Understanding Electric Vehicle Refuelling Demand and Parking Patterns in Forecasting, Planning and Scheduling: A Literature Review

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***Abstract*— Vehicle electrification presents challenges and opportunities across multiple sectors, including the automotive, energy and infrastructure domains. Battery charging and swapping are the two primary technologies for refuelling electric vehicles (EVs). However, the involvement of multiple participants and various factors makes EV refuelling a complex and multi-domain issue. Since conventional conductive charging requires vehicles to remain stationary for a period of time, parking naturally provides opportunities for EV charging. Therefore, parking and EV charging are intrinsically connected in how they are organised and planned. This paper presents a comprehensive literature review on the features of EV refuelling demand and its relation to parking patterns. The review focuses on key study issues related to the interaction between EVs and the power grid, namely forecasting, planning, and scheduling. These issues are examined at three different scales: the individual, station, and regional levels. Based on the findings from the literature, an integrated framework is provided to capture the features and linkages between refuelling demand and parking patterns across the different study issues and scales. Finally, the paper proposes several open issues that could be explored in future studies from the perspective of integrating parking and refuelling analysis.**

***Index Terms*—Electric vehicle; Refuelling demand; Parking pattern; Review**

I. Introduction

Electric vehicles (EVs) are rapidly growing in their use around the world, but the success of EV technology is partially reliant on the development of charging and battery swapping facilities [1], [2], [3]. This development needs to fit with the refuelling demands of EV users while considering the impacts of load on the electricity grid [4]. The integration of EVs with the grid raises questions about how, when, and where users choose to recharge [5]. Meanwhile, refuelling cost and experiences of EV users might affect their (and other users') future purchase decisions [6], [7], [8], [9]. Therefore, deeply understanding EV refuelling demand is crucial for the development of the EV industry.

The elements included in EV refuelling demand are complex, involving transportation studies [10], electrical studies, and behaviouristics [11], among other factors. Diverse understandings of the EV refuelling demand can be found according to different stakeholders in the refuelling process. For example, EV users focus more on the quality of service (QoS) and costs, while EV charging station operators are more concerned with profitability and construction costs [12], [13]. The involvement of multiple stakeholders and diverse considerations in the issues of forecasting, planning and scheduling, which are the three main focuses in the field of the interaction between EVs and the grid, makes EV refuelling demand a multi-domain integration challenge.

Prior published reviews have adopted several concepts to understand EV refuelling demand, which can be mainly categorised into the macro perspective [14], [15], [16], [17] and micro perspective [1], [18], [19]. Macro reviews consider the need for more EV facility construction and more power capacity, as the deployment of EVs increases. Energy policy, economic development and zero-carbon electricity are the main factors identified as affecting EV refuelling demand in previous reviews. Refuelling demand considered from the macro-perspective is relatively broad and generalised, focusing on large-scale trends and infrastructure needs, rather than individual charging behaviours. In contrast, the micro perspective on refuelling demand concentrates on specific issues, such as facility planning [20], [21], [22], [23], trend forecasting [1], [15], [24], [25], [26], [27], and operational strategy optimisation [14], [21], [28], [29], [30], [31]. The original contributions of this review paper, relative to existing review papers, are twofold. First, unlike prior reviews that have typically focused on individual aspects, this paper integrates forecasting, planning, and scheduling and explores the interrelationships among them, thereby providing a comprehensive framework for analysing EV–grid interactions. Second, we systematically review and clarify the role and conceptual boundaries of EV refuelling demand across these study issues,

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as these conceptual definitions have been relatively ambiguous in previous studies and often are inconsistent across multiple fields.

Specifically, integrated with some recent reviews of charging technologies [21], [29], [30] and battery swapping technologies [23], [31], some key issues that emerge may be summarised as follows:

1) The classification and management of EV refuelling demand.
2) The association between refuelling demand and activity-based travel behaviour.
3) The prediction of parking duration and energy requirements during a charging event.
4) The optimal charging strategies from the EV user's perspective.
5) The impact of charging load on the power distribution network.

These five issues are inherently connected. The classification of EV refuelling demand and its linkage with travel behaviour lays the foundation for predicting parking duration and energy requirements. These predictions inform user-oriented charging strategies, whose aggregated outcomes ultimately shape the impact on the power distribution network.

It can be noted that there are multiple perspectives on EV refuelling demand depending on the study issues and study scales [32]. For example, in terms of different study issues, the EV refuelling demand focuses on power demand in some operation optimisation studies, while the focus is on user charging willingness in the context of facility planning. The charging demand at an individual level is concerned more with a user's habits and preferences, while the regional-level charging demand focuses on results aggregated into spatial-temporal distributions rather than focusing on one single charging event. Therefore, a gap exists in the differing conceptualisations and considerations of EV refuelling demand across different issues and study scales. It motivates us to provide a comprehensive review paper that bridges these perspectives, offering a more integrated understanding of EV refuelling demand.

Parking is a particularly important activity in this context. Considering conventional conductive power transmission, the parking time and location of EVs provides an opportunity to recharge a vehicle. The connection time between EVs and the grid is limited by the arrival- and departure time, while the charging power may be constrained by technical parameters (e.g., voltage bias, power loss) of the power distribution network where the parking site is located [29], [33]. More importantly, EV parking provides an opportunity for conducting an EV charging power profile optimisation, such as designing a delay charging scheme or utilising vehicle-to-grid (V2G) technologies to reduce the impact of the charging load on the power distribution network, based on the parking time after a complete charging process [34], [35], [36], [37]. Therefore, exploring EV parking patterns may help in analysing EV charging demand, as parking is a pre-condition of charging. Understanding the relation between refuelling demand and parking patterns may therefore support future grid operations (e.g., potential EV charging load in different regions), facility planning (e.g., appropriate construction locations) and policymaking (e.g., demand-driven subsidies for the construction of parking lot chargers).

As mentioned above, this paper aims to provide an integrated review of EV refuelling demand and parking patterns across forecasting, scheduling and planning issues, particularly related to the interaction between EVs and the grid. This review focuses on the systematic description of the above three issues and the considerations of the EV refuelling demand and parking patterns, rather than the detailed technical developments in one issue. The key questions addressed in this paper include the following aspects:

(1) What features, issues and study scales have been considered in previous studies of EV refuelling demand?
(2) What features, issues and study scales have been considered in previous studies of EV parking patterns?
(3) How have previous studies incorporated EV parking patterns into the analysis of EV refuelling demand?

Based on these questions, the present paper provides insights into to the extant literature in the following ways:

(1) A survey of EV refuelling demand and parking patterns from the micro-perspective level is provided based on different study scales (i.e., individual-, station- and regional levels). EV refuelling demand is characterised by time, location, power and energy; while parking pattern modelling is classified into statistical, activity-based and scenario-based methods based on time, location and intention features.

(2) Previous methods related to EV refuelling demand forecasting issues are critically reviewed. The planning issue is categorised into siting and sizing and reviewed based on the main optimisation objectives and solutions. The scheduling issue is also examined according to the main optimisation objectives and solutions, while considering the charging technologies (e.g., V2G, fast charging). The study scales, refuelling demand features and parking pattern modelling methods are labelled for each study.

(3) An integrated framework incorporating the issues of forecasting, planning and scheduling is proposed, with the aim to link the relations between and features of refuelling demand and parking patterns. Open research issues are presented at the end of this review.

The structure of this paper is as follows: Section II firstly provides the key terms used in this paper and their definitions. Section III provides a classification of the study scales related to EV refuelling demand in the context of forecasting, planning and scheduling. Section IV focuses on a literature review of EV refuelling demand features. Section V summarises the modelling methods adopted in previous studies of EV parking patterns. The models and solution methods considered for forecasting, planning and scheduling are reviewed in Section VI, with a particular focus on the consideration of EV refuelling demand and parking patterns. Section VII provides a framework integrating the above three issues, highlighting features related to refuelling demand and parking patterns, followed by a discussion of some open issues. Finally, Section VIII concludes this review paper.

II. Key terms and their definitions

We firstly summarised the key terms used in this paper and proposed their definitions as some of them have different meanings in multiple fields. Before delving into the detailed discussions, clarifying these terms ensures a common understanding and provides a consistent framework for the subsequent analysis. These key terms are generally divided into three main parts:

(1) *Key terms related to study issue*. Previous studies identify forecasting, planning, and scheduling as the three main study issues in the interaction between EVs and the power grid. Forecasting refers to predicting EV refuelling demand and charging behaviours. Planning involves designing and allocating infrastructure and resources, such as charging stations and energy capacity, to meet anticipated demand efficiently. Scheduling concerns the real-time coordination of charging activities, including the assignment of charging power and timing to individual EVs, in order to optimise objectives such as cost, grid stability, or user satisfaction. In these study issues, the study scale can be classified according to the scope considered: individual level (focusing on EV users), station level (considering users and charging stations), and region level (encompassing users, stations, and the wider power grid). These issues and related scales provide the main benchmarks and features for reviewing current publications in this paper.

