station $k$ can be computed by $\frac{E_i(SoC_i' - SoC_i - SoC_i^k)}{R_k} = \frac{E_i(SoC_i' - SoC_i) - \eta_i D_{i,k}}{R_k}$, where the energy consumption $E_i SoC_i^k$ for driving to station $k$ can be computed by $\eta_i D_{i,k}$.

Given the charging requests, the charging network selects a subset of the submitted charging requests and then allocates appropriate charging station and charging time to the selected requests. The feasible charging schedules $\Phi$ ensure that the selected users could complete their charging as early as possible restricted by their time windows and $SoC$. Each feasible schedule $\phi \in \Phi$ contains the finish times for charging allocated to each selected user, and user has a value on the finish time $ft_i$. Valuation function $v(\cdot)$ measures how user is satisfied with the schedule. Specifically, user $i$'s value $v_i(ft_i; \phi)$ is a function of finish time $ft_i$ within the time window $[\overline{dt}_i, \overline{ct}_i]$, which is assumed to be bounded, non-empty and convex on the solution space. Each user will not accept any schedule $\phi$ with the finish time $ft_i$ being later than her latest completion time $\overline{ct}_i$.

The final charging schedule may not accommodate all the requests due to the limited charging capacity. Let $Z_i^k$ be the decision variable and $Z_i^k = 1$ if user $i$ is selected in schedule $\phi$, otherwise $Z_i^k = 0$. $k \in M \cap AC_{i,k}$ indicates user $i$ can only be assigned to her available charging stations $AC_{i,k}$. Let $Y_{j,i}^k$ be the precedence decision variable, and $Y_{j,i}^k = 1$ if user $i$ charges immediately after user $j$ at charging station $k$, otherwise $Y_{j,i}^k = 0$, where $k \in M, i, j \in N$ and $i \neq j$. Note that $Y_{j,i}^k = 0$ if at lease one of users $i$ and $j$ is not selected, or if both are selected but not adjacent at the same charging station $k$. In addition, let $Y_{0,i}^k = 1$ if user $i$ is selected and the first one to charge on a charging point, otherwise $Y_{0,i}^k = 0$; and let $Y_{i,n+1}^k = 1$ if user $i$ is selected and the last one to charge on a charging point, otherwise $Y_{i,n+1}^k = 0$.

We formulate this charging scheduling problem as a mixed-integer linear program, in which the charging destination and time are allocated to each selected request, with an objective of maximizing users' total values on the finish time. The model mathematically solves

$$max \sum_{i \in N} \sum_{k \in M} Z_i^k v_i(ft_i) \tag{4.1}$$

subject to

$$ft_i = \sum_{k \in M} Z_i^k (st_i + \frac{E_i(SoC_i' - SoC_i) - \eta_i D_{i,k}}{R_k}) \quad \forall i \in N \tag{4.2}$$

$$\overline{dt}_i + \frac{D_{i,k}}{\rho_i} \leq st_i + H(1 - Z_i^k) \quad \forall k \in M, \quad i \in N \tag{4.3}$$

$$st_i + \frac{E_i(SoC_i' - SoC_i) - \eta_i D_{i,k}}{R_k} \leq \overline{ct}_i + H(1 - Z_i^k) \quad \forall k \in M, \quad i \in N \tag{4.4}$$

$$Z_i^k \leq AC_{i,k} \quad \forall k \in M, \quad i \in N \tag{4.5}$$

$$\sum_{k \in M} Z_i^k \leq 1 \quad \forall i \in N \tag{4.6}$$

$$\sum_{i=1}^{n} Y_{0,i}^k \leq CP_k \quad \forall k \in M \tag{4.7}$$

$$\sum_{j = \{0\} \cup (N \backslash \{i\})} Y_{j,i}^k = Z_i^k \quad \forall k \in M, \ \forall i \in N \tag{4.8}$$

$$\sum_{j = \{0\} \cup (N \backslash \{i\})} Y_{j,i}^k = \sum_{j = \{n+1\} \cup (N \backslash \{i\})} Y_{i,j}^k \quad \forall k \in M, \ i \in N \tag{4.9}$$

$$Y_{j,i}^k + Y_{i,j}^k + HZ_i^k + HZ_j^k \leq 2H + 1 \quad \forall k \in M, \ i,j \in N, \ i \neq j \tag{4.10}$$

$$\begin{aligned} st_j + \frac{E_j(SoC_j' - SoC_j) - \eta_j D_{j,k}}{R_k} + HZ_i^k + HZ_j^k + HY_{j,i}^k \leq st_i + 3H \\ \forall k \in M, \ i,j \in N, \ i \neq j \end{aligned} \tag{4.11}$$

$$Z_i^k, \ Y_{i,j}^k, \ Y_{0,i}^k, \ Y_{i,n+1}^k \in \{0,1\} \quad \forall k \in M, \ i,j \in N, \ i \neq j \tag{4.12}$$

$$st_i \in \mathbb{R}_+ \quad \forall i \in N. \tag{4.13}$$

Constraints (4.2) presents user $i$'s finish time for charging, which is the summation of the scheduled start time $st_i$ and the charging time $\frac{E_i(SoC_i' - SoC_i) - \eta_i D_{i,k}}{R_k}$ at charging station $k$. Constraints (4.3) ensures that if user $i$ is scheduled to charge at station $k$, the start time $st_i$ for charging should not be earlier than her earliest arrival time $\overline{dt}_i + T_{i,k}$. And $H$ is a large positive constant for the linearization of the logical constraint "if". Constraints (4.4) ensures that if user $i$ is scheduled to station $k$, she should finish before latest completion time for charging $\overline{ct}_i$. Constraints (4.5) forces that user $i$ can only be assigned to her available charging stations $AC_{i,k}$. Constraints (4.6) ensures at most one of these charging stations can be selected for user $i$'s charging. Constraints (4.7) indicates that charging station $k$ has at most $CP_k$ charging points, in other words, this station can select at most $CP_k$ of all BEVs as the first one to charge. Constraints (4.8) and (4.9) indicate that if user $i$ is selected and scheduled to charge at station $k$, her charge should either be the first one, or after some other users'. Similarly, her charge should either be the last one, or before some other users'. Constraints (4.8) and (4.9) set the decision variables $Y^k_{j,i}$, $Y^k_{0,i}$ and $Y^k_{i,n+1}$ to zero if user $i$ is not scheduled to charge at station $k$. Constraints (4.10) indicates the determined precedence charging sequence between user $i$ and $j$: if they are selected and adjacent at station $k$, one user should charge either before or after the other one. Constraints (4.11) ensures that if two users $i$ and $j$ are adjacent at station $k$ and user $i$ charges immediately after user $j$, user $i$ does not start before $j$ is completed. Constraints (4.12) and (4.13) define the the domain of decision variables $X^k_i$,$Y^k_{i,j}$,$Y^k_{0,i}$ and $Y^k_{i,n+1}$, as well as start time $st_i$ of user $i$.

Various MILP models are proposed to EV charging scheduling problems [26, 57, 136]. Our model differs from these works in two aspects: (1) unlike single station scheduling model [57], we address a multi-station scheduling problem, where destination selection and charging timing allocation are jointly solved, instead of solving an isolated one; (2) they adopted meta-heuristic solutions in a centralized setting, we propose an auction-based mechanism to capture users' strategic interaction where the their value information is distributed and unknown. The mathematical model extends our previous work on single-station scheduling [35] to multiple-station scenario considering the driving time and distance.

In the next section, we consider user's valuation as private information in a market setting. This allows us to focus on the strategic interaction between the charging network and users, where the self-interested users may misreport their values who only strive to maximize their own utility. In addition to the computational complexity inherited from solving MILP, decentralized charging scheduling needs also to address the complexity from the strategic behaviors of users. To represent users' selfishness and rationality, we call them as agents in multi-agent systems and use "agent" and "user" interchangeably in the rest of this paper.

## 4.5 Incentive-Compatible Combinatorial Auction

In this section, we construct an auction mechanism to model the strategic interaction between users and charging stations. A mechanism is essentially the procedure through which we try to give incentives in order to achieve our desired social goal [141]. Rather than investigating a given strategic interaction of game theory, mechanism design starts with certain desired behaviors on agents and asks what strategic interaction among these agents might give rise to these behaviors [23]. In this section, we construct an incentive-compatible combinatorial auction (ICCA) to model the strategic interaction between users and the charging network. The system-wide goal is defined with a social choice function in an environment of incomplete information and strategic behaviors of users. We begin with the preliminaries about mechanism design.

### 4.5.1 Preliminaries

We first construct a basic mechanism environment for the decentralized charging scheduling problem and illustrate the related definitions about mechanism design.

**Theorem 4.1 (Mechanism Environment)** *A mechanism environment* $\Gamma = \{N, \{\Theta_i\}_{i \in N}$ $\{A_i\}_{i \in N}, \Phi, \{v_i\}_{i \in N}\}$, *which consists of*

- *a set of agents* $N$, $N = \{1, 2, ..., n\}$;
- *a set of types* $\Theta_i$ *for each agent* $i \in N$;
- *a set of actions* $A_i$ *for each agent* $i \in N$;

- *a set of outcomes* $\Phi$*; and*

- *a valuation function* $v_i : \Theta_i \times \Phi \rightarrow \mathbb{R}$*, for each agent* $i \in N$*.*

(1) Type $\Theta$ characterizes the uncertainty over agent utility function as private information; each agent only knows her own type. In general, a type encapsulates all the information possessed by agents that is not common knowledge, which includes their beliefs about other agents' utilities, and beliefs about their own utilities [23]. $\Theta_i$ is the type space of user $i$, and $\Theta = \prod_{i=1}^{n} \Theta_i$ denotes the set of all possible type profiles, and each type profile $\theta$ is defined as $\theta = (\theta_1, \theta_2, ..., \theta_n)$. Agent $i$'s type $\theta_i \in \Theta_i$ will influence how she values the charging schedules based on $\overline{dt}_i$, $\overline{ct}_i$ and $SoC_i$. For instance, a user with a tight available time window or low $SoC$ level would tend to pay more for obtaining the same schedule compared to one with a relative loose time window or high $SoC$.

(2) Action $A_i$ is the set of all possible bids of user $i$ in auction according to her strategy $s_i \in S_i$. Agent $i$ chooses the action $a_i = s_i(\theta_i) \in A_i$ based on her type $\theta_i \in \Theta_i$. The action profile is completely determined by the strategy functions of agents. Action profile $A$ is denoted as the Cartesian product of the action set of all agents: $A = \prod_{i=1}^{n} A_i$, $a \in A$ and $a = (a_1, a_2, ..., a_n)$.

(3) The set of outcomes $\Phi$ include all feasible schedules that maximize the objective under the time constraints of users and the limited charging capacity. Each feasible outcome is a vector of guaranteed finish time assigned to each selected user. It is generated by a social choice among users which maps the type profile of all users to a single outcome, i.e., $f : \prod_{i=1}^{n} \Theta_i \rightarrow \Phi$.

(4) The valuation function $v_i$ of user $i$ is the monetary measurement on an outcome $\phi$ based on her own type $\theta_i$, that is, $v_i(\phi, \theta_i) : \Theta_i \times \Phi \rightarrow \mathbb{R}$. It reflects how users satisfy with and how much they want to pay for the finish time $ft_i$ in schedule $\phi$ given their types. Users will have a higher value on an earlier finish time in our setting.

In general, a direct revelation mechanism implies that the only action available to each agent is to announce her private information. Since an agent's private information is her type in a mechanism design setting, direct mechanism implies $A_i = \Theta_i$. Next we introduce direct revelation mechanism environment:

**Theorem 4.2 (Direct revelation mechanism environment)** *A direct revelation mechanism environment* $\Gamma_d = \{N, \{\Theta_i\}_{i \in N}, \Phi, \{v_i\}_{i \in N}\}$ *is a mechanism environment*

$\Gamma = \{N, \{\Theta_i\}_{i\in N}, \{A_i\}_{i\in N}, \Phi, \{v_i\}_{i\in N}\}$ *for which* $A_i = \Theta_i$ *for each agent* $i \in N$.

**Theorem 4.3 (Direct revelation mechanism)** *A direct mechanism* $M_d = (x, \{p_i\}_{i\in N})$ *is a mechanism over a direct revelation mechanism environment.*

We then present some important definitions for the mechanism design after setting ICCA in a direct revelation mechanism environment.

**Theorem 4.4 (Implementation)** *Fix a certain mechanism environment* $\Gamma$*, a direct revelation mechanism* $M = (x, \{p_i\}_{i\in N})$ *implements the social choice* $\prod_{i=1}^{n} \Theta_i \to \Phi$*, if this mechanism* $M$ *has a dominant strategy equilibrium* $(s_1^*, s_2^*, ..., s_n^*)$ *for which*

$$f(\theta_1, \theta_2, ..., \theta_n) = x(s_1^*(\theta_1), s_2^*(\theta_2), ..., s_n^*(\theta_n)). \tag{4.14}$$

**Theorem 4.5 (Revelation principle)** *If a social choice function* $f(\theta_1, \theta_2, ..., \theta_n)$ *is implementable, then it is also truthfully implementable.*

The revelation principle indicates that any mechanism can be transformed into an equivalent incentive-compatible direct-revelation mechanism under weak conditions, such that it implements the same social-choice function. This property ensures the truthfulness of direct-revelation mechanism.

We then present the definition of efficiency, which is served as the objective of the auctioneer (charging network) in the auction. An efficient mechanism aims to maximize the sum of the values across all agents, i.e., the social welfare.

**Theorem 4.6 (Efficiency)** *In a direct revelation mechanism environment* $\Gamma_d = \{N, \{\Theta_i\}_{i\in N}, \Phi, \{v_i\}_{i\in N}\}$*, for each feasible type profile* $\theta = (\theta_1, \theta_2, ..., \theta_n) \in \Theta$*, the efficiency of an outcome* $\phi \in \Phi$ *is the sum of values from all agents* $\sum_{i\in N} v_i(\phi, \theta_i)$*. Thus, the efficiency is a function* $E_d : \Theta \times \Phi \to \mathbb{R}$ *with*

$$E_d(\phi, \theta) = \sum_{i\in N} v_i(\phi, \theta_i). \tag{4.15}$$

### 4.5.2 Auction Framework

ICCA includes a decision policy and a payment policy to deal with the strategical behaviors of agents in a mechanism design environment. The objective is to maximize the sum of the values across all agents in the auction. First of all, we define the auction as follows:

**Theorem 4.7 (Auction)** *$M = (x, \{p_i\}_{i \in N})$ over a mechanism environment $\Gamma = \{N, \{\Theta_i\}_{i \in N}, \{A_i\}_{i \in N}, \Phi, \{v_i\}_{i \in N}\}$ consists of*

- ***a decision policy**: a decision function that maps the possible action profile to a set of outcome, which is $x : \prod_{i=1}^{n} A_i \to \Phi$;*
- ***a payment policy**: a payment function that maps the strategy space $A = \prod_{i=1}^{n} A_i = A_1 \times A_2 \times ... \times A_n$ to a real number $\mathbb{R}$: $A \to \mathbb{R}$ for agent $i$. The non-included agents in auction pay zero.*

#### Auction Procedure

This auction proceeds as follows: each agent submits her value on each element of all feasible charging schedules $\Phi$. The auctioneer then chooses $\phi^*$ from $\Phi$ as the optimal schedule such that $\phi^*$ maximizes $\sum_{i \in N} v_i(ft_i)$. If agent $i$ is not selected in the schedule, then $\sum_{k \in M} Z_i^k = 0$, which indicates that she contributes nothing to the outcome. In addition, the auctioneer also computes a schedule for each $i \in N$ such that the schedule solves $max \sum_{j \neq i} v_j(\phi_{-i}, \theta_j)$, which is the schedule without the participation of user $i$. After the final schedules are generated, agent $i$ pays to the auctioneer. ICCA also adds the potential of accommodating dynamic events (such as random arrivals) by running multiple bidding events over a sequence of time. If a user has any change of charging requests, she may update and participate in the next bidding event. This research provides the first investigation for deterministic scenarios that can be extended against uncertainties and dynamics in practice.

#### Decision Policy

The decision policy $x$ computes the feasible outcome $\phi$ based on the actions taken by agents, i.e., $\phi = x(a_1, a_2, ..., a_n) = x(v_1, v_2, ..., v_n)$, $\phi \in \Phi$. The optimal outcome $\phi^*$ is the one of the feasible outcomes $\Phi$ that maximizes the total values. It is equivalent to solve the winner determination model, namely the centralized scheduling model under constraints (4.2)-(4.13). The winner determination model for the optimal outcome $\phi^*$ solves

$$\phi^* = arg \max_{\phi \in \Phi} \sum_{ft_i \in \phi} Z_i^k v_i(ft_i, \theta_i), \tag{4.16}$$

subject to constraints (4.2)-(4.13).

The affiliation $ft_i \in \phi$ denotes that the finish time $ft_i$ of agent $i$ is included in the provisional schedule $\phi$. And $v_i(ft_i, \theta_i)$ is the valuation for the schedule $\phi$. It can be seen that this auction is efficient given Theorem 4.6: Efficiency.

### Payment Policy

There is no guarantee that the self-interested agents will truthfully report their value information. Such misreports may have undesirable consequences which may lead to an outcome that is far from the "social good". Therefore, convincing agents to reveal their truthful values as their weakly dominant strategy is a key to an efficient mechanism. To this aim, the VCG mechanism based payment policy [140] in ICCA has been proposed:

$$p_i(a) = \max_{\phi \in \Phi} \sum_{j \neq i} v_j(\phi, \theta_j) - \sum_{j \neq i} v_j(\phi^*, \theta_j). \tag{4.17}$$

The payment is the monetary units that agent needs to pay, decided by the action profile $a = (a_1, a_2, ..., a_n) \in A$. The first term of the Eq. (4.17) is to maximize the sum of values of all other agents could have achieved without agent $i$, the outcome is $\phi = x(a)$ at this time. The second term represents the efficiency they have due to agent $i$'s participation, and $\phi^*$ is the outcome worked out by decision policy. The intuition behind VCG payment policy forces each agent to internalize the externalities she causes to others, which indicates each agent must pay the damage that she causes to others due to her presence.

The truthfulness of mechanism only holds when agent payment $p_i$ does not depend on her own type $\theta_i$, but on others' type $\theta_{-i}$ and the outcome $\phi$ decided by decision policy. Winners must pay the aforementioned payment to the auctioneer, resulting in a total utility of $p - p = 0$ to her. Agents who do not win in the auction pay zero and get zero utility.

### Quasi-Linear Utility Function

The *utility* $u_i$ maps agent $i$'s type and all action profile to a real number, i.e., $\Theta_i \times \prod_{i=1}^{n} A_i \to \mathbb{R}$. In auction, utility function is captured by the difference of valuation function $v_i(\cdot)$ and payment function $p_i(\cdot)$ that each possible type $\theta_i$ and action profile $a = (a_1, a_2, ..., a_n)$ will give her, i.e.,

$$u_i(a, \theta_i) = v_i(x(a_1, a_2, ..., a_n), \theta_i) - p_i(a). \tag{4.18}$$

The action space $A$ is assumed to be compact, convex and non-empty, and utility function $u_i$ of agent $i$ is continuously on strategy space $A$ and concave in her strategy space $A_i$. We model this incentive-compatible combinatorial auction as a direct revelation mechanism, which solves a series of the optimization problems by revealing agents' true values. Given this, the aforementioned utility function $u_i(a, \theta_i) = v_i(x(a_1, a_2, ..., a_n), \theta_i) - p_i(a)$ of agent $i$ becomes

$$\begin{aligned} u_i(\phi, \theta_i) &= v_i(x(\theta_1, \theta_2, ..., \theta_n), \theta_i) - p_i(\theta) \\ &= v_i(\phi, \theta_i) - p_i(\theta), \end{aligned} \tag{4.19}$$

where $\theta$ is type profile and $\theta = (\theta_1, \theta_2, ..., \theta_n) = (\theta_i, \theta_{-i}) \in \Theta$.

## 4.6 Game-Theoretical Properties

The private preference, represented by users' value, measures how they are satisfied with the outcomes. Given the basic problem and mechanism design environment, we prove three important game-theoretical properties of ICCA: individual rationality, incentive compatibility and weak budget balance.

### 4.6.1 Individual Rationality

As the premise of an auction, agents should have incentives to participate voluntarily, a.k.a., individual rationality. We present two important concepts in the first place.

**Theorem 4.8 (Choice-set monotonicity)** *An mechanism environment exhibits choice-set monotonicity if for every agent $i \in N$, the set of outcome $\Phi_{-i}$ that is achievable without agent i presented is a weak subset of outcome with agent i, i.e., $\forall i,\ \Phi_{-i} \subseteq \Phi$.*

This property implies that removing any user in the auction weakly decreases–that is, never increases–the mechanism's set of feasible outcomes $\Phi$. Put it in another word, if auctioneer removes one user from the auction, the possible number of feasible outcomes weakly goes down.

**Theorem 4.9 (Non-negative externality)** *An mechanism environment exhibits non-negative externality if for every agent $i \in N$, all outcomes can be made without agent $i$, the valuation function $v_i$ of this agent on these outcomes is non-negative, i.e., $v_i(\phi, \theta_i) \geq 0$, $\forall i \in N,\ \phi \in \Phi_{-i}$.*

This property indicates that every user obtains non-negative utility for any outcome that can be achieved without her participation. If a user is removed from the auction, the mechanism is impossible to choose something that may cause her pain, or bring a negative utility to her. That implies that users will not suffer a loss if they do not reserve a charge.

**Proposition 1:** ICCA holds outcome-set monotonicity and non-negative externality.

**Proof** If a new user is introduced into the auction, auctioneer has to spend more time searching for the optimal outcome in a larger solution space, therefore, outcome-set monotonicity is satisfied. In this setting, no user negatively values the charging as each user wants to get its energy demand satisfied. Thus, there is no negative externality.

**Theorem 4.10 (Individual Rationality (IR))** *A direct revelation mechanism $M_d = (x, \{p_i\}_{i \in N})$ is individually rational if each agent $i \in N$ receives non-negative utility by participation, that is*

$$u_i(\phi, \theta_i) = v_i(\phi, \theta_i) - p_i(\theta) \geq 0, \quad \forall \theta_i \in \Theta_i. \tag{4.20}$$

Agents are not forced to participate in a mechanism by the individual willingness. This property indicates that users have an incentive to participate in this auction with an assuring non-negative utility. Note that this individual rationality is *ex post* IR[7] for

[7]The other two IRs are *ex ante* IR and *interim* IR. *ex ante* IR states that an agent has to choose to participate in the auction before knowing her own types, thus the agent's expected utility over all possible types and outcomes must be at least much as its expected utility without participation. While *interim* IR states that an agent knows her own types but has only distributional knowledge on other agents' types.

the situation in which the outcome is already determined, and agents can withdraw from the bidding process after observing the potential utility they will have.

**Proposition 2:** ICCA is *ex post* individually rational when choice-set monotonicity and non-negative externality hold, that is, BEV users have the incentive to participate in the charging scheduling process with a non-negative utility.

**Proof** Let $\phi^*$ be the optimal outcome that maximizes the social welfare, and $\phi_{-i}$ is the outcome without agent $i$, where $\phi_{-i} = arg \max_{\phi \in \Phi} \sum_{j \neq i} v_j(\phi, \theta_j)$, by choice-set monotonicity. Thus, agent $i$'s utility function is

$$\begin{aligned} u_i(\phi^*, \theta_i) &= v_i(\phi^*, \theta_i) - p_i(\theta) \\ &= v_i(\phi^*, \theta_i) - (\sum_{j \neq i} v_j(\phi_{-i}, \theta_j) - \sum_{j \neq i} v_j(\phi^*, \theta_j)) \\ &= \sum_{i \in N} v_i(\phi^*, \theta_i) - \sum_{j \neq i} v_j(\phi_{-i}, \theta_j). \end{aligned} \tag{4.21}$$

Based on the choice-set monotonicity, we can conclude

$$\sum_{j \in N} v_j(\phi^*, \theta_j) \geq \sum_{j \in N} v_j(\phi_{-i}, \theta_j), \tag{4.22}$$

which indicates any added agents have a positive effect on the social welfare, suggesting that the sum of values will increase.

Furthermore, from non-negative externality, we have

$$v_i(\phi_{-i}, \theta_i) \geq 0. \tag{4.23}$$

If we take agent $i$ away from $\sum_{j \in N} v_j(\phi_{-i}, \theta_j)$, it will become smaller, i.e.,

$$\sum_{j \in N} v_j(\phi_{-i}, \theta_j) \geq \sum_{j \neq i} v_j(\phi_{-i}, \theta_j), \tag{4.24}$$

then,

$$\sum_{i \in N} v_i(\phi^*, \theta_i) \geq \sum_{j \neq i} v_j(\phi_{-i}, \theta_j). \tag{4.25}$$

Therefore, the utility of agent $i$ is always non-negative when participating:

$$u_i(\phi^*, \theta_i) = v_i(\phi^*, \theta_i) - p_i(\theta) \geq 0. \tag{4.26}$$

### 4.6.2 Truthfulness

The selfish users tend to lie about their true values if it can lead to an individually favorable outcome. In terms of this, we need to incentivize the users to tell the truth in order to achieve the desired social goal. Specifically, if agent $i$ chooses to misreport her true type with another valuation $\hat{a}_i = s_i(\hat{\theta}_i)$, the new outcome should be $\phi' = x(s_i(\hat{\theta}_i), s_{-i}) = x(\hat{a}_i, a_{-i})$ due to the misreport of agent $i$. From the definition of direct revelation mechanism, we use $x(\hat{\theta}_i, \theta_{-i})$ instead of $x(\hat{a}_i, a_{-i})$ to represent the outcome due to the untruthful type $\theta_i$, i.e., $\phi' = x(\hat{\theta}_i, \theta_{-i})$. In the following we will prove that each agent cannot benefit herself by misreporting her true value in auction.

**Theorem 4.11 (Truthfulness)** *a.k.a. strategy-proof (SP) or dominant strategy incentive compatible, indicates truthfully reporting is a weakly dominant strategy for agent $i \in N$ under a VCG mechanism. That is, for each agent $i \in N$, $\forall \theta_i, \hat{\theta}_i \in \Theta_i$ and $\forall \theta_{-i} \in \Theta_{-i}$, it has*

$$u_i(x(\theta_i, \theta_{-i}), \theta_i) \geq u_i(x(\hat{\theta}_i, \theta_{-i}), \theta_i). \tag{4.27}$$

The above condition implies the best response for user $i$ is to report her true type $\theta_i$, irrespective of the strategies of others. To prove the truthfulness of ICCA, we use the proposition on the character of truthfulness by Giannakopoulos *et al.* in [141], which proves that any mechanisms that satisfy the following conditions are truthful.

**Theorem 4.12 (Truthfulness characterization)** *A mechanism $M_d = (x, \{p_i\}_{i \in N})$ is truthful iff*

*1) Each agent's payment $p_i(\theta)$ does not depend on her won type $\theta$, but on the other agents' types $\theta_{-i}$ and the outcome $\phi = x(\theta_1, \theta_2, ..., \theta_n)$ decided by $M_d$, i.e.,*

$$\begin{aligned} \phi = x(\theta_i, \theta_{-i}) = x(\theta_i', \theta_{-i}) \\ \rightarrow p_i(\theta_{-i}) = p_i(\theta_i, \theta_{-i}) = p_i(\theta_i', \theta_{-i}). \end{aligned} \tag{4.28}$$

*2) Decision policy $x$ decides the optimal outcome, assuming fix the other agents' types $\theta_{-i}$, outcome for every agent $i \in N$, i.e.,*

$$x(\theta_i, \theta_{-i}) \in arg \max_{\phi \in x(\Theta_i, \theta_{-i})} (v_i(\phi, \theta_i) - p_i(\theta_{-i})). \tag{4.29}$$

*[Proposition 2.13 in [141]]*

The proof can be found in [141], we do not put it here due to the space limit. We directly use it to prove the truthfulness of ICCA after introducing the conditions for implementing truthfulness of a mechanism.

