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Electric vehicle scheduling: State of the art, critical challenges, and future research opportunities

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ABSTRACT

Electric vehicles can be perceived as a means to achieve carbon reduction, energy efficiency, and sustainable development of the transportation industry. Electric vehicle sales and deployment are increasing rapidly over time. However, electric vehicle deployment should be conducted in a planned manner, as electric vehicles have some limitations (e.g., limited driving range, refueling capacity, carrying capacity). The electric vehicle scheduling problem should be studied in detail to overcome such limitations, as it addresses them while optimizing the paths and timetables of electric vehicles. A number of studies have been dedicated towards electric vehicle scheduling. Yet, there is a lack of survey studies that cover a structural recapitulation of the electric vehicle scheduling efforts and provide a thorough overview of the existing tendencies, operations research aspects, problem-specific properties, and future research needs. For this reason, this study offers a structured survey of the existing research studies, which assessed electric vehicle scheduling. The collected studies are grouped into three categories for a detailed review, namely general electric vehicle scheduling, electric vehicle scheduling with power grid considerations, and electric vehicle scheduling with environmental considerations. A detailed description of the relevant studies along with a summary of findings and future research needs are provided for each of the study categories. In addition, a representative mathematical model is outlined for each study category in order to guide the future research. The outcomes of this research are expected to provide interesting and important insights to different groups of professionals in the field of electric vehicles.

1. Background

The emergence of electric vehicles (EVs) is evident from the consistent increase in the global EV sales. In particular, the global EV sales have increased from 125 thousand in 2012 to 6.75 million in 2021 – see Fig. 1 [1]. EVs are gradually replacing conventional vehicles, as their market share has reached 8.3 % in 2021 from 0.2 % within less than a decade – see Fig. 2 [1]. The future of road transport can be imagined from such trends. The emergence of EVs can be justified from various perspectives (e.g., environmental standpoint, sustainability goals, and fossil fuel crisis). The environmental standpoint alone can justify this emergence. The U.S. Environmental Protection Agency (EPA) reported

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Fig. 1. Global EV sales by year between 2012 and 2021.

that the transportation sector contributed to 27 % of greenhouse gas emissions in the U.S. as of 2020 [2]. In order to alleviate the environmental concerns, the U.S. has pledged to transform the gas and oil industry into a low-carbon industry [3]. Other countries also have similar objectives. As an example, Denmark and China have a goal to reach net zero emissions by 2050 and 2060, respectively [4]. Moreover, the world is experiencing a crisis related to fossil fuel, which is essential for conventional vehicles, and it has become strikingly evident from the fossil fuel price hikes due to recent political issues and conflicts [5]. EVs, on the other hand, may not require fossil fuel (for electricity generation) and operate on renewable energy. In order to pave the way for EVs, the U.K. has aimed to end conventional vehicle sales by 2040 [6].

Although EVs continue gaining their popularity, their development and deployment are associated with a number of challenges. Prominently, their batteries are still at the developmental stage and impede mobility as well as feasibility due to short range [7]. Moreover, there is a shortage in the number of EV recharging stations or infrastructure. In addition, lack of power for EV recharge, absence of a universal recharge procedure, and various uncertainties (e.g., fluctuations in electricity cost) curtail EV sales and deployment. A proper set of scheduled EV trips, considering the limited driving ranges of EVs and/or recharge at various recharging stations, could be effective in mitigating the aforementioned issues [7–9]. The EV scheduling problem, therefore, has garnered growing attention over time, especially in the past decade. It involves deploying a number of EVs to serve a group of customer nodes. Service of customer nodes must be completed within a specified amount of time due to limited battery capacity. The EVs can stop at a set of recharging stations to recharge their batteries, as they may not be able to serve all of the customer nodes without recharge. Under the EV scheduling problem, the routes of the EVs are optimized, so that they can adequately serve all of the customer nodes. As opposed to EV routing, EV scheduling is associated with several other features, such as time windows, explicit modeling of EV arrivals at customer nodes, and delivery deadlines, in addition to optimization of routes. An arrival time window could be enforced at each customer node and recharging station, and schedules for the nodes should be assessed accordingly. Furthermore, communications between electric vehicles (e.g., coordination between vehicles and prioritization for recharging) and communications between electric vehicles and infrastructure (e.g., charging stations) are essential for the design of effective vehicle schedules [7–9].

A number of studies have been conducted to improve the EV scheduling and operations, as EVs have garnered growing attention. Hence, a need for comprehensive literature surveys on EV scheduling becomes more and more apparent. Some survey studies can be found in the literature with a full or partial focus on EV scheduling (see Table 1). As an example, Yang et al. [10] performed a detailed review of computational scheduling methods for EVs with a primary emphasis on the types of mathematical formulations proposed and solution approaches without providing the actual representative mathematical formulations for different types of the EV scheduling models. Amjad et al. [9] focused on EV scheduling and charging issues in smart cities. However, the survey mostly covered a holistic overview of the issues associated with EV scheduling and charging without presenting the supporting mathematical models. Perumal et al. [11] conducted a comprehensive survey of EV planning and scheduling but primarily concentrated on electric buses. More recently, Savari et al. [7] performed a review of the studies associated with the EV deployment and highlighted the importance of effective EV scheduling to maintain the adequate battery status. However, the main emphasis was given to EV charging technologies and charging station recommendation schemes.