(2) *Key terms related to EV refuelling demand*. EV refuelling demand encompasses both battery charging demand and battery swapping demand, which are currently the two primary pathways for replenishing electricity in EVs. From the perspective of the refuelling process, these demands can be further characterised in terms of energy, time, location, and power requirements. Energy demand captures the quantity of electricity consumed over time, whereas power demand describes the rate at which electricity is delivered at a specific instant. Across the current publications, the definition of EV refuelling demand is relatively ambiguous, as it often represents one or more of these four characteristics. Therefore, in this paper, we sought to investigate the clarify the conceptual boundaries of EV refuelling demand in previous literature.

(3) *Terms related to EV parking patterns*. Parking patterns describe the behaviours of EVs while parked and can be characterised by time (e.g., plug-in and unplug times, duration of parking), location (e.g., charging station or regional context), and intention (e.g., charging purpose or general parking). Across the literature, the representation of parking patterns varies depending on the research scale and focus, highlighting the need for a consistent description.

III. Study Scales

EV users are the fundamental unit for generating refuelling demand. Stations or regions do not generate the EV refuelling demand, which is aggregated from users in those stations or regions. The problem of forecasting on larger scales is essentially one of aggregation of individuals. It should also be emphasised that the core driver to achieve scheduling or planning remains satisfying the refuelling demand of individual EV users in different ways, such as utilising the Time-of-Use (ToU) pricing to guide users' charging behaviours to reach the goal of the grid management. However, considerations of EV refuelling demand and the modelling of EV parking patterns are different across different study scales. In this paper, the study scale of the EV refuelling demand and parking pattern problem is categorised into the individual-, station- and regional levels (as shown in Fig.1). For an individual charging process, plug-in time, unplug time, charging power, and the corresponding charging energy are four key factors (see 'individual-level' in Fig.1). From the station perspective, these factors are aggregated across all charging EVs, and the analysis extends beyond single charging sessions to include their temporal distributions (see 'station-level' in Fig.1). At the regional level, however, demand should be assessed jointly in both temporal and spatial dimensions, with the time horizon extending well beyond individual sessions to long-term projections over the next several years (see 'region level' in Fig. 1).

The classification of the study scale primarily considers the focus of the study issue being addressed. For example, in terms of a charging scheduling issue in a charging station, when the optimisation objective is to reduce the charging cost of individual users, the study scale is on the individual level, which means the focus is on an EV user rather than the operator of the charging station [38]. It should be noted that the charging power of the charging station is limited to the power distribution network. Therefore, the maximum charging power of all EV users simultaneously should be less than the limit from the power distribution network, which means the objective of reducing the charging cost of individual users is constrained by the power limit of the charging station, especially when there are many users in a station simultaneously. The most typical case is the bi-level framework with an upper-level consideration in keeping the safety of the power distribution network and a lower-level optimisation objective at an individual scale [39], [40], [41]. The output of the upper-level is the constraint of the lower-level. In contrast, if the objective is to minimise the energy cost of a charging station while still scheduling the charging schemes of EV users, the study scale should be classified at the station level, as the focus is centred on the charging station rather than individual EV users [42]. The charging demand of an individual user is the constraint to achieving the optimisation objective. Moreover, the multiple objectives of an optimisation model, including both maximising the charging demand of individual users and maximising the total revenue of the charging station, should be defined as two study scales [43].

The classification of study scales can be found in the tables in the Appendix. Specifically, at the individual level, the focus is primarily on the trade-offs between travel mileage, refuelling

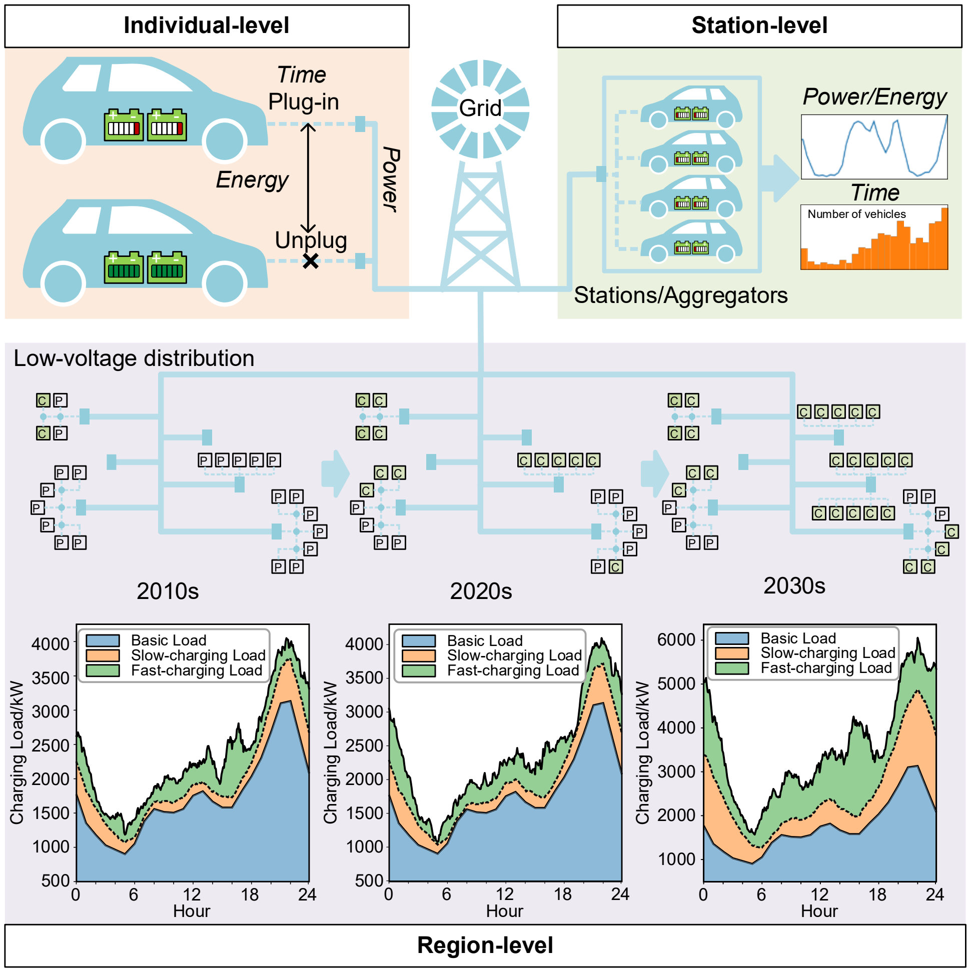

Fig.1 The study scales and features of EV refuelling demand and parking pattern.
Note: The simulation is based on the IEEE 33-bus system with 10,000 vehicles. The slow-charging and fast-charging load are determined by the market share in different years. The EV charging behaviours are collected from [41] and the basic grid load is a typical shape in a residential area.

time and price [44], [45]. Individuals are more concerned with how to refuel enough electricity to satisfy their next trip within the limited parking time available. At the station level, the refuelling demand of a station or a limited area (e.g., parking lot, residential site) is formed from the integration of individual user demands. Therefore, one of the primary objectives for station operators is to maximise the number of EVs fulfilling their recharging requirements. Additionally, optimising the management of parking space and charger operation is highly beneficial, as both efforts contribute to increasing operational profits for station operators. From an economic perspective, reducing operational costs and initial construction costs are two other key objectives explored in previous studies. When station operators also function as aggregators (an entity that coordinates distributed energy resources, such as EVs, to collectively provide services to the electricity grid [46]) or establish protocols with local grid operators, they can generate additional revenue through V2G (for charging stations), battery-to-grid (B2G) (for battery swapping stations), or coordination with the power distribution network. Grid-side indicators such as minimising power loss, reducing peak charging power, and stabilising load fluctuations are prioritised to ensure the safety and reliability of the power distribution network. Consequently, the objectives at the station level can be categorised into three fundamental areas: QoS for EV charging, economic objectives, and grid-side objectives. When considering the regional-level demand, the objectives are still based on these three aspects. However, the matching and scheduling among refuelling demand, facility supply, and grid operation are considered more in the spatial-temporal dimensions [47], which highlights the importance of planning issues in regional-level research.