**Proposition 3:** In ICCA, BEV users will obtain the best or at least not worse outcome by truthfully reporting their types, regardless of types of other users. That is, this auction with VCG payment policy is truthful (dominant strategy incentive compatible).

**Proof** We prove that this auction satisfies the above two conditions in truthfulness characterization. Recall that the payment policy is $p_i(a) = \max\limits_{\phi\in\Phi} \sum_{j\neq i} v_j(\phi, \theta_j) - \sum_{j\neq i} v_j(\phi^*, \theta_j)$, for all type profiles $\theta = (\theta_i, \theta_{-i}) \in \Theta$ and outcomes $\phi = x(\theta_i, \theta_{-i}) \in \Phi$. As mentioned above, user's payment does not directly depend on her type, but on other users' types. Thus condition (1) holds.

Next, fix some agent $i$ with type $\theta_i \in \Theta$ and type profiles $\theta_{-i}$, for every possible outcome $\phi \in x(\Theta_i, \theta_{-i})$, the utility function is

$$\begin{aligned} u_i(\phi, \theta_i) &= v_i(\phi, \theta_i) - p_i(\theta_{-i}) \\ &= v_i(\phi, \theta_i) - (\sum_{j\neq i} v_j(\phi_{-i}, \theta_j) - \sum_{j\neq i} v_j(\phi, \theta_j)) \\ &= v_i(\phi, \theta_i) + \sum_{j\neq i} v_j(\phi, \theta_j) - \sum_{j\neq i} v_j(\phi_{-i}, \theta_j) \\ &= \sum_{i\in N} v_i(\phi, \theta_i) - \sum_{j\neq i} v_j(\phi_{-i}, \theta_j), \end{aligned} \tag{4.30}$$

and due to the reality that second term of the last line $\sum_{j\neq i} v_j(\phi_{-i}, \theta_j)$ is independent of outcome $\phi$, therefore,

$$\begin{aligned} \phi &= arg \max_{\phi\in x(\Theta_i, \theta_{-i})} (v_i(\phi, \theta_i) - p_i(\theta_{-i})) \\ &= arg \max_{\phi\in x(\Theta_i, \theta_{-i})} \sum_{i\in N} v_i(\phi, \theta_i). \end{aligned} \tag{4.31}$$

Notice that $x(\Theta_i, \theta_{-i}) \in \Phi$ and $x(\theta_i, \theta_{-i}) \in x(\Theta_i, \theta_{-i})$, thus condition (2) of truthfulness characterization gives $x(\theta_i, \theta_{-i}) \in arg \max\limits_{\phi\in x(\Theta_i, \theta_{-i})} \sum_{i\in N} v_i(\phi, \theta_i)$.

Therefore,

$$x(\theta_i, \theta_{-i}) \in arg \max_{\phi\in x(\Theta_i, \theta_{-i})} (v_i(\phi, \theta_i) - p_i(\theta_{-i})). \tag{4.32}$$

The aforementioned two conditions are satisfied and the truthfulness of ICCA is established[8].

Add it all up, users cannot benefit themselves by misreporting their true values on the schedules, because such utility is not larger than by reporting the true values under VCG payment. Therefore, the weakly dominant strategy for each agent is to truthfully report her values regardless of others' strategies.

### 4.6.3 Weak Budget Balance

The charging network will never take a loss, but may make a profit in ICCA. To prove this, we first present the definition of revenue and no single-agent effect.

**Theorem 4.13 (Revenue)** *The revenue of a direct revelation mechanism $M_d = (x, \{p_i\}_{i \in N})$ is the sum of payments for the outcome $\phi$ across all agents $i \in N$ which is*

$$R_d(\theta) = \sum_{i \in N} p_i(\theta). \tag{4.33}$$

**Theorem 4.14 (No single-agent effect)** *An environment exhibits no single-agent effect if for each agent $i$, every possible valuation $v_{-i}$ of agents other than $i$, and for all decisions that maximize the social welfare: $\phi = arg \max_{\phi \in \Phi} \sum_{j \in N} v_j(\phi, \theta_j)$, there exists a choice $x'$ that is feasible without agents $i$ and that has*

$$\sum_{j \neq i} v_j(\phi', \theta_j) \geq \sum_{j \neq i} v_j(\phi, \theta_j). \tag{4.34}$$

No single-agent effect property states that the social welfare across all users other than $i$ weakly increases by removing agent $i$ from the auction. In other words, if we remove any BEV user $i$ and pick some other schedules instead, the remaining users without $i$ will be happier for the new choice than the old choice with $i$. Dropping a user just reduces the amount of competition for the limited charging space in these stations, which in return increases the probability for other users to obtain a better schedule.

[8] Every Groves mechanism is truthful under these two conditions in truthfulness characterization. Obviously, ICCA is a sort of Groves mechanisms.

**Theorem 4.15 (Weak budget balance)** *A mechanism is weakly budget balanced if each agent $i \in N$ makes a non-negative payment to the auctioneer for all feasible type profiles $\theta \in \Theta$, thus the revenue collected by the auctioneer is non-negative, which is*

$$\sum_{i \in N} p_i(\theta) \geq 0, \ \forall \theta \in \Theta. \tag{4.35}$$

This property states that there can be a payment made from agents to auctioneer, but no payment from auctioneer to agents. In other words, BEV users should pay for the charging service to the charging network, and the payments from all users are exactly the revenue of the charging network.

**Proposition 4:** ICCA is weak budget-balanced when the no single-agent affect property holds.

**Proof** We prove that the sum of transfers across all users to the charging network is greater than or equal to zero in ICCA. According to the payment function, we have the sum of payments of all users as

$$\sum_{i \in N} p_i(\theta) = \sum_{i \in N} (\sum_{j \neq i} v_j(\phi_{-i}, \theta_j) - \sum_{j \neq i} v_j(\phi^*, \theta_j)), \tag{4.36}$$

where $\phi_{-i}$ is the outcome made by auctioneer without user $i$. Given no single-agent effect property we have

$$\sum_{j \neq i} v_j(\phi_{-i}, \theta_j) \geq \sum_{j \neq i} v_j(\phi^*, \theta_j), \quad \forall i \in N. \tag{4.37}$$

Therefore, the result follows directly with

$$\sum_{i \in N} p_i(\theta) \geq 0. \tag{4.38}$$

Add it all up, we have proved that ICCA satisfied individual rationality, incentive compatibility and weak budget balance. These elegant game theoretical properties have demonstrated how users' strategic behaviors impact the outcomes of the mechanism, and help us to gain deep insight on the interaction between the stations and users.

## 4.7 A Case Study

This section aims to demonstrate the applicability of ICCA to concrete scenarios through a case study. We take the DC-charging (level-3) station data at Manhattan, New York as an example, which is taken from ChargePoint[9]. Consider totally five DC charging stations (CSs), shown as A, B, C, D and E in Fig. 4.2, with different plug type: $M$ (CHAdeMO: A, B, and D, charging rate $R$: 65 $kW$), $S$ (Tesla supercharger: C, E, charging rate $R$: 150 $kW$). The number of charging points (CPs) at each station is 1, 1, 4, 2 and 4, respectively, as shown in Fig. 4.2 (the number in black circle), totally 12 points. The charging point is serially numbered as 1 to 12 corresponding to charging station A-E, for example, CP1 is in charging station CS-A, and CP 3-6 are in CS-C.

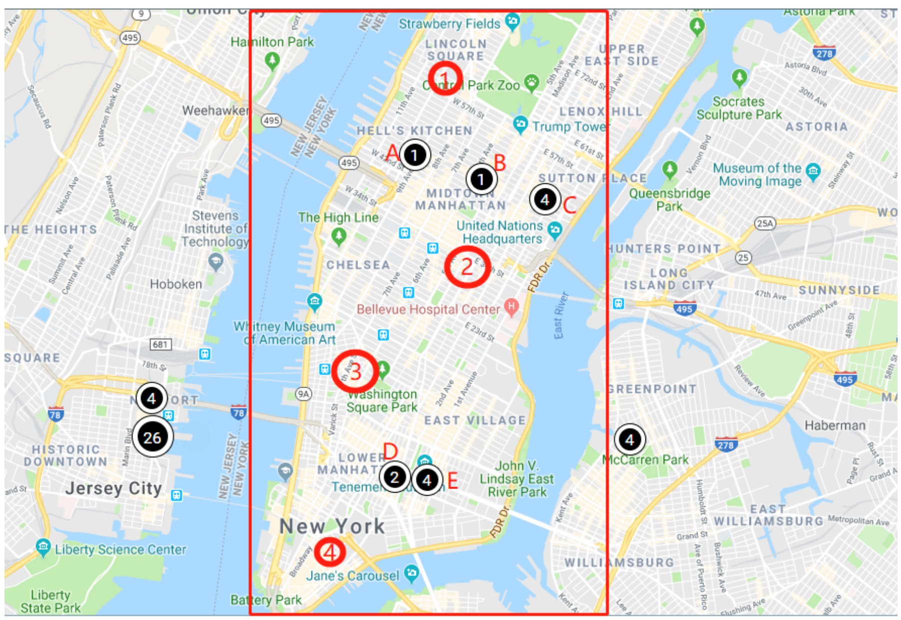



Figure 4.2: Distribution of charging stations and user requests in Manhattan, New York

There is a group (totally 50) of BEV users either driving Nissan Leaf (8 users) or Tesla Model S (42 users), with the battery capacity $E_i$ of $60kWh$ (Nissan Leaf) and $100kWh$ (Tesla Model $S$), respectively. Each BEV is initially randomly located in the red square area (1, 2, 3, 4). To simplify the initial locations of these BEVs, we assume that they are mainly located in four areas, see the red circle in the map. The two

[9]ChargePoint, https://na.chargepoint.com/charge_point.

bigger circles (2 and 3) in the center have 18 users each, and two smaller circles (1 and 4) on the edge have 7 users each. We set the energy consumption as 13.6 $kWh/100km$, and set Nissan Leaf as 10.8 $kWh/100km$ in mild weather city conditions[10]. The average driving speed $dv$ of New York city is set as $30km/h$ ($\approx 18mph$)[11].

The charging request $Q_i = \left\langle \overline{dt}_i, \overline{ct}_i, EVt_i, SoC_i, SoC'_i, E_i, GIS_i \right\rangle$ of BEVs is set as: $\overline{dt}_i$ is randomly drawn from $[12.0, 15.0]$ and $\overline{ct}_i$ is set as 18. The initial $SoC_i$ of these vehicles is randomly set between 10% and 50%, i.e, from a uniform distribution $U(10, 50)$, and they all want to charge BEVs to 80% ($SoC'_i = 80\%$). The current location $GIS_i$ is randomly selected from location 1, 2, 3 and 4. And the distances from BEV's initial locations to each station are shown in Table 4.2 given the data from Google map. The charging time[12] is simply set as $\frac{E_i SoC_i}{R_k}$. User's type is not known by others, and the valuation $v_i(\phi, \theta_i)$ of users is the money they want to pay for the schedule $\phi$ based on their current $SoC_i$ and is assumed as a non-increasing function. The valuation is assigned from a distribution between \$5 and \$10 as pairwise function in the following:

$$v_i = \begin{cases} 10, \quad if\ 0 \leq SoC_i \leq 20\% \\ 0.1 * (100 - SoC_i), \quad if\ 20\% < SoC_i \leq 40\% \\ 5, \quad if\ 40\% < SoC_i \leq 100\%. \end{cases}$$

Table 4.2: Distance ($km$) from BEVs to charging stations

| BEV location | CS-A | CS-B | CS-C | CS-D | CS-E |
|---|---|---|---|---|---|
| Group-1 | 1.8 | 2.9 | 3.6 | 7.4 | 7.8 |
| Group-2 | 1.5 | 1.1 | 2.0 | 4.3 | 4.7 |
| Group-3 | 5.8 | 4.0 | 5.4 | 2.2 | 2.8 |
| Group-4 | 8.5 | 9.0 | 9.2 | 2.1 | 2.4 |

To guarantee the optimality of the solutions, the code for this auction is developed in ILOG Optimization Programming Language (OPL), and solved by ILOG CPLEX 12.6.3. The experiment is carried out on a PC with a processor of Intel (R) Core (TM) i5-6500U CPU @ 3.2GHz, 8GB memory.

The optimal schedule $\phi^*$ satisfying Constraints (4.2)-(4.13) is shown in Fig. 4.3. As can be seen therein, the start time, finish time, charging time, sequence and

[10]Electric Vehicle Database, https://ev-database.org/.

[11]http://infinitemonkeycorps.net/projects/cityspeed/.

[12]As a reference, it takes around 40 minutes to charge a Tesla model S from 20%-80% $SoC$ using a Tesla supercharger, here we consider the charging curve is stable during 20%-80%.

destination of each BEV is presented in the Gantt chart. The revenue, which is the sum of values of all users, is \$352.9. The computational time is 95.2$s$. Each user pays to charging station according to VCG policy in Eq. (4.17) after auction terminates.

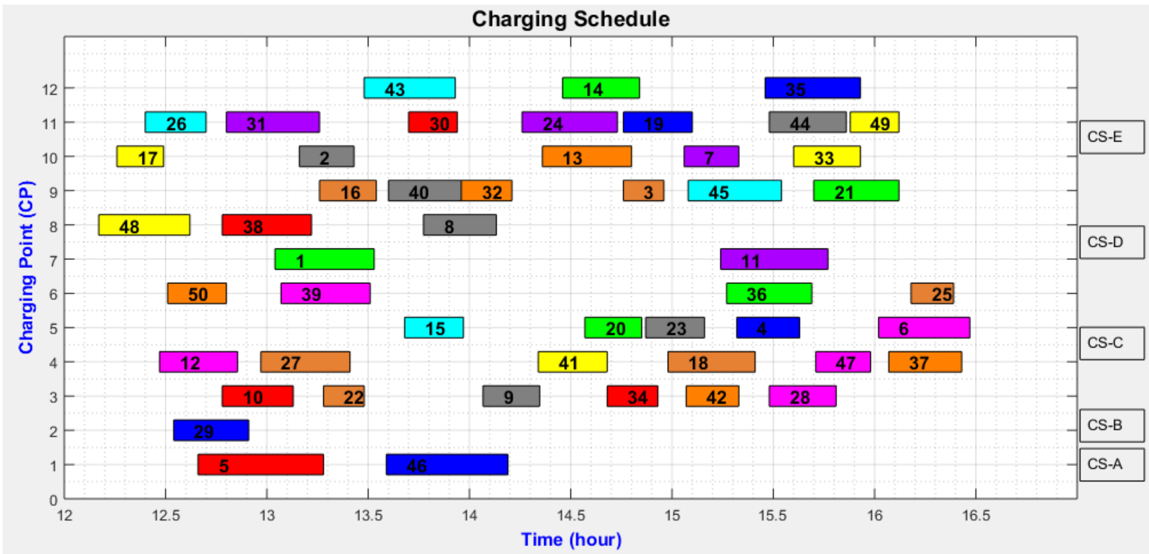



Figure 4.3: Optimal schedule by ICCA in Gantt chart

## 4.8 Summary

This work developed an incentive-compatible combinatorial auction for a multi-charging station scheduling problem in a charging network. This auction provides a potential reservation-based charging solution for a portion of users who have strict time requirements and private preferences, with a specific bidding language and a winner determination model developed for the charging schedule. An extensive game-theoretical analysis is conducted to prove that the potential users who require the reserved charging service are attracted to participate voluntarily and truthfully report their private values on the finish time as a weakly dominant strategy. Moreover, this mechanism is weakly budget balanced. We also carried out a real-world case study in Manhattan, New York to validate the implementability of this auction, and the optimal solution can achieve a revenue for the network with \$352.9.

Our future work will consider more complex interactions between users by extending the single-charge to multi-charge scheduling in a charging network, such as for highway travellers, logistics freights, or electric taxis. The competition between agents may trap a market in a bad equilibrium where all agents play myopic strategies without performing sufficient exploration for a social-desirable outcome. Thus, leading users to cooperate and fitting their demands together is also an important mechanism design issue of our future work on the agenda. Meanwhile, the uncertainties of users' energy demands, arrivals, or their private preferences will be considered when designing a market-based mechanism.

# Chapter 5

# Iterative Bidding for Highway Charging Scheduling

## 5.1 Background

The increasing share of EVs requires the coordination of adequate charging facilities such that EVs can be timely recharged within the driving range. The current charging network, such as ChargePoint, adopts first-come-first-serve basis. Hours-long of charging time compared to minutes of refuelling a gasoline vehicle, as well as the unpredictable waiting time at a public charging station, would degrade users' satisfaction and the utilization of the limited public charging capacities. Especially, the scarcity of charging facilities at highways makes some trans-city trips unplanned. Therefore, long waiting time and scarce highway charging facilities are main challenges for the highway EV travels.

Given this, it is of great importance to schedule and reserve the charging activities at highways in advance, in order to improve the utilization of charging facilities [40], and reduce users' waiting time at charging stations by ensuring their desired charging destination will always be available when they arrive [108]. Moreover, a day-ahead charging demand dispatching enables to reduce voltage deviation and power loss in the distribution networks [25, 142]. In this work, we consider the restricted charging space of the charging network that allows only a certain fixed number of EVs to charge simultaneously at highway charging stations, the impact of fast charging load on the voltage quality of local distribution networks is neglected.

## 5.2 Related Work

Extensive works apply queuing theory for the highway routing problems, enabling to reduce users' waiting time and balance the traffic flow among multiple charging stations [65, 97, 108]. This distributed approach schedules the the set of EVs' charges to different charging stations, which is often applied to the highway charging scheduling problem. For instance, S. Bae and A. Kwasinski [109] proposed a spatial and temporal model of electric vehicle charging demand, which first predicts arriving rate of Es by the fluid dynamic traffic model, and then forecasts the charging demand by the M/M/s queueing theory. Besides queuing theory for the multiple charging coordination problem, J. Timpner and L. Wolf proposed a coordinated charging strategy to integrate the reservation and dynamic charging requests into the charging schedule, in order to improve the utilization of the limited charging places [41]. And R. Xie et al. proposed a data driven robust optimization approach to deal with the demand dispatching problem [25]. Simulated annealing is applied to minimize a total system cost inclusive of infrastructure investment, battery cost and user cost [143].

However, most of the existing scheduling coordination approaches, either queueing model or heuristic algorithms, does not consider users' strategic behaviors in the decentralized environment. The self-interested users may reveal an incomplete availability (available time window) if that leads to the prioritized charging and less waiting time, and these strategic misreports may constrain the solution space and jeopardize the utilization efficiency of the charging network. Moreover, the high efficiency of the queueing theory is justified by the assumption that users can wait infinite long, which is not practical in realistic scenarios.

## 5.3 Our Contribution

We solve a decentralized highway charging scheduling problem by an auction-based approach, in which users are allowed to progressively elicit their complete time window. Our approach allows users to reveal their availability as needed, unlike Vickrey-Clarke-Groves (VCG) mechanism to incentivize users to truthfully report their complete information as a dominant strategy [53]. In particular, we explore the relationship between charging resource utilization and user' waiting time.

The remainder of this work is organized as follows, Section 5.3 describes and formulates the highway charging scheduling problem. Section 5.4 implements the highway scheduling problem through a bidding-based framework. Section 5.5 evaluates the efficiency and user satisfaction performance of the proposed bidding framework. Finally, we conclude the paper and discuss future improvements in Section 5.6.

## 5.4 Highway Charging Scheduling Problem Formulation

We consider the highway charging scheduling as a decentralized decision making process in which the charging network interacts with a group of users, who travel with different entries and exits at an inter-city auto-route. Day-ahead before departure, each user submits a charging request, which consists an earliest entry time and a latest exit time (their travel time window, or availability), to reserve her highway charging stops. We assume that users prefer a short travel time within this time window. The highway charging stations are connected as a charging network to support EV's trans-city travel, such stations have limited charging capacity, which is restricted by the number of chargers. In order to find the best trade-off between the charging capacity utilization and the preferences of users, the charging network should properly determine, for each user, which charging station to enter, when to start and how long to charge at this charging station.

Formally, consider a set of highway charging stations denoted as $K$, and a set of $n$ EV users denoted as $N$. Each user $j$ ($j \in N$) has a charging request, which is characterized by a 6-tuple $< \overline{edt_j}, \overline{lxt_j}, SoC_{j,0}, SoC_{j,k_j}, GIS_{j,0}, GIS_{j,out} >$, where $\overline{edt_j}$ is the earliest entry time of user $j$ at highway, and $\overline{lxt_j}$ is the latest exit time of user $j$. User $j$ has to travel within this time window $[\overline{edt_j}, \overline{lxt_j}]$. $SoC_{j,0}$ is the initial State of Charge ($SoC$) of user $j$ when entering the highway, and $SoC_{j,k_j}$ is the final $SoC$ that user $j$ requires when leaving the highway, here we use subscript $k_j$ to represent the charging station where user $j$'s last charge performs. $GIS_{j,0}$ is the highway entry of user $j$, and $GIS_{j,out}$ is the highway exit of user $j$.

We consider a simplified scheduling model by assuming that the number of charging stops and the demand energy at each stop are fixed for each user, need to mention that the charging station selection and routing problem is a hot research issue in highway charging scheduling [144]. In the following, we introduce the parameter, variables and the mathematical model for the problem.

**Parameter**

$M$ Set of charger $i \in M$. Let $m$ be the number of all chargers at these highway charging station.

$K_j$ The set of charges that user $j$ performs at highway charging stations, and use $k$ to represent the potential charging station of user $j$ during her travel, where $k \in K_j$.

$D_{x,y}$ The distance between position $x$ and $y$. Note that this position can either be the charging station or be the highway entry (exit) place of EV users. For example, $D_{k,k+1}$ is the distance between charging station $k$ and $k+1$, where $k, k+1 \in K$. Moreover, $D_{0,k}$ indicates the distance between user $j$'s departure place $GIS_{j,0}$ and charging station $k$. Similarly, $D_{k,k_j}$ indicates the distance between charging station $k$ and user $j$'s destination $GIS_{j,out}$.

$T_{j,x,y}$ The driving time of user $j$ from position $x$ to $y$. The driving time $T_{j,k,k+1}$ from charging station $k$ to $k+1$ can be estimated by $\frac{D_{k,k+1}}{V}$. Similarly, let $T_{j,0,k}$ be the driving time from user $j$'s departure place $GIS_{j,0}$ to charging station $k$, where $T_{j,0,k} = \frac{D_{0,k}}{V}$. And $T_{j,k,k_j}$ is the driving time from charging station $k$ to her destination $GIS_{j,out}$, where $T_{j,k,k_j} = \frac{D_{k,k_j}}{V}$.

$O_{j,k}$ User $j$'s charge at charging station $k$, $k \in K_j$.

$A_{i,j,k}$ The available charger $i$ of $O_{j,k}$ of user $j$, $A_{i,j,k} = 1$ if charger $i$ is located in charging station $k$ for $O_{j,k}$ of user $j$, $A_{i,j,k} = 0$ otherwise.

$SoC_{j,k}$ Required $SoC$ of charge $O_{j,k}$ of user $j$, where $SoC_{j,k} \in [0, 1]$. The charging time of $O_{j,k}$ on charger $i$ can be computed by $\frac{SoC_{j,k} * E_j}{R_i}$, where $E_j$ is the battery capacity ($kWh$) of users $j$, and $R_i$ is charging rate ($kW$) of charger $i$, which is assumed to be constant at all times, $i \in M$.

**Decision variable**

$Z_j$ If user $j$ is selected in the final schedule.

$xt_j$ Exit time of user $j$ at location $GIS_{j,out}$.

$st_{i,j,k}$ Start time of charge $O_{j,k}$ on charger $i$.

$$X_{i,j,k} = \begin{cases} 1,\ if\ charger\ i\ is\ selected\ for \\ charge\ O_{j,k}\ of\ user\ j \\ 0,\ otherwise \end{cases}$$

*To make the variable consistent, we set $X_{i,j,0}$ to 1.

$$Y^i_{j',k',j,k} = \begin{cases} 1,\ if\ charge\ O_{j',k'}\ of\ user\ j'\ performs \\ immediately\ before\ O_{j,k}\ of\ user\ j\ on \\ charger\ i \\ 0,\ otherwise \end{cases}$$

$$Y^i_{\alpha,j,k} = \begin{cases} 1,\ if\ charge\ O_{j,k}\ performs\ first\ on \\ charger\ i \\ 0,\ otherwise \end{cases}$$

$$Y^i_{j,k,\beta} = \begin{cases} 1,\ if\ charge\ O_{j,k}\ performs\ last\ on \\ charger\ i \\ 0,\ otherwise \end{cases}$$

where $i = 1, ..., m, j = 1, ..., n, k = 1, ..., |K_j|$.

**Mathematical model**

This centralized model is built in the flexible job shop (FJc)[13] scheduling environment, in which each user has its own recharge plan to execute at a set of highway charging stations. The charging scenario at each charging station is set in the Parallel machine (Pm) environment, in which the charge of any user at one charging station is processed on any one charger and any charger in this charging station can charge.

Taken users' charging requests as input, this centralized model computes the exit time for each request, with an objective of maximizing the number of EVs that charging network can serve, which is to solve

$$max \sum_{j \in N} Z_j \tag{5.1}$$

[13] A flexible job shop is a generation of the job shop and the parallel machine environments. There are $c$ work centers (charging stations) with at each work center a number of identical machines (chargers) in parallel.

subject to

$$\overline{edt}_j + T_{j,0,1} \leq st_{i,j,1} + H * (1 - Z_j), \quad \forall i \in M, j \in N \tag{5.2}$$

$$xt_j = \sum_{i \in M} (st_{i,j,1} + \sum_{k,k+1 \in K_j} (\frac{SoC_{j,k} * E_j}{R_i} + T_{j,k,k+1})), \qquad \forall j \in N \tag{5.3}$$

$$xt_j \leq \overline{lxt_j} + H * (1 - Z_j), \quad \forall j \in N \tag{5.4}$$

$$st_{i,j,k} + \frac{SoC_{j,k} * E_j}{R_i} + T_{j,k,k+1} \leq st_{i,j,k+1} + H * (1 - Z_j), \qquad \forall i \in M,\ k, k+1 \in K_j,\ j \in N \tag{5.5}$$

$$\sum_{i \in M} X_{i,j,k} = Z_j, \quad \forall k \in K_j, j \in N \tag{5.6}$$

$$X_{i,j,k} \leq A_{i,j,k}, \quad \forall i \in M, k \in K_j, j \in N \tag{5.7}$$

$$\sum_{j \in N} \sum_{k \in K_j} Y^i_{\alpha,j,k} \leq 1, \quad \forall i \in M \tag{5.8}$$

$$\sum_{j',k' \in \{\alpha\} \cup K_{j'}} Y^i_{j',k',j,k} = X_{i,j,k}, \qquad \forall i \in M, k \in K_j, j \in N \tag{5.9}$$

$$\sum_{j',k' \in \{\alpha\} \cup K_{j'}} Y^i_{j',k',j,k} = \sum_{j',k' \in K_{j'} \cup \{\beta\}} Y^i_{j,k,j',k'}, \qquad \forall i \in M, k \in K_j, j \in N \tag{5.10}$$

$$Y^i_{j',k',j,k} + Y^i_{j,k,j',k'} \leq 1, \qquad \forall i \in M, k \in K_j, k' \in K_{j'}, j, j' \in N, j \neq j' \tag{5.11}$$

$$st_{i,j',k'} + \frac{SoC_{j',k'} * E'_j}{R_i} \leq st_{i,j,k} + H * (1 - Y^i_{j',k',j,k}), \qquad \forall i \in M, k \in K_j, k' \in K_{j'},\ j, j' \in N, j \neq j' \tag{5.12}$$

$$0 \leq st_{i,j,k}, \quad \forall i \in M, k \in K_j, j \in N \tag{5.13}$$

$$Z_j, X_{i,j,k}, Y^i_{j',k',j,k}, Y^i_{j,k,j',k'}, Y^i_{\alpha,j,k}, Y^i_{j,k,\beta} \in \{0,1\},$$
$$\forall i \in M, k \in K_j, k' \in K_{j'},\ j, j' \in N, j \neq j'. \tag{5.14}$$

where $K_j, K_{j'} \in K$, and $K_j \neq K_{j'}$.