Therefore, there is a lack of holistic survey studies that cover a structural recapitulation of the EV scheduling problem with a detailed review of the existing tendencies, operations research aspects, representative mathematical formulations, problem-specific properties, and future research needs. For this reason, this study offers a structured survey of the existing research studies, which assessed EV scheduling. The studies related to communications between electric vehicles (e.g., coordination between vehicles and prioritization for recharging) and communications between electric vehicles and infrastructure (e.g., charging stations) are directly captured by this survey as well. More specifically, the main contributions of this work to the existing state of the art can be explicitly outlined as follows:

- ✓ This survey conducts a structured review of 165 studies, which assessed EV scheduling and associated factors that may influence EV scheduling decisions.

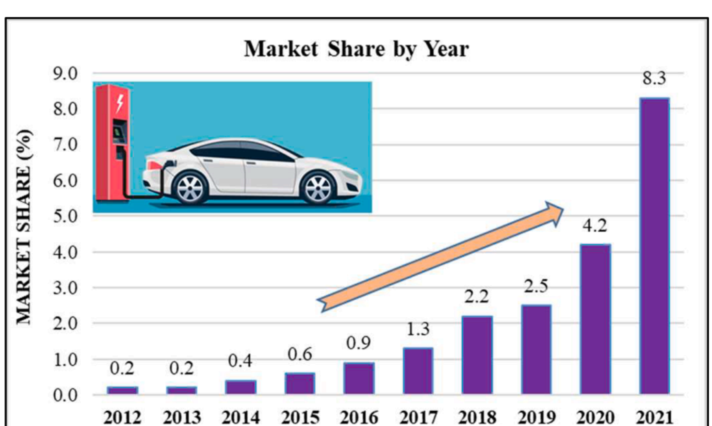

Fig. 2. EV market share by year between 2012 and 2021.

Table 1
The main features of the previous relevant survey studies and the present survey.

References	Focus on EV scheduling	Application areas	Overview of decision problems	Problem-specific properties	Mathematical models	Scheduling objectives	Categorical future research needs
Mukherjee and Gupta [12]	Partial	✓	✓	—	—	✓	✓
Huang et al. [13]	Partial	—	✓	—	—	✓	—
Yang et al. [10]	Full	✓	—	—	—	✓	—
Tang et al. [8]	Partial	✓	—	—	—	✓	✓
Al-Ogaili et al. [14]	Partial	—	—	—	—	✓	✓
Amjad et al. [9]	Full	✓	—	—	—	✓	✓
Golla and Sudabattula [15]	Partial	✓	—	—	—	✓	—
Kucukoglu et al. [16]	Partial	—	✓	✓	✓	✓	✓
Perumal et al. [11]	Full	—	✓	✓	✓	✓	—
Savari et al. [7]	Partial	—	✓	✓	—	✓	—
Current study	Full	✓	✓	✓	✓	✓	✓

✓ Different variants of the EV scheduling problem are investigated, including general EV scheduling, EV scheduling with power grid considerations, and EV scheduling with environmental considerations.
✓ In order to guide the future research, representative mathematical models for the considered variants of the EV scheduling problem are outlined.
✓ This study provides a holistic overview of the collected studies by focusing on their formulation types, model objectives, problem-specific properties, solution approaches, and major considerations.
✓ Various limitations of the existing EV scheduling studies are identified in order to outline future research needs.

The remaining sections of this manuscript are organized as follows. Section 2 presents a detailed description of the generic EV scheduling problem, whereas Section 3 explains the literature search process. Section 4 presents a detailed literature review and discusses the main findings that were discovered as a part of the conducted literature survey. Section 5 summarizes the main research activities that were conducted throughout the present survey and provides the key concluding remarks.

2. Description of the EV scheduling problem

A concise description of a typical EV scheduling problem is presented in this section of the manuscript. The nomenclature used in the EV scheduling problem description and all the mathematical models presented in the manuscript is further summarized in Table 2. The EV scheduling problem involves a set of nodes $V' = V \cup F'$, where V and F' indicate the set of customers and dummy trips to recharging stations (in order to facilitate multiple trips to the set of recharging stations F), respectively. There is only one depot, but every trip starts at depot instance $\{0\}$ and ends at depot instance $\{N+1\}$. Moreover, depot instances $\{0\}$ and $\{N+1\}$ are used as subscripts with sets in order to indicate if a set includes the respective depot instance (e.g., $V'_0 = V' \cup \{0\}$, $V'_{N+1} = V' \cup \{N+1\}$, $V'_{0,N+1} = V' \cup \{0\} \cup \{N+1\}$, $F'_0 = F' \cup \{0\}$). Fig. 3 illustrates some typical EV routes, where the solid line is used to denote the route of the first vehicle, and the dashed line is used to denote the route of another vehicle.