IV. Features of EV Refuelling Demand

With the growth in EV usage, EV refuelling demand has become a critical factor influencing the stability and sustainability of the electricity grid. EV refuelling refers to the process of recharging the battery of an EV with electricity at specific locations, such as homes, workplaces, shopping malls, charging stations or battery swapping stations. This process involves connecting vehicles or batteries to the electricity grid, factoring in plug-in and unplug times, locations, electricity requirements, and charging power. Based on previous studies, the features of EV refuelling demand include four aspects: time, location, power and energy. The features of EV refuelling demand can be found in the tables in the Appendix.

A. Time Demand

'Time demand' is a term used to represent when EV users would like to charge a vehicle or swap a depleted battery, which is a part of a user's electricity refuelling willingness [10], [48], [49], [50]. It mostly includes vehicle plug-in time/battery swapping time, connection duration, unplug time and electricity refuelling frequency. In some cases, time demand can be described as the number of charged EVs at a given point in time [43], [51], [52], [53], [54], [55], [56]. The time demand distributions might be affected by usage behaviours [35], battery state-of-charge (SOC) [57], ToU [58], availability of chargers [59] and even the electricity refuelling methods [60].

At the individual level, understanding time demand helps users reduce refuelling costs, whilst providing insights into the times of the connection between different EVs and the grid. This is crucial for optimising resources in charging stations or battery swapping stations. At the station level, time demand aggregated from individual users can be used to coordinate the scheduling of power distribution networks. The overlap between charging time demand of EV users and peak electricity demand periods may lead to stress on the power quality and operational safety of the electricity grid [61]. At the larger regional level, time demand (as incorporated into spatial-temporal demand distributions) may be used to support grid operation and facility deployment.

B. Location Demand

Location demand is another basic information aspect of EV refuelling demand. It is also a key component of refuelling willingness, representing where EV users prefer to recharge their vehicles. In general, it represents the EV refuelling demand in a specific site (i.e., a description of the location type) at the individual- and station levels, while the spatial distribution and patterns of change are the focus of the regional-level studies. The considerations of location demand mainly include refuelling location types, spatial distributions and mobility patterns. Typically, refuelling location types involve home charging, work charging, public charging stations or battery swapping stations, among others. EV parking location can provide potential candidate sites. Therefore, the spatial distribution of location demand has significant implications for the planning and management of EV facilities, particularly in the siting and sizing issue [48], [54], [62], [63], [64], [65]. In addition, location demand is often coupled with the power distribution network, as power limitations are a critical factor in EV refuelling facility construction [66]. Aligning EV refuelling demand with charger availability and power supply can enhance facility efficiency and improve operational profitability [67]. Identifying the low refuelling demand locations and guiding users to refuel their vehicles can also be beneficial to the EV charging service.

C. Energy Demand

Energy demand is defined as the total electricity (usually with a unit of kWh) required by a vehicle from the power grid or through swapping a battery at a station (e.g., per charging session, daily, weekly) [43], [68], [69], [70]. Satisfying individual EV energy demand is a key metric for assessing the performance of any charging scheduling scheme, i.e., for assessing the QoS experienced by EV users [41]. A better understanding of energy demand at a station level could support EV charging load analysis and forecasting, enabling optimisation of the balance between energy supply and consumption, such as shifting charging energy to off-peak hours to reduce grid strain and maximising the use of renewable energy resources [35], [50], [58], [71], [72], [73], [74], [75]. When this information is combined with knowledge of location demand at a regional level, charging stations or BSSs can be strategically placed to meet both energy and location demand of EVs. This facilitates better planning and optimisation of infrastructure, ensuring efficient energy distribution that aligns with EV usage patterns. Such measures not only improve service quality but also contribute to a more resilient and sustainable energy system by reducing grid stress and increasing the integration of renewable energy sources.

D. Power Demand

Power demand is defined as the instantaneous power consumption (usually with a unit of kW) of a vehicle or battery as it accesses the electricity grid at any time during the charging process, representing the charging rate [48], [76], [77]. Different from focusing on a continuous period, the instantaneous EV power demand reflects the real-time power required at a specific moment. Power levels, fluctuations and the impact on the electricity grid are the main concerns at the individual, station and regional levels. Higher power demand can lead to a rapid increase in stress on the electricity grid, affecting the power quality and even the operational security. Charging power is the direct object scheduled when designing an optimal charging scheme. For EVs with swappable batteries, battery swapping is a more suitable option when users have an urgent refuelling demand. Different from grid-connected charging, there has more flexible charging time for the batteries swapped the EVs, as it doesn't serve for the vehicle's next trip immediately. Therefore, the impact of charging power of these swapped batteries may not work on the power distribution network immediately, which means the battery swapping stations have more advantages in optimising the power system load and reducing the pressure on the grid. Moreover, when considering facility planning, power demand serves as a critical indicator for determining the grid configuration of a node [10], [35], [49], [50], [63], [72], [78], [79], [80], [81]. In general, different charging technologies, such as direct current (DC) fast charging, alternating current (AC) slow charging, V2G in charging stations, vehicle-to-vehicle (V2V), and even battery swapping technology are the main approaches to satisfy EV power demand.

V. PARKING PATTERN MODELLING

Referring to the parking behaviours of internal combustion engine vehicles, three dimensions of the EV parking pattern are identified: time, location, and intention [82], which share some similarities with EV refuelling demand. Time refers to the duration of parking, which influences the potential charging

TABLE I
DEFINITIONS AND LINKS BETWEEN THREE KINDS OF PARKING PATTERN MODELLING METHODS.

Method	Core idea	Pattern source	Focus	Relations to others
Scenario-based	Fixed patterns for specific contexts	Predefined parameters / typical cases	Population	• Can be derived from Statistical data • Can be combined with Activity-based methods to capture individual differences.
Statistical	Macro-level patterns from historical data	Fitted distributions / empirical data	Population	• Can provide macro-level distributions for Activity-based methods • Can validate the reasonableness of Scenario-based parameters
Activity-based	Parking as part of individual travel chains	Daily activity sequences	Individual	• Can be aggregated into statistical distributions • Can be combined with Scenario-based methods to reflect individual differences.

window—longer parking times (e.g., at home or work) are conducive to slow, overnight, or daytime charging, while shorter stays (e.g., at shopping centres) often align with fast-charging needs. Location indicates where the vehicle is parked, which supports the construction of charging facilities. Unlike internal combustion engine vehicles that refuel at centralised fuel stations, EVs charge at a variety of locations, including residential areas, workplaces, and public parking lots, while battery swapping has a similarity with traditional gas stations. Finally, intention describes the purpose behind parking, which affects the likelihood and necessity of charging. For instance, drivers parking with the intention of running errands may seek a quick top-up, while those parking at home overnight may aim for a full charge.

A. Parking Time Pattern

Parking time primarily encompasses vehicle arrival time, departure time and parking duration. These three indicators are combined to formulate the EV parking time pattern, which subsequently supports power allocation, energy scheduling, and grid impact assessment. There are four main approaches used to establish parking time patterns: scenario-based methods, statistical methods, aggregation-based methods, and activity-based models (as shown in Table.1).

i) Scenario-based method: This method defines parking time patterns by constructing a set of fixed, context-specific situations (scenarios, such as residential buildings, workplace parking lots, and shopping centres), typically based on location type or user group. Each scenario reflects relatively stable behaviour patterns in a specific place. For example, residential areas typically exhibit long-duration, overnight parking, as most users leave their vehicles parked from evening until the next morning. Workplace locations are characterised by medium- to long-duration parking during daytime working hours, with vehicles arriving in the morning and departing in the late afternoon. For instance, Sánchez-Martín et al. [83] used scenarios based on a household mobility pattern (morning departure and evening arrival-parking pattern) and commercial mobility pattern (morning arrivals and evening departures). Kumar et al. [84] considered the combination between EVs and metro railways, utilising 15-minute and 30-minute parking duration patterns. Wu et al. [85] used scenarios based on some extracted, typical patterns of public usage vehicles such as day-long stops, morning peak-time stops, daytime stops, afternoon peak-time stops, and nighttime stops. Nevertheless, the parking time pattern of this method is determined by predefined parameters rather than by sampling or stochastic simulation. Thus, the modelling is suitable for a specific scenario, while the differences between EV users cannot be reflected well.

ii) Statistical method: This method is another fundamental and widely used approach for establishing EV parking time patterns. It characterises parking behaviour by assuming that key variables (arrival time, departure time, and parking duration) follow given statistical distributions and generates parking events through probabilistic sampling from these distributions. Two of the above three distributions are assumed to generate parking events. It is typically assumed that these variables follow a standard statistical distribution, such as the uniform distribution [55], Poisson distribution [56], [61], [72], [73], Gaussian distribution [86], Gamma distribution [70], generalized extreme value distribution [87], exponential distribution [70] or even empirical distributions [62], [80], [88], [89], [90], [91], [92], [93]. Monte Carlo (MC) methods are commonly employed to simulate EV parking behaviour. Different from the fixed patterns in scenario-based methods, parking behaviours are extracted from feature distributions, which means that user's behaviours are not fixed but follow some specific statistical rules. Therefore, more potential parking patterns can be considered in this modelling, which could support more accurate demand forecasting, infrastructure planning, and evaluation of different operational scenarios.