Constraints (5.2) force that if user $j$ is selected in the schedule, her starting time of first charge $st_{i,j,1}$ should not be earlier than her arriving time at the first charging station. Here we slightly abuse the subscript "1" in $T_{j,0,1}$ and $st_{i,j,1}$ to represent user $j$'s first charge in $K_j$, note that "1" indicates the first element in $K_j$ and may not match the charging station code $k$ of her first charge. $H$ is a large positive constant to ensure the "if" logic. Constraints (5.3) define the exit time of user $j$. Constraints (5.4) determine that the exit time allocated to user $j$ should not be later than her latest exit time $\overline{lxt_j}$ at highway if she is selected. Constraints (5.5) force that starting time $st_{i,j,k+1}$ of user $j$ at charging station $k+1$ should not be earlier than her arriving time at this charging station if she is selected. Constraints (5.6) force each charge $k$ of user $j$ can be performed at most on one charger if she is selected. Constraints (5.7) denote that the capable chargers for user $j$'s charge at charging station $k$. Constraints (5.8) ensure that at most one charge can be performed the first at charger $i \in M$. Constraints (5.9) and (5.10) ensure that if charge $O_{j,k}$ of user $j$ is selected to be performed at charger $i$ in charging station $k$, it should be either the first one to charge, or after the charge of other users. Similarly, for charge $O_{j,k}$ of user $j$ at charger $i$, it should be either the last one to charge, or before other users' charge. Constraints (5.11) denote that if charge $O_{j,k}$ of user $j$ and charge $O_{j',k'}$ of user $j'$ are adjacent at charger $i$, one charge has to be performed before or after the other, which forces their precedence relationship. If they are not adjacent, $Y^i_{j',k',j,k}$ and $Y^i_{j,k,j',k'}$ are both zero. Constraints (5.12) ensure that if charge $O_{j,k}$ of user $j$ charges immediately after charge $O_{j',k'}$ user $j'$ at charger $i$, charge $O_{j,k}$ cannot start until $O_{j',k'}$ is completed. Constraints (5.13) are non-negative constraint for $st_{i,j,k}$. Constraints (5.14) denote that the decision variables $Z_j, X_{i,j,k}, Y^i_{j',k',j,k}, Y^i_{j,k,j',k'}, Y^i_{\alpha,j,k}$, and $Y^i_{j,k,\beta}$ are binary.

Given the availability information of users, the charging network aims to accommodate as many charging requests as possible into the schedule, such that the limited charging resources can be efficiently utilized. The optimal schedule can be obtained with users' full availability revealed by solving the above model. However, in real-world scenarios, EV users are reluctant to reveal their complete availability because it will increase the possibility of being assigned a long travel time, which indicates a long waiting time[14]. A rational user tends to only reveal partial availability (a short time window), which will bring less time for charging. However, such strategic behaviors will compromise the efficiency of the schedule.

In this centralized model, users' time window $[\overline{edt}, \overline{lxt}]$ is assumed to be known a priori and can be taken into account in the scheduling process. In next section, we will remove this assumption and consider users' time window as private information in decentralized setting. We focus on the strategic interaction between the charging network and the users, in which users may report a shorter time window instead of their tenacious time window if that can reduce their waiting time at highway charging stations. Given this self-interested behavior, we call them agents and apply the iterative bidding framework of our previous work [35] in Chapter 3 to solve this decentralized highway charging scheduling problem.

## 5.5 Iterative Auction Design

The auction-based approach is an iterative auction containing three major components: bids, a winner determination model and an iterative bidding procedure. The bids are agents' preferred time window for charging. The winner determination model computes provisional charging schedules, which maximize the number of the EVs that the charging network can serve. The iterative bidding procedure enables the charging network (auctioneer) and the users to negotiate on the exit time in an iterative way and evolves the provisional schedules towards an optimal one.

### 5.5.1 Bids

Agents can express her preferences over different time windows through bids. Agent $j$'s bid is defined as a 3-tuple $< Q_j, \overline{edt_j}, lxt_j >$, where $Q$ represents the $SoC_{j,0}$, $SoC_{j,k_j}$, $GIS_{j,0}$ and $GIS_{j,out}$ of user $j$'s charging request. $\overline{edt_j}$ is her earliest entry time, and $lxt_j$ is the latest exit time in this bid, which implies the exit time $xt_j$ allocated to her is within the time window $[\overline{edt_j}, lxt_j]$.

[14]Specifically, the travel time is the summation of the total driving time, the total charging time and waiting time at charging stations. Since the driving time can be easily estimated if the trip distance and the highway driving speed are given, and the charging time depends only upon the level of charge. The travel time only depends on the waiting time at charging stations.

### 5.5.2 Winner Determination Model

In winner determination, the auctioneer computes a new provisional schedule at the current round as long as the bidding is not terminated. At round $t$, the provisional schedule $s^t$ solves:

$$\max_{s^t \in S^t} \sum_{lxt_j \in s^t} Z_j(lxt_j), \tag{5.15}$$

subject to

$$xt_j \leq lxt_j + H * (1 - Z_j(lxt_j)), \quad \forall j \in N \tag{5.16}$$

and constraints (5.2)-(5.3) and (5.5)-(5.14).

where $K_j, K_{j'} \in K$ and $K_j \neq K_{j'}$. $S^t$ is the set of all feasible schedules at round $t$, given the valid bids submitted by agents. The affiliation $lxt_j \in s^t$ indicates the exit time $xt_j$ allocated to agent $j$ is before the latest exit time $lxt_j$ in $s^t$. Constraint (5.2)-(5.3) and (5.5)-(5.14) remain the same as they are in the centralized model, except that $Z_j$ turns to be $Z_j(lxt_j)$.

### 5.5.3 Iterative Bidding Procedure

The iterative bidding procedure is depicted as pseudo-code in Algorithm 2. First of all, each agent $j$ has a charging request and constructs her initial bid by selecting the available time window with the earliest exit time, which indicates that this user starts to charge as soon as she arrives at the charging station, at this time, she has a lowest travelling time. After that, agents use it as the first-round bid and submit it to auctioneer. Each agent only submits one bid each round. The auctioneer solves the winner determination taking these bids as input at round $t-1$ ($t \geq 1$), and presents the provisional schedule $s^{t-1}$ to the agents. At the beginning of round $t$, each agent needs to decide whether to update her bid, by extending the latest exit time $lxt$ until her latest exit time $\overline{lxt_j}$ (extend the available time window). Agents will not accept a schedule with the exit time $xt_j$ that exceed her $\overline{lxt_j}$, that is, $lxt_j \leq \overline{lxt_j}$.

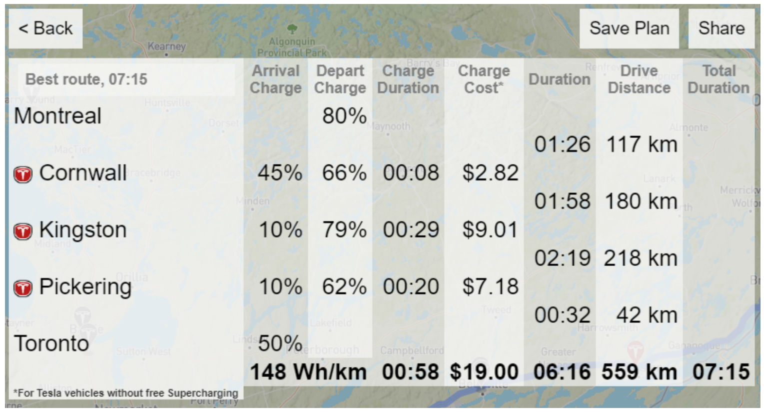
If an agent was not awarded in the provisional schedule at round $t-1$, she has two time updating options for availability: (1) she can add the current exit time $lxt$ that she bidded at round $t-1$ by $\varepsilon$, where $\varepsilon$ is the minimum increment imposed by the auctioneer; or (2) she can also keep the submitted $lxt$ unchanged by submitting an empty bid. In this case, the auctioneer will consider she has entered into the final

**Algorithm 2** Iterative Bidding Framework

**Require:** $N$, bids of all agents, $\varepsilon$
**Ensure:** $s$ // The final schedule
1: $t \leftarrow 0$ // $t$: round index;
2: $isTerminated \leftarrow false$ // termination index;
3: *Agent* $j \in N$ *sets her initial bid*;
4: **for** $j = 1 \rightarrow N$ **do**
5:     Update the latest exit time and final state;
6:     **if** $t - 1 > 0$ **then**
7:         **if** *agent* $j$ *is selected in* $s^{t-1}$ **then**
8:             Submit an empty bid at round $t$;
9:         **else**
10:             For the previous bid in the round $t - 1$;
11:             $lxt_j^t \leftarrow lxt_j^{t-1} + \varepsilon$;
12:         **end if**
13:     **end if**
14:     *Send the updated bid to the auctioneer*;
15: **end for**
16: *For the auctioneer*:
17: *Receive bids and Update* $isTerminated$;
18: **if** $isTerminated == false$ **then**
19:     $s^t \leftarrow \max_{s^t \in S^t} \sum_{lxt_j \in s_t} Z_j(lxt_j)$;
20:     Send result $s^t$ back to each agent j;
21:     $t \leftarrow t + 1$;
22:     Go to step 5;
23: **else**
24:     break;
25: **end if**

bid status, in which she is forbidden from updating her bid in future rounds. If one agent is awarded in the provisional schedule $s^{t-1}$, she can maintain her latest exit time $lxt$ unchanged and submit an empty bid at round $t$.

Once the bids are received from the agents, the auctioneer first removes the invalid bids at current round, these bids will not be considered in the following winner determination procedure. Invalid bids are defined as containing (1) new bid with updated time window from agents who have already declared their final bidding status in previous rounds; and (2) the time window which is shorter than the lowest travel time (without waiting for charging) of the charging request. The auctioneer then checks the termination condition against the valid bids. The bidding terminates if there is no more new availability added. That is, each agent in the last round has



| Best route, 07:15 | Arrival Charge | Depart Charge | Charge Duration | Charge Cost* | Duration | Drive Distance | Total Duration |
|---|---|---|---|---|---|---|---|
| Montreal | | 80% | | | | | |
| | | | | | 01:26 | 117 km | |
| Cornwall | 45% | 66% | 00:08 | $2.82 | | | |
| | | | | | 01:58 | 180 km | |
| Kingston | 10% | 79% | 00:29 | $9.01 | | | |
| | | | | | 02:19 | 218 km | |
| Pickering | 10% | 62% | 00:20 | $7.18 | | | |
| | | | | | 00:32 | 42 km | |
| Toronto | 50% | | | | | | |
| | **148 Wh/km** | | **00:58** | **$19.00** | **06:16** | **559 km** | **07:15** |



Figure 5.1: Charging plan from Montreal to Toronto by ABRP

submitted an empty bid. If the termination condition is satisfied, the auctioneer implements the final schedule. If not, the auctioneer will update agents' time availability by adding agents' newly extended time window and solve the winner determination model taking the updated availability information as input.

Through this iterative bidding framework, agents progressively reveal their complete time window as necessary as the bidding proceeds, the utilization efficiency of charging network is obtained at the cost of availability revelation of users. If all agents have revealed their full availability at the termination of bidding, the winner determination model will work out an optimal schedule which maximizes the number of users that can accommodate. In next section, we will explore the relation between the charging capacity utilization and users' availability revelation through a computational study.

## 5.6 A Computational Study

### 5.6.1 Experiment Setting

In this computational study, consider a group of Tesla users ($n = 25$) driving Model 3 (Standard Range, battery capacity $E = 70kWh$) from Montreal to Toronto at autoroute ON-401W. The initial $SoC_{j,0}$ is set as 80% when entering the highway, and the final required $SoC_{j,k_j}$ is set as 50% when leaving the highway. As for the charging stop plan, we take the route schedule of A Better RoutePlanner for Tesla[15]. There

[15]ABRP, https://abetterrouteplanner.com/.

are 3 Tesla super-charging stations along the trip (located at Cornwall, Kingston and Pickering) and each station has 4 chargers ($m = 12$), the charging rate of these chargers is equally set to $R = 100kw$ (Level 3 charge with through a 480V DC plug). The recommended route plan by ABRP is shown in Fig. 5.1, the energy consumption is 148 $Wh/km$ at the driving speed of $V = 110km/h$. Each user should charging 3 times during this trans-city travel, the distance $D_{x,y}$ between each charging location (Montreal to Cornwall, Cornwall to Kingston, Kingston to Pickering, and Pickering to Toronto) is $117km$, $180km$, $218km$ and $42km$, respectively. The driving time $T_{j,x,y}$ is roughly set as $1.5h$, $2h$, $2.5h$ and $0.5h$, respectively. The required $SOC$ of each charge $SoC_{j,k}$ is roughly set as 20%, 70% and 50%, respectively. As a summary, the total trip distance is $559km$, and takes at least $7.5h$ (driving time $6.5h$ + charging time $1h$) to reach destination (without waiting in any charging station).

As for the charging request of each user, the earliest entry time $\overline{edt_j}$ is drawn from a uniform distribution in the range of 8-11 $a.m.$, and the latest exit time $\overline{lxt_j}$ is the summation of $\overline{edt_j}$, the shortest travelling time $7.5h$ and the waiting time. We set two group of users with different allowable maximum waiting time ($1h$ and $2h$). Thus, the latest exit time $\overline{lxt_j}$ is drawn from $U(8, 11) + 7.5 + 2$ (loose one for group 1), and $U(8, 11) + 7.5 + 1$ (tight one for group 2).

For group 1 and 2, we randomly generate ten problem instances for each group to validate the performance of iterative bidding. For iterative bidding, we set three increments $\varepsilon$ as 0.25, 0.5 and 1. We use ILOG CPLEX 12.6.3 as optimization engine for solving the winner determination of iterative bidding and the centralized model. The iterative bidding control logic is coded using the OPL Script language. All experiments are carried out in a PC with a processor of Intel(R) Core(TM) i5-7200U CPU @2.50GHz, 8GB memory.

### 5.6.2 Evaluation Metrics

We then define two evaluation metrics to validate the performance of iterative bidding.

1) Utilization $U(s)$ of charging network is measured as the total number of users that the charging network can serve, that is, $U(s) = \sum_{lxt_j \in s} Z_j(lxt_j)$.

2) Average waiting time $awt$ of iterative bidding is measured by the ratio of the

total waiting time of the selected users and the number of the selected users,

$$awt = \frac{\sum_{j \in N} (lxt_j - mtt_j) Z_j(lxt_j)}{\sum_{lxt_j \in s} Z_j(lxt_j)}, \tag{5.17}$$

where $mtt_j$ is the minimum travel time of user $j$ without delay, in this experiment, $mtt_j = 7.5$.

### 5.6.3 Results and Analysis

We compare the results of the iterative bidding framework with the optimal schedule (with the complete time window $[\overline{edt_j}, \overline{lxt_j}]$ revealed). We test the utilization of charging network and users' waiting time of these two approaches. For each approach, we run the ten problem instances of two different groups and take the average value. The computational results of two groups by iterative bidding and the centralized model are shown in Fig. 5.2, Fig. 5.3 and Fig. 5.4. We also list the results of the optimal solution and iterative bidding in terms of $\varepsilon = 0.25$, 0.5 and 1 in Fig. 5.2 and Fig. 5.3.

We can infer from Fig. 5.2 and Fig. 5.3 that the iterative bidding can achieve a 100% utilization against the results obtained by the centralized model (regarded as 100% efficiency) for both two groups and three increments $\varepsilon$. Iterative bidding can accommodate all 25 users into the charging schedule for group 1, and 18 users for group 2, which achieves the same efficiency as the centralized optimization does. Group 2 can only serve 18 users because these users have a relative less availability, and charging network has to reject other 7 users' requests due to its limited charging spaces and users' time window. Moreover, we observe that iterative bidding with a relative small increment (for instance, $\varepsilon = 0.25$ compared to 1) takes more rounds to terminate, which is less efficient than the larger increments. For instance, group 1 with increment $\varepsilon = 0.25$ takes 9 rounds to terminate, while the bidding with $\varepsilon = 1$ only takes 3 rounds. The reason is that the large increment will force users to reveal a longer time window (more availability), which will improve the computational efficiency within a larger solution space.

By observing Fig. 5.4, we conclude that the average waiting time of the selected users has a positive correlation with the utilization of the charging capacity, the high efficiency is obtained at an waiting time cost in iterative bidding. For instance, with $\varepsilon = 0.25$ for group 1, the average waiting time for the selected user is 1.22 $h$ when

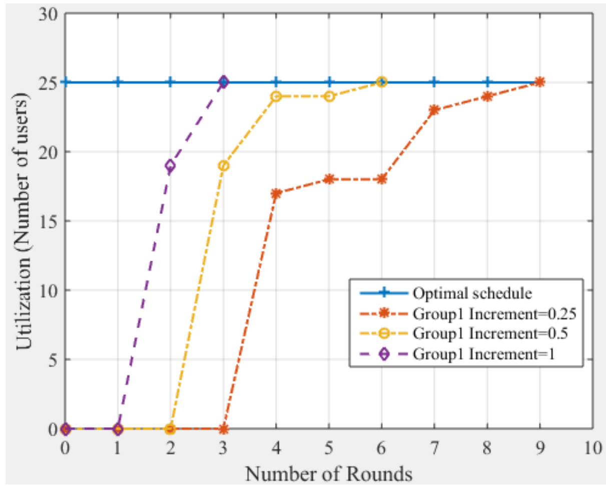



Figure 5.2: Utilization of Group 1 by iterative bidding

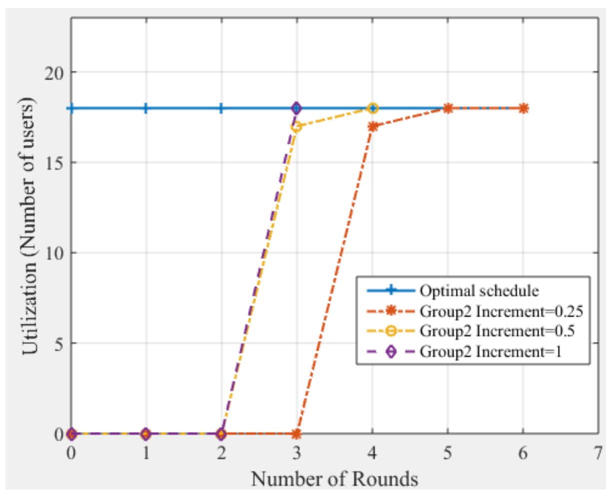



Figure 5.3: Utilization of Group 2 by iterative bidding

including 25 users, and is 1 $h$ when including 17 users. And the average waiting time becomes smaller when $\varepsilon$ is larger.

## 5.7 Summary

In this work, we study a decentralized EV charging scheduling problem in a highway environment, and we explore the relation between the utilization of charging capacity and the waiting time of users. We propose a bidding-based framework for coordinating multiple charging requests at a set of charging stations, and users are allowed to progressively reveal their complete availability, in order to reduce their

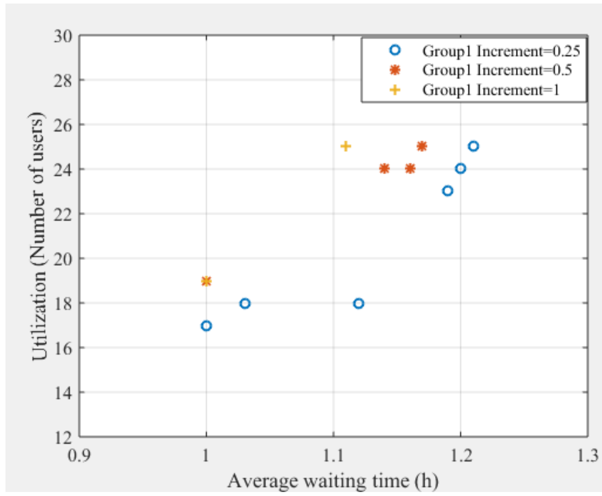



Figure 5.4: Tradeoff between utilization and average waiting time (Group 1)

waiting time. The computational experiments shows that iterative bidding achieves 100% efficiency compared with that of the optimal solution, and a larger increment in iterative bidding finds a reasonably good solution with much less computation costs and less rounds. Moreover, users' average waiting time increases along with the improvement of charging capacity utilization.

For future research, we will integrate the charging stop planning into the multiple charging station coordination. That is, the charging network should determine, for each user, which charging station to stop and how much to charge at this stop. Moreover, we plan to build an integrated simulation environment to deal with the dynamic charging requests.

# Chapter 6

# Simultaneous Auction Design for Multi-Charge Scheduling on Highway Charging Stations

## 6.1 Background

The longer-range BEVs have larger energy density of battery, which requires more powerful charging systems to expedite the time for a full charge [145]. Unlike Tesla who has an early charging advantage of putting a capital-intensive effort to build out its highway network of proprietary superchargers, most BEVs have to rely on third-party chargers during highway travels.

Moreover, drivers may need to perform several charges on highway charging stations. Specifically, highway charging has three features: (1) *Scarce fast charging facilities*: although we have seen large pledges on private chargers, the commitments for highway chargers indicate fewer units [13]. The insufficiency of highway fast chargers will intensify driver's range anxiety during long-distance travels; (2) *Close environment*: highways are less congested than urban roads, making it easier to estimate the driving time and energy consumption when reserving a series of charges; (3) *Separate and simultaneous market*: real-world highway charging stations typically operate separately, dynamically and concurrently, and charging requests are largely distributed spatially and temporally along the highway. Thus, centralized optimization is not directly applicable for highway charging scheduling when BEV users have distinct preferences and privately held information when reserving several charges.

The limited capacity of highway charging stations could be easily exceeded on peak hours or holidays, the first-come-first-serve charging without coordination gradually becomes insufficient to accommodate the increasing charging requests. As a result, it may lead to an unpredictable long waiting time and make it hard for drivers to plan their travels [99]. In such scenarios, the risk-averse BEV users tend to plan ahead and pay a reservation fee for charging at several desirable stations; and highway stations would also be interested in opening a portion of chargers and providing reserved-charge as a service to those who has stringent plans or private preferences. To tackle this mismatch between limited charging capacity and increasing on-road BEVs, the multiple charges of highway drivers have to be carefully coordinated so as to improve user experience and avoid embarrassing long waiting time. As a result, charging demands among different charging stations could be balanced and, at the same time, the revenue of highway charging network can be maximized.

However, deploying a scheduling mechanism turns out to be a challenge when coordinating users' charging requests at separate and simultaneous markets. Users should interact with distinct markets simultaneously and decide a combination of several single charges at different stations in order to reach the destination within a period. Achieving an efficient resource utilization among highway stations requires good strategies to coordinate the charging timing of different requests in advance. Furthermore, investigation of such coordination mechanism indicates that the efficacy of particular strategies depends critically on users' preferences and strategies about the requirements for and values of possible charges. In such market setting, it is reasonable to assume that users react selfishly and may not follow system orders, as a misrepresentation of their preferences may create advantageous charging schedules [146]. Typical strategic behaviors of users at simultaneous markets include tacit collusion [147], bid sniping [148] and exposure problem [147]. To address user's strategic behaviors and preferences in charging scheduling across multiple stations, highway charging must be managed by market-based scheduling mechanisms with sufficient incentives offered to users in order to well coordinate their charges.

Allocating multiple resources in separate and simultaneous markets through simultaneous ascending auction (SAA) can be a deliberate design choice. SAA considers simultaneous markets where agents bid on discrete items [148]. However, bidding on discrete time or energy items is not intuitive for users to express their requests and preferences in highway charging case, and meanwhile brings a huge valuation burden to them. Moreover, the mechanism should accommodate the changes of reserved charges and new requests. In terms of this, we propose a simultaneous multi-round auction (SMRA) based on the classic SAA of [148] to solve our highway multi-charge scheduling problem (HMCSP) in a decentralized and dynamic setting. In SMRA, we allow users to bid on the continuous time window which can considerably decrease the valuation complexity in preference elicitation; moreover, users can simultaneously express their preferences on charging stops and energy demands of each stop using the bid structure developed specifically for highway charging network. During the strategic interaction with auctioneer, users can adaptively adjust their bids placed at different stations and progressively reveal their true preferences as necessary, such that they can gradually discover how their demands fit together with their utility maximized and privacy protected.

## 6.2 Related Work

BEV charging scheduling on highways is not as densely researched as in urban areas. The majority of work on highway charging scheduling falls into the temporal and spatial routing and traffic flow cooperative control using queueing theory, such as [39, 40, 65, 99, 109, 149]. Queueing theory is a stochastic model for random BEV arrivals, aiming to coordinate the queues of charging stations. For instance, Gusrialdi *et al.* [65] developed a distributed strategy to schedule vehicle flows into neighboring charging stations, such that BEVs are all appropriately served along the highway and that all the charging resources are uniformly utilized. Each BEV can decide whether or not to enter the next charging station in order to avoid excessively long waiting times. In addition, V. del Razo *et al.* [40] proposed a scheduling method for planning charging stops on a highway trip based on A* shortest-path algorithm, with an objective of reducing user's waiting times and efficiently using the charging infrastructure. In [40], users should calculate a desired set of charging stops and charging times to make a reservation at the corresponding charging stations.

Our work differs from above in three aspects: (1) The aforementioned works aim to schedule multiple single charges of users separately which adopts a greedy and myopic strategy to find a charging station with the minimum waiting time. However, we aim to coordinate user's multiple charges simultaneously by guiding their charging requests to be appropriately distributed among different charging stations through negotiation. (2) Queueing theory based scheduling algorithm does not consider the decentralized nature of charging markets, where the system wide efficiency depends crucially on the elicitation of private information of the selfish users and how they compromise with each other on charging locations, time and energy. We consider highway charging stations as separate and simultaneous markets where users can negotiate with others on their charges. (3) Instead of reducing user's waiting time as an objective, we aim at charging network revenue maximization, which implies accommodating a maximum of users into the highway reservation system and obtaining user's highest satisfaction on charging schedules.

There are also other centralized approaches for charging scheduling except for queueing theory [63, 144, 150, 151, 152]. For instance, S. Pelletier *et al.* [63] planned the logistics vehicles charging schedule at the depot ahead of time, so as to allow the vehicles to complete their routes at minimal cost. From the scheduling perspective, their mathematical formulation is similar as ours in scheduling vehicles' multiple charges and delivery routes for electric freights, but they did not consider the coordination among different charging stations. Liu *et al.* [150] considered the dependency among the station selection, the charging option at each station and the charging amount settings in solving the urban charging scheduling problem. Different from modelling it as a hierarchical mixed-variable optimization problem and solving it by an evolutionary algorithm [150], we make several decisions for charging scheduling simultaneously and propose an auction mechanism to solve it considering user's strategic behaviors in a charging market.