The distance and travel time between a pair of nodes $[i,j], i \in V'_{0,N+1}$, $j \in V'_{0,N+1}$ can be denoted as d_{ij} and t_{ij}, respectively. EVs are deployed to fulfil the demand at each node $q_i, i \in V'_{0,N+1}$ without exceeding their capacity C. Let $s_i, i \in V'_{0,N+1}$ represent the processing time (or service time) at node i. In addition, EVs are not allowed to arrive at a node outside its time window $[e_i, l_i], i \in V'_{0,N+1}$. Each EV has a battery capacity Q and a charge consumption rate h, which can be applied per unit of distance or unit of time. Thus, they replenish their batteries at the recharging stations at a recharging rate of g. In order to optimize EV routes, a binary decision variable $x_{ij}, i \in V'_{0,N+1}, j \in V'_{0,N+1}$ is used. The

Table 2
Nomenclature.

Sets	Description of sets
$\{0\}, \{N+1\}$	depot instances
F	set of recharging stations
F'	set of dummy trips to recharging stations
$F'_0 = F' \cup \{0\}$	set of dummy trips to recharging stations and depot instance $\{0\}$
V	set of customers
$V' = V \cup F'$	set of customers and dummy trips to recharging stations
$V'_0 = V' \cup \{0\}$	set of customers, dummy trips to recharging stations, and depot instance $\{0\}$
$V'_{N+1} = V' \cup \{N+1\}$	set of customers, dummy trips to recharging stations, and depot instance $\{N+1\}$
$V'_{0,N+1} = V' \cup \{0\} \cup \{N+1\}$	set of customers, dummy trips to recharging stations, and depot instances $\{0\}$ and $\{N+1\}$
Decision variables	**Description of decision variables**
$x_{ij} \in \{0,1\}\ \forall i \in V'_{0,N+1}, j \in V'_{0,N+1}$	$=1$ if a direct trip exists between nodes i and j ($=0$ otherwise)
$\tau_i \geq 0\ \forall i \in V'_{0,N+1}$	arrival time at node i
$u_i \geq 0\ \forall i \in V'_{0,N+1}$	cargo load upon arrival at node i
$y_i \geq 0\ \forall i \in V'_{0,N+1}$	remaining battery capacity upon arrival at node i
Parameters	**Description of parameters**
$d_{ij} \geq 0\ \forall i \in V'_{0,N+1}, j \in V'_{0,N+1}$	distance between a pair of nodes $[i,j]$
$t_{ij} \geq 0\ \forall i \in V'_{0,N+1}, j \in V'_{0,N+1}$	travel time between a pair of nodes $[i,j]$
$q_i \geq 0\ \forall i \in V'_{0,N+1}$	demand at node i
$s_i \geq 0\ \forall i \in V'_{0,N+1}$	processing time (or service time) at node i
$e_i \geq 0\ \forall i \in V'_{0,N+1}$	start of time window at node i
$l_i \geq 0\ \forall i \in V'_{0,N+1}$	end of time window at node i
$\theta_i \geq 0\ \forall i \in F'$	capacity of recharging station i
$L \geq 0$	peak load restriction at each recharging station
$C \geq 0$	load capacity of each EV
$Q \geq 0$	battery capacity of each EV
$h \geq 0$	charge consumption rate of each EV
$g \geq 0$	recharging rate of each EV
$\mu^{CO_x} \geq 0$	amount of carbon oxides EVs typically emit per unit distance
$\mu^{NO_x} \geq 0$	amount of nitrogen oxides EVs typically emit per unit distance
$\mu^{SO_x} \geq 0$	amount of sulphur oxides EVs typically emit per unit distance
$M \geq 0$	large positive number

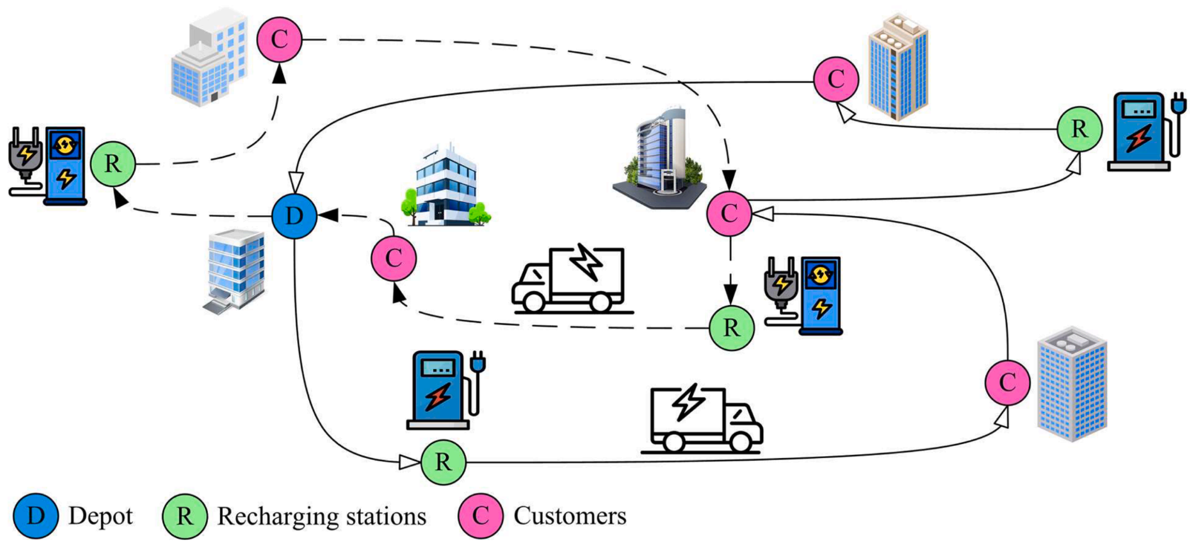

Fig. 3. Typical EV routes.