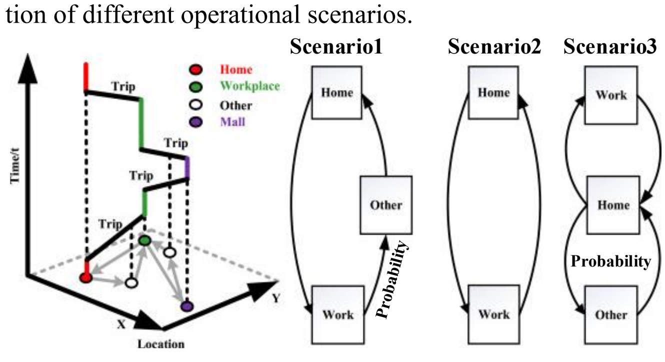

Fig.2. A typical activity-based model with driving, parking and charging [29].

iii) Activity-based model: This method is commonly used to simulate the individual daily travel behaviour of EV users. It integrates driving patterns, charging patterns, and parking patterns, making parking time patterns just one component of the overall chain. An activity-based model includes both a statistical process and a scenario-based process, and both contribute to deriving individual-level features from aggregate behavioural characteristics in a simulation process. For example, statistical methods can estimate the probability of individuals' travel time, location or stop duration [29], [65], [94], while scenario-based methods help summarise usage patterns and to classify users into categories (such as 'Scenario 1—After-work trip' and 'Scenario 2—Work trip' in Fig.2). This approach is more applicable to users with regular travel habits, such as commuting passenger EVs and franchised buses. In contrast, establishing patterns for users with highly variable behaviour can be more challenging than for those with regular routines. Sometimes, to alleviate these kinds of irregular features, cluster algorithms are used to identify and extract activity categories. For example, Cui et al. [95] applied a Gaussian Mixture Model (GMM) and a Light Gradient Boosting Machine (LightGBM) model based on charging time, dwelling duration after charging, charging duration and charging power to cluster and recognise the charging and parking patterns. This was used to enhance the forecast accuracy of individual charging behaviour and to schedule the charging scheme to maintain security the power quality in an IEEE-33 bus system. Zhang et al. [94] used a k-means model to recognise six types of EV users with different parking proportions during the daytime (6 a.m.-6 p.m.) and night (6 p.m.-6 a.m.). These results supported the development of trip chain models and the siting of charging facilities. These results supported the development of trip chain models and the siting of charging facilities. Nevertheless, parking time pattern modelled by the activity-based methods is function of the user preference, like charging habits, willingness to wait, and user type. Different users exhibit variations in travel purposes, temporal flexibility, and preferences for fast or slow charging. This heterogeneity directly affects individual parking time distributions and charging behaviours. This heterogeneity needs to be accounted for in activity-based models to improve the accuracy of charging demand forecasts and provide more reliable guidance for the planning and scheduling of charging infrastructure.

B. Parking Location Pattern

The location of EV parking is closely related to EV refuelling choices, parking duration, and power supply availability. Generally, large-scale GPS data are utilised to analyse and establish EV parking location patterns. Understanding these patterns is a key consideration in the planning of charging facilities.

i) Scenario-based method: Residential, workplace and commercial parking patterns are commonly extracted to forecast and schedule EV refuelling demand. Parking time patterns vary significantly across different locations; for instance, parking durations at residences tend to be longer and more stable, whereas workplace and commercial parking durations are generally shorter and more variable. Some previous studies have considered shifts in parking locations, such as Needell et al. [96] who considered the combination of home parking and workplace parking. Nevertheless, a fixed parking location pattern is assumed in most existing studies, mostly included in EV demand forecasting and EV charging schedules.

ii) Statistical method: The objective of this method is to recognise the location distribution of current EV parking so as to support the construction of charging facilities or battery swapping stations. Therefore, several studies have used statistical methods to identify aggregate parking locations, such as square-shaped [97], [98], hexagon-shaped (i.e., Hierarchical Hexagonal Grid [94]) and multiple shapes (i.e. Voronoi diagrams [99]). Cluster algorithms are another suitable class of methods to solve this issue. For example, Zhang et al. [94] and Zhang et al. [65] both applied Density-Based Spatial Clustering of Applications with Noise (DBSCAN) model to aggregate parking and charging locations based on GPS data.

iii) Activity-based method: Parking behaviour of EVs plays a crucial role in refuelling demand, especially when analysed through parking location patterns. The activity-based method considers how different parking locations—such as residential areas, workplaces, public lots, and on-street parking—affect charging behaviours. For instance, residential parking supports overnight charging, workplace parking enables long-duration daytime charging, while public and on-street parking requires fast-charging solutions due to high turnover. By integrating traffic flow and parking data, activity-based methods help optimise charging station planning and utilisation. However, challenges such as limited parking availability and regulatory constraints remain significant obstacles. In the simulation of an individual activity, scenario-based and statistical methods are applied in a manner similar to parking time pattern modelling. These approaches allow for more precise estimation of charging demand by capturing the variability of user schedules, trip purposes, and parking durations. Scenario-based methods enable researchers to assess refuelling and parking demand under different assumptions, such as increased EV adoption rates or shifts in workplace policies, while statistical approaches draw on historical data to reflect actual behavioural distributions. By combining these methods, researchers can achieve a more robust representation of real-world parking and charging locations.

C. Parking Intention Pattern

The EV parking intention pattern describes the motivation and activity for parking, including the purpose of parking and associated behaviours. When combined with EV parking location patterns—such as home, workplace parking, etc. [100]—it provides a comprehensive representation of parking intentions. However, for multi-functional locations such as commercial and industrial parking, parking intentions may be less predictable and harder to recognise. Matching parking intentions with parking locations can help obtain more accurate information to support EV electricity refuelling management. Several studies have explored the definition of EV parking intention patterns. For example, Pasaoglu et al. [101] defined the concept of 'active parking', which means the car is parked after a trip that is not the last trip of the day, while if the car is parked before the first trip of the day or after the last trip of the day, it should be recognised as an inactive parking. These two parking patterns may be integrated into the charging scheduling process,

TABLE II
BI-LEVEL FRAMEWORK USED IN EV REFUELLING FACILITY PLANNING AND BATTERY CHARGING SCHEME SCHEDULING

<table>
<tr><th colspan="2">Secondary issue</th><th>Highlights</th><th colspan="2">Primary issue</th><th>Highlights</th></tr>
<tr><td>Leader</td><td>Siting</td><td rowspan="2">• Sizing depends on selected sites; site selection considers capacity feasibility.
• The issue is a combination between region-level and station-level.</td><td rowspan="2">• Upper</td><td rowspan="2">• Planning</td><td rowspan="4">• Upper-level decisions constrain operation; lower-level feedback refines planning.
• Bidirectional effects and coordinated optimisation of long-term planning and short-term scheduling.</td></tr>
<tr><td>Follower</td><td>Sizing</td></tr>
<tr><td>Leader</td><td>Grid/Station operation</td><td rowspan="2">• Captures the two-way interaction between system operation and user behaviour; forms an internal bi-level structure within scheduling
• The issue is a combination between station/region-level and individual-level.</td><td rowspan="2">• Lower</td><td rowspan="2">• Scheduling</td></tr>
<tr><td>Follower</td><td>Charging scheme</td></tr>
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exploiting the fact that active parking may have more flexibility. Furthermore, EV users' willingness to wait exhibits considerable heterogeneity across various parking contexts. Differences in the purpose of the stop, temporal flexibility, and perceived urgency can significantly shape waiting tolerance, introducing additional uncertainty when linking parking intentions to charging-scheduling decisions.