In terms of market-based resource allocation, *game models* [116, 153] and *auctions* [31, 154] have gained successful applications on charging scheduling as they tackle the strategic behaviors and private preferences of the self-interested users. A market-based scheduling mechanism considers allocating resources indexed by time to alternative agents based on their bids. However, most developed mechanisms are applied to singe-charge cases [116, 153], and users can only bid on discrete time or energy items, which is not straightforward for users to express their preferences in highway charging. Moreover, combinatorial auctions [31] are often not practical because of the difficulty of coordinating the allocations of the various charging resources in simultaneous markets, which requires coordination among multiple charges. In terms of this, simultaneous auctions are considered as a deliberate choice for multiple resources allocation in separate markets, where bidders are allowed to bid on multi-object simultaneously and win multiple objects. SAA has been the standard auction format for distribute network frequencies allocation for airwaves and spectrum sales worldwide, until quite recently, for many years [147, 148]. Typical cases are 3G spectrum auction in the U.K. [155] and 5G spectrum license allocation recently [156]. It is easy to implement for many multi-object markets, however, it can also lead to substantial strategic problems for bidders. Based on [148], we extend SAA to highway charging scheduling problem by designing new bid format for users to express their preferences and new winner determination model for optimization, as well as a series of bidding rules to avoid strategic problems. To the best of our knowledge, this is the first work that adopts auction solutions to solve highway charging scheduling problems.

## 6.3 Our Contribution

The main contributions of this work can be specified as,

(1) We mathematically formulate a mixed-integer linear program for the centralized HMCSP. Based on the parallel machine scheduling model, we extend the decisions for each user to be simultaneously made on the entry and exit time, the number of stops and the corresponding locations, the charging time and energy demand at each stop in a charging network.

(2) We establish an auction framework to solve the HMCSP in a separate and simultaneous charging market. As an extension of classic SAA, users are allowed to compromise and negotiate with others on charging time, energy and locations simultaneously at different highway charging stations. Besides, the scheduling constraints are integrated into winner determination model, and a series of bidding rules are developed to avoid exposure problem and other strategic behaviors of users.

(3) We propose a dynamic scheduling algorithm to address the adjustments of the day-ahead reservations and unexpected arrivals in a dynamic and flexible manner. Extensive experiments demonstrate that SMRA can obtain a good trade-off between

the efficiency and information revelation, and the dynamic algorithm can further improve its performance.

The remainder of this work is organized as follows: Section 6.4 presents the mathematical model for the HMCSP. Section 6.5 implements the simultaneous multi-round auction design for HMCSP in the decentralized setting and presents the dynamic scheduling algorithm. Section 6.6 conducts a computational study to validate the performance of the proposed auction. Finally, 6.7 draws a conclusion.

## 6.4 Highway Multi-Charge Scheduling Problem Formulation

The system model for HMCSP comprises three components: BEVs, a system controller (auctioneer) and the highway charging network (chargers installed at highway service stations), as shown in Fig. 6.1. A BEV user may need to stop more than once at highway stations if her travel is longer than the battery range. The system has a communication infrastructure for BEVs and charging stations to communicate with the auctioneer, in order to receive and send the charging requests or station availability information.

Before a BEV user enters highway, she first investigates the current State-of-Charge ($SoC$) of her BEV and estimates a rough time window for the travel, then she submits a request to the auctioneer to book her preferred charges with decisions made on the charging stops, time and energy of each stop at the corresponding highway charging stations. After receiving these requests, the auctioneer needs to coordinate the multiple charges of users and manage the bidding process, and charging stations will solve a series of optimization problems to properly allocate the limited charging capacity. The system objective is to maximize the revenue of the charging network. In this model, we neglect the impacts of user's charging activities on the stability of highway charging network as it is not our focus. And kindly noting that user's charge cannot be suspended or stopped by others once started at any stations.

There is a set of level-3 DC fast charging stations along the highway denoted as $K$. Charging station $k \in K$ has $q_k$ identical chargers, each of which shares a constant charging rate $R_k$. We denote a charger as $i$ and the set of all chargers in highway charging stations as $M$. Let $m$ be the number of all chargers, thus $\sum_{k \in K} q_k = m$.

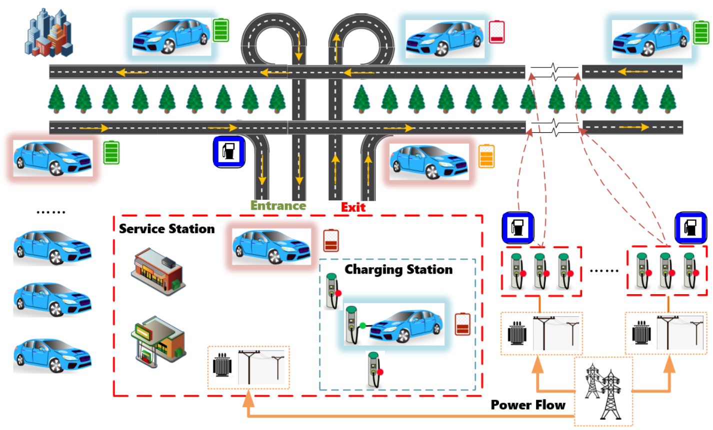



Figure 6.1: Highway BEV charging case.

Each highway charging station has several chargers to serves multiple BEV users, who travel in both directions with multi-charge to perform The nomenclature for mathematical model is summarized in Table 6.1.

Consider a set of $n$ users as $N$, and each user $j \in N$ has a request $Q_j$ to be processed, which is characterized by a 6-tuple $Q_j = \langle \overline{edt_j}, \overline{lxt_j}, SoC_{j,0}, SoC_{j,k_j}, GIS_{j,0}, GIS_{j,out} \rangle$: where $\overline{edt_j}$ is the earliest entry time of user $j$ on highway and $\overline{lxt_j}$ is her latest exit time. User $j$ has to finish her travel within this feasible time window $[\overline{edt_j}, \overline{lxt_j}]$. $SoC_{j,0}$ is her initial $SoC$ at departure place $GIS_{j,0}$, and $SoC_{j,k_j}$ is her required $SoC$ when arriving at her destination $GIS_{j,out}$. User $j$ should decide a desired set of charging stops, time and energy at $K$, and we use $K_j \subseteq K$ to represent the set of charging stations that user $j$ chooses and stops on highway.

Highway charging scheduling aims at an optimization of four decisions simultaneously to maximize the charging network revenue, which determines (1) the entry time $t_j^e$ and exit time $t_j^x$ for user $j$ on highways; (2) a set of charges performed on highway charging stations, which includes the number of stops $|K_j|$ and the corresponding stations $K_j$; (3) the energy demand $SoC_{j,k}$ for user $j$'s charge $O_{j,k}$ at charging station $k$; and (4) the start time $st_{i,j,k}$ at charger $i$ and the corresponding charging time for acquiring $SoC_{j,k}$ of charge $O_{j,k}$.

A feasible schedule $\phi$ contains the specific charging schedule for users' requests, which selects a subset of requests and schedule their charges restricted by the limited charging capacity. Let $Z_j = 1$ if user $j$ is selected, otherwise $Z_j = 0$. Each user shall have a value for each feasible schedule $\phi \in \Phi$, and she only knows her own value but

Table 6.1: Nomenclature of Chapter 6

| | **Index and Sets** | | **Parameters** |
|---|---|---|---|
| $i$, $M$ | Index and set of highway chargers | $n$,$m$ | Total number of users and chargers |
| $j$, $j'$, $N$ | Index and set of BEV users | $E_j$ | Battery capacity of user $j$ |
| $k, k'$, $K$ | Index and set of highway charging stations | $q_k$, $R_k$ | Number of chargers and charging rate of station $k$ |
| | **Decision Variables** | $D_{j,x,y}$ | Distance between position $x$ and $y$ for user $j$ |
| $t_j^e$ | Entry time of user $j$ at $GIS_{j,0}$ | $K_j$ | Set of charges of user $j$ |
| $t_j^x$ | Exit time of user $j$ at $GIS_{j,out}$ | $O_{j,k}$ | User $j$'s charge at station $k$ |
| $st_{i,j,k}$ | Start time of charge $O_{j,k}$ on charger $i$ | $\overline{edt_j}$, $\overline{lxt_j}$ | The earliest entry time and the latest exit time of user $j$ |
| $SoC_{j,k}$ | Allocated $SoC$ of $O_{j,k}$ at station $k$ | $SoC_{j,0}$, $SoC_{j,k_j}$ | Initial and final $SoC$ that user $j$ requires |
| $Z_j$ | Binary variable - 1 If user $j$ is selected, else 0 | $c_k^r$, $c_k^e$ | Reservation cost, energy price per unit time of station $k$ |
| $X_{i,j,k}$ | Binary variable - 1: If charger $i$ is selected for charge $O_{j,k}$, else 0 | $\rho_j$ | Average driving speed of user $j$ on highway |
| $Y^i_{j',k',j,k}$ | Binary variable - 1: If $O_{j',k'}$ performs immediately before $O_{j,k}$ on charger $i$, else 0 | $\tau_j$ | Energy consumption per kilometer of user $j$ |
| $Y^i_{\alpha,j,k}$ ($Y^i_{j,k,\beta}$) | Binary variable - 1: If $O_{j,k}$ performs first (last) on charger $i$, else 0 | $GIS_{j,0}$, $GIS_{j,out}$ | Highway entry position and destination of user $j$ |

not others, and this value is not affected by other users, as defined by *private value model* in [127]. The charging network revenue is represented by the total charging costs of all users. User $j$'s charging cost $c_j(\cdot)$ includes the sum of the energy costs $\sum_{k\in K_j} c_k^e \frac{SoC_{j,k}E_j}{R_k}$ and the reservation costs $\sum_{k\in K_j} c_k^r \frac{SoC_{j,k}E_j}{R_k}$ for the multiple charges on highways. The energy price $c_k^e$ per time unit of charging station $k$ is fixed, and user $j$ has a value for the maximum reservation price that she may pay per each time unit, where $c_k^r \leq v_j$. Users are interested in multiple time slots of the schedulable resource, with value determined by the earliest deadline by which they can complete their corresponding charges.

The HMCSP, modelled as an mixed-integer linear program, solves the optimization problem $\varphi^*_{cen}$ such that the constraints (6.2a) - (6.2r) are satisfied and the charging network revenue is maximized. Add it up, the centralized HMCSP model mathematically solves

$$\varphi^*_{cen}: \quad \max \sum_{j\in N} Z_j \sum_{k\in K_j} \frac{SoC_{j,k}E_j}{R_k}(c_k^e + v_j) \tag{6.1}$$

subject to the constraints (6.2a) - (6.2r) as below.

Constraints (6.2a) and (6.2b) determine the time constraint for user $j$'s charge.

$H$ is a large positive constant to ensure the "if" logic.

$$\overline{edt}_j \leq t_j^e + H(1 - Z_j), \quad \forall j \in N \tag{6.2a}$$

$$t_j^x \leq \overline{lxt}_j + H(1 - Z_j), \quad \forall j \in N \tag{6.2b}$$

Constraints (6.2c) force that the start time of user $j$'s first charge $st_{i,j,1}$ should not be earlier than her arriving time at her first station. $D_{j,0,k}$ represents the required distance from user $j$'s departure place $GIS_{j,0}$ to station $k$, and her driving time to the first station 1 is estimated by $\frac{D_{j,0,1}}{\rho_j}$, where $\rho_j$ is user $j$'s average driving speed on highways. Here we slightly abuse the subscript "1" in $D_{j,0,1}$, $st_{i,j,1}$ and $X_{i,j,1}$ to represent user $j$'s first charge in $K_j$, note that "1" indicates the first element in $K_j$ that may not be consistent with station index $k$ of her first charge.

$$t_j^e + \frac{D_{j,0,1}}{\rho_j} \leq st_{i,j,1} + H(1 - Z_j), \quad \forall i \in M, j \in N \tag{6.2c}$$

Equations (6.2d) define user $j$'s arriving time, where $\frac{SoC_{j,k} * E_j}{R_k}$ is the charging time for user $j$'s charge $O_{j,k}$ at station $k$. $X_{i,j,k}$ is binary variable and equals to 1 if charger $i$ is selected for charge $O_{j,k}$ of user $j$, otherwise $X_{i,j,k} = 0$. Specifically, subscript 0 and $k_j$ respectively represents the first and the last charging station where user $j$ stops, $\{0, k_j\} \in K_j$.

$$t_j^x = \sum_{i \in M} X_{i,j,k_j} st_{i,j,k_j} + \frac{SoC_{j,k_j} E_j}{R_k} + \frac{D_{j,k,k_j}}{\rho_j}, \ \forall j \in N \tag{6.2d}$$

Constraint (6.2e) determines the total required energy demand $SoC_j^{req}$ of user $j$, where $SoC_j^{req} = \sum_{k,k+1 \in K_j} \frac{\tau_j D_{j,k,k+1}}{E_j} + SoC_{j,out} - SoC_{j,0}$. And $\tau_j D_{j,x,y}$ represents the required energy for user $j$ to drive from position $x$ to $y$, where $\tau_j$ is the energy consumption per kilometer of user $j$' BEV at speed $\rho_j$. Constraints (6.2f) determine the energy allocation of user $j$'s adjacent charge $O_{j,k}$ and $O_{j,k+1}$. Constraints (6.2g) force that start time $st_{i,j,k+1}$ of user $j$ at station $k+1$ should not be earlier than her arriving time.

$$SoC_j^{req} \leq \sum_{k \in K_j} SoC_{j,k}, \tag{6.2e}$$

$$\frac{\tau_j (D_{j,k-1,k} + D_{j,k,k+1})}{E_j} \leq SoC_{j,k} + SoC_{j,k+1}, \tag{6.2f}$$

$$st_{i,j,k} + \frac{SoC_{j,k}E_j}{R_k} + \frac{D_{j,k,k+1}}{\rho_j} \leq st_{i,j,k+1} + H(1 - Z_j), \quad \forall i \in M, k-1, k, k+1 \in K_j,\ j \in N \tag{6.2g}$$

Constraints (6.2h) and (6.2i) ensure that charge $O_{j,k}$ of user $j$ is processed at most once on its eligible chargers $A_{i,j,k}$. Specifically, her charge $O_{j,k}$ can only use at most one charger at station $k$, as described in constraints (6.2j).

$$\sum_{i \in M} X_{i,j,k} \leq Z_j, \quad \forall k \in K_j, j \in N \tag{6.2h}$$

$$X_{i,j,k} \leq A_{i,j,k}, \quad \forall i \in M, k \in K_j, j \in N \tag{6.2i}$$

$$\sum_{i \in M} X_{i,j,k} \leq \lceil SoC_{j,k} \rceil, \quad \forall k \in K_j, j \in N \tag{6.2j}$$

Constraints (6.2k) ensure that at most one request can be selected as the first one at charger $i$. Specifically, let $Y^i_{\alpha,j,k} = 1$ if charge $O_{j,k}$ of user $j$ performs first on charger $i$, otherwise $Y^i_{\alpha,j,k} = 0$. And let $Y^i_{j,k,\beta} = 1$, if charge $O_{j,k}$ of user $j$ performs last on charger $i$, otherwise $Y^i_{j,k,\beta} = 0$.

$$\sum_{j \in N} \sum_{k \in K_j} Y^i_{\alpha,j,k} \leq 1, \quad \forall i \in M \tag{6.2k}$$

Constraints (6.2l) and (6.2m) determine the charging sequence of user $j'$'s charge $O_{j',k'}$ and user $j$'s charge $O_{j,k}$ if they are performed on charger $i$.

$$\sum_{j' \in N \setminus \{j\}, k' \in \{\alpha\} \cup K_{j'}} Y^i_{j',k',j,k} = X_{i,j,k}, \tag{6.2l}$$

$$\sum_{j' \in N \setminus \{j\}, k' \in K_{j'} \cup \{\beta\}} Y^i_{j,k,j',k'} = X_{i,j,k}, \quad \forall i \in M, k \in K_j, j \in N \tag{6.2m}$$

Constraints (6.2n) determine the precedence of user $j$'s charge $O_{j,k}$ and user $j'$'s charge $O_{j',k'}$ if they are processed on the same charger. Constraints (6.2o) ensure that if user $j$'s charge $O_{j,k}$ performs immediately after user $j'$'s $O_{j',k'}$ at charger $i$, $O_{j,k}$ does not start before the previous $O_{j',k'}$ is completed.

$$Y^i_{j',k',j,k} + Y^i_{j,k,j',k'} \leq 1, \tag{6.2n}$$

$$st_{i,j',k'} + \frac{SoC_{j',k'}E'_j}{R_k} \leq st_{i,j,k} + H(1 - Y^i_{j',k',j,k}), \quad \forall i \in M, k \in K_j, k' \in K_{j'},\ j, j' \in N, j \neq j' \tag{6.2o}$$

Constraints (6.2p) - (6.2r) define the domains of decision variables in this centralized HMCSP model.

$$t^e_j, t^x_j, st_{i,j,k} \in \mathbb{R}_+, \tag{6.2p}$$

$$SoC_{j,k} \in [0, 1], \tag{6.2q}$$

$$Z_j, X_{i,j,k}, Y^i_{j',k',j,k}, Y^i_{j,k,j',k'}, Y^i_{\alpha,j,k}, Y^i_{j,k,\beta} \in \{0, 1\}, \quad \forall i \in M, k \in K_j, k' \in K_{j'},\ j, j' \in N, j \neq j'. \tag{6.2r}$$

The HMCSP mathematical model is built on the flexible job shop (FJc) model, which is NP-hard [157]. A flexible job shop is a generation of the job shop and the parallel machine environments. In specific, there are $c$ highway charging stations (work centers), each with several identical chargers in parallel, and each user has a set of charges to execute through the multiple highway stations. Different from traditional FJc scheduling, the number of charging stops of each user, the potential site for each charge and the charging timing at each stop are all decision variables in our mathematical model. Moreover, the charging scheduling at each charging station is built on the Parallel machine (Pm) model [157], where the charge of any user at one charging station is processed on any one charger and any charger in this station can execute.

The centralized optimal solutions provide a deep insight and baseline on potential social welfare and systematic optimal charging scheduling that can be extended to the decentralized environment. It is served as the bench-mark for performance evaluation of the decentralized charging scheduling. In particular, we assume that users' value functions are known by the auctioneer in this centralized setting, and the same efficient outcome is obtained as the VCG mechanism [130], where each user is incentivized to truthfully reveal their real preferences. However, the centralized setting with perfect information is impractical in real-world implementation and it is time-consuming to solve as well.

## 6.5 Simultaneous Multi-Round Auction

In a separate and simultaneous charging market, we remove the assumptions about user's publicly known value in the centralized setting, but instead consider user's values as private information. In terms of this, multi-agent system architecture provides a natural modeling of highway charging stations, where these users and the highway charging stations can be modelled as strategic, rational and self-interested agents in the context of decentralized system engineering.

In such an environment, we propose a simultaneous multi-round auction (SMRA) to solve HMCSP, which contains three major components: *users' bids*, *a winner determination model* for a single station and *a bidding procedure* at multiple stations. The demand set allows users to express their preferred charging stops, time and bidding prices at different charging stations. The winner determination for each charging station takes users' bids as input and solves the selection and charging scheduling problems that maximizes the sum of the bidding prices of users (the revenue of the highway charging stations). The bidding procedure at multiple stations is an interactive process for users to negotiate with stations on the time and prices in an iterative way.

The reservation process can be implemented on users' smart phones, online platforms or apps, where users can set their demand directly. The iterative bidding starts after all users set up their requests, and executes automatically by the software, so that users do not need to stay online and bid manually. The bidding process can be triggered repeatedly at regular time intervals (hour- or certain minutes-ahead) to accommodate the dynamic charging events. After iterative bidding process, charging station will update the schedule and send it to the participated users.

In our previous works, we proposed an iteration bidding based auction to deal with the allocation of charging time and space in a stand-alone charging station in Chapter 3. We further extended the iterative auction for single charging station scenario in Chapter 3 to solve multiple stations in highway charging scheduling Chapter 5. The mechanism developed is a combinatorial auction paradigm, which only allows users to bid on different combinations of entry and exit time and win at most one bid; while the mechanism designer determines user's specific charging time at each station with the fixed number of stops and energy demands. As an extension of Chapter 5, we expand the decisions to be made in this work, which allows users to decide their charging stops, energy demand and time window at each station. Moreover, users can negotiate with others and flexibly adjust their bids in the course of auction.

### 6.5.1 Bids and User-Side Strategy

User can express her preferences and interact with charging stations strategically through a conditional statement, i.e., bids, when developing their bidding strategy on coordinating their energy demands and charging time at different stations. Bids enable auctioneer to explore how users will behave when faced with separate markets for complements through the strategic interaction. Compared to the discrete items in classic SAA [148], the time slots in our model are not perfectly substituted in these stations, as users do not reserve non-adjacent time slots. The limited substitution across time slots motivates us to develop efficient bid tuple instead of bidding on discrete items, enabling users to represent their time and energy demands in a connected and continuous way.

**Definition 6.1 (Bids)** *A bid represents a real commitment of resources by the bidder, with which the preferences over different charging schedules are expressed through a conditional statement, involving the start time and the price.*

User $j$ has a set of bids $b_j = \{b_{j,k}\}_{k \in K_j}$ placed at their preferred stations $K_j$, which reserve the individual charges at different stations simultaneously. Each bid $b_{j,k}$ at station $k$ is characterized by a 3-tuple $b_{j,k} := \langle st_{j,k}, ft_{j,k}, p_{j,k} \rangle$, where $st_{j,k}$ and $ft_{j,k}$ are user $j$'s required start time and the finish time for charging at station $k$, respectively. And $p_{j,k}$ is the reservation price per time unit. Other than the energy cost $c_k^e$, user $j$ should also pay totally $p_{j,k}(ft_{j,k} - st_{j,k})$ for reserving the charging service at station $k$.

With respect to the multi-round bidding at each station, we use $\boldsymbol{b_j^{\omega}} := \{b_{j,k}^{\omega}\}_{k \in K_j}$ to represent the bid at round $\omega$, $\omega \in \Omega$, where $b_{j,k}^{\omega} = \left\langle st_{j,k}^{\omega}, ft_{j,k}^{\omega}, p_{j,k}^{\omega} \right\rangle$. Note that superscript $\omega$ is sometimes omitted in the following, in order to make some notations clear. The submitted bid $b_{j,k}^{\omega}$ by user $j$ indicates the charged energy $SoC_{j,k}E_j$ from station $k$ at at round $\omega$, that is, $SoC_{j,k}E_j = R_k(ft_{j,k}^{\omega} - st_{j,k}^{\omega})$, where $R_k$ is the charging rate of station $k$. After the winner determination of station $k$, user $j$ will receive the bidding result about whether she is selected or not at round $\omega$.

In order to obtain the preferred schedules and coordinate the charges at these highway charging stations, users should decide the best locations, time and energy allocation for charging, such that they can minimize the charging costs $c_j = \sum_{k\in K_j} \frac{SoC_{j,k}E_j}{R_k}(c_k^e + p_{j,k})$ and maximize their utility. Specifically, users have two decisions to be made on the energy allocation and charging time at different stations, as follows.

### Decision on energy demands

User $j$ can flexibly adjust the energy allocation $SoC_{j,k}$ at charging station $k$ with constraint (6.3a) and (6.3b) satisfied as follows:

$$\sum_{k,k+1\in\{0\}\cup K_j} \frac{\tau_j D_{j,k,k+1}}{E_j} + SoC_{j,out} - SoC_{j,0} \leq \sum_{k\in K_j} SoC_{j,k}, \tag{6.3a}$$

$$\tau_j(D_{j,k-1,k} + D_{j,k,k+1}) - SoC_{j,k}E_j \leq SoC_{j,k+1}E_j, \tag{6.3b}$$

where (6.3a) determines the total energy charged at stations $K_j$, and (6.3b) restricts the energy $SoC_{j,k+1}$ being charged at station $k+1$ should cover the energy consumption given the remaining $SoC_{j,k}$ at the last station $k_j$, $\forall k, k+1 \in K_j$.

### Decision on charging time

Besides, user $j$ should also consider the constraints for start time $st_{i,j,k}$ for each charge when placing her bid $b_{j,k}^{\omega}$ at station $k$. Note that user $j$ will reject the schedule with the charging time that exceeds her feasible travel time window $[\overline{edt_j}, \overline{lxt_j}]$. User $j$'s start time $st_{j,k}$ at station $k$ is restricted by constraint (6.4a) - (6.4c),

$$\overline{edt_j} + \frac{D_{j,0,1}}{\rho_j} \leq st_{j,1}, \tag{6.4a}$$

$$st_{j,k} + \frac{SoC_{j,k}E_j}{R_k} + \frac{D_{j,k,k+1}}{\rho_j} \leq st_{j,k+1}, \quad \forall k, k+1 \tag{6.4b}$$

$$st_{j,k_j} + \frac{SoC_{j,k_j}E_j}{R_k} + \frac{D_{j,k,k_j}}{\rho_j} \leq \overline{lxt}_j. \tag{6.4c}$$

Constraint (6.4a) defines the start time for the first charging of user $j$. Constraint (6.4b) indicates that the earliest start time at charging station $k+1$ should not be earlier that the finish time at charging station $k$. Constraint (6.4c) restricts that the arriving time does not exceed her latest exit time $\overline{lxt_j}$.

User $j$ first decides energy demand $SoC_{j,k}$ and start time $st_{j,k}$ at each station $k \in K_j$, and then generates her bid $b^{\omega}_{j,k} = \left\langle st^{\omega}_{j,k}, ft^{\omega}_{j,k}, p^{\omega}_{j,k} \right\rangle$ for station $k$, where $ft^{\omega}_{j,k} = st^{\omega}_{j,k} + \frac{SoC_{j,k}E_j}{R_k}$. User $j$'s action is her demand profile $S_j(\boldsymbol{p})$ of bid given the reservation price vector $\boldsymbol{p}$ across all stations, which determines where to place her bids, when and how much to charge for each bid. The selfish users are utility maximizers regardless of the social welfare. In auction, utility is a function of user's type $\theta_j$, which measures her private preferences and encodes all information that is not publicly known.

**Definition 6.2 (Quasi-linear utility function [158])** *Utility $u_j : \Theta_j \times \prod_{j=1}^{n} \boldsymbol{B_j} \rightarrow \mathbb{R}_+$, maps user j's type and all action profile to a real number. Utility $u_j$ is captured by the difference of value $v_j$ and cost $c_j(\cdot)$ that each possible type $\theta_j$ and action profile $b = (b_1, b_2, ..., b_n)$ will give her, i.e.,*

$$u_j(b_j, \boldsymbol{p_j}; \theta_j) := v_j(b_j; \theta_j) - c_j(b_j, \boldsymbol{p_j}), \tag{6.5}$$

*where $b_j = \{b_{j,k}\}_{k \in K_j}$, $b_j \in \boldsymbol{B_j}$ and $\boldsymbol{p_j} = \{p_{j,k}\}_{k \in K_j}$.*

The charging cost is $c_j = \frac{SoC_{j,k}E_j}{R_k}(c^e_k + p_{j,k})$. User $j$ aims to maximize her utility $u^{\omega}_j(b^{\omega}_j, \theta_j)$ when placing bids by computing the demand set $S_j(\boldsymbol{p^{\omega}_j}) = \{S_{j,k}(p^{\omega}_{j,k})\}_{k \in K_j}$, and $\boldsymbol{p^{\omega}_j} := \{p^{\omega}_{j,k}\}_{k \in K_j} \in \mathbb{R}^{K_j}_+$ is user $j$'s bidding price at stations $K_j$ for round $\omega$. After observing the result at round $\omega$, user $j$ updates their bidding prices of $b^{\omega}_{j,k}$ placed on each station $k \in K_j$ and adjusts her bids thereafter.