value of x_{ij} is 1 if a direct trip exists between nodes i and j. Additional indices (e.g., an index for each EV) may be used with this decision variable as well. Furthermore, positive decision variables $\tau_i, i \in V'_{0,N+1}$, u_i, $i \in V'_{0,N+1}$, $y_i, i \in V'_{0,N+1}$ are employed to indicate the arrival time, cargo load, and remaining battery capacity upon arrival at a node, respectively. A number of objective functions can be optimized in the EV scheduling problem, including minimization of the total recharging cost, number of EVs, operational cost, traveled distance, total tardiness in the completion of tasks, and others [9–11].

3. Literature search

This study applied the content analysis method to perform a review of the literature on EV scheduling [17]. Scopus, Web of Science, and the main scientific publishers (e.g., Springer, IEEE, Wiley, Elsevier, Sage) were accessed to collect the relevant literature. A number of representative keywords were adopted to direct the search process, including electric vehicle scheduling, EV scheduling, electric vehicle charge scheduling, EV charge scheduling, electric vehicle battery scheduling, EV battery scheduling, electric vehicle task scheduling, EV task scheduling, etc. Based on the structured keyword search, a number of studies were detected. A total of 165 studies among them were identified to be the most closely related to the main theme of the present survey on EV scheduling. The literature search indicated that the EV scheduling problem has attracted more and more attention from the scientific community, as implied by the increase in the number of EV scheduling studies every year (see Fig. 4). This trend can be justified by the fact that conventional vehicles have caused substantial greenhouse gas emissions, while the rise of EVs has been bolstered with the emergence of the latest technologies and the growing demand for sustainable solutions in the transportation industry.

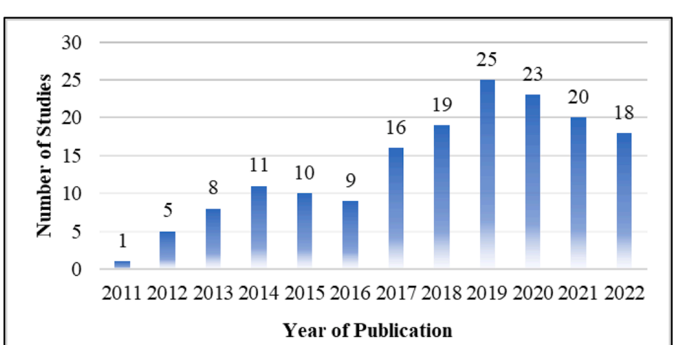

Fig. 4. Distribution of the selected studies by the year of publication.

This literature survey specifically captured the scientific studies published in peer-reviewed journals (a total of 140 studies published in journals), conference proceedings (a total of 24 studies published in conference proceedings), and book chapters (a total of 1 book chapter). Table 3 presents a distribution of the selected studies by journal, where it can be seen that the literature survey captured the studies published in prominent journals, including IEEE Transactions on Smart Grid, IEEE Transactions on Intelligent Transportation Systems, Energies, Applied Energy, Energy, IEEE Transactions on Power Systems, Electric Power Systems Research, IEEE Access, IEEE Transactions on Vehicular Technology, Electrical Power and Energy Systems, IEEE Transactions on Industrial Informatics, IEEE Transactions on Sustainable Energy, Sensors, Sustainable Cities and Society, as well as other journals and conference proceedings. The collected scientific studies were further classified into the following main categories:

1) *General EV Scheduling* – this category of studies concentrates on the basic features of the EV scheduling problem, including utilization of EVs, determination of EV routes, and arrival times of EVs at nodes.
2) *EV Scheduling with Power Grid Considerations* – this category of studies specifically concentrates on the interactions of EVs with power grids and/or recharging stations.

Table 3
Distribution of the selected studies by journal.

Journal	Number of studies
IEEE Transactions on Smart Grid	15
IEEE Transactions on Intelligent Transportation Systems	9
Energies	8
Applied Energy	6
Energy	6
IEEE Transactions on Power Systems	6
Electric Power Systems Research	5
IEEE Access	5
IEEE Transactions on Vehicular Technology	5
Electrical Power and Energy Systems	4
IEEE Transactions on Industrial Informatics	4
IEEE Transactions on Sustainable Energy	4
Sensors	4
Sustainable Cities and Society	4
Others	80

3) *EV Scheduling with Environmental Considerations* – this category of studies specifically concentrates on modeling the reduced yet considerable harmful environmental impacts of EV scheduling (e.g., emissions).