VI. ISSUES AND SOLUTIONS

A. Forecasting

Refuelling demand forecasting refers to predicting the power demand [81], energy demand [102], and the number of vehicles [52], which can be classified into time demand by Section III, for specific locations in future periods. The forecasting results can provide valuable insights for grid operation, charging facility planning, and energy management, helping to optimise resource allocation and reduce the operational risks of the power distribution network caused by EV charging load. Parking patterns help predict when, where, and for how long vehicles will remain parked, which directly influences the timing and frequency of charging behaviour. A better understanding of parking patterns leads to more accurate estimates of refuelling demand, particularly in relation to charging facility layout and optimisation of EV charging schemes. Incorporating users' heterogeneous charging preferences, such as preferred charging periods, charging power choices, and willingness to wait, can further improve the accuracy of forecasting models, as these behavioural differences significantly influence when and how EV users decide to charge under different parking scenarios. Additionally, forecasting the parking patterns of EVs with battery-swapping capability can help coordinate battery charging schemes at battery swapping stations. Battery swapping operators only need to prepare enough fully charged batteries, while using other batteries for B2G. A forecasting-related literature review is provided in Table A I in the Appendix.

From the perspective of the forecasting period, it can be categorised into short-term [103], [104], [105], medium-term [106] and long-term forecasting [107], which correspond respectively to the issues of power scheduling, facility construction, and policy decisions. In terms of long-term forecasting, time series models, deep learning (DL) and scenario establishment are the main approaches. This is commonly a more macro issue, excluding the specific behavioural analysis of individual EV users or the operation of individual charging facilities. Considering the other two sorts of periods, two approaches exist for EV charging demand forecasting: model-based and data-driven [25]. In terms of model-based methods, trip chain model and agent-based model (ABM) combined with MC algorithm are the most popular methods to forecast EV electricity refuelling demand [65], [94], [108], [109], [110]. In general, the driving-charging-parking behaviour of individual EV users are simulated and then aggregated into the refuelling demand of the region. Regarding data-driven methods, time series models (i.e., AutoRegressive Integrated Moving Average [52], [111]), machine learning (ML) (e.g., Support Vector Machine [74]), DL (i.e., Convolutional Neural Network, Recurrent Neural Network, Multilayer Perceptron [25], [37], [102] and Long Short-Term Memory [103], [104], [105]) and ensemble learning (i.e., Extreme Gradient Boosting [112], [113], LightGBM [95]) have been widely used in previous studies [25]. With the advent of the era of big data, increased attention has been paid to intelligent prediction methods based on data, especially multiple-source data collection and integration (vehicle data, station data, traffic data and grid data).

B. Planning

EV refuelling facility planning, which can also be described as siting and sizing, is one of the most important factors in determining EV development. The issue of siting is typically considered at the regional level, while the issue of sizing is usually addressed at the station level. The parking pattern is a key factor in the siting and sizing issue. For example, parking duration in residential areas is usually over 8 hours, making such locations suitable for slow-AC chargers [114]. In contrast, parking durations along major highways are much shorter, making these locations more suitable for fast-DC chargers or battery swapping stations. Parking facilities, such as parking lots and on-street parking zones, are considered ideal locations for charging stations, especially in government districts, commercial centres, and along major highways [109]. Urban building regulations often mandate a certain percentage of parking spaces to be equipped with charging facilities. For example, in the U.S., commercial areas are required to allocate 5% of their parking spaces for charging stations, whereas in the U.K., a 10% requirement was proposed in 2022. As a result, the space of a parking lot largely determines the amount of chargers [115], [116]. See **Appendix** for detailed literature review results.

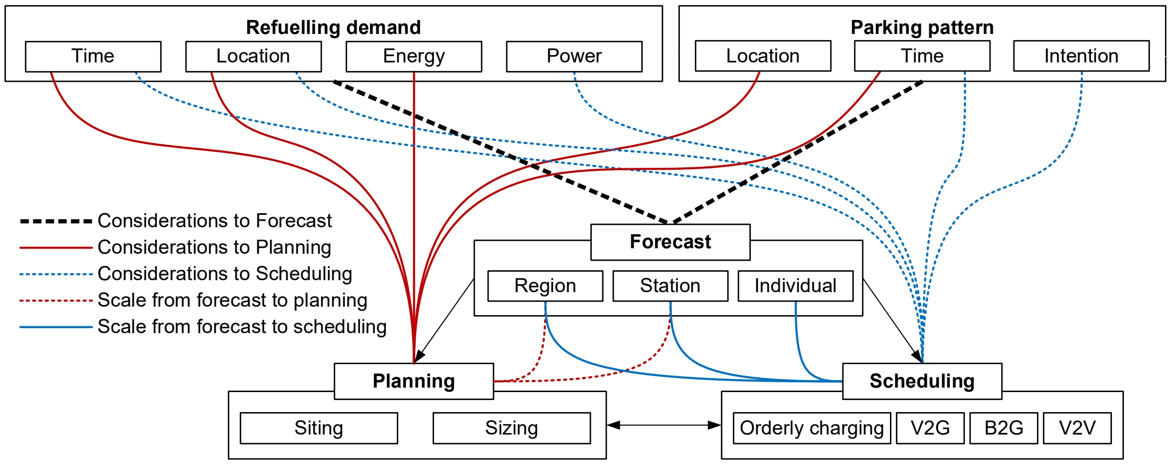

Fig.3. The integrated framework for the issues of forecasting, planning and scheduling, including the main considerations and the links in refuelling demand and parking pattern.

In terms of the siting issue, node, path, and activity-based approaches are the basic considerations in previous studies [117]. The node-based approach is the most used method for the location problem. The objective is to place charging stations at candidate locations (nodes) to meet demand, though this problem is NP-hard, meaning exact solutions are impractical within a reasonable time due to exponential growth in computational complexity with problem size. As a result, heuristic methods are often employed to provide approximate solutions within feasible timeframes. A second approach, the path-based approach, focuses on a flow-capturing model. Here, the goal is to position charging stations along paths with the highest vehicle flows, considering origin-destination trips, to maximise user coverage. Unlike the node-based approach, it responds dynamically to vehicle flows rather than a static view of demand. Lastly, the activity-based approach takes a broader view by considering the entire activity of an agent and their vehicle over a period, including origins, destinations, distances, paths, and parking duration. This approach aims to determine optimal locations for charging infrastructure based on user behaviour and activity patterns.

In terms of the sizing issue, determining the appropriate number and type of chargers or battery swapping facilities at a station involves balancing demand, power availability, and economic feasibility. Key factors include anticipated vehicle arrivals, charging or swapping duration, and station throughput, often modelled using queuing theory to minimise the charger investment cost or maximise the total profits constrained by satisfying EV user refuelling demand and reducing wait times [86], [118]. The combination of the parking pattern and sizing issue may be illustrated by the core function in queuing theory. Taking $M/M/c/N$ as an example [12], representing a scenario of a charging station with c chargers and N parking spaces, the first M represents the vehicle arrival time distribution, while the second M represents the charging duration except for EVs that do not leave the site immediately. The parking time pattern can reflect the capacity of the station directly, which stresses the importance of the parking pattern in the issue of siting and sizing.

The combination of siting and sizing is a common approach in planning. Facility siting is always the first layer, while the number of chargers and their power are determined in the subsequent step. At the upper level (the leader layer in Table. II), siting determines candidate locations at the regional or macro scale, considering traffic flow [119], parking patterns [12], land availability [120], and grid access to meet overall charging demand and coverage targets. At the lower level (the follower layer in Table. II), sizing specifies the number of chargers [12], their power ratings, and possible battery swapping capacities [121] at each site, taking into account users' parking duration and local load constraints. The upper-level siting results provide constraints and candidate positions for the lower-level sizing, while the sizing outcomes can feedback to influence siting decisions, e.g., some candidate sites may be adjusted or discarded due to insufficient capacity or economic infeasibility. This coupling can be implemented through bi-level optimisation, with the upper-level objective typically aiming to maximise regional coverage or user satisfaction, and the lower-level objective focusing on minimising investment cost [122] or user waiting time [123]. From a parking modelling perspective, the upper level mainly considers parking locations, whereas the lower level emphasises parking duration for capacity allocation.

C. Scheduling

The issue of scheduling here is mainly oriented towards charging technology, while battery charging optimisation is the concern of a BSS, which is an internal inventory management issue with less consideration necessary for the EV parking pattern. Information on parking patterns is a useful input to support offline or day-ahead planning, and real-time planning when considering scheduling issues [54]. Economy-related objectives (e.g., minimising charging cost [51], minimising charging cost, maximising total profit [69]), grid-related objectives (e.g., minimising deviation of the transformer load profile [71], minimising load fluctuation [35] and minimising peak demand of the power system [96]) and operation-related objectives (e.g., maximising QoS of EV users [41], minimising battery ageing [124]) have been the main optimisation considerations in previous studies, relevant to different participants in the system.