**Definition 6.3 (Demand set)** *User j's demand set $S_{j,k}(\boldsymbol{p^{\omega}_j})$ includes all bids placed at her desirable charging stations $K_j$ which maximizes her utility $u_j$ given the price vector $\boldsymbol{p^{\omega}_j}$, that is, $S_{j,k}(\boldsymbol{p^{\omega}_j}) = \{b_{j,k} | u_j(b_{j,k}, p_{j,k}; \theta_j) \geq max_{b'_{j,k} \in b_j} u_j(b'_{j,k}, p_{j,k}; \theta_j), u_j(b_{j,k}, p_{j,k}; \theta_j) \geq 0, b_{j,k} \in b_j\}$, with two decisions made on the energy allocation* (6.3a) - (6.3b) *and charging time* (6.4a) - (6.4c)*.*

Once users have placed their bids at different stations, they will sufficiently bid at these stations $K_j$ restricted by the activity rule and bid withdrawal rule (which will be discussed in the next section). When reaching to a zero utility, they will recompute their utility-maximizing bids placed at charging station $K'_j$ until they cannot further improve their utility.

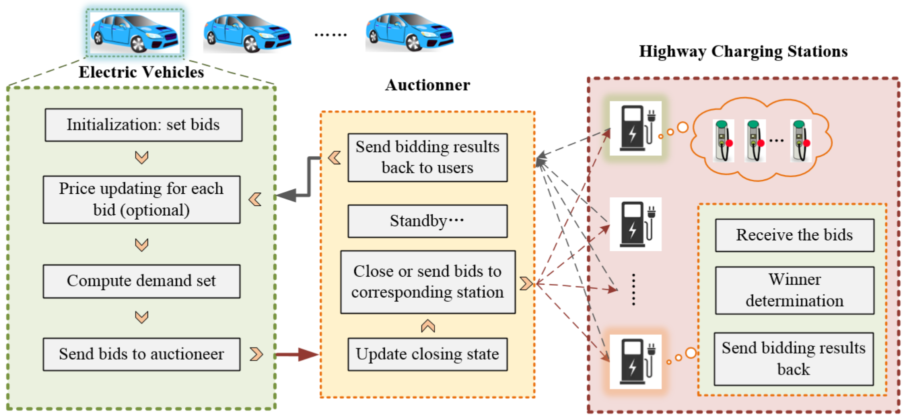



Figure 6.2: An overview of SMRA framework.

### 6.5.2 Bidding Procedure at Multiple Charging Stations

When dealing with highway charging scheduling, separate auctions are running individually at different charging stations, and each auction has multiple rounds of bidding. Note that the price vector $\boldsymbol{p_k^\omega}$ is different from $\boldsymbol{p_j^\omega}$ for users, where $\boldsymbol{p_k^\omega} := \{p_{j,k}^\omega\}_{j \in N_k} \in \mathbb{R}_+^{N_k}$ is the bidding price of users $N_k$ bidded at charging station $k$ for round $\omega$, and $N_k$ is the set of users who bid at station $k$.

The SMRA framework is shown in Fig. 6.2. Basically, this auction framework includes EVs, auctioneer and highway charging stations. Auctioneer should collect the bids from users, classify the bids according to station number and send the corresponding bids to each station. After winner determination, auctioneer gathers the bidding results and sends back to each user. Moreover, auctioneer should address and accommodate the dynamic charging requests entering the system.

Each charging station first sets up the ask prices as $\boldsymbol{p^0} := \{p_k^0\}_{k \in K} \in \mathbb{R}_+^K$. The ask price is a reference value that reflects the basic cost for charging, which can incentivize competition and avoid inefficient outcomes. Any bidding prices lower than it are deemed invalid and will be rejected by the auctioneer. At the beginning of round $\omega$ ($\omega > 0$), users take them as the first-round bidding prices at station $k$ and compute the utility-maximizing bids through $b_{j,k}^\omega : \arg\max_{b_{j,k}^\omega} u_j(b_{j,k}^\omega, \boldsymbol{p_j^\omega}; \theta_j)$, after that, users submit their bids as a profile $(b_{j,k}^\omega)_{k \in K_j}$ and send to station $k$ at round $\omega$ for bidding.

Once the bids are received from the users, auctioneer first removes the invalid bids whose bidding price $p_{j,k}^\omega$ is ineligible or lower than the ask price $p_k^0$ of station $k$, and then checks the *closing* condition. An auction is quiescent when a round passes with no new admissible bids. The auctions proceed concurrently, and all close when all of them are simultaneously quiescent. If the closing condition is satisfied, auctioneer implements the final schedule and the charges are reserved at prices equal to the standing high bids to the corresponding users at each charging station. Otherwise auctioneer takes the set of valid bids as input and send them to the corresponding stations for solving the winner determination for round $\omega$.

After stations solve the winner determination individually at the end of round $\omega$, auctioneer will make known of the current scheduling result of charging station $k$ by screening out the detailed information about the standing high bids at different stations. At any station, the standing high bids are defined to be the highest bids made thus far (or zero if there have been no bids). The bidding results that users received include a set of decision variables for the selection of users at each charging station: $Z_j^\omega := \{Z_{j,1}^\omega, ..., Z_{j,k}^\omega, ..., Z_{j,k_j}^\omega\}$, with which users can adjust their bids and participate in next round. Before that, users should update their bids at the beginning of next round $\omega+1$ based on the previous result $Z_j^\omega$. If user $j$ is not selected by station $k$ at round $\omega$, she has three options for round $\omega+1$:

- She can increase the bidding prices for the same bids or the updated bids at station $k$ following the reservation-price updating policy;
- She can keep her bidding prices unchanged. In this case, she is forbidden from increasing the prices at any of her bids in future rounds at station $k$;
- She can withdraw her bids from station $k$. In this case, she is forbidden from bidding again at this station in future rounds. In other words, her future bids will be rejected.

**Definition 6.4 (Bidding-price updating policy)** *If the standing high bids at round $\omega$ are given by the vector $\boldsymbol{p_*^\omega} \in \mathbb{R}_+^K$, then the personalized price vector facing user $j$ at round $\omega+1$ is round $\boldsymbol{p_j^\omega} = \{p_{j,k}^\omega\}_{k\in K_j} = (p_{j,k}^\omega, \{p_{j,k'}^\omega + \epsilon\}_{k'\in K_j\setminus\{k\}})$. That is, user $j$'s price at station $k$ that has been assigned is $j$'s own standing high bids $p_{j,k}^{\omega+1} = p_{j,k}^\omega$, when $Z_{j,k}^\omega = 1$. However for non-standing high bids at other stations, the bid prices are the current bids plus the minimum bid increment $\epsilon > 0$ imposed by the station $k'$, i.e., $p_{j,k'}^{\omega+1} = p_{j,k'}^\omega + \epsilon$, when $Z_{j,k'}^\omega = 0$. Since the users are rational, in general they do not increase bids with an increment that is greater than $\varepsilon$.*

In other words, if user $j$ is included in the provisional schedule $\phi_k^\omega$ at station $k$, she can maintain her bids unchanged for next round $\omega + 1$. After updating the bidding prices at charging stations, users recompute their demand sets and utility-maximizing bids and the updated bidding prices and join round $\omega+1$. However, the self-interested users may behave strategically at different charging stations due to the information asymmetry in the decentralized markets, and gain economic benefits regardless of the social welfare of all users.

Moreover, some other rules are required to ensure the social welfare against users' strategic behaviors:

### Eligibility

A user's *eligibility* to place new bids is controlled by the activity rule. That is, a user may not have active bids on time window that exceed her total energy demand $SoC_j^{req}$ at charging stations, established by users to cover the time length for which they wish to be eligible.

### Activity rule

The charging stations may encounter with user's *parking strategy* in auction, which implies that a bidder maintains eligibility by parking its bids in particular spots that the bidder is not interested in and then moves to its true interest later. Moreover, some users may hold on their bids, conceal information and wait for a better deal after sufficient competition among other users, they may even wait until the last minute to bid seriously [148]. This *bid sniping* will degrade the scheduling efficiency and the overall social welfare. To avoid it, the *activity rule* is required to create pressure on users to bid actively and reduce their wait-and-see strategy. This will increase the auction pace, information available to users and improve the bidding efficiency. During SMRA, user is considered as *active* for a bid at a round if she makes eligible new bids or she is the winner (owns the standing high bid) from the previous round. Users' activity is constrained not to exceed their eligibility at each round, otherwise their bids will be regarded as invalid and rejected by the auctioneer.

### Conditional withdrawal

In the most common version of the bidding rules, users are permitted to withdraw bids from any station, but it will cause a penalty, i.e., they cannot place bids at such stations in future rounds. The purpose of such conditional withdrawal rule is to ensure a sufficient competition among the users at a station. In addition, it can partially avoid the *exposure problem*, in which users may face risks of ending up winning only a subset of items from their desired bundle and paying too much for this subset [147]. Besides, combinatorial auction with package bid and demand reduction can also avoid exposure problem. However, package bids may favor bidders seeking large aggregations due to a variant of the threshold problem [159].

### Straightforward bidding (a.k.a. myopic bidding)

It describes a strategy where, in each round of SMRA, user bids on a maximal demand set which maximizes her utility [160]. Straightforward bidding followed by the activity rule promotes truthful bidding throughout the auction process, although winners do not need to reveal their true valuation publicly, and it accelerates the bidding pace.

To sum up, SMRA allows users to progressively reveal their true valuations and thus induces price discovery and explore the real valuation of users in an iterative way. During the course of an auction, users can acquire useful information by scrutinizing the bidding behaviors of their competitors.

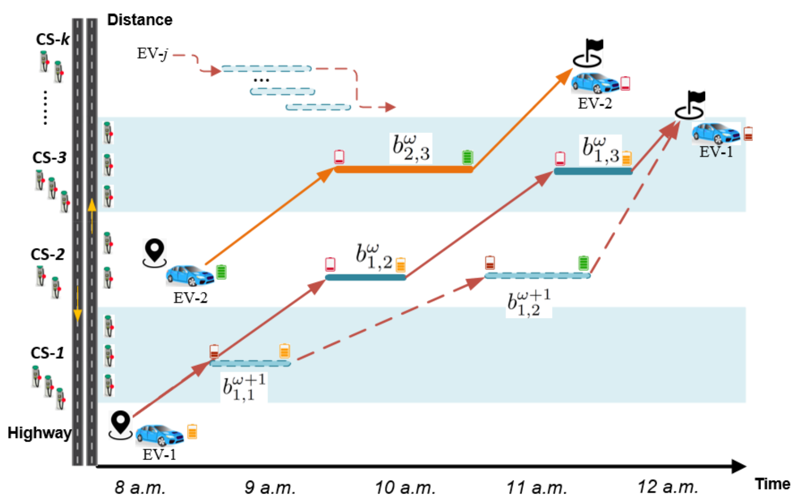



Figure 6.3: User strategy for bidding at simultaneous markets: a space-time path.

To better illustrate the bidding process across multiple stations, an example is shown in Fig. 6.3, with which we can gain a basic idea on how users can gradually fit their demands with others. Specifically, at round $\omega$, user 1 and 2 place their bids like $b_1^\omega = \{b_{1,2}^\omega, b_{1,3}^\omega\}$ and $b_2^\omega = \{b_{2,3}^\omega\}$. User 1 chooses charging station 2 and 3 as stops, where $b_{1,2}^\omega = \langle 9:30, 10:00, p_{1,2}^\omega \rangle$ and $b_{1,3}^\omega = \langle 11:20, 11:50, p_{1,3}^\omega \rangle$. She pays $p_{1,2}^\omega$ and $p_{1,3}^\omega$ at charging station 2 and 3 respectively to reserve the charge. And user 2 chooses charging station 3 to recharge her BEV and she needs only one charge $b_{2,3}^\omega = \langle 9:30, 11:30, p_{2,3}^\omega \rangle$ to reach destination. If user 1 is not selected by station 3 due to the heavy competition therein, she may have to increase $p_{1,3}^\omega$ by $\epsilon$ for round $\omega+1$ at this station, i.e., $p_{1,3}^{\omega+1} = p_{1,3}^\omega + \epsilon$. She will keep increasing the price $p_{1,3}$ until reaching its valuation $v_{1,3}$ in future rounds. In this case, user 1 may tend to reschedule and charge at station 1 and 2 instead, i.e., $b_1^{\omega+1} = \{b_{1,1}^{\omega+1}, b_{1,2}^{\omega+1}\}$, where $b_{1,1}^{\omega+1} = \langle 8:40, 9:10, p_{1,1}^{\omega+1} \rangle$ and $b_{1,2}^{\omega+1} = \langle 10:40, 11:30, p_{1,2}^{\omega+1} \rangle$, as the reservation price at station 1 is lower than at station 3 because she is a new bidder at station 1 who takes the ask price $p_1^0$ as first-round price.

### 6.5.3 Winner Determination Model of Single Charging Station

After receiving users' bid $\{b_{j,k}^\omega\}_{j\in N_k}$, charging station $k$ solves the winner determination for round $\omega$ as a 0-1 integer programming, which generates the stand-high bids and decides whether user $j$'s bid $b_{j,k}^\omega$ is selected in terms of $\boldsymbol{p_k^\omega}$. The provisional winner determination at round $\omega$ mathematically solves $\arg\max_{\phi^\omega\in\Phi^\omega} \sum_{Z_{j,k}^\omega \in \phi^\omega} Z_{j,k}^\omega (ft_{j,k}^\omega - st_{j,k}^\omega)(c_k^e + p_{j,k}^\omega)$ as an objective (6.6), where $\Phi^\omega$ is the set of all feasible schedules satisfying the constraints (6.7a) - (6.7f). That is, station $k$ solves

$$\max \sum_{j\in N_k} Z_{j,k}^\omega (ft_{j,k}^\omega - st_{j,k}^\omega)(c_k^e + p_{j,k}^\omega) \tag{6.6}$$

subject to

$$\sum_{j\in N_k} Y_{\alpha,j}^k \le q_k, \tag{6.7a}$$

$$\sum_{j'\in\{\alpha\}\cup(N_k\setminus\{j\})} Y_{j',j}^k = Z_{j,k}^\omega, \quad \forall j \in N_k \tag{6.7b}$$

$$\sum_{j'\in\{\beta\}\cup(N_k\setminus\{j\})} Y_{j,j'}^k = Z_{j,k}^\omega, \quad \forall j \in N_k \tag{6.7c}$$

$$Y^k_{j',j} + Y^k_{j,j'} + HZ^\omega_{j,k} + HZ^\omega_{j',k} \leq 1 + 2H,\ \forall j, j' \in N_k, j \neq j' \tag{6.7d}$$

$$\begin{aligned} ft^\omega_{j',k} + HZ^\omega_{j,k} + HZ^\omega_{j',k} + HY^k_{j',j} \leq st^\omega_{j,k} + 3H, \\ \forall j, j' \in N_k, j \neq j' \end{aligned} \tag{6.7e}$$

$$Z^\omega_{j,k}, Y^k_{j,j'}, Y^k_{\alpha,j}, Y^k_{j,\beta} \in \{0, 1\}, \quad \forall j, j' \in N_k, j \neq j', \tag{6.7f}$$

where constraint (6.7a) ensures that the station $k$ can charge at most $q_k$ BEVs simultaneously. Constraints (6.7b) determine a selected user $j$'s charge should either be the first one on a charger at station $k$, or after some others'. Similarly, constraints (6.7c) enforce that a selected user $j$'s charge should either be the last one or before some others'. Constraints (6.7d) determine the charging sequence of user $j$ and $j'$ if they are selected and adjacent at the same station. Constraints (6.7e) ensure that user $j$ shall not start before $j'$ is completed if they are selected and $j'$ charges immediately after $j$ on a charger. Constraints (6.7f) define the domains of the decision variables.

### 6.5.4 Dynamic Scheduling Algorithm

In practical scenarios, users may need to modify their reserved charges due to the traffic congestion or other unforeseen circumstances. Furthermore, arriving late at a station may affect the following charges at other stations. Thus the charging network should accommodate new requests and respond to their upcoming reservations periodically, such that the surplus charging capacity can be fully utilized and the revenue and user's satisfaction can be further improved. However, it is not practical to synchronize users' requests and ask all users to start the bidding process at a predefined time point. Therefore, we consider two stages for a complete scheduling process, i.e., SMRA before departure (the first stage) and then repair the SMRA schedule $\phi^{final}_{smra}$ in next day (the second stage: *dym*). The second stage sets one day of 24 hours as the operation period $T = 1, 2, ..., 24$, where the $t$-th hour (round) is denoted by $t \in T$. A set of new arriving users is denoted as $N^{dym}$.

To this end, we propose a dynamic heuristic algorithm for the second stage to allow BEV users to modify their reserved charges or submit a new request in a hour-ahead manner. The dynamic events include the change of existing charges of SMRA and new arrivals $j' \in N^{dym}$. If users want to reschedule their reservation, they should first

**Algorithm 3** Dynamic Scheduling

**Require:** $N, N^{dym}$, $K$, completed schedule by SMRA $\phi_{smra}^{final}$, incoming charging requests set $\{Q_j^{dym}\}_{j \in N^{dym}}$;

**Ensure:** $\phi^{final}$; // The final charging schedule

**for** each $t \in T$ **do**
  **for** user $j' \in N \cup N^{dym}$ **do**
    Observe the station availability of round $t$;
    Set bids $b_{j',k}^{t+1}$ for round $t+1$;
    Send it to the auctioneer;
  **end for**
  Auctioneer: collects and sends users' bids to each corresponding station;
  **for** charging station $k \in K$ **do**
    Solve the winner determination;
    Send the results back to the auctioneer;
    Update the availability;
  **end for**
**end for**

send a order to cancel their reserved charges at the corresponding stations, and then request their new charges using bids after the station availability is updated. The scheduling repair executes every hour $t$, a newly arriving request may pick a round in the process and join in the bidding. The bids at the second stage are represented as $b_{j',k}^t = \langle st_{j',k}^t, ft_{j',k}^t, p_{j',k}^t \rangle$, $\forall j', k, t$, which includes a start time $st_{j',k}^t$, a finish time $ft_{j',k}^t$ and a price $p_{j',k}^t$ that a user wants to pay at round $t$. Noting that user's charging time can stretch over two rounds. Bids in the second stage share a similar structure with it in SMRA, differently the bidding process executes in a one-shot manner.

Each charging station needs to repair its schedule or redo the scheduling at time $t$ if a dynamic event makes the original scheduling infeasible. Algorithm 3 illustrates the pseudo-code of dynamic scheduling algorithm. Specifically, each station first publish its updated availability to users, and then it takes current bids collected from the auctioneer as input and uses it to compute new schedules $\phi_k^t$ at the end of hour $t-1$. The winner determination model for each station is simply to allocate the charging resources to the highest bids at time $t$. After that, each station updates its new availability and progresses to next hour. In terms of such one-shot charging scheduling, all users who are bidding in the second stage will truthfully report their values in order to obtain their preferred charges in next hours.

## 6.6 Experimental Study

This section evaluates the performance of SMRA in terms of the efficiency, information revelation, penetration level and computational time through extensive computational studies.

### 6.6.1 Experimental Evaluation Metrics

#### Efficiency

$eff(\phi_{smra}^{final})$ of SMRA is measured as the ratio of the final round bidding result $\varphi_{smra}^{final}$ of SMRA with the objective value by solving the centralized model $\varphi_{cen}^{*}$ : $\max \sum_{j\in N} Z_j \sum_{k\in K_j} \frac{SoC_{j,k}E_j}{R_k}(c_k^e + v_j)$. And $\varphi_{smra}^{final}$ is the sum of users' bidding prices of the final schedule, i.e., $\varphi_{smra}^{final} = \max \sum_{j\in N} Z_j \sum_{k\in K_j} \frac{SoC_{j,k}E_j}{R_k}(c_k^e + p_{j,k})$,

$$eff(\phi_{smra}^{final}) := \frac{\varphi_{smra}^{final}}{\varphi_{cen}^{*}} * 100\%. \tag{6.8}$$

#### Information revelation

$IR(\phi_{smra}^{final})$ is measured as the ratio between the sum of the revealed bidding prices $p_{j,k}$ by users for all schedules at charging station $K_j$ and the sum of their true values $v_j$, i.e.,

$$IR(\phi_{smra}^{final}) := \frac{\sum_{j\in N}\sum_{k\in K_j} Z_{j,k}p_{j,k}}{\sum_{j\in N}\sum_{k\in K_j} Z_{j,k}v_i} * 100\%. \tag{6.9}$$

$IR(\phi_{smra}^{final})$ implies the average information revelation over all users, i.e., the extent to which a user has revealed her real value for the bids placed at station $k \in K_j$.

#### Sum of utility

$U(\phi_{smra}^{final})$ is measured as the sum of users' utility, i.e.,

$$U(\phi_{smra}^{final}) := \sum_{j\in N}\sum_{k\in K_j} Z_{j,k}(ft_{j,k} - st_{j,k})(v_i - p_{j,k}). \tag{6.10}$$

### Penetration level

$PL(\phi)$ is measured by the number of users selected by the auctioneer in the final schedule, as:

$$PL(\phi) := \sum_{j \in N} Z_j / n. \tag{6.11}$$

### Utilization level

$UL$ is measured as the ratio between the total charging time of all selected users and the operation time $T_o$ of the charging network, defined as:

$$UL := \sum_{j \in N} Z_j \sum_{k \in K_j} \frac{SoC_{j,k} E_j}{R_k}. \tag{6.12}$$

### Running time

The computing time needed to close the SMRA, or for the centralized model optimization.

## 6.6.2 Experiment Setup

In this computational study, consider a set of EV users $n$ driving Tesla Model 3 (Standard Range, battery capacity $E = 70kWh$) between Montreal to Toronto at autoroute ON-401W. There are three Tesla super-charging stations along the trip (located at Cornwall, Kingston and Pickering) $K = \{1, 2, 3\}$ providing charging services for the bidirectional travellers. Each station installs $q_k$ chargers, with the charging rate equally set to $R = 100kW$ (Level 3 charge with through a 480V DC plug). The energy price $c_k^e$ at these stations is set as \$0.44 per minute (\$26.4 per hour) in Canada[16]. The distance $D_{x,y}$ between Montreal and Cornwall, Cornwall and Kingston, Kingston and Pickering, as well as Pickering and Toronto is $117km$, $180km$, $218km$ and $42km$, respectively. The driving speed $\rho_j$ on highways is set as 100 $km/h$, then the driving time $T_{j,x,y}$ (direction: Montreal to Toronto) can be roughly estimated as $1.2h$, $1.8h$, $2.2h$ and $0.5h$, respectively. Note that $T_{j,x,y}$ is reverse as to Toronto to Montreal direction. The energy consumption per kilometer $\tau_j$ is set as $0.157kWh/km$[17].

[16] https://www.tesla.com/en_CA/support/supercharging.

[17] InsideEV: Tesla Model 3 Standard Range, https://insideevs.com/news/348093/energy-consumption-epa-compared-may-2019/.

We generate three groups of problem instances, where the number of users and total chargers (CPs) on highways of each group is configured as Group 1 (10 users with 6 CPs), Group 2 (20 users with 9 CPs), and Group 3 (30 users with 12 CPs), respectively. Each charging station has 1/3 CPs. Each group has ten random-generated test cases, including the charging request $Q_j = \langle \overline{edt_j}, \overline{lxt_j}, SoC_{j,0}, SoC_{j,k_j}, GIS_{j,0}, GIS_{j,out} \rangle$. Among these components, the earliest entry time $\overline{edt_j}$ is drawn from a uniform distribution $U(0, 12)$ between 0 a.m. and 12 a.m.. And the latest exit time $\overline{lxt_j}$ should be $\overline{edt_j} + 12$. User $j$'s initial $SoC_{j,0}$ when entering the highway at $GIS_{j,0}$ is drawn from a uniform distribution $U(80, 100)\%$, and her required $SoC_{j,k_j}$ when arriving at her destination $GIS_{j,out}$ is is drawn from a uniform distribution $U(20, 50)$ (%). Among each group, there are 50% of users travelling from Montreal to Toronto, and 50% of users travelling from Toronto to Montreal. The value of users $v_j$ on the reservation price is a function of her initial $SoC_{j,0}$, that is, $v_j = 5 + 25 * (100 - SoC_{j,0})$, which implies that users tend to pay more if they have a low state-of-charge. As for the parameter for SMRA, we assume the ask price $p_k^0$ at all charging station $K$ is \$2 per hour. The price increment $\varepsilon$ has two values as \$1 (A) and \$2 (B) to test its effect on the performance of SMRA.

The results of SMRA are compared with the centralized model of HMCSP. The efficiency, information revelation, penetration level and running time of these two methods are tested for three different groups of problem instances and two different increments $\varepsilon$. To guarantee the optimality of solutions, the centralized model is coded in ILOG Optimization Programming Language and solved by IBM ILOG CPLEX Optimizer 12.6.3 as optimization engine. The auction process is coded in Java (Eclipse IDE 2019-09), with which its winner determination is solved by ILOG CPLEX. All experiments are carried out in a desktop with a processor of Intel(R) Core(TM) i7-4790U CPU @3.60GHz, 16GB memory.

### 6.6.3 Results and Analysis

The performance (including efficiency, information revelation and computational time) of the three groups of SMRA ($\varepsilon = 1$ and 2) and the centralized optimization are shown in Fig. 6.4, the left side of (a), (b) and (c) presents the curves of the optimal solution and SMRA in terms of eff and IR; while the bar graph on the right side is the computational time (T) of the two approaches for each instance. Some other indexes,

Table 6.2: Performance of six groups (mean value of 10 test cases)

| Group No. | Revenue | IR | Utility | PL | Time | NR |
|---|---|---|---|---|---|---|
| G1-Opt. | \$722.4 | 100% | \$0 | 10/10 | 2.8s | 0.0 |
| G1-SMRA-A | \$576.7 | 61.6% | \$277.4 | 10/10 | 12.2s | 2.0 |
| G1-SMRA-B | \$593.2 | 62.3% | \$272.3 | 10/10 | 7.4s | 2.0 |
| G2-Opt. | \$1,405.1 | 100% | \$0 | 20/20 | 61.3s | 0.0 |
| G2-SMRA-A | \$1,169.2 | 65.3% | \$487.4 | 18/20 | 45.5s | 8.0 |
| G2-SMRA-B | \$1,176.2 | 66.0% | \$477.6 | 18/20 | 41.4s | 6.0 |
| G3-Opt. | \$2,325.2 | 100% | \$0 | 30/30 | 328.5s | 0.0 |
| G3-SMRA-A | \$2,072.8 | 73.6% | \$614.3 | 28/30 | 83.2s | 22.1 |
| G3-SMRA-B | \$2,025.6 | 71.9% | \$652.8 | 26/30 | 61.7s | 16.2 |
| G4-Opt. | N/A | N/A | \$0 | N/A | >72h | 0.0 |
| G4-SMRA-A | \$3,827.8 | N/A | \$432.8 | 44/50 | 142.6s | 26.4 |
| G4-SMRA-B | \$3,691.2 | N/A | \$401.4 | 43/50 | 112.5s | 20.9 |
| G5-Opt. | N/A | N/A | \$0 | N/A | N/A | 0.0 |
| G5-SMRA-A | \$6,561.3 | N/A | \$1,037.4 | 81/100 | 203.7s | 39.4 |
| G5-SMRA-B | \$6,241.7 | N/A | \$968.5 | 79/100 | 189.2s | 36.5 |
| G6-Opt. | N/A | N/A | \$0 | N/A | N/A | 0.0 |
| G6-SMRA-A | \$10,126.6 | N/A | \$1,215.1 | 122/300 | 466.3s | 45.8 |
| G6-SMRA-B | \$9,454.2 | N/A | \$1,096.6 | 116/300 | 385.7s | 46.4 |

IR: information revelation; PL: penetration level; NR: number of rounds.

such as the revenue, penetration level (PL), users' utility, time and number of rounds (NR) of SMRA under different $\varepsilon$ are presented in Table 6.2.