A distribution of the selected studies by study category is illustrated in Fig. 5, which implies that EV scheduling with environmental considerations has received comparatively less attention, as only 31 of the selected studies (18.79 % of the total number of studies) were on EV scheduling with environmental considerations. On the other hand, EV scheduling with power grid considerations and general EV scheduling have received more attention, as 71 studies (43.03 % of the total number of studies) and 63 studies (38.18 % of the total number of studies) from these two categories, respectively, were identified. As per expectations, some studies were eligible for multiple study categories. Such studies were categorized according to their primary focus.

4. Review of the existing literature

This section presents a detailed review of the selected studies, including a concise description of studies, holistic summary of the reviewed studies (mainly focusing on the proposed mathematical formulation types, model objectives, problem-specific properties, solution approaches, and major considerations), and future research needs for each study category.

4.1. General EV scheduling

The general EV scheduling problem is thoroughly investigated in this section. The general EV scheduling problem can be mathematically formulated as follows:

General EV Scheduling Problem (GEVSP):

$$min \sum_{i \in V_0^{'}, j \in V_{N+1}^{'}} d_{ij} x_{ij} \tag{1}$$

Subject to:

$$x_{ii} = 0 \ \forall i \in V_{0,N+1}^{'} \tag{2}$$

$$\sum_{j \in V_{N+1}^{'}} x_{ij} = 1 \ \forall i \in V \tag{3}$$

$$\sum_{j \in V_{N+1}^{'}} x_{ij} \leq 1 \ \forall i \in F^{'} \tag{4}$$

(continued on next column)

(continued)

$$\sum_{i \in V_0^{'}} x_{ij} = \sum_{i \in V_{N+1}^{'}} x_{ji} \ \forall j \in V^{'} \tag{5}$$

$$\tau_i + (s_i + t_{ij}) x_{ij} - M(1 - x_{ij}) \leq \tau_j \ \forall i \in V_0, j \in V_{N+1}^{'} \tag{6}$$

$$\tau_i + g(Q - y_i) + t_{ij} x_{ij} - M(1 - x_{ij}) \leq \tau_j \ \forall i \in F^{'}, j \in V_{N+1}^{'} \tag{7}$$

$$e_i \leq \tau_i \leq l_i \ \forall i \in V_{0,N+1}^{'} \tag{8}$$

$$u_j \leq u_i - q_i x_{ij} + C(1 - x_{ij}) \ \forall i \in V_0^{'}, j \in V_{N+1}^{'} \tag{9}$$

$$u_i \leq C \ \forall i \in V_{0,N+1}^{'} \tag{10}$$

$$y_j \leq y_i - (h \cdot d_{ij}) x_{ij} + Q(1 - x_{ij}) \ \forall i \in V, j \in V_{N+1}^{'} \tag{11}$$

$$y_j \leq Q - (h \cdot d_{ij}) x_{ij} \ \forall i \in F_0^{'}, j \in V_{N+1}^{'} \tag{12}$$

$$x_{ij} \in \{0,1\}, \tau_i, u_i, y_i \geq 0 \ \forall i \in V_{0,N+1}^{'}, j \in V_{0,N+1}^{'} \tag{13}$$

The objective function (1) of the general EV scheduling problem minimizes the total traveled distance. Constraint set (2) enforces the avoidance of redundant trips. Constraint set (3) guarantees that each customer is visited once, while constraint set (4) regulates trips to recharging stations. Constraint set (5) conserves the flow of trips. Constraint sets (6) and (7) maintain time feasibility when traveling from one node of the transportation network to another, where M is a large positive number. In particular, the arrival time at node j is estimated based on the arrival time at preceding node i, processing/service time at node i, and travel time between nodes i and j – see constraint set (6). In case node i is a recharging station; then, the arrival time at node j is estimated based on the arrival time at preceding node i, recharging time at node i, and travel time between nodes i and j – see constraint set (7). Constraint set (8) enforces a time window at each node. More specifically, each vehicle cannot arrive at a particular node before the start of time window at that node and after the end of time window at that node. Constraint sets (9) and (10) ensure demand fulfillment through regulating the cargo load upon arrival at each node and directly considering vehicle carrying capacity. Constraint sets (11) and (12) guarantee that the remaining battery capacity remains non-negative. Constraint set (13) specifies the attributes of the variables used in the **GEVSP** mathematical model. Some typical EV routes for the general EV scheduling

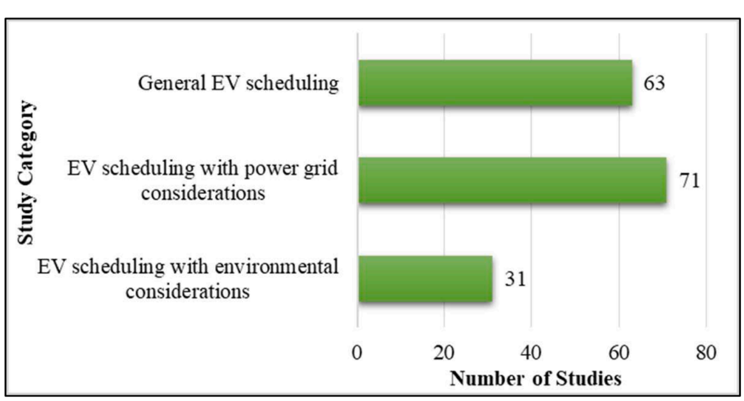

Fig. 5. Distribution of the selected studies by study category.

problem are shown in Fig. 3.