Adjusting the EV or battery charging scheme is the key method to achieve these optimal objectives, such as delay charging, V2G and V2V technology. In terms of delay charging technology, Cui et al. [41] defined three kinds of charging priority based on the dwelling duration after the completion of the charging process, using historical charging records. Charging power may then be determined dynamically based on this priority. Yu et al. [80] considered both regular charging behaviour and two kinds of irregular charging behaviour (with long and short parking duration) to allocate the charging power to improve the revenue of the charging pole. With a higher penetration of EVs, a strategy of first-come-first-served may put undue stress on the electricity grid. In that situation, knowledge of the parking time pattern in different locations provides the potential to design alternative charging strategies incorporating such delays. In terms of V2G technology, Zeng et al. [125] proposed the use of parking patterns with charging and discharging labels; time-oriented constraints were the main consideration in the optimisation model. Makeen et al. [124] also used a duration-based parking pattern (i.e., 1-hour and 2-hour) to design a V2G scheme. In summary, the time pattern of EV users is the basic requirement to design an efficient EV charging scheme. From Table A III in the Appendix, it can also be found that location-specific parking patterns (i.e., Residential [71], [78], Workplace [108]) and intentions (i.e., Commuting [58]) are also key dimensions used to address the scheduling issue. These patterns, when properly analysed and incorporated, can enable smoother and more sustainable scheduling strategies that align better with grid demands, economic goals, and user satisfaction.

There are also studies that consider bi-level optimisation approaches for scheduling problems. In most cases, the operation of the grid or the charging station is considered as the upper level (see Table. II), while individual EV users or aggregators constitute the lower level. Upper-level decisions, such as available capacity and load allocation, typically define the feasible actions of lower-level actors. Conversely, the responses of lower-level actors, including user charging behaviour and timing choices, determine and constrain the operational strategies of the upper-level system. This leader–follower structure within scheduling effectively captures the two-way interaction between system operation and user behaviour. In this kind of bi-level framework, the parking/charging pattern analysis are used in the lower level to determine the potential of the scheduling options for an EV user.

VII. Discussions

Fig.3 provides a framework integrating the EV refuelling demand features, parking patterns, study scales and main foci in forecasting, planning and scheduling, three important issues studied when considering the interaction between EVs and the grid. EV refuelling demand and parking patterns are the inputs to these problems. In general, forecasting plays a pivotal role in supporting planning decisions (like the rows in Fig.3), such as siting and sizing, as well as scheduling strategies, including orderly charging and V2G integration, while planning and scheduling can be constraints or considerations for each other.

In practice, as the basis for scheduling and planning, forecasting errors in EV refuelling demand or parking behaviour can propagate into planning decisions, leading to inappropriate site selection or capacity allocation. These planning decisions then constrain the flexibility of short-term scheduling, potentially causing local overloads or underutilisation of charging resources. Furthermore, once siting and sizing decisions are implemented based on forecasted data, they are difficult to adjust later, amplifying the long-term impact of initial forecasting errors.

From the perspective of the combination of planning and scheduling, these two kinds of issues can also be used in a bi-level framework. Such an optimisation formulation is able to recognise the hierarchical dependence between the two sub-problems, where planning issues are at the upper level and charging scheduling issues are at the lower level [126], [127]. This bi-level framework is more complex than those addressing the planning or scheduling issue alone, as more complicated information is considered, and more complex inter-dependencies arise. For example, such a framework can simultaneously account for factors such as battery state, charging station locations, and operational constraints, rather than treating them separately. Therefore, several key challenges arise in this context and need to be considered carefully in future modelling.

(1) The siting and sizing problem is an NP-hard optimisation task. When incorporating scheduling issues such as charging power allocation and dispatch, the computational time and resources required for the solution procedure must be carefully considered.
(2) The decision in the upper level is a long-term optimisation, while it is a short-term or even real-time decision that is made at the lower level. This kind of temporal scale difference may lead the results of a long-term decision to be incompatible with the requirements of a short-term scheduling task. Thus, a dynamic feedback and coordination should be considered from the lower level to the upper, over the different time-scales.
(3) There are many sources of data uncertainty in the optimisation, for example, travel demand for EV users, parking time and duration, load fluctuations and renewable energy generation. Due to the nested structure and inter-level dependency of the bi-level framework, these uncertainties can propagate between levels and significantly affect the stability and optimality of the overall solution.

Therefore, future studies should focus on a more integrated approach that simultaneously optimises forecasting, planning, and scheduling, ultimately improving the synergy between EV refuelling demand and grid stability.

Some open issues that can be identified are:

1) Parking pattern forecasting in EV scheduling.

Focusing on the issue analysed in Section V, the question of parking duration after the completion of the charging process plays a crucial role in scheduling the charging scheme [35], [73], [95]. However, unlike forecasting charging behaviour, accurately predicting departure time remains a challenge. While information such as plug-in time, charger power, and battery

SOC allows for precise forecasting of the charging end time, departure time—an essential component of parking patterns—remains difficult to predict, regardless of whether the focus is on an individual, a station, or a region. As a result, some studies have only provided a range of potential parking durations after the completion of the charging process, rather than a precise duration or departure time. If it is not clear how much time is available for scheduling, the EV will likely leave without enough energy to the satisfaction of the user.

User profiles and usage behaviours play a key role in forecasting parking patterns User behaviour regularity significantly impacts the scheduling system. In general, users can generally be categorised into two groups: regular and irregular users. Regular users typically charge and park at fixed times and locations, making their behaviour highly predictable. Based on a small amount of information, such as commuter users spending relatively regular time at home and work, the charging scheme can be optimised to satisfy both the grid and the user. In contrast, irregular users display more random charging behaviour, such as the EVs in a public parking lot. For these users, preferences such as desired charging speed or willingness to participate in partial charging can greatly influence departure times and scheduling flexibility. It may not be possible to get an accurate departure time only by regularity analysis, which may result in an underperforming scheduling strategy and inefficient utilisation of charging resources. Parking pattern forecasting models can be included in this scheduling process. More information, such as historical parking duration, and user-specific mobility patterns should be considered to enhance the accuracy of the forecast.

2) Diversity of spatially varying parking patterns and refuelling demand.

The EV travel pattern is closely linked to the urban spatial structure, leading to spatial heterogeneity in EV refuelling demand. As illustrated in the above sections, public parking lots might be the most suitable candidates to construct a charging station, while installing an EV charger at an on-street parking lot or residential parking area is another viable option. However, user parking patterns vary significantly across these different parking spaces, and hence not all candidates have the potential to be a charge location. Moreover, heterogeneity among EV users further complicates infrastructure planning. Differences in travel frequency, trip purpose, vehicle type, charging preferences, and willingness to wait can lead to varying charging demand and parking durations, even at the same location. Existing literature lacks considerations of randomness and variability, both of which are essential for accurately capturing spatial and temporal variations in refuelling demand [128]. For instance, many studies predominantly focus on personal EVs, which exhibit relatively regular travel and charging patterns [12], [89], [107]. In contrast, research on public usage EVs, which demonstrate greater randomness in their usage behaviours, often relies on predefined candidate locations for infrastructure planning [91], [129]. Therefore, future research should prioritise developing more comprehensive models that better incorporate spatial and temporal dynamics, as well as user heterogeneity. Considering the parking intention may also be a good option for the planning of charging facilities. For one parking location, different parking intentions may result in different durations. However, the visit must be of a certain duration before it is beneficial, in terms of received energy, for the EV owner to make the effort of plugging in [117]. This may affect the utilisation rate of the chargers installed in a parking lot.

3) Parking-lot charging mandates and feasibility

In this review paper, we highlighted the combination of parking lots with the installation of chargers. This is one potential way to quickly employ chargers and expand the EV charging network. Indeed, several countries have already proposed requirements to promote the construction of such facilities. For example, the local government in Orlando requires that EV charging stations must be installed at a certain percentage of parking spots [130]. In Germany, owners of non-residential buildings with more than 20 parking spaces are required to install the mandated EV charging points [131]. However, there are still remaining issues to be resolved in terms of charger deployment in parking lots. First, the high installation and maintenance costs may discourage property owners, particularly when the expected utilisation rate of the chargers is uncertain. Second, the additional demand on the local electricity grid can pose capacity and stability issues, requiring costly upgrades or smart energy management systems. Third, the allocation and management of charging spaces raises practical concerns, such as how to prevent long-term occupation of chargers by fully charged vehicles. Finally, ensuring equitable access to charging infrastructure, both geographically and across different user groups, remains a significant policy and planning challenge [132], [133], [134].