### Trade-off between efficiency and information revelation

It can be seen from Fig. 6.4 that SMRA can achieve a relative high efficiency and a minimal information revelation against the results obtained by the centralized model (regarded as 100% efficiency and 100% information revelation) among these three groups, which indicates SMRA has an advantage of protecting user's privacy. The average efficiency is G1: 79.83% (A) and 82.11% (B); G2: 83.2% (A) and 83.71% (B); G3: 89.14% (A) and 87.11% (B). The average revenue, information revelation, as well as some other indexes of 10 problem instances can be found in Table 6.2. In addition, the efficiency has a positive correlation with the information revelation from the figure, which implies the high efficiency of SMRA is always accompanied by a high level of information revelation. When dealing with smaller groups, such as Group 1, $\varepsilon = 2$ usually has a higher efficiency than $\varepsilon = 1$ because there are not many rounds at this time. SMRA with $\varepsilon = 1$ achieves a higher efficiency as well as a higher revelation compared to $\varepsilon = 2$ when dealing with a larger problem size (such as Group 3). The small increments requires more rounds before termination, which increases the possibility to find better solutions. We can infer that SMRA obtains a better trade-off between efficiency and privacy than the centralized optimization.

#### Utility and information revelation

We can see from Table 6.2 that SMRA has an advantage of improving the overall utility across all users. The average social welfare is respectively \$274.85, \$482.5 and \$633.55 for these three groups, compared to the centralized optimization (zero utility). The less information about valuation that a user reveals, the more utility she can obtain.

#### Computational time, penetration level and bidding rounds

It can be seen from Fig. 6.4 and Table 6.2 that the computational time and rounds are increasing, while the penetration level is decreasing with the problem size. Especially for the centralized model, the time increases drastically from 10 users to 30 users due to the NP-hardness of the problem. We can see from Fig. 6.4a that the centralized model costs less time than SMRA when dealing with smaller-size instances, but the time increases greatly in Fig. 6.4b and Fig. 6.4c. Moreover, SMRA with $\varepsilon = 1$ usually needs more rounds to terminate as well as more time compared to $\varepsilon = 2$. Taking Group 3 as an instance, G3-SMRA-A takes averagely 83.2s to terminate, while G3-SMRA-B takes 61.7s, but SMRA takes less time compared to the centralized optimization when dealing with a larger-size problem (328.5s). The reason is that price updating policy will reveal more value information of users in each round in terms of the limited charging capacity, a smaller increment theoretically has a higher efficiency.

#### Bidding process

Fig. 6.5 shows the revenue and time during the SMRA of one problem instance of Group 3, as an illustrative example. The cure (left side) implies the changing of revenue along the bidding process (totally 22 rounds for G3-A and 16 rounds for G3-B); and the bar graph (right side) is the execution time (T) of each round. We can see that the revenue (objective function) of the auction is continuously increasing. Instance with $\varepsilon = 1$ acquires a larger revenue of \$2,056.8 compared to $\varepsilon = 2$ of

\$2,020.5 (the optimal value is \$2,318.6 obtained from the centralized model), and takes respectively 22 rounds (82.8s) and 16 rounds (61.6s) to close. We also observe that the revenue is decreased at some certain rounds because some users switch to other charging stations and rebid with the ask price in new stations following the *best response* strategy.

### Scalability validation

We designed three more groups to validate the scalability of SMRA: Group 4 (50 users with 24 CPs), Group 5 (100 users with 30 CPs) and Group 6 (300 users with 45 CPs). Noting that each charging station still has 1/3 CPs. The optimal solution cannot be obtained for solving the centralized model due to the time complexity of our formulation, which will cost more than 72 hours without results in our experiment environment. The results are listed in Table 6.2: G4-G6 SMRA-A&B. For instance, the average revenue of G4 is around \$3,827.8 and \$3,691.2 for $\varepsilon = 1$ and 2, respectively. SMRA performs quite good in dealing with large size scheduling problems.

### Dynamic charging scheduling: a simulation study

We develop a simulation to predict the performance of the dynamic scheduling algorithm through observing the outcomes from uncertain inputs, with three more experiments continuing with Group 1-3. The objective is to test how much dynamic scheduling can improve the revenue and the resource utilization level compared to the optimal solution and SMRA-A (with $\epsilon = 1$). Moreover, we observe the changing of user's utility and information revelation during the second stage. We assume there are randomly 1 or 2 users who need to change their reserved charges by delaying for $U(0.5, 1)$ hours. The generation of users' requests and their values are the same as SMRA. The arrival rate of EVs at each time $t$ is assumed to follow a Possion distribution $p(\lambda) = \frac{\delta^{\lambda}}{\lambda!}e^{-\delta}, \lambda = 0, 1, ...,$ where we take $\delta = 1$.

Fig. 6.6 (a) and (b) presents an instance of dynamic scheduling in a Gantt Chart. Note that CP (1 & 2), (3 & 4) and (5 & 6) belongs to charging station 1, 2, and 3, respectively. CP1 $\rightleftarrows$ CP6: Montreal $\rightleftarrows$ Toronto. $x0y$ means user $x$'s No. $y$ charge, i.e., 103: user 1's third charge of her trip from Montreal to Toronto. These two figures show the start time, end time and charging duration of user's each charge at these chargers. Green boxes are the charges without change, and red ones are new requests

Table 6.3: Simulation results of dynamic scheduling for Group 1-3. (Mean value of 10 test cases)

| Group No. | UL | Revenue | IR | Utility | PL |
|---|---|---|---|---|---|
| G1-Opt. | 30.7% | $722.4 | 100% | $0 | 10/10 |
| G1-SMRA-A | 30.7% | $576.7 | 61.6% | $277.4 | 10/10 |
| G1-SMRA-B | 30.7% | $593.2 | 62.3% | $272.3 | 10/10 |
| **G1-Dym** | **42.4%** | **$692.2** | **67.7%** | **$270.9** | **10/10+5/25** |
| G2-Opt. | 37.9% | $1,405.1 | 100% | $0 | 20/20 |
| G2-SMRA-A | 34.1% | $1,169.2 | 65.3% | $487.4 | 18/20 |
| G2-SMRA-B | 34.1% | $1,176.2 | 66.0% | $477.6 | 18/20 |
| **G2-Dym** | **45.3%** | **$1,378.7** | **71.0%** | **$468.1** | **18/20+8/26** |
| G3-Opt. | 45.6% | $2,325.2 | 100% | $0 | 30/30 |
| G3-SMRA-A | 42.5% | $2,072.8 | 73.6% | $614.3 | 28/30 |
| G3-SMRA-B | 39.5% | $2,025.6 | 71.9% | $652.8 | 26/30 |
| **G3-Dym** | **53.7%** | **$2,464.6** | **77.8%** | **$602.9** | **28/30+10/26** |

UL: utilization level; IR: information revelation; PL: penetration level
**G1-Dym 10/10+5/25**: 10 out of 10 in SMRA, 5 out of 25 in dynamic scheduling

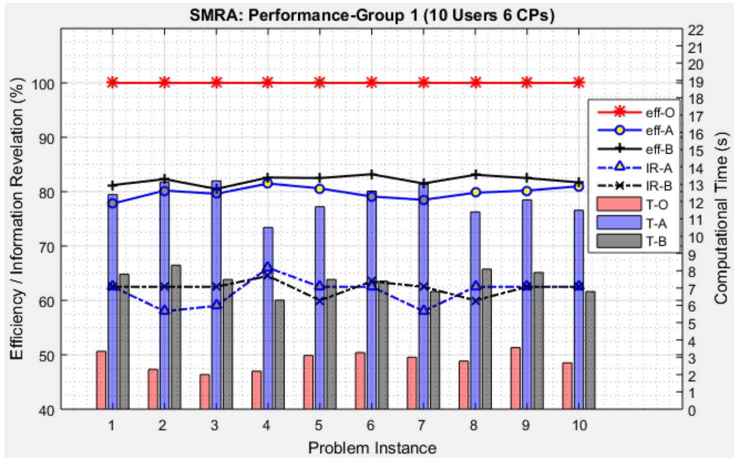
at the second stage. And we see that user 4 (yellow box) has delayed her charges at charging station 1 and 2. At station 1, she is reallocated to charger 1.

The results are presented in Table 6.3, we can see that the revenue is improved by around 20%, 18% and 19%, respectively for Group 1-3. And the utilization level is also improved to 42.4%, 45.3% and 53.7% respectively by dynamic scheduling. These three groups respectively accommodate 5 of 25, 8 of 26 and 10 of 26 users into the charging network. Moreover, we observe that the total utility even decreases a little despite the increase of users because, each participant reports its true value, which may even compromise some users' utility who change their reserved charges. Meanwhile, the information revelation also increases due to this.

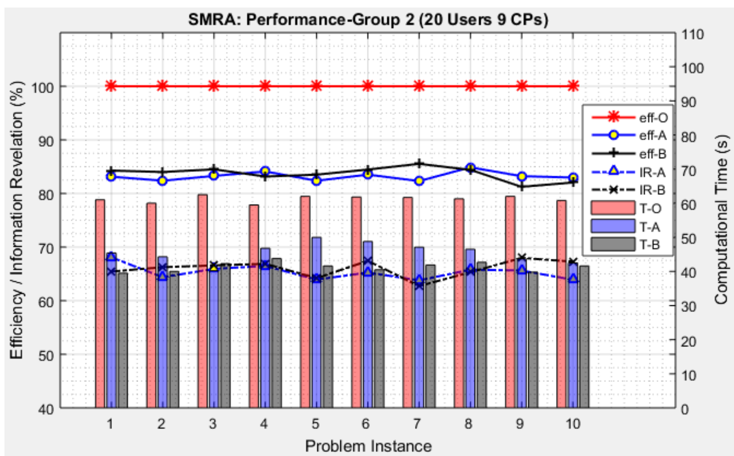
## 6.7 Summary

We proposes a simultaneous multi-round auction for a highway charging scheduling problem, where users can reserve and bid on their preferred charges simultaneously at different charging stations. This auction framework includes bids, a winner determination model and bidding procedure, which allows users to progressively reveal their real values on charging schedules with the adaptive decisions made on the preferred charging stops, time and energy at their preferences. The mechanism design complexity in such separate and simultaneous market is well tackled through a set of bidding rules. We also propose a dynamic scheduling algorithm to address the change of users' charges after reservation and new arrivals of other BEVs in next day. In order to validate its performance, we conduct a extensive computational study, and the results demonstrate that SMRA can achieve on average 85% efficiency with a partial information revelation compared with the optimal solution. And SMRA can greatly improve the utility of all users. Moreover, we analyze the relationship between scheduling efficiency and information revelation and the properties of SMRA in terms of different increments. The simulation study shows that the proposed dynamic scheduling algorithm can further improve the revenue of the charging network by around 19% as well as the overall resource utilization level by around 11%. Overall, SMRA can obtain an efficient implementation in practical scenarios.

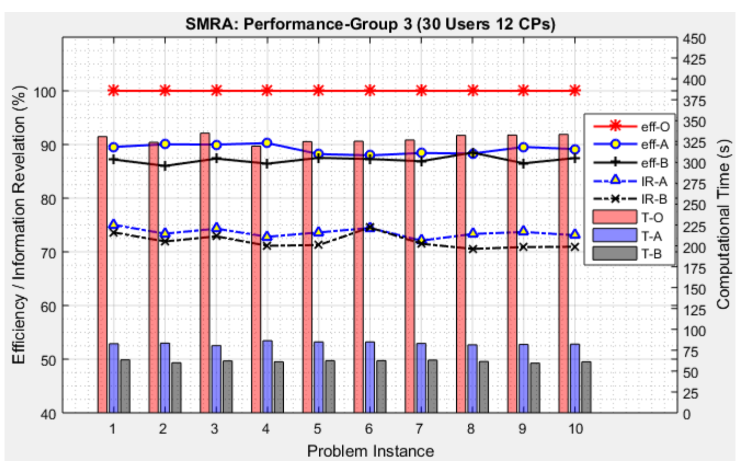
The proposed iterative bidding provides a potential reservation-based charging solution for a portion of users who have strict time requirements and private preferences in a decentralized setting, but the acceptance and practicality of the bidding methodology is not the focus of this work and waits to be verified in real-world markets. We aim to derive and validate the bidding solutions to deterministic single bidding event, which provides the baseline for dynamic scenarios. The robustness against uncertainties and dynamics, such as the changes of user preferences, or uncertain BEV arrivals, is our future work on agenda. Moreover, we will extend this single charging station environment to multiple charging stations where the coordination therein should be carefully addressed with efficient mechanism design.




(a)




(b)




(c)

Figure 6.4: Efficiency (eff), information revelation (IR) and computational time of three groups: (a) Group 1; (b) Group 2; and (c) Group 3 for the centralized optimization (O) and SMRA ($\varepsilon = \$1$ (A) and $\varepsilon = \$2$ (B)).

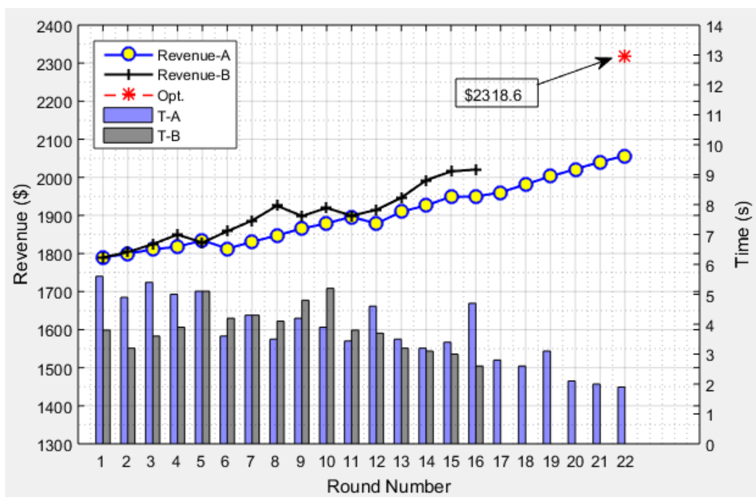
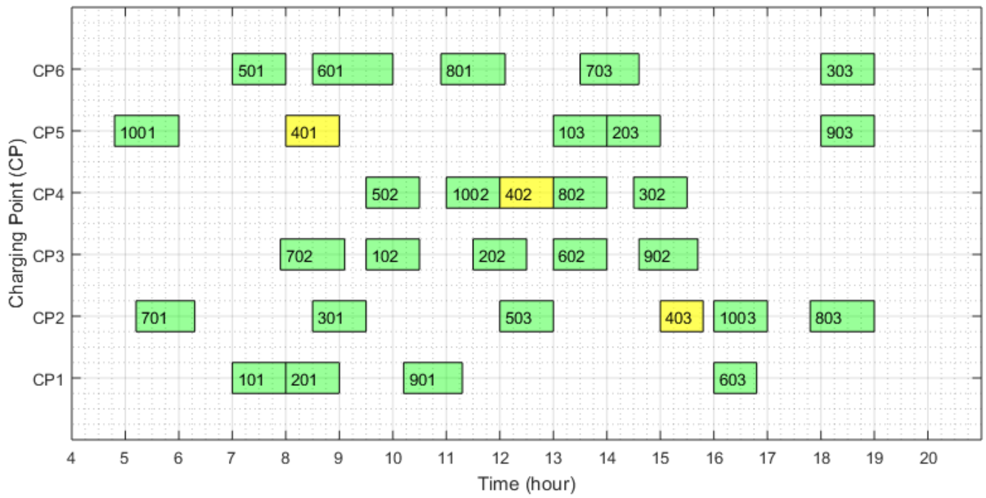
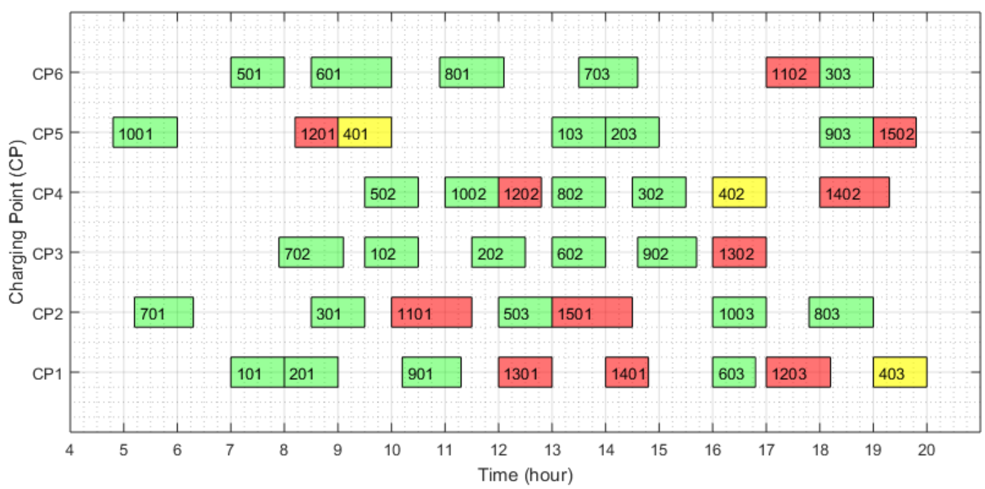



Figure 6.5: Performance trends of SMRA: an instance of Group 3 with $\varepsilon = \$1$ (A) and \$2 (B).




(a)




(b)

Figure 6.6: Gantt Chart: an instance of Group 1 (10 users 6 CPs) for dynamic scheduling, where (a): SMRA scheduling result, and (b): dynamic scheduling result.

# Chapter 7

# Reinforcement Mechanism Design for Electric Vehicle Demand Response in Microgrid Charging Stations

## 7.1 Background

The high penetration of EVs may aggravate the peak loads, which also influences the energy prices in the electricity market and consequently the efficiency of charging scheduling [30]. This situation motivates microgrid to provide incentives for EV users to adjust the timing of charging [161]. In such a case, *demand response* (DR) enables users to manage their charging preferences through time-varying prices or incentives at different periods to help improve the grid stability by shifting on-peak charging demands towards off-peak periods [34, 162].

However, two gaps exist in the current DR-based dynamic pricing mechanisms: First, most works neglect users' self-interested nature and their preferences on power demands, simply assuming that users' demands are predefined or drawn from a given distribution [47, 163]. In the literature, electric energy tariffs are the most common way to incentivize users to modify or predict their consumption habits in order to stabilize the grid loads with an assumption that the charging actions do not affect the electricity price. However, users should also participate in the price settlement acting both as a price taker and a price maker. In realistic scenarios, users' charging demands are flexible given their utility with reference to the price. Second, some incentive-based DR mechanisms that adopt game theoretical approaches focus on computing the Nash equilibrium-based solutions for the energy management at each hour or in a short period of time [32, 164, 165]. However, the Nash equilibrium solutions, based on user's best response strategy regarding the price signal, are always myopic and not optimal, especially in maximizing the long-term objectives.

In terms of user's strategic behaviors in a market environment, dynamic pricing should be formulated as a *mechanism design* problem, which can naturally capture the conflicting preferences of the self-interested users and obtain socially desirable outcomes, e.g., the maximal long-term revenue of charging station and the social welfare [166]. However, it is challenging to develop such a pricing mechanism for EV-based demand response in a charging market, where users are modelled as the self-interested agents who aim only to advance their own benefits rather than the system wide efficiency. Particularly, the selfish users will take advantage of the energy-flexibility by adjusting their power demands for economic benefits [167]. In addition, their decisions are affected by multiple factors, making it inapplicable to assume user's demand information is single-dimensional, statistically known, and does not change over time [15]. In the charging market, users may not be fully rational due to information asymmetry and may not follow the price signal offered by the charging station. Moreover, there is no explicit utility model for users, whose private information is subject to stochastic changes over time. Add it all up, the information that affects the dynamic pricing is uncertain, unknown and changing dynamically over time, which is accumulated from users' random arrivals and changing preferences on charging demands. Such a strategic interaction between the charging stations and users will exclude many candidates from existing demand-dependent pricing schemes, especially when the demand-price profile and valuation function of users are not precisely known. Therefore, designing a pricing mechanism needs to address the stochastic process governing the agent's preferences with changing populations over time [158].

To this end, mechanism design can be integrated with various machine learning techniques in order to accommodate a variety of dynamic settings across periods and agents' feedback and their preferences, especially for dynamic pricing to obtain more profits than those possible from a single sale price [168]. In order to address dynamics in mechanism design, a systematic approach called *automated mechanism design* solves the mechanism design problems as a search problem via artificial intelligence techniques [16]. It takes the input information of a set of agents and returns a mechanism that maximizes an objective such as expected revenue over the agents' valuation distribution. Within this context, P. Tang proposed a modelling and algorithmic framework, i.e., *reinforcement mechanism design* [15], to solve the mechanism design as a sequential decision-making problems and optimize the economic mechanisms in dynamic environments, where a designer can make use of the data generated in the process and automatically improve future design using reinforcement learning algorithms.

## 7.2 Related Work

Reinforcement learning has been widely used in decision-making under uncertain scenarios in energy systems control such as electric vehicles and smart appliances in the smart grid [112, 169, 170, 171]. It is able to explore how the proposed demand response programs can be used for foresighted users in dynamic environments. For instance, a reinforcement learning algorithm is proposed in [171] to deal with dynamic pricing and energy consumption scheduling in microgrid. The service provider acts as a broker who purchases energy from the utility company and sells it to customers, while the customers schedule their energy demands following the retail charging price. Furthermore, an incentive-based DR algorithm that integrates reinforcement learning and deep neural network is proposed in [163] to purchase energy resources from its subscribed customers, in order to balance energy fluctuations and enhance grid reliability. However, most of these works model the electricity price as a component of state and assume users are price-takers whose actions do not affect the electricity price; moreover, users are assumed to consistently follow stable patterns that are observable. Different from them, we aim to estimate user's strategic response to the prices during a sequential decision-making process.

## 7.3 Our Contribution

We propose a novel reinforcement mechanism design framework based on [15] to address a DR-based dynamic pricing problem in an islanded microgrid charging station, taking EV users' strategic behaviors and other dynamics into account. This framework extends an one-time, static mechanism to a sequential, dynamic one, considering the characteristics of power loads, random EV arrivals, uncertain charging demands and the private preferences of the self-interested users. Different from the classic mechanism design, we solve the dynamic pricing as a sequential decision-making process, where the charging station adaptively sets the charging prices at each hour so as to maximize its long-term revenue as well as the social welfare across all users.

In such a decentralized and dynamic environment, users act as not only the price-taker, but also the price-maker. They are incentivized to flexibly adjust their charging demands and reduce the energy consumption of load peak periods by observing the charging price and the outcome or feedback that is relevant to them; meanwhile the charging station is interested in long-term objectives such as the cumulative revenue over time with different price parameters. The strategic interaction between the charging station and users is modelled as a finite Markov decision process (MDP) and solved by Q-learning which determines the optimal pricing for charging station over time and explores users' best response on the charging demands. To the best of our knowledge, this is the first work in the existing literature that adopts reinforcement mechanism design framework to address EV-based demand response problems via dynamic pricing.

The remainder of this work is organized as follows: Section 7.4 introduces the preliminaries and problem formulation. Section 7.5 illustrates the reinforcement mechanism design framework. Section 7.6 presents the experimental study. Section 7.7 draws a conclusion and outlooks our future research.

## 7.4 EV-Based Demand Response Problem Formulation

### 7.4.1 System Model

We set one day of 24 hours as the operation period $\mathcal{T} = 1, 2, ..., 24$, where the $t$-th hour is denoted by $t \in \mathcal{T}$. We consider an islanded microgrid where a charging station controls the energy allocated to each connected EV over time with an objective to maximize its long-term revenue. This station is connected with microgrid and installed with a solar panel and an energy storage system. Its power capacity is characterized by $G_t^b$ and $G_t^r$, where $G_t^b$ is the power offered by microgrid that is limited by the transformer, and $G_t^r$ is the power of photovoltaic array and storage system connected to this station. The charging station has $m$ identical chargers which can simultaneously charge at most $m$ EVs at any time $t$. It is noted that vehicle-to-grid paradigm is not considered in this system model.

Consider a set of users $\mathcal{I}$ who come and leave the charging station within $\mathcal{T}$, and each user $i \in \mathcal{I}$ has a charging request to be processed by this charging station. The request is defined as a 4-tuple: $\langle \overline{at}_i, \overline{dt}_i, SoE_i^{ini}, E_i \rangle$, where $\overline{at}_i$ and $\overline{dt}_i$ are user $i$'s earliest arrival time and latest departure time, respectively. User $i$ should complete her charge within time window $[\overline{at}_i, \overline{dt}_i]$. $SoE_i^{ini}$ is the initial State-of-Energy ($SoE$) of user $i$ when she plugs into a charger, and $E_i$ is the battery capacity of her EV. Noting that $SoE_{i,t} = E_i * SoC_{i,t}$, where $SoC_{i,t}$ is the State-of-Charge (%) of EV at $t$.

Before plug-in, user $i$ has a minimum energy demand $e_i^{min} \in [0, E_i - SoE_i^{ini}]$, and she should also decide her demand $x_{i,t} \in \mathbb{R}_+$ at for each $t \in [\overline{at}_i, \overline{dt}_i]$ and ensure that the total charged energy $\sum_t x_{i,t}$ does not exceed the maximum energy volume restricted by the battery capacity, i.e., $\sum_{t \in [\overline{at}_i, \overline{dt}_i]} x_{i,t} \in [e_i^{min}, E_i - SoE_i^{ini}]$. In addition, let $\mathcal{I}_t$ be the set of connected EVs at $t$, where $\mathcal{I}_t \subseteq \mathcal{I}$; and let $n_t$ be the number of EVs plugged in at $t$, where $\forall t \in \mathcal{T},\ n_t \leq m$.

The charging station first sets the energy price $\lambda_t \in \Lambda$ per unit power at $t$ and announces it to users, and then users respond to $\lambda_t$ by demanding an optimal amount of power $x_{i,t}$. Then the station starts charging EVs and observes the outcome as well as the revenue at the end of $t$. These two events will continue to take place sequentially. The total charging demands $X_t$ of all connected users at $t$ is $\sum_{i \in \mathcal{I}_t} x_{i,t}$, and the energy-related revenue of station is $\lambda_t \sum_{i \in \mathcal{I}_t} x_{i,t}$. A user also has to pay a fixed parking fee $\tau^p$ every hour, and the parking-related revenue at $t$ is $\tau^p n_t$.

The scheduling result (an outcome) at $t$ satisfies all the charging demands of the connected EVs, maximizing the cumulative revenue of energy and parking, as follows:

$$R_{cs}^{total} = \sum_{t\in\mathcal{T}}(\lambda_t \sum_{i\in\mathcal{I}_t} x_{i,t} + \tau^p n_t - \tau^e[\sum_{i\in\mathcal{I}_t} x_{i,t} - G_t^b]^+). \tag{7.1}$$

If the total demands $X_t$ exceeds the capacity $G_t^b$, the charging station has to start using the spare energy sources $G_t^r$ and pay extra energy costs with the per unit price $\tau^e$, i.e., $\tau^e[\sum_{i\in\mathcal{I}_t} x_{i,t} - G_t^b]^+$, where $[y]^+ = max\{0, y\}$. In our model, we assume the backup energy sources $G_t^r$ are always enough for the excessive demands from users, i.e., $\forall t \in \mathcal{T},\ [\sum_{i\in\mathcal{I}_t} x_{i,t} - G_t^b]^+ \leq G_t^r$.