4.1.1. Description of the relevant studies

Hernández-Arauzo et al. [18] used the framework of the dynamic constraint satisfaction problem for the EV charging scheduling problem. The study investigated a real-world recharging station, which had a three-phase electric feeder and analyzed the imbalance in its lines. Variable capacity was considered while aiming to minimize the total tardiness. Evaluation through simulation experiments indicated that the proposed methodology outperformed a standard dispatching rule. Wen et al. [19] allowed both full and partial recharge of EVs at recharging stations. The study presented a mixed-integer programming formulation, where the charging function was linear with the amount of charge. An Adaptive Large Neighborhood Search heuristic was presented that was based on repair-destroy operators as well as diversification and post-optimization phases. Benchmark instances were generated, which revealed that the heuristic provided optimal and near-optimal solutions for small-size problems and good-quality solutions for large-size problems. Zhang and Li [20] assessed the charging of EVs at parking lots, stating that such a strategy could lead to reduced payback time. A non-cooperative game theoretic approach was undertaken, where each player aimed to maximize its utility. A coupled constraint was enforced, based on which the action of each player was influenced by the actions of the others. It was concluded that the coupled constraint distinguished the game of charging EVs at parking lots from other scenarios of EV charging.

Nejad et al. [21] designed an online pricing and scheduling framework, where EV owners could name recharging prices. Incentives for energy providers and EV owners were incorporated during pricing. Furthermore, energy providers could sell unutilized energy as a part of load balance. Comprehensive experiments demonstrated that correct reporting of the amount and price of recharging were integral for EV owners. Tang and Zhang [22] examined the charging scheduling of EVs where the future demand for recharging was unknown. However, historical data and statistical information could provide insights for the future demand. Hence, an online charging scheduling problem was presented that had a resemblance with the finite-horizon dynamic programming problem. A model predictive control-based algorithm was devised as the solution methodology. Numerical simulations revealed that the devised algorithm was able to provide near-optimal solutions for the considered problem instances. Vagropoulos et al. [23] applied the price-taking approach so as to conduct self-scheduling of EVs. The effect of EV charge scheduling on power systems was conducted. A case study for a Greek insular system demonstrated various impacts of smart and direct charging, which included energy costs and energy system operations.

Álvarez et al. [24] developed an Artificial Bee Colony Algorithm for recharge scheduling of EVs in community parking, with each EV having a separate spot in a parking lot. In order to minimize the total tardiness, the Artificial Bee Colony Algorithm replicated a series of evolutionary operators. The algorithm made proper use of contracted power at recharge stations and satisfied customer demand. García-Álvarez et al. [25] scheduled the charging periods of EVs while solving two variants of the tackled problem, including static and dynamic. Unlike the static variant, the due dates, arrival times, and charging times of EVs were not known in the dynamic variant. Two metaheuristics were developed as solution methodologies, which included an algorithm inspired by the Greedy Randomized Adaptive Search Procedure and a Memetic Algorithm that used the skeleton of Variable Neighborhood Search. Experimental results demonstrated that the proposed algorithms outperformed the Genetic Algorithm and a priority rule-based method by up to 12 %. Ki et al. [26] examined an EV recharger with multiple ports, particularly, a specified number of ports for input from power sources and another specified number of ports for outputs to EVs. EVs were allowed to arrive randomly and stay for a certain amount of time. During their stay, they had to be recharged to the greatest extent. A heuristic algorithm was designed, which employed an open-source linear programming solver and generated EV schedules under 8 s for a case study undertaken by the authors.

Rabiee et al. [27] analyzed queuing at a recharging station and aimed to maximize the total profit, especially in the long term. The delay time of EVs was reduced as well. It was indicated that maximizing the profit for a short time might not maximize it in the long term. Numerical experiments revealed that the proposed strategy could assist in awarding more profits to EV owners in the long term. Rigas et al. [28] formulated the EV scheduling problem as a maximum flow problem in order to promote a mobility-on-demand scheme. A mixed-integer programming model was presented to maximize the total number of completed tasks or EV utilization. Two sets of offline and online algorithms were developed for the proposed optimization model, and they provided high-quality solutions. Alinia et al. [29] designed online scheduling algorithms to promote on-arrival commitment, i.e., a feature to ensure that EVs would be informed upon making their recharge request whether they could be recharged within their specified deadlines or not. A grouping strategy was employed by the algorithms, so that EV users could reveal their accurate profiles. Comprehensive experiments showed that user satisfaction was improved through on-arrival commitment.