4) V2G potential by integrating charging and parking sessions

With the development of vehicle electrification, V2G and B2G technologies have become increasingly important for the coordinated operation of EVs and the grid. However, the large-scale integration of V2G services faces challenges across three main dimensions: technical feasibility, adoption barriers, and regulatory constraints. Addressing these issues is essential for robust, flexible, and effective deployment of V2G in urban environments.

(1) Technical feasibility

The potential of V2G is primarily determined by battery capacity and charging/discharging limits, which directly interact with EV charging demand. For instance, vehicles with larger batteries or higher charging/discharging rates can provide greater flexibility for grid services while still meeting the owners' mobility requirements. Conversely, if battery constraints or charging schedules limit energy availability, the capacity to participate in V2G is reduced. Additional technical challenges include battery degradation [135], interoperability issues between vehicles and chargers, and the absence of standardised communication protocols [136], [137]. To address these issues, policy measures should focus on developing durable high-capacity batteries, establishing interoperability standards, integrating real-world charging patterns into V2G scheduling, and deploying bidirectional chargers at strategic parking locations.

(2) Adoption barriers

User behaviour and parking characteristics greatly influence V2G participation. Constraints include limited parking duration, user concerns over battery degradation or potential mobility restrictions, and heterogeneity in travel habits, parking times, and charging requirements. In many cases, drivers prioritise maintaining sufficient charge for subsequent journeys, which reduces their willingness to allow energy to be discharged back to the grid. Variations in access to suitable parking facilities and the uneven availability of bidirectional chargers further restrict participation. Together, these behavioural and spatial factors introduce significant uncertainty into the number, timing, and duration of vehicles that can be relied upon for V2G services. Potential measures to overcome these barriers include providing financial incentives or reduced charging fees, implementing user education and engagement programmes to raise awareness of V2G benefits and to explain participation requirements, and offering reserved or priority parking for V2G-enabled vehicles to increase accessibility and utilisation [138].

(3) Regulatory constraints

The deployment of V2G infrastructure and its effective utilisation can be limited by policy and regulatory factors. Challenges include insufficient availability and uneven distribution of bidirectional chargers, a lack of coordinated planning for charger locations, and the absence of flexible parking or operational policies that support V2G. Furthermore, complex permitting procedures to obtain the necessary permits, differing local regulations, and the lack of clear standards for V2G operations can slow deployment and increase costs. The regulatory framework may also fail to provide adequate incentives for operators or users to participate in V2G schemes [137]. Policy measures to address these constraints include deploying bidirectional chargers at strategic locations, such as workplaces, residential areas, and commercial zones, and introducing flexible parking and EV management regulations to facilitate priority access for V2G vehicles.

4) Behaviour changes in future scenario analysis and assessment

In terms of EV refuelling demand and parking patterns, there are many highly subjective features involved. Most previous studies have modelled the future using previous or current EV refuelling demand features, however, there may be many changes with improvements in technology (e.g., higher battery energy density, battery swapping technology commercialisation), major events (e.g., COVID-19), and due to the influence of policymaking (e.g., subsidy reduction). For example, Lin et al. [139] noted that in the period 2019-23, with advances in battery technology and increased use of EVs, the charging habits of EV users have shifted, with a greater preference for nighttime charging and therefore new preferences for charging times, resulting issues, charging prices, and distance of charging infrastructures from home locations. Cui et al. [140] found that between 2018 and 2021 there had been a 15 % rise in daily distances travelled by electric taxis, alongside a 26.5 % increase in all-electric driving range and a 29.9 % increase in charging power. In contrast, personal EV travel distance showed little change, despite a 50.8 % increase in AER and a 13.9 % increase in charging power. Nevertheless, it is essential to assess whether behavioural features derived from small sample sizes or early-stage EV adopters remain valid in future high-penetration EV scenarios [141].

Early adopters often exhibit distinct usage patterns, such as higher technological enthusiasm, greater willingness to pay for charging services, and different mobility habits compared to the mainstream market [142]. As EV adoption scales up, new user groups with varying socio-economic backgrounds, driving demands, and charging preferences will emerge, potentially leading to significant shifts in refuelling demand and parking behaviours, key factors within the user behaviour layer. Therefore, future scenario assessments should incorporate longitudinal studies and diverse user datasets to ensure robustness in predicting large-scale EV adoption impacts. Longitudinal studies can track the same users or groups over time, capturing changes in travel behaviour, charging habits, and parking preferences, which are critical for understanding evolving patterns [141]. Incorporating diverse user datasets, including different geographic regions, socioeconomic groups, vehicle types, and usage profiles, can help account for heterogeneity in user behaviour and improve the generalisability of the predictions. These approaches enhance robustness by reducing reliance on any single sample or location, ensuring that the findings remain stable and applicable across different contexts and making the relevant models more transferable to other datasets and tasks (e.g., forecasting charging demand at new locations).

VIII. Conclusion

With the development of the interaction between EVs and the grid, forecasting, planning and scheduling have emerged as key study issues. From an integrated perspective, these issues are interrelated. Therefore, this paper provides a comprehensive review of all three aspects. Firstly, study scales are categorised into three levels: individual, station, and regional. Secondly, refuelling demand characteristics in previous studies are classified based on four dimensions—time, location, power, and energy—across different study scales and issues. Parking patterns are also reviewed in terms of modelling approaches along three dimensions: time, location, and intention. Finally, for each research issue, the considerations of refuelling demand and parking demand are examined in detail. The main solutions proposed to address each issue are also reviewed. In future studies, clarifying refuelling demand across different study scales, integrating more comprehensive parking patterns, and strengthening the interconnections among forecasting, planning, and scheduling can enhance the construction and operation of EV facilities and promote the interaction between EVs and the grid.

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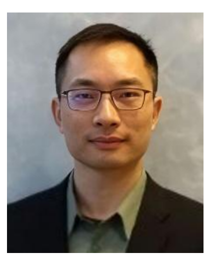

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TABLE A I

FORECASTING-RELATED LITERATURE REVIEW.

Ref.	Scale			Parking Pattern	Demand				Solutions
	I	S	R		T	L	E	P	
[10]			√	Scenario-based: Residential; Commercial	√	√		√	ML
[50]		√		Scenario-based: Private; Public car park; Public on-street	√		√	√	ML; Fuzzy model
[53]		√		Scenario-based: Paid; Free	√				ML
[55]		√		Statistical: Uniform distribution	√		√		DL
[65]	√			Activity-based	√	√		√	ML; Trip chain
[66]			√	Scenario-based: Residential; Workplace; Food centre; Shopping mall; Public Park	√		√	√	ABM
[70]			√	Scenario-based: Workplace; Statistical: Gamma and exponential distributions	√	√	√		MC
[72]		√		Statistical: Gaussian distribution	√			√	MC
[74]		√		Scenario-based: Workplace	√		√	√	ML; DL
[75]		√		Activity-based	√		√	√	ABM
[76]	√		√	Activity-based: Bynes Inference	√	√	√	√	Trip chain
[77]			√	Scenario-based: Campus	√		√		ML
[90]	√			Statistical: Empirical distribution	√		√		DL
[94]			√	Activity-based		√		√	Trip chain
[143]	√		√	Scenario-based: Home(night) parking; Workplace (daytime) parking; Other location parking	√	√	√	√	ABM
[144]	√		√	Activity-based	√	√	√	√	ABM
[145]		√		Intention-based: ‘Park to Charge’; ‘Park to Home’; ‘Park to Work’	√		√	√	ML; DL

Note: I, S, R, T, L, E, and P represent Individual, Station, Region, Time, Location, Energy and Power, respectively.

TABLE A II

PLANNING -RELATED LITERATURE REVIEW.