### 7.4.2 Dynamic Pricing Mechanism

As users' valuation function and demand-price curve are not precisely known by the charging station. While the sequential decisions made by the station relies on the knowledge of users' charging demands at each hour, which come from the rough estimation of the maximum energy requirements according to the battery capacity of the vehicle model. To maximize the long-term revenue, charging station has to develop efficient mechanisms to elicit an estimated relation between the price and users' charging demands through the strategic interaction.

We first construct a mechanism design environment.

**Definition 7.1 (Mechanism Environment)** *A mechanism environment* $\Gamma = \{\mathcal{I}, \{\Theta_i\}_{i\in\mathcal{I}}, \{\mathcal{X}_i\}_{i\in\mathcal{I}}, \Phi, \{v_i\}_{i\in\mathcal{I}}\}$ *consists of*

- *a set of users* $\mathcal{I}$*, where* $\mathcal{I} = \{1, 2, ..., n\}$*;*
- *for every user* $i \in \mathcal{I}$*, a set of types* $\Theta_i$*;*
- *for every user* $i \in \mathcal{I}$*, a set of actions* $\mathcal{X}_i$*;*
- *a set of outcomes* $\Phi$ *and*
- *for every user* $i \in \mathcal{I}$*, a valuation function* $v_i$*.*

Specifically, (1) the type of user encapsulates all the information possessed by users that is not publicly known. Type will affect user's valuation over the outcomes, and thus bring uncertainties in determining the charging demands. In our model, user $i$'s type $\Theta_i$ is her current $SoC$ level. (2) Action set $\mathcal{X}_i$, a function of user $i$'s type $\Theta_i$ at each hour, includes her all possible demands. An action profile $\boldsymbol{X}$ is denoted as the Cartesian product of the action set of all users: $\boldsymbol{X} = \prod_{i=1}^{n} \mathcal{X}_i$, and $\boldsymbol{x} = (x_1, x_2, ..., x_n) \in \boldsymbol{X}$. (3) The set of outcomes $\Phi$ includes the energy allocation at each hour given the users' demands. (4) User $i$'s valuation $v_i$ is the measurement on an outcome $\phi$ based on her type, i.e., $v_i(\phi; \theta) : \Theta_i \times \Phi \to \mathbb{R}_+$, which reflects user's demand-price curve. The system-wide goal of mechanism design is defined with a social choice function $f : \prod_{i=1}^{n} \Theta_i \to \Phi$, which maps the type profile of all users to a set of outcomes. Social choice selects the optimal outcome given agent types [130].

In this mechanism design environment, dynamic pricing mechanism is essentially the procedure through which achieves a desired social goal by providing incentives to users. This dynamic pricing mechanism contains a decision policy and a payment policy, as follows:

**Definition 7.2 (Pricing Mechanism)** *A pricing mechanism* $(\boldsymbol{x}, \{p_i\}_{i \in \mathcal{I}})$ *over a mechanism environment* $\Gamma$ *consists of*

- *A decision policy* $\boldsymbol{x} : \Lambda \to \{x_{i,t}\}_{i \in \mathcal{I}}$*, which maps the charging prices* $\Lambda$ *to the charging demands of users at* $t$*;*
- *For each user* $i$*, a payment function* $p_i : \boldsymbol{X} \to \mathbb{R}_+$*, which maps the action profile* $\boldsymbol{X}$ *of all users to a real number.*

In our study, user $i$ pays $p_{i,t} = \lambda_t x_{i,t} + \tau^p$ at $t$. This pricing mechanism proceeds as follows: charging station sets the charging price $\lambda_t$ at each hour $t$ from the parameterized class $\Lambda$, and finds a policy that enjoys desirable cumulative revenue. Users observe the announced price signal at the end of time $t$, and then react strategically to determine their demands $x_{i,t+1}$ for the next hour. At the end of $t+1$, charging station receives an outcome as well as the associated immediate reward.

## 7.5 Reinforcement Mechanism Design Framework

To implement the pricing mechanism in sequential periods, we formalize the strategical interaction between the charging station and users as an MDP and solve the dynamic pricing with Q-learning, considering the uncertainties coming from the charging demands and random arrivals of EVs. The reinforcement mechanism design framework is illustrated in Fig. 7.1. In this section, we first introduce the preliminaries about MDP; and then present the detailed MDP formulation for the charging station and the Q-learning algorithm; finally, we analyze user's strategy in this dynamic pricing mechanism.

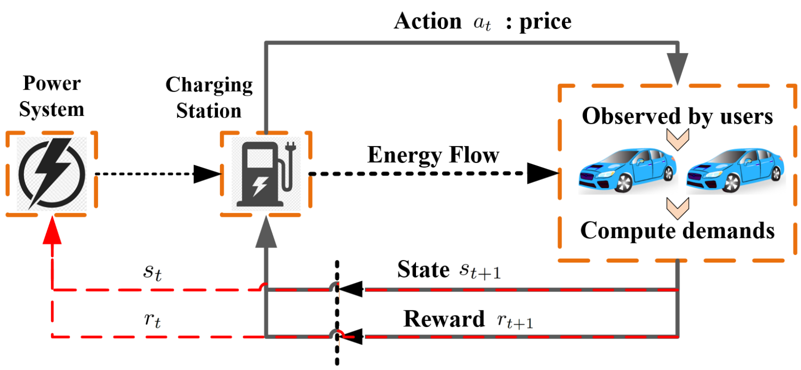



Figure 7.1: MDP model for the interaction between charging station and users.

### 7.5.1 Preliminaries

The station-user interaction is formulated as an Markov decision process [172], which is typically characterized by a 5-tuple $\langle \mathcal{S}, \mathcal{A}, P, r, \gamma \rangle$, where $\mathcal{S}$ is a finite set of states $s_t \in \mathcal{S}$ and $\mathcal{A}$ is a finite set of actions $a_t \in \mathcal{A}$. The function $P : \mathcal{S} \times \mathcal{S} \times \mathcal{A} \to [0, 1]$ defines the state transition probabilities, where $p(s_{t+1}|s_t, a_t)$ represents the transition probability from $s_t$ to $s_{t+1}$ after $a_t$ is taken. The stochastic process satisfies the Markov property: $p(s_{t+1}|s_0, a_0, ..., s_t, a_t) = p(s_{t+1}|s_t, a_t)$. The function $r : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ defines the expected rewards for state–action pairs, where $r(s_t, a_t)$ is the immediate reward received when $a_t$ is taken at $s_t$. Let $R_t$ denote the discounted sum of rewards from the state $s_t$, then $R_t = \sum_{t \in \mathcal{T}} \gamma^t r(s_t, a_t)$, where $\gamma \in (0, 1]$ is the discount factor. In the case of charging scheduling, a station chooses a charging price from the given set in the current state, and users respond strategically based on the price. At the end of $t$, charging station receives an immediate reward associated with the outcome. Then the time progresses to $t + 1$ with all information updated accordingly.

### 7.5.2 Charging Station Side Analysis

In this MDP, a state consists of the base power capacity and battery capacity information of the connected EVs; the action for a charging station is to set the charging price; and the immediate reward is the total expected station revenue at the current hour. Specifically, the variables are defined as follows:

#### States

A state $s_t$ is defined as a 3-tuple: $\langle G_t^b, E_t^{req}, n_t \rangle$, which consists of the base load $G_t^b$ of the charging station, the total required energy $E_t^{req}$ from all users, and the number of connected EVs $n_t$ at $t$. In this study, $E_t^{req} \approx \sum_{i \in \mathcal{I}_t}(E_i - SoE_i^{ini})$, where $E_t^{req}$ is an estimation of the total maximal energy that all connected EVs can charge based on each user's battery capacity and her initial $SoE$. The optimal action for charging station is determined by observing the current state.

#### Actions

An action taken by the charging station is the decision of charging price $\lambda_t$ at $t$ and the allocation of energy based on the limited energy supply $G_t^b$ and the required user demands $E_t^{req}$. The price has three levels: off-peak $\lambda_t^l$, mid-peak $\lambda_t^m$ and on-peak $\lambda_t^h$, where $\Lambda = \{\lambda_t^l, \lambda_t^m, \lambda_t^h\}, \lambda_t \in \Lambda$. After these actions are taken, $s_t$ is updated according to the strategy of users with respect to the outcome $x_{i,t}$ of time $t$.

#### Reward

The immediate reward $r_t$ at $s_t$ of the charging station is defined as its expected revenue:

$$r_t = \lambda_t \sum_{i \in \mathcal{I}_t} x_{i,t} + \tau^p n_t - \tau^e [\sum_{i \in \mathcal{I}_t} x_{i,t} - G_t^b]^+. \tag{7.2}$$

To maximize the total reward, Q-learning is the most widely used model-free reinforcement learning algorithm due to its simplicity, in which the agents learn the optimal policy through their interaction with the environment [172]. In our study, charging station learns the optimal pricing through the strategic interaction with users. Q-learning uses the Q value $Q(s_t, a_t)$ as an expected reward for a state-action pair $(s_t, a_t)$. While the real reward is represented by $Q'(s_t, a_t)$ and consists of the immediate reward $r(s_t, a_t)$ and the future expected Q value: $Q'(s_t, a_t) = r(s_t, a_t) +$

**Algorithm 4** Q-learning based Demand Response

**Require:** The price set $\Lambda$, the maximum episode $\mathcal{H}$;
**Ensure:** The optimal policy $\pi^*$, $\forall t \in \mathcal{T}$;
**for** $h = 1 \rightarrow \mathcal{H}$ **do**
  **for** each hour $t \in \mathcal{T}$ **do**
    Choose $a_t$ by $\epsilon$-greedy policy;
    Take action $a_t$;
    **for** each user $i \in \mathcal{I}$ **do**
      User $i$ observes the price and submits their optimal demands $x_{i,t}$;
    **end for**
    Charging station observes $r(s_t, a_t)$, $s_{t+1}$;
    Update the Q value;
  **end for**
**end for**

$\gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1})$. And the Q value is updated by $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \sigma[r(s_t, a_t) + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)]$, $\forall (s_t, a_t)$, where $\sigma$ is the learning rate. As proven in existing literature [112, 173], Q-learning obtains a near-optimal policy by driving the action-value function towards the optimal action value $Q^*(s, a)$ through iterations.

Solving an MDP is to determine the optimal policy $\pi^*(a|s) : \mathcal{S} \rightarrow \mathcal{A}$ for the dynamic pricing, which is to select the optimal action (charging price) for each state $t \in \mathcal{T}$. Numerically, the optimal policy can be calculated by: $\pi^*(a_t|s_t) \leftarrow \arg\max_{a_t} \sum_{s_{t+1}} p(s_{t+1}|s_t, a_t)[r(s_t, a_t) + \gamma \max_{a_{t+1}} Q^*(s_{t+1}, a_{t+1})]$. The process of Q-learning–based demand response algorithm is shown in Algorithm 4.

Specifically, a charging station chooses the current action $a_t$ with the $\epsilon$-greedy strategy subject to the observations, which can avoid staying in the local optimum by balancing the exploitation and exploration during the learning process [173]. The $\epsilon$-greedy algorithm continues to explore, with probability 1- $\epsilon$ of selecting the best action, and with probability $\epsilon$ of selecting a random action. In our study, the optimal action is used in about 90% of the price ($\epsilon = 0.1$), and takes a completely random action in about 10% of the cases to explore and meet bigger possible rewards.

### 7.5.3 User Side Strategy

EV users act both as a price-taker and a price maker, who observes the charging price and adaptively adjust their charging demands for each hour. While the charging station observes the outcome at the end of current hour and determines the price for the next. The bidding process can be automatically implemented on smart phones or other platforms, where users only need to set up their charging requests and the preference information. This section explores how users respond to the charging prices in order to achieve a maximal revenue by encouraging users to adapt their charging demands.

The final total energy $\sum_{t\in[\overline{at}_i,\overline{dt}_i]} x_{i,t}$ that user $i$ will charge is not predetermined; instead it relies on the charging price $\lambda_t$ and the current $SoE_{i,t}$ at each $t$. During $t$, users will consume the energy $x_{i,t}$ required at $t-1$, so that $SoE_{i,t+1} = SoE_{i,t} + x_{i,t}$, and then recompute their optimal demands for $t+1$ based on the updated charging price and $SoE$.

As the self-interested agents, users will always maximize their utilities when computing the optimal charging demands. In our model, we do not consider the strategic interaction and competition among users but focus on the station-user interaction, because users have no information about others' preferences and no conflicting interests with others. We then present the definition of user's utility.

**Definition 7.3 (Quasi-linear Utility Function [158])** *User $i$'s utility is captured by the difference of her valuation $v_i(\cdot)$ for demand $x_{i,t}$ and the charging cost $p_{i,t}$ at $t$ based on her type $\Theta_i$ and price $\lambda_t$, i.e.,*

$$\begin{aligned} u_i(x_{i,t}, \lambda_t; \theta_{i,t}) &= v_i(x_{i,t}; \theta_{i,t}) - p_{i,t} \\ &= v_i(x_{i,t}; \theta_{i,t}) - (\lambda_t x_{i,t} + \tau^p). \end{aligned} \tag{7.3}$$

From above, the optimal demands $x^*_{i,t} \in \mathbb{R}_+$ for hour $t$ are obtained by solving $\arg\max_{x_{i,t}} u_i(x_{i,t}, \lambda_t; \theta_{i,t})$, in terms of their type $\theta_{i,t} \in \Theta_i$ and the charging price $\lambda_t$. And user $i$'s charging cost $p_{i,t}$ includes the energy cost $\lambda_t x_{i,t}$ and parking fee $\tau^p$. We assume that user's valuation function follows a *Logarithm* function in economics [174, 175]. Users are also assumed to have a decreasing marginal valuation as $SoC$ increases, which implies the higher $SoC$ level they have, the less satisfaction (lower valuation) they will get from the same amount of energy. Specifically, user's valuation is defined as the marginal value of obtaining a certain amount of energy $x_{i,t} = \Delta SoC_{i,t} * E_i$ given $SoC_{i,t-1}$, and $\Delta SoC_{i,t} = SoC_{i,t} - SoC_{i,t-1}$. Fig. 7.2 presents an illustrative example including two different $SoC$-valuation functions of user 1 and 2. Specifically, user 1 and 2 have different valuation functions, leading to different increase of values in terms of the same increase of $SoC$ due to their individual types. It can be seen that user 1 is more sensitive than user 2 in terms of the increase of $SoC$. Moreover, the marginal valuation is decreasing with the increase of $SoC$. For instance, user 1 has an increased value of \$0.71 from 30% to 50% $SoC$; however, she has only \$0.44 for charging from 50% to 70% $SoC$. This general $SoC$-price curve also demonstrates that users always consume less energy when charging price is higher.

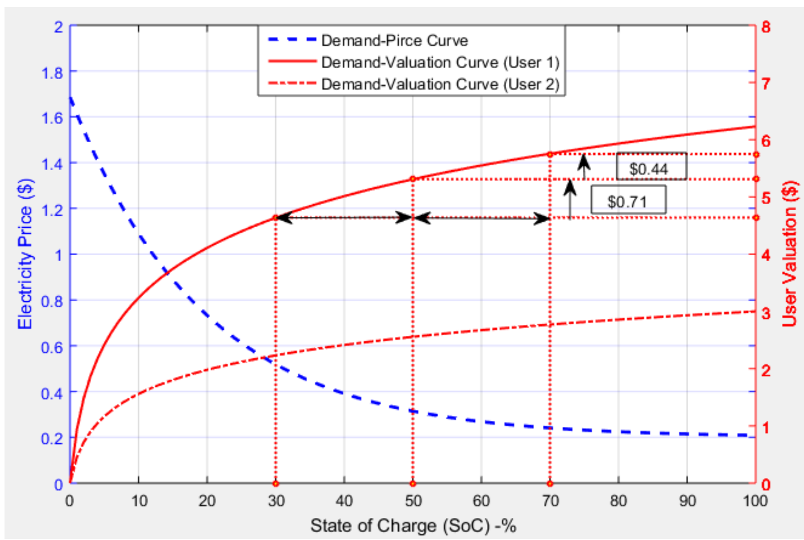



Figure 7.2: An example of $SoC$-valuation/price curve of users.

To analyze user's best response in generating the optimal demands, we first present the concept of individual rationality.

**Definition 7.4 (*Ex-ante* Individual Rationality)** *The pricing mechanism is* ex-ante *individual rational if each user $i \in \mathcal{I}$ receives a non-negative utility by participation regardless of her type at $t$. That is, with user $i$'s participation, we have*

$$u_i(x_{i,t}, \lambda_t; \theta_{i,t}) = v_i(x_{i,t}; \theta_{i,t}) - p_{i,t} \geq 0, \ \forall t \in \mathcal{T}. \tag{7.4}$$

In other words, *ex-ante* individual rationality holds if users can always achieve as much expected utility from participation as without participating, regardless of knowing her own type or other users' types [130].

**Definition 7.5 (Best Response)** *User's best response $x^*_{i,t}$ is the charging demand that maximizes her utility based on her current $SoE_{i,t}$ and type $\Theta_i$ given the charging price $\lambda_t$. That is, the optimal demand is defined as $x_{i,t}$ : $u_i(x_{i,t}, \lambda_t; \theta_{i,t}) \geq max_{x'_{i,t}} u_i(x'_{i,t}, \lambda_t; \theta_{i,t})$, $u_i(x_{i,t}, \lambda_t; \theta_{i,t}) \geq 0$, $x_{i,t}, x'_{i,t} \in [0, E_i - SoE^{ini}_i - \sum_{t' \in [\overline{at}_i, t-1]} x_{i,t'}]$.*

User $i$ will stop charging under two conditions, which indicates $x^*_{i,t} = 0$ for $t$: First, for any charging demands that produce $u_i(x_{i,t}, \lambda_t; \theta_{i,t}) < 0$, which indicates that continuing charging brings no more marginal values to her. Second, the current $SoE$ reaches to EV's battery capacity limit, i.e., $E_i - SoE^{ini}_i - \sum_{t' \in [\overline{at}_i, t-1]} x_{i,t'} < x_{i,t}$.

**Theorem 7.1** *The dynamic pricing mechanism is* ex-ante *individual rational.*

**Proof** The set of outcomes $\Phi_{-i}$ that is achievable without user $i$ is a weak subset of outcomes with user $i$, i.e., $\forall i,\ \Phi_{-i} \subseteq \Phi$. The utility $u_i$ of user $i$ is non-negative on all outcomes without her, i.e., $u_i(\phi'; \theta_{i,t}) = 0$, $\forall \phi' \in \Phi_{-i}$. Noting that users are uncertain about their total demands $\sum_{t \in [\overline{at}_i, \overline{dt}_i]} x_{i,t}$ before charging, and their real demands are affected by the physical battery capacity and initial $SoE$. A rational user will stop charging when she obtains a negative utility, i.e., when the charging cost $p_{i,t}$ exceeds the valuation $v_i(x_{i,t}; \theta_{i,t})$ brought by this amount of energy $x_{i,t}$. The parking fee is a constant cost in the utility function that can reduce a user's wait-and-see strategy to charge at a cheaper price in the future. Therefore, myopic users have no tendency to delay their charge. Therefore, user $i$'s best response $x^*_{i,t} \leftarrow \arg\max_{x_{i,t}} u_i(\cdot)$ implies her optimal charging demands with the trade-off between valuation and cost, which admits a maximum utility under the current price $\lambda_t$. The expected utility accrued from the rational users is always non-negative. Add it up, the proposed dynamic pricing mechanism is *ex-ante* individual rational.

**Definition 7.6 (Weak Budget Balance)** *A mechanism is weakly budget balanced if all users make a non-negative payment to the charging station for all feasible type profiles, and the total payment is non-negative, i.e.,*

$$\sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{I}_t} p_{i,t} = \sum_{t \in \mathcal{T}} (\lambda_t \sum_{i \in \mathcal{I}_t} x_{i,t} + \tau^p n_t) \geq 0. \tag{7.5}$$

It can be seen that this pricing mechanism is weakly budget balanced. That is, there can only be a payment made from users to the station, but no payment from the station to users.

Followed by above properties, there exists a Nash equilibrium in this pricing mechanism if both of the charging station and users act on their best response based on the actions taken by the other side.

**Definition 7.7 (Nash Equilibrium)** *The set* $(\lambda_t^*, \boldsymbol{x_t^*})$ *is the Nash equilibrium of this pricing mechanism [30], if charging station follows the equilibrium strategy* $\lambda_t^* \in \Lambda$ *given the best response* $\boldsymbol{x_t^*}$ *of all users at* $t$*, we have*

$$r(\lambda_t^*, \boldsymbol{x_t^*}(\lambda_t^*)) \geq r(\lambda_t, \boldsymbol{x_t^*}(\lambda_t)), \quad \forall \lambda_t \in \Lambda. \tag{7.6}$$

where $\boldsymbol{x}$ is the action profile of all users, such that $\boldsymbol{x_t^*}(\lambda_t^*)$ is their collective best response, i.e., the optimal demands $(x_{i,t}^*)_{i \in \mathcal{I}}$ in terms of price $\lambda_t^*$. It can be inferred from the Theorem 4 in [175] that the set $(\lambda_t^*, \boldsymbol{x_t^*})$ is a Stackelberg equilibrium of the strategic interaction between the charging station and users, if the price set $\Lambda$ is a non-empty, convex, and compact subset of an Euclidean space $\mathbb{R}$, and the utility function $u_i$ of user $i$ is continuous in $\Lambda$ and concave in $\lambda_t$.

## 7.6 Experimental Study

### 7.6.1 Experiment Setup

We design two experiments with different charging station sizes: $m = 10$ for Group 1 and $m = 30$ for Group 2. Both of them are Level-2 AC (240-volt) station supporting an output power of $> 3.7kW$ and $\leq 22kW$. We use the real-world 24-hour data of user power consumption at public charging stations[18], where the 20% and 50% of this commercial load are used as the base load supply $\{G_t^b\}_{t \in \{1,...,24\}}$ for 10 chargers (Group 1) and 30 chargers (Group 2), respectively.

The arrival rate of EVs at each hour $t$ is assumed to follow a Possion distribution $p(k) = \frac{\delta^k}{k!} e^{-\delta}, k = 0, 1, ...,$ where $\delta = 4$ represents the Group 1 scenario, and $\delta = 6$ represents the Group 2 scenario. User $i$'s latest departure time $\overline{dt}_i = t + \mathcal{U}[2, 5]$, where $\mathcal{U}$ is a uniform distribution, and her initial $SoC$ is randomly distributed in $\mathcal{U}[10, 50]$ (%); then $SoE_i^{ini} = SoC_i^{ini} * E_i = 0.01 * \mathcal{U}[10, 50] * 30 = \mathcal{U}[3, 15]$. We assume that

[18] SCE load profiles, https://www.sce.com /regulatory/load-profiles, ID: GS-1, 08/20/2019

all EVs have an equivalent battery capacity $E_i = 30kWh$ and supports a maximum charging power $50kW$. The minimum energy demand $e_i^{min}$ of user $i$ is randomly drawn from $[0, E_i - SoE_i^{ini}]$.

We build user's valuation function $v_i$ based on the natural logarithm function following [175] and assume EV users share the same utility function, noting that our algorithm applies to heterogeneous utility functions with different $\alpha_i$. The valuation-$SoC$ function is shown as:

$$v_{i,t}^{SoC} = \begin{cases} \alpha_i \ln(\beta_i + SoC_{i,t}), & if\ 0 \leq SoC_{i,t} \leq \overline{SoC}_i \\ \alpha_i \ln(\beta_i + \overline{SoC}_i), & if\ \overline{SoC}_i \leq SoC_{i,t} \end{cases} \tag{7.7}$$

where $SoC_{i,t} = (SoE_{i,t-1} + x_{i,t-1})/E_i$. Noting that demand $x_{i,t}$ at every $t \in [\overline{at}_i, \overline{dt}_i]$ satisfies $x_{i,t} \in [0, E_i - SoE_i^{ini} - \sum_{t' \in [\overline{at}_i, t-1]} x_{i,t'}]$, such that the total energy charged will not exceed the battery capacity. $\alpha_i$ is randomly drawn from $0.2 * E_i * \mathcal{U}[0,1]$ according to the different demand profile of users, and $\beta_i = 1$. $\overline{SoC}_i$ is the threshold of the marginal valuation (often set as 80%), because EVs' $SoC$ or the charging voltage will not significantly increase at a saturation stage according to the battery charging profile[19]. The valuation is measured by the marginal gain for obtaining $x_{i,t}$ subject to the current $SoC$, i.e., $v_i(x_{i,t}; \theta_{i,t})$ for demand $x_{i,t}$, which is $E_i\alpha_i[\ln(\beta_i + SoC_{i,t}) - \ln(\beta_i + SoC_{i,t-1})]$. The optimal demands for $t$ is computed by $x_{i,t} \leftarrow \arg\max_{x_{i,t}} u_i(x_{i,t}, \lambda_t; \theta_{i,t}) \pm \xi$, where $\xi$ is an uncertain factor over user demands, $\xi \in [0.05E_i, 0.1E_i]$.

This experiment study uses the charging price in the U.S. public charging stations as the reference, which is around $\$0.15/kWh$ after tax[20]. Accordingly, the charging price of off-peak $\lambda_t^l$, mid-peak $\lambda_t^m$ and on-peak $\lambda_t^h$ hour in our model is set as $\$0.1/kWh$, $\$0.15/kWh$ and $\$0.2/kWh$, respectively. The parking cost $\tau^p$ is \$1 per hour. The extra energy purchasing fee $\tau^e$ is $\$0.35/kWh$. And we set 7:00 p.m. to 7:00 a.m. as off-peak hour, 7:00 a.m. to 11:00 a.m. and 5:00 p.m. to 7:00 p.m. as mid-peak hour, and 11:00 a.m. to 5:00 p.m. as on-peak hour in a general case[21].

We compare the pricing policy by the Q-learning with the uncontrolled and static strategy, namely the predetermined Time-of-Use (TOU) pricing, for these two groups

[19]Battery University, https://batteryuniversity.com/learn/article/charging_ lithium_ion_batteries.
[20]Global EV Outlook 2019: Scaling up the transition to electric mobility, https://www.iea.org/gevo2019/.
[21]TOU Pricing and Schedules, https://www.powerstream.ca/customers/rates-support-programs /time-of-use-pricing.html.

of experiments. TOU pricing reflects the cost of producing electricity at different times of day based on demand, which basically has three periods: on-peak, when energy demand and cost is high, mid-peak, when energy demand and cost is moderate, and off-peak, when energy demand and cost is low[22]. A user's best response and strategy under TOU pricing, as well as other experimental parameters, including random EV arrivals and user side information, etc., share the same setting as they are in the dynamic pricing mechanism.

In this experiment, Q-learning algorithm and static TOU pricing have ten parallel experiments for each group, and one experiment iterates for 10,000 times (iterations); and the solutions are used to define a policy. Each iteration calculates the total rewards (revenue) $R_{cs}^{total}$ (1) of a day ($24h$). To better display the performance of two methods in terms of the revenue, we take the average rewards of 100 iterations as one episode, and each experiment has totally 100 episodes.

We use the Q-learning algorithm to approximate $Q(s, a)$ which takes a state $s$ as input and outputs a vector of $Q$-values corresponding to the actions of charging station: $\lambda_t \in \{\lambda_t^l, \lambda_t^m, \lambda_t^h\}$. The pricing mechanism and Q-learning algorithm are coded in Python and use reinforcement learning environments from the OpenAI Gym. The experiments are carried out on a PC with a processor of Intel (R) Core (TM) i5-6500U CPU @ 3.2GHz, 8GB memory.