Gkourtzounis et al. [30] proposed an EV-sharing system, where EVs could be hired and driven between pick-up and drop-off locations. Customers provided the information regarding their trip requests, and EVs were assigned to them in order to maximize the number of served customers. Scheduling algorithms were presented for short- and long-term reservations. Furthermore, a software package was developed for transportation companies in order to facilitate efficient management of a mobility-on-demand scheme. Gong et al. [31] emphasized the importance of scheduling of recharging station resources, such as service workers and charging piles. In fact, it was claimed that they were the most important resources of EV recharging stations. In this regard, a model was formulated to examine the impact of the number of service workers as well as charging pile maintenance time and replacement policy on the profit of recharging stations. High-profit results were returned by AnyLogic, a simulation platform. Liu et al. [32] incorporated uncertainties in photovoltaic generation and battery swapping demand for the day-ahead scheduling of an EV-based battery swapping station. A chance-constrained program with the objective of minimizing the electricity cost was formulated, which involved a deterministic transformation and a Genetic Algorithm-based solution. Extensive simulations indicated that the program provided a reasonable recharge strategy for battery-swapping stations that had different appetites for risk.

Park et al. [33] developed a fuzzy logic-based scheduling heuristic to reduce EV congestion. According to three fuzzy inputs, namely the distance between EVs and recharging stations as well as charging time and speed, the developed scheduling heuristic aimed to balance the recharge request rate and waiting time before recharge. Numerical experiments showcased the efficiency of the presented methodology for the studied decision problem. Yang [34] proposed a price-sensitive early charging model for EVs to reduce electricity costs. A data mining-based speedup factor was designed to categorize recharging demand by electricity charge. It was found that the proposed methodology was robust in the sense that its control factor, which was determined by electricity charge, was not affected by the in-consideration EV state-of-charge. Kurniawan et al. [35] tackled low and high distribution transformer voltage issues through the distribution of power from EVs. Various types of EVs were considered. Based on a case study conducted for Jakarta (Indonesia), various government policies of that region were examined using the proposed approach. Also, the effectiveness of distribution transformers' peak load level and loss reduction along with voltage stability improvement was demonstrated.

Liu and Ceder [36] examined the installation of stationary chargers at public transit stations for the scheduling of public transit EVs. A bi-objective model was developed to assess the effects of partial and full charging strategies. The model objectives aimed to minimize the number of EVs and the number of chargers. A lexicographic-based approach along with a max-flow approach were developed as solution methodologies. The conducted simulation analysis indicated that the proposed approach was effective in practice. Srithapon et al. [37] incorporated power arbitrage for the charge scheduling of urban EVs. An optimization model was formulated to minimize the total cost, which included several features in the objective function, such as transformer aging, power loss, and peak demand. The loss of power arbitrage benefit was considered as well. It was illustrated that the proposed strategy could prolong the lifetime of transformers and benefit distribution system operators and EV owners. Sun et al. [38] performed the day-ahead scheduling of EVs to facilitate overnight recharge within a low-voltage network. A linear power flow approximation was conducted to simplify the formulated cost-minimization model. Furthermore, various risks (e.g., voltage violations, network overloads) were mitigated through probabilistic distributions of arrival times, departure times, and daily trip distances. The impact of the associated uncertainty was demonstrated through numerical experiments.

Yao et al. [39] studied the heterogeneous fleet variant of the EV scheduling problem. Particularly, heterogeneity in energy consumption, recharging time, and driving range was captured. A heuristic was presented that allowed substitution of EVs. Real-world data for a public transit network in Beijing, China was used to demonstrate the effectiveness of the proposed methodology. Devendiran et al. [40] noted a total of four phases in the selection and prioritization of EV recharging stations within a vehicular ad-hoc network, which include driving, recharge planning, recharge scheduling, along with battery recharging. An exponential Harris Hawks Optimization algorithm was employed for the scheduling framework, which provided good-quality solutions for a large number of EVs. Kalakanti and Rao [41] applied both slow and fast recharge while scheduling EVs, instead of having a fixed recharge speed. Some other aspects of EV scheduling were incorporated, including waiting time, scalability, congestion, and recharge rate for the formulated mixed-integer quadratically constrained program. A hybridization of the Firefly Algorithm and Particle Swarm Optimization was used as a solution method. Qureshi et al. [42] generated EV routes while facilitating an intelligent energy management system. Moreover, the study developed an authentication scheme to promote the security of EVs. Evaluations against the state-of-the-art schemes demonstrated the promising potential of the proposed methodology.

Wang et al. [43] tackled the multi-depot EV scheduling problem within the scope of public transit. A Column Generation-based algorithm was proposed that had influences of the Genetic Algorithm. The proposed algorithm involved two stages. An initial set of columns was created at the first stage, which represented EV routes. At the second stage, a subset of columns was generated with the Genetic Algorithm, which signified the final solutions. Simulation results illustrated that the proposed algorithm was about 40 times faster than the Branch-and-Price Algorithm. Zdunek et al. [44] proposed an on-off EV recharge scheduling scheme where the ports in a recharging station could be switched on and off as a means to conserve energy. Maximal currents and individual charging rates were incorporated into the model, which was solved with the Frank-Wolfe Algorithm. Computational experiments that were conducted as a part of the study demonstrated the effectiveness of the proposed methodology. Wu et al. [45] aimed to obtain global optimal solutions for the two objective functions with respect to EV scheduling, namely minimization of the recharging cost and minimization of the peak load. The study demonstrated that global optimality for the aforementioned objective functions could be reached through locally optimal greedy choices and a non-myopic recharging strategy considering the future demand. Several other studies have assessed the general EV scheduling problem [46–80].