Ref.	Issue	Scale		Parking pattern	Main Objectives	Demand				Problem formulation
		S	R			T	L	E	P	
[91]	Siting		√	Statistical: Empirical data	Minimise investment of charging facilities	√	√		√	MILP
[80]	Scheduling Sizing	√		Statistical: Empirical data	Maximise n-year net present value of charging pole investment and daily profit of charging station	√		√		SP; LP
[146]	Siting		√	Intention-based: Residential; Guest	Maximise utilisation rate and equity of charging station	√	√			-
[86]	Siting Sizing		√	Statistical: Gaussian distribution	Maximise profit of parking lot	√	√	√		MINLP
[92]	Siting		√	Statistical: Empirical data	Minimise total construction cost and total benefit reduction	√	√			MINLP
[62]	Siting Sizing		√	Statistical: Empirical data	Minimise total investment of charging facility	√	√		√	MILP
[93]	Sizing		√	Statistical: Empirical data	Minimise net annual energy cost and installed PV capacity	√			√	MOP
[89]	Siting		√	Statistical: Empirical data	Minimise sum of distances from locations of all charging events to their closest charging stations	√	√			CO
[118]	Siting Sizing		√	Activity-based	Minimise sum of the extra travel time and waiting time of EVs; Maximise profit of charging parking lots	√	√		√	Bi-level

Ref.	Planning	I	S	R	Parking pattern	Main Objectives	T	L	E	P	Problem formulation
[61]	Sizing		√		Statistical: Poisson distribution Scenario-based: Long-term workplace; Long-term residential	Minimise daily operating cost; Maximise dynamic payback period and investment profits	√			√	MILP
[147]	Siting			√	Scenario-based: Residential; Commercial	Minimise power loss, voltage deviation and total cost of the system	√	√		√	Bi-level
[39]	Siting Sizing			√	Activity-based	Maximise annual profits of charging station; Minimise holistic charging cost of EV users	√	√	√	√	Bi-level; MINLP
[64]	Siting			√	Statistical: Double-peak distributions	Minimise total annual construction cost, operation cost of EVCSs, maintenance cost of EVCSs and annual detour time for EV users	√	√	√		DP
[148]	Siting			√	Scenario-based: Residential; Commercial; Government Park; Transportation hub	Minimise both the penalty for EV charging demand shortfall and the time required to travel to charging facilities	√	√			MILP
[66]	Siting			√	Scenario-based: Residential; Workplace; Food centre; Shopping mall; Public Park	Maximise profit of all stakeholders and utilisation of the park lots	√	√		√	NLP

Note: 1. I, S, R, T, L, E, and P represent Individual, Station, Region, Time, Location, Energy and Power, respectively.

2. Mixed-Integer Linear Programming (MILP); Mixed-Integer Nonlinear Linear Programming (MINLP); Stochastic Programming (SP); Linear Programming (LP); Dynamic Programming (DP); Nonlinear Programming (NLP); Multi-objective programming (MOP); Combinatorial Optimisation (CO)

TABLE A III

SCHEDULING -RELATED LITERATURE REVIEW.

Ref.	Charging technologies	Scale			Parking pattern	Main Objectives	Demand				Problem formulation
		I	S	R			T	L	E	P	
[69]	V2G			√	Statistical: Traffic pattern data	Maximise profits of multi-energy operator	√		√		MILP
[73]	L2		√		Statistical: Poisson and exponential distributions	Maximise revenue of multi-department charging hubs	√		√		BMILP
[55]	FC		√		Statistical: Empirical data	Minimise maximum number of simultaneous charging sessions	√				MILP
[74]	V2G		√		Scenario-based: Workplace	Minimise charging cost and deviation from desired SOC	√		√	√	MILP
[36]	V2G; V2V		√		Statistical: Empirical data	Minimise cost of power procurement	√			√	LP
[71]	SC; V2G			√	Scenario-based: Residential Statistical: Survey data	Minimise deviation of the transformer load profile	√		√		QP
[38]	Limited	√			Statistical: Empirical data	Minimise charging cost of all users	√		√	√	NLP
[149]	3.7 kW; V2G		√	√	Scenario-based	Maximise aggregator profits	√	√	√		MILP
[58]	15 kW G2V; 10 kW V2G	√			Statistical: Commuting pattern	Maximise profit of consumers	√			√	MINLP
[42]	11 kW		√		Statistical: Empirical data	Minimise operating costs of the charging station	√		√		MILP
[125]	V2G; V2V		√		Scenario-based: Charging EV; Discharging EV	Maximise the trading volume of electricity	√		√		MILP
[56]	Limited		√		Sharing parking between 8:00–18:00 Statistical: Poisson and exponential distributions	Maximise utilisation of parking and charging resources and profitability of the parking platform.	√				BMILP
[150]	V2G			√	Scenario-based: Residential (from 6 p.m. to 7 a.m.); Workplace (from 6 a.m. to 6 p.m.)	Maximise profits of multi-energy hubs	√		√		MILP

[51]	AC SC		√		Scenario-based: Residential; Commercial Statistical: Survey data	Minimise charging costs	√				-
[80]	1.9 kW; 19.2 kW; 50 kW		√		Scenario-based: Shopping mall Statistical: Empirical data	Maximise net present value of charging pole investment	√			√	Bi-level SP
[43]	1.8 kW/30min	√	√		Scenario-based: Regular users; Irregular users with long parking lot occupancies; Irregular users with short parking lot occupancies	Maximise number of EVs fulfilling their recharging requirements and total revenue of the parking lot	√				LP
[78]	60 kW	√	√		Scenario-based: Residential	Minimise charging station spaces, charging infrastructure investment and purchasing costs from grid	√			√	LP
[124]	V2G; V2V			√	Scenario-based: 1-hour continuous; 2-hour continuous; Random	Minimise battery aging cost; Maximise V2G profits of EV users	√		√	√	MILP
[151]	Fast and slow charging			√	Scenario-based: Residential; Workplace; Other location	Maximise QoS of charging service	√			√	-
[152]	Limited		√		Scenario-based: Residential (from 5 p.m. to 12 p.m.); Workplace parking pattern (from 9 a.m. to 1 p.m. and 6 p.m. to 11 p.m.)	Minimise energy costs; Maximise energy elasticity	√		√	√	MILP
[153]	V2G; 3.3 kW; 19.2 kW			√	Scenario-based: Short parking duration pattern with higher power; Long parking duration pattern with lower power	Maximise amount of electricity charged by EV; Demand response	√				MOP
[154]	V2G; V2V			√	Scenario-based: Residential; Workplace; Industrial	Minimise operation costs	√			√	MINLP
[155]	3.3 kW; 6.6 kW; 10 kW; V2G		√	√	Statistical: Empirical data	Minimise daily operational charging cost and charging peak power	√			√	MILP
[34]	Flex; Flex+; Flex++; V2G			√	Scenario-based: Residential; Workplace; Public charging station Statistical: Survey data	Minimise necessary curtailment to stay within allowed grid bounds and squared component loading; Maximise charging flexibility potential	√	√	√		MILP
[108]	V2G			√	Scenario-based: Residential; Workplace; Industrial; Commercial	Minimise daily operation cost of a multi-regional integrated energy system	√	√		√	RO
[96]	L1; L2			√	Scenario-based: Home; Home (delayed); Home + Work; Home (delayed) + Work	Minimise peak demand of power system; Maximise utilisation of PV power generation	√			√	MILP
[156]	2.5 kw; 5 kw; 7.5 kw; 10 kw		√		Scenario-based: 1-hour duration; 2-hour duration; 3-hour duration; 4-hour duration	Maximise profits and social welfare	√		√	√	MILP
[157]	Limited		√		Scenario-based: Residential	Minimise grid dependency; Maximise user satisfaction, PV power utilisation and operational costs	√		√	√	DP
[154]	V2G		√		Scenario-based: Typical parking pattern	Minimise operation costs, charging costs; Maximise utilisation rate of renewable energy	√		√	√	MILP
[41]	FC		√		Scenario-based: Short-duration with high-priority charging demand; Medium-duration with medium-priority charging demand; Long-duration with low-priority charging demand	Maximise QoS of EV users	√			√	Bi-level
[35]	FC; SC	√	√		Activity-based: Driving-Charging-Driving pattern; Driving-Parking-Charging-Driving pattern; Driving-Parking-Charging-Parking-Driving pattern; Driving-Charging-Parking-Driving pattern; Driving-Charging-Parking-Charging-Driving pattern	Minimise individual charging cost and load fluctuation of the residential area	√			√	MILP

Note: 1. I, S, R, T, L, E and P represent Individual, Station, Region, Time, Location, Energy and Power, respectively.

2. Flex, Flex+, and Flex++ denote different levels of flexibility in smart charging systems. Each level represents an increasing ability to adjust the timing, rate, or location of vehicle charging in response to system needs, such as grid constraints, renewable energy availability, or electricity pricing. Specifically, Flex corresponds to basic flexibility, allowing minor adjustments in charging schedules; Flex+ indicates moderate flexibility, enabling more substantial shifts in charging times or rates; and Flex++ represents the highest level of flexibility, allowing highly dynamic optimization, such as shifting charging across multiple time periods or locations to maximize efficiency, reduce costs, or support grid stability.

3.Limited means there is a constraint on the charging power which defines the limits in terms of the maximum and minimum bounds in the optimisation models.

4. Mixed-Integer Linear Programming (MILP); Binary and Mixed-Integer Linear Programming (BMILP); Mixed-Integer Nonlinear Linear Programming (MINLP); Stochastic Programming (SP); Robust Optimisation (RO); Linear Programming (LP); Multi-objective programming (MOP); Nonlinear Programming (NLP); Dynamic Programming (DP)