### 7.6.2 Results and Analysis

Fig. 7.3 demonstrates the performance of two groups using Q-learning algorithm and TOU pricing, respectively, which reports an error band-with the mean and standard deviation during training the cumulative reward (revenue). Each band takes the mean and standard deviation of the station reward of ten parallel experiments ($y$-axis) at each episode ($x$-axis). In Fig. 7.3 (a) (Group 1), the station revenue of these 100 episodes for the Q-learning and TOU are around \$476.44 and \$442.32, with an variance of \$6.81 and \$3.19, respectively. The average revenues of Group 2 are presented in Fig. 7.3 (b), which are \$1,321.25 with a variance of \$92.15 and \$1,032.74 with a variance of \$6.13 for dynamic pricing and TOU, respectively. The Q-learning with dynamic pricing mechanism can improve the station revenue for around 7.71%

[22]https://www.hydroone.com/rates-and-billing/rates-and-charges/electricity-pricing-and-costs#:~:text=Time%2Dof%2DUse%20(TOU)&text=TOU%20pricing%20reflects%20the%20cost,demand%20and%20cost%20is%20low.

compared to the TOU pricing for Group 1 and around 27.93% for Group 2, which indicates charging station can make more \$34.12 (Group 1) and \$288.51 (Group 2) profits a day. Moreover, it can be seen that the dynamic mechanism presents a better performance for the larger charging station size with more users, as can be seen that Group 2 improves averagely 27.93% compared to TOU pricing in terms of the revenue. A larger station size implies more options for the demand response.

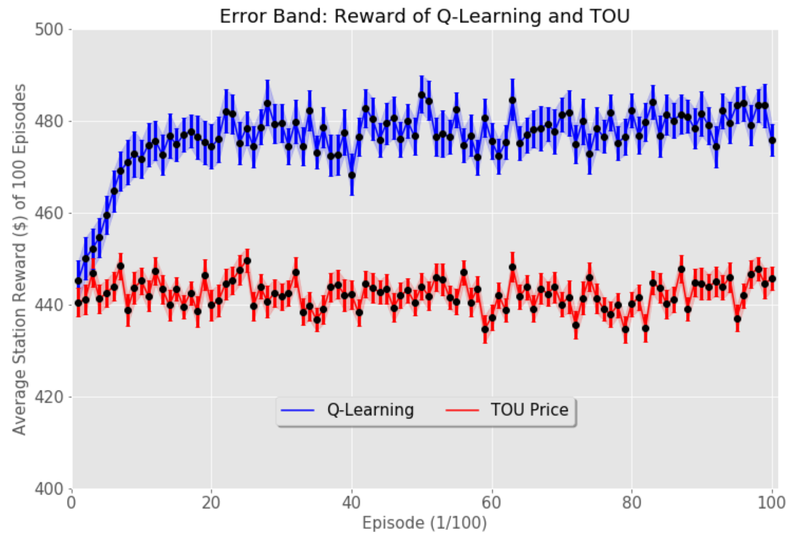
We pick one experiment with 10,000 iterations of Group 2 and present its rewards with three different epsilons ($\epsilon = 0.05$, 0.1 and 0.25, respectively) in Fig. 7.4. It demonstrates that Q-learning algorithm converges to an average reward of \$1,326.61 with $\epsilon = 0.1$. In addition, Fig. 7.5 presents one iteration of dynamic pricing under Q-learning, with the curve of users' charging demands and the electricity price from 1:00 a.m. to 12:00 p.m.. The stack bar (left blue) shows the charging demands of each connected EV at each hour in terms of the charging price (right red). It can be seen that when the energy supply is low, the charging price can efficiently reduce the energy consumption from users and postpone the charging activities of some users from peak-hours to off-peak hours, such that the load stability can be well maintained.

**Nash equilibrium.** It can be seen from Definition 7.7 that the Nash equilibrium exists if $\Lambda$ is a non-empty, convex, and compact subset of an Euclidean space, while the utility function is continuous in $\Lambda$ and concave in $\lambda_t$. We can easily see that the first condition holds. Combined with the Definition 7.3: utility and the valuation function (7), the second order derivative of user $i$'s utility $u_i$ is $\frac{\partial^2 u_i}{\partial \lambda_t^2} = 0$, $\forall t \in \mathcal{T}$. Hence, the second condition also holds. Therefore, Nash equilibrium exists if the best price setting can be learned for each hour under a lack of user-side information. Since the reward obtained by the Q-learning algorithm is an expected value, the pair $(\lambda_t^*, \boldsymbol{x_t^*})$ is an approximation of Nash equilibrium at $t$ after training the optimal policy $\pi^*$ by Q-learning. Different from identical-interest Nash equilibrium of stochastic game that computes the joint optimal policy of all players [176], MDP model therein acts as a leader-follower mode, like [30, 175]. The equilibrium strategy exists in the supply and demand side where users have no conflicting interests with each other.

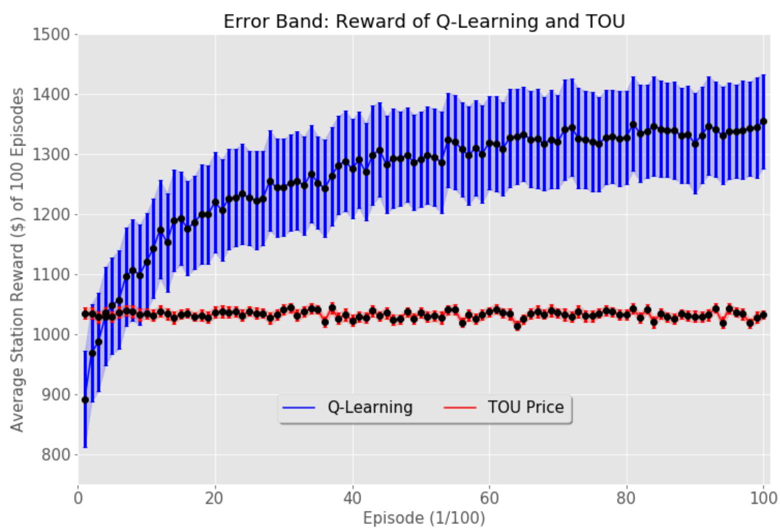
## 7.7 Summary

This work proposes a reinforcement mechanism design framework to solve a dynamic pricing problem of an islanded microgrid charging station in a dynamic charging market. The sequential strategic interaction between the charging station and users is modelled as an MDP and solved by the Q-learning algorithm. The optimal price settlement is learned by Q-learning considering the random arrivals of EVs and the uncertain charging demands of users in this sequential decision-making process. The experimental results show the charging station revenue by our approach can be improved by a maximum of 27.93% compared to the TOU pricing.

In our model, users are myopic agents who only care about their own utility in a short period of time (e.g., one hour), while computing the optimal charging demand needs more information about future parameters. For example, users may tend to wait for a better deal at a lower price in future and take the potential risk of an increased costs. Our future work will model user's decision-making as an MDP and explores the optimal joint policy of all users that gives them the maximal expected sum of discounted utilities. Moreover, more strict and detailed game theoretical proof should be developed to discuss the gap between the pair $(\lambda_t^*, \boldsymbol{x}_t^*)$ and Nash equilibrium, as well as its convergence.




(a)




(b)

Figure 7.3: Error band by Q-learning (upper curve) and TOU pricing (lower curve) of 100 episodes. Group (1): with 10 chargers; Group (2): with 30 chargers.

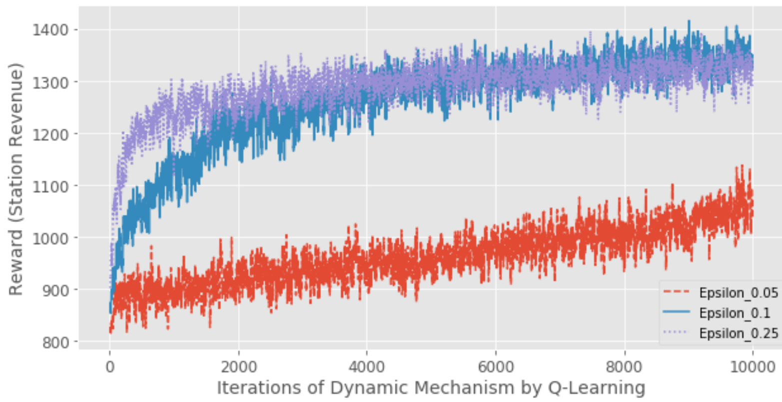



Figure 7.4: (Smoothed) Rewards of Q-learning in training for Group 2 (with 30 chargers): one experiment example with 10,000 iterations.

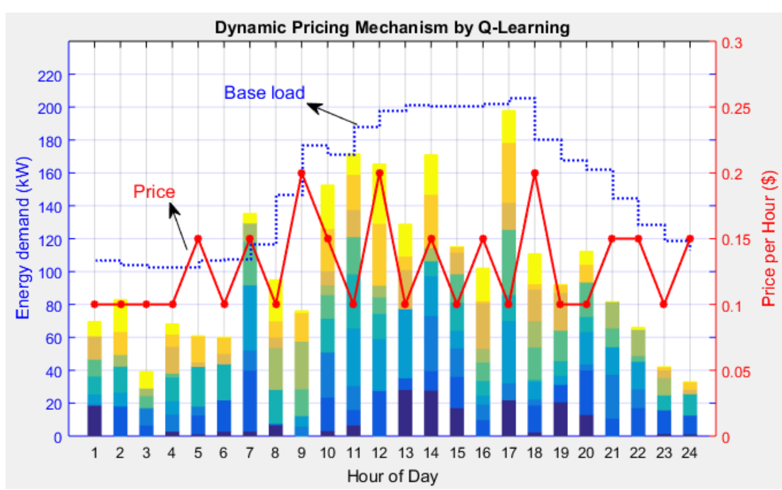



Figure 7.5: User charging demands for charging in terms of the best charging price learned by Q-learning: one iteration example.

# Chapter 8

# Future Research

## 8.1 Directions and Opportunities

Multi-agent systems architecture provides a natural modeling of the distributed and dynamic aspects of charging markets in the smart infrastructure, the existing agent-based simulation platforms from both academic and commercial sectors will provide invaluable tools for validating emerging modelling and techniques for solving the charging scheduling problems. When modeling the EV charging scheduling system, the relevant stakeholders, such as electric-based vehicles, consumers, charging stations, logistics companies, distribution network operators, and energy generators, can be modelled as agents, who are intelligent, rational, and self-interested individuals in the context of decentralized system engineering.

In this section, we discuss some potential research opportunities in the design of market-based mechanisms for addressing the game-theoretic behaviors of stakeholders in a decentralized and stochastic environment. Under the multi-agent systems architecture, future research is hoped to go towards automated coordination systems for EV charging by applying mechanism design, game theory, automated negotiation protocol, robust optimization, and machine learning based approaches, in the implementation of real-time coordination and forecasting methods that can be used by the stakeholders to adjust its forthcoming operation and properly schedule their charges.

### 8.1.1 Decentralized, Dynamic, Data-driven Environment

In practical, most EV-related problems is operating in a highly stochastic and decentralized environment. The challenge for a decentralized, dynamic, data-driven (3D) environment aims at seamlessly integrating the various uncertainties of system and users and agents' preference information with the real-time charging scheduling, and use the price and availability signal to adjust the charging demand to optimize the system performance and maximize the social welfare. The interoperability between different stakeholders, privacy maintenance from user side, uncertainties and dynamics in the charging market are the key dimensions of the charging scheduling problem in the smart infrastructure. Therefore, dynamic information about drivers' demands and charging stations' availability have been extensively researched through stochastic and decentralized approaches.

For instance, in terms of an aggregated electric vehicle charging scheduling problem with energy storage, an offering/bidding strategy of an ensemble of charging stations coupled in the day-ahead electricity market is proposed in [84], where aggregator should determine optimal bidding/offering strategy for the amount of energy to sell and buy from the market to meet the aggregated demands. The uncertainty modelling of the market price used robust optimization and aggregated charging station demand used stochastic optimization. However, robust optimization applied on the joint transportation and energy management is still rare in the literature.

In addition to the uncertainties of EV arrivals, charging demands, energy generations, and prices that have been addressed in current works, decentralized environment should integrate users' valuation uncertainty under the financial constraints and uncertain distribution of their valuations. The incentive mechanism could be developed to deal with the changing of private information over time based on dynamic auction.

### 8.1.2 Automated/Learning-Based Mechanism Design

In the intelligent transportation and smart grid system management, game theoretic-based auction design with machine learning, on the top of different pricing schemes and stochastic optimization approaches, are required to incentivize EV drivers to express their preferences and modify their habits to achieve an overall efficiency in a distributed and dynamic competitive market. Users are encouraged to be, as not only a price-taker, but also a price-maker, to actively join the price setting in resource allocation process. Moreover, unlike incentive mechanisms, stakeholders' privacy should be protected which lowers the revelation of their private information.

To our best knowledge, these is no such an effective mechanism for tackling decentralized and stochastic EV charging scheduling problem. An optimal auction paradigm with deep learning is proposed in [177], where the rules of an auction are modelled as a neural network, and use machine learning for the automated design of auctions with budget constraints. More efforts for solving charging scheduling should be put into developing efficient market based mechanisms in decentralized and stochastic environment, such that self-interested stakeholders are coordinated and the desirable outcome can be obtained under the information asymmetries, exogenous uncertainties from dynamic environments, endogenous uncertainties from stakeholders' preferences and utilities, as well as the resource constraints.

## 8.2 Economic Reasoning and Artificial Intelligence: Machina Economicus Paradigm

A market prospective can unlock economic opportunities for MAS optimization; furthermore, AI techniques will facilitate the evolution from manual mechanism design to automated and data-driven mechanism design when gathering, distributing, storing, and mining data and state information in SI. However, the self-oriented or myopic learning goals may degrade the system-wide efficiency, where the synchronous strategy learned by these independent AIs may cause bad equilibrium in MAS in some cases, for instance, it may create another load peak in demand response. Therefore, AIs should be able to rationally respond to others' behaviors and interact like humans, while the system should also design the rules of interaction for these artificial and economic agents (selfish AIs) in MAS that creates synergies between machine learning and game theory.

With regard to 3D prospective in SI, AI field strives to build rational agents capable of perceiving the world around them, taking actions and making decisions to advance specified goals. Such new specie of machine is called as **machina economicus** [178], who is a synthetic homo economicus and can best approximate rationality given the limits of their computational resources in MAS. Machina economicus will display human like intelligence and a market view in their learning ability. They can better respect the idealized assumptions of rationality made in the economic systems than human agents, and meanwhile own much stronger abilities of computation and decision-making.

Multi-agent reinforcement learning (MARL) is the framework and field of study for addressing the learning tasks of multiple agents to obtain an optimal Nash equilibrium [179]. Some typical works can be found in [180, 181, 182]. MARL can be a deliberate framework for managing machina economicus ecosystems; however, a reality is that machina economicus could be strategic in sharing information and feedback on other AIs. Given this, the prospect of an economy of AIs has inspired expansions to new mechanism design settings, where AIs are provided with economic incentives and encouraged, as not only a policy-learner, but also a policy-maker, to jointly coordinate the operation of SI components and pursue their own benefits that are aligned with the social good. The era of AI and IoT motivates us to perform sufficient explorations for designing machina economicus systems and the related interaction or negotiation protocols, which decides when, what information and with whom to communicate in SI, such that agents can learn and generalize from the strategic interactions in unconstrained domains with the information asymmetries and dynamics being well tackled.

## 8.3 Promising Practices in Future Smart Infrastructures

The synergetic development of machina economicus and SI will raise many promising practices in 3D environments. The design of machina economicus ecosystems will admit more complex interfaces in intelligent transportation systems, smart grids, and smart cities, which at the same time provides collaboration opportunities with machine learning, innovative collective intelligence and interaction rules in game theory, as well as research thrust to machina economicus-centered system structures. In what follows, we will discuss several promising practices that concretely embody the machina economicus paradigm combining the current research gaps in 3D environment with the technology advances in the smart infrastructure.

### 8.3.1 Grid-Interactive Transportation System Management

The implementation of transportation electrification provides more opportunities for low/zero-carbon vehicles, which should be incorporated with government policy goals, land-use planning, urban design and associated system management as integral components of the overall system design and modelling strategies [183]. Grid-interactive transportation system links users, EVs, charging facilities, power grid and renewable energies together to deliver satisfactory urban mobility services, manage AVs, and optimize energy utilization [68, 101]. The key is to achieve Nash welfare against system integration complexity. Another typical application domain is smart traffic control, which integrates the heterogeneous data streams, such as IoT, smart sensors, or social media [184]. The future traffic control will not only requires traffic flow prediction and dynamic pricing to avoid congestion, but also connect with AVs and drivers to obtain more travel and preference information.

Most game theoretical, stochastic optimization and machine learning based approaches are mainly applied for solving energy management problems [33, 42, 46, 104], yet rarely developed for space assignment and routing in transportation fields. The future charging scheduling problems is supposed to achieve a systematic efficient outcome that maximizes the social welfare and charging resource utilization, taken into account the drivers' transport needs with charging demands, and the limited number of charging points and power capacity of the charging service equipment.

### 8.3.2 Pricing-Driven Demand Response in Smart Grids

Designing market-oriented pricing scheme for charging turns out to be challenges in an EV-centered network. Multiple charging stations need to set electricity prices independently based on local observations and the presence of other stations, which indicates the expected reward for a policy of a specific station depends partially on the pricing settlement the other stations in the network. However, the demand response field has rare works on simultaneous dynamic pricing scheme for multiple entities, most of them adopts centralized approaches [85, 185]. Since all stations are updating their prices simultaneously, the environment becomes non-stationary from the perspective of any individuals, making the coordination of policies and maximization of long-term revenue of the network challenging. It is important to consider long-term revenue of a charging network with the characteristics of power loads, unexpected arrivals, uncertain charging demands and private preferences of the self-interested users. Multi-agent reinforcement mechanism design framework, as an extension of reinforcement mechanism design [15], can be a deliberate choice for EV-based dynamic pricing problem for a microgrid charging network. The charging prices for several charging stations are determined over a period simultaneously, with an objective of maximizing the long-term revenue of the charging network considering the characteristics of power loads, unexpected arrivals, uncertain charging demands and private preferences of the self-interested users. The strategic station-user interaction is modelled as a sequential mechanism design problem over a time period; while the coordination among stations is modelled as an Markov game and solved by multi-agent reinforcement learning algorithms.

### 8.3.3 Electrified Mobility-on-Demand: Autonomous Vehicle Operation in Smart Cities

Autonomous vehicles (AVs) can automatically plan their route, park in the charging station and support V2G [186]. The future Robo-taxi, individual or shared AV will possess great potential to coordinate the pick-up services, path planning, battery management, and charging/discharging/swapping schedules through bidding at different markets. The goal is to maximize their long-term economic benefits, efficiently manage the charging time, utilize the renewable energies and charging space, and serve mobility-on-demands in urban areas. Such intelligent and connecting vehicles are able to reason about other machina economicus and operationalize rationality to make complex compromise-benefit trade-offs given the data received from the charging facilities, customer mobility demands and/or smart grids, and thus can pursue the individual well-beings with the system efficiency.

### 8.3.4 V2X-Based Energy Management in Microgrids

Vehicle to X (grid, vehicle, building, or home) paradigm can unlock further flexibility potentials [2]. Vehicle to grid [187], Vehicle to vehicle [188], Vehicle to building/home [180, 182] should allow EVs and DERs to actively participate in the automated control process with their privacy and preferences being respected. These technologies enable a smoother integration of EVs with power systems and variable renewable energies, which should allow EVs and distributed energy resources to actively participate in the automated control process with their privacy and preferences being respected. To achieve a systematic operational efficiency, ahead-of-time scheduling and real-time control framework can integrate photovoltaic charging station supply, charging and discharging of EVs, and real-time energy management [189]. Furthermore, incentive-based mechanisms should be designed to make electricity users understand the operational implications of, and agree to, autonomously chosen trading decisions and participate in these markets. On the top of the existing literature, multi-layer sequential decision-making framework for energy management can jointly solve electricity purchasing and dynamic pricing of charging stations, and charge/discharge control of EVs. The multi-stage strategic interaction of station-station, station-user and user-user can achieve social good solutions with efficient interacting rules and machine learning algorithms.

### 8.3.5 Machina Economicus at Heterogeneous Markets

The selfish, intelligent agents may be designed, deployed, owned, or operated by a myriad of different parties. The agents have different distribution of types [190]. Market operations in the smart infrastructure need to adjust to a larger variety of heterogeneous entities and allocate resources in a fair and Nash-optimal manner [191]. Addressing the conflicting goals requires not only effective learning approaches and framework, but also proficient interaction rules and negotiation protocols, which will create more potential applications. Simultaneous auction framework can be a deliberate choice for agent to interact at different markets and compete for multiple resources simultaneously, which has been successfully applied to spectrum auction [147]. Moreover, there is potential to transfer models, data and knowledge across heterogeneous markets in terms of the insufficiency of data and domain of interest, which will greatly improve the performance of learning by avoiding much expensive data-labeling efforts [192]. This is especially critical in learning agent's utility function in the smart infrastructure; economic theory always uses a generalized logarithmic utility model as the premier model of financial markets [193]. However, the distribution of agent preference always changes and varies in different real-world applications that makes logarithmic model inaccurate, and it is expensive or impossible to collect the training data and rebuild the models. Transfer learning between application domain and shape the rewards by learning the increments based on the baselines of classic utility models could be a deliberate way.

## 8.4 Closing Remarks

The future smart infrastructures will focus on the management of intelligent and selfish AIs that directs the performance of the whole system. In the AI era, new frontiers of network topology, management, and operation schemes of the smart infrastructure are emerging, which remains many fundamental open issues and challenges in the machina economicus-centered ecosystem. These questions encourage us to explore and understand how to design and manage such ecosystem in the smart infrastructure that represents the economy of AI. Currently, AI has surpassed humans in some domains but more likely acted to assist human's decision-making. We expect the future AI is capable of thinking and behaving like humans, and replace more human side decision-making, and additionally, learn to interact and cooperate with other AIs. Along this trend, our main focus will be on designing, implementing and optimizing the smart infrastructure and make it robust against machina economicus's rationality and the collective, strategic behaviors, as well as the critical features in 3D environments.

An economic-AI prospective that we present is arising various challenging issues and encouraging applications in the smart infrastructure. For instance, autonomous driving is creating a hybrid society comprising vehicles and cyber systems, and brings numerous social and economic impacts of V2X coordination to future grid-interactive transportation. Towards the advances of AI technology, economic theory has the appealing prospect of widening the applicability of machine learning and optimization techniques to more real-world applications. Achieving system-wide optimality is sometimes inapproachable, we instead aim to pursue slightly sub-optimal, computational beneficial equilibria with multi-objective optimization, game theory, machine learning, and data-driven decision-making framework. Additionally, the computational costs associated with the deployment of such framework should be small. By incorporating the data collected from IoT devices, numerical simulations, agent inputs, or physical experiments, machine learning techniques can model and accelerate the sequential/online decision-making process, and address data that is not known analytically for complex system prediction.

To achieve integrated economic-efficient solutions, we expect that the techno-economic framework can be developed in the future as an integrated solution for managing and operating large-scale machina economicus ecosystems in the smart infrastructure, such that the objectives related to the infrastructure and the economic requirements can be fulfilled when facing with big data, constraints and uncertainties in predictions of system status, as well as agent's strategic behaviors. Such expected computational intelligence framework can incorporate the domain knowledge or predictions about smart infrastructures in 3D environment and the private information about agents' preferences in mechanism design or optimization to enhance the operational efficiency and guarantee good equilibrium conditions of the whole system. Studying and understanding how to achieve such social equilibrium in the machina economicus-centered smart infrastructure is a strong venue for the future work.

# Chapter 9

# Conclusion

In this Ph.D. dissertation, we presented our research accomplishments in the field of advanced mechanism design for EV charging scheduling problem and dynamic pricing-based demand response problem in the smart infrastructure. We discussed the background and presented a review of the related works as well as a taxonomy for the classification to lay the foundation of this research. We identified the important features and theoretical foundation of the charging scheduling and demand response problems in urban areas, highways or microgrids; after that, we mathematically model these charging scheduling problems and solved them by designing specific market-based mechanisms in different scenarios. We discussed the advantages and limitations of our approaches and identified their application areas, and we also validated each proposed mechanism, either theoretically or experimentally. Finally, we outlined future directions of research that may stem from my current research.

In this thesis, we focus on a market prospective on charging resource allocation in decentralized environments and investigated many different aspects of such mechanism design problems to get a comprehensive picture of the domain and our methodology. The key contribution is to design specific market-based mechanisms and interaction rules for addressing EV charging scheduling problems. To be specific, we integrate the scheduling problem specific solving structure and optimization techniques to auction-based decentralized scheduling system design. Moreover, we also integrate mechanism design with reinforcement learning to accommodate a variety of dynamic settings and agents' changing preferences. The proposed advanced mechanism design framework provides various collaboration opportunities with the research expertise of machine learning with innovative collective intelligence and interaction rules in game theory and optimization theory. We believe that our thesis will have a significant contribution to both the green energy industry and academic research. In addition, the successful implementation of our methodology will encourage researchers to look into the promising practices in intelligent transportation system, smart grid and smart city environments that may be supported by AI technology, game theory, optimization and mechanism design-based approaches in general.

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# List of Publications

## Journal papers

- **L.Y. Hou**, J. Yan, and C. Wang, "Incorporating Rationality into Artificial Intelligence: Machina Economicus Paradigm, Methodologies, and Practices in the Smart Infrastructure", ***IEEE Computational Intelligence Magazine***, 2020.10. (Under Review)

- **L.Y. Hou**, J. Yan, C. Wang, and L.J. Ge, "A Simultaneous Multi-Round Auction Design for Scheduling Multiple Charges of Battery Electric Vehicles on Highways", ***IEEE Transactions on Intelligent Transportation Systems***, 2020.4. (Revision Required)

- **L.Y. Hou**, J. Yan and C. Wang, "An Incentive-Compatible Combinatorial Auction Design for Charging Network Scheduling of Battery Electric Vehicles", ***Journal of Integrated Design and Process Science***, 2020.4. (Revision Required)

- **L.Y. Hou**, C. Wang and J. Yan, "Bidding for Preferred Timing: An Auction Design for Electric Vehicle Charging Station Scheduling", ***IEEE Transactions on Intelligent Transportation Systems***, vol. 21, no. 8, pp. 3332-3343, Aug. 2020

## Conference papers

- **L.Y. Hou**, S. Ma, J. Yan, C. Wang and J.Y. Yu, "Reinforcement Mechanism Design for Electric Vehicle Demand Response in Microgrid Charging Stations", *The International Joint Conference on Neural Networks* **(IJCNN'20)**, 2020.3.

- **L.Y. Hou**, J. Yan and C. Wang, "Accommodating More Users in Highway Electric Vehicle Charging through Coordinated Booking: A Market-Based Approach", *in 2019 IEEE 23rd International Conference on Computer Supported Cooperative Work in Design* **(CSCWD'19)**, 2019, pp. 476–481.

- **L.Y. Hou** and C. Wang, "Market-Based Mechanisms for Smart Grid Management: Necessity, Applications and Opportunities", in *2017 IEEE International*

*Conference on Systems, Man, and Cybernetics* **(SMC'17)**, 2017, pp. 2613–2618.

## Book chapters

- **L.Y. Hou**, C. Wang, and J. Yan, "Electric Vehicle Charging Scheduling in Green Logistics: Challenges, Approaches and Opportunities", in ***Sustainable City Logistics Planning: Methods and Applications - vol.1***, ed. Anjali Awasthi, Katarzyna Grzybowska, Nova Publisher. 2019.5.