4.1.2. Summary of studies

A detailed summary of findings for the reviewed studies on general EV scheduling is provided in Table 4. Note that Table 4 includes the term "EV aggregation", which essentially represents the intermediation between EV fleets, power systems, and other relevant elements within the EV networks. EV aggregators could be retailers, distribution system operators, or independent market participants who profit from providing services to power grids (e.g., parking lot owners) and could enable vehicular communications. The review of the selected studies on general EV scheduling revealed that a substantial number of the reviewed studies formulated mixed-integer programs with the objective of minimizing the total cost. Some other objective functions were considered in the state of the art as well, including minimization of the total tardiness, minimization of the completion time, maximization of the number of completed tasks, maximization of social welfare, maximization of the total profit, minimization of the total waiting time, and minimization of the peak load. Furthermore, it was found that the majority of the reviewed studies did not employ EV aggregators, enforce time windows, and use renewable energy. Moreover, metaheuristic algorithms (including different variations of Evolutionary Algorithms) and heuristic algorithms were determined to be popular methods for the general EV scheduling optimization problems.

4.1.3. Future research needs

- Multi-objective optimization and tradeoffs between various objectives (e.g., welfare maximization, battery cost minimization, battery state-of-charge maximization) should receive more interest from researchers in the following years [26,29,41].
- Recharging behaviors of EV owners in relation to market clearing price could be investigated in more detail by the future studies on general EV scheduling [27]. Robust mechanisms for coordination and communication among EV owners could facilitate the recharging operations.
- Excessive recharge of EVs may lead to highly fluctuating demands over the power grid and, therefore, requires significant attention and proper modeling in the following years [81].
- Charging controllers may not have detailed information regarding the required amount of energy and departure time of each EV, which may lead to system losses. Potential access of charging controllers to this information should be investigated and modeled by the future studies [41].
- Important data are under constant threats with the fast development of information technology. EV scheduling methods should secure data in order to provide more reliable and safe schedules [42,67,68].
- Distribution network constraints could be modeled with more tractable methodologies (e.g., full alternating current optimal energy flow) in order to schedule large EV fleets through networks including millions of nodes [82].
- A combination of users (e.g., residential, commercial, industrial) should be incorporated while modeling user behavior [15,50]. Implementation of coordination and communication mechanisms between users will assist with the design of effective EV schedules.
- A detailed review of the state of the art discovered a variety of solution algorithms that can be used for general EV scheduling. More advanced solution approaches could be further explored by the future studies, including exact optimization methods [83–85], adaptive and self-adaptive algorithms [86–88], decomposition algorithms [89–91], hybridized algorithms [92–94], and various relaxation techniques [95,96].
- Detailed financial benefit analyses of EV scheduling models need more attention from the future studies on general EV scheduling [15].

Table 4
Summary of findings: studies on general EV scheduling.

References	Formulation type	Model objectives	Optimization type	EV aggregation	Time windows	Use of renewable energy	Solution approaches	Notes/Major considerations
Hernández-Arauzo et al. [18]	MIP	Minimize the total tardiness	SOO	—	N/A	—	Heuristic	Real-world recharging station with a three-phase electric feeder
Wen et al. [19]	MIP	Minimize the total cost	SOO	—	Strict	—	Adaptive large neighborhood search	Partial recharge
Zhang and Li [20]	N/A	N/A	N/A	✓	N/A	—	N/A	Game theory; Parking lot charging
Nejad et al. [21]	IP	Maximize the total user valuation	SOO	—	Strict	—	Heuristic	Online recharge pricing
Tang and Zhang [22]	N/A	Minimize the total cost	SOO	—	Soft	—	Heuristic	Online charging scheduling
Vagropoulos et al. [23]	MIP	Minimize the total cost	SOO	✓	Strict	—	N/A	Price taking
Álvarez et al. [24]	N/A	Minimize the total tardiness	SOO	—	N/A	—	Artificial bee colony algorithm	Community parking
García-Álvarez et al. [25]	N/A	Minimize the total tardiness	SOO	—	N/A	—	Greedy randomized adaptive search procedure; Memetic algorithm	Static and dynamic problems
Ki et al. [26]	MIP	Maximize the recharging amount; Minimize the recharging cost; Minimize the completion time; Maximize the charging balance	MOO	—	Strict	—	Heuristic	Recharge with multiple ports
Rabiee et al. [27]	N/A	Maximize the total profit	SOO	—	N/A	—	Heuristic	Analysis of short- and long-term profit
Rigas et al. [28]	MIP	Maximize the total number of completed tasks; Maximize the EV utilization	MOO	—	Strict	—	Heuristic	Mobility-on-demand
Alinia et al. [29]	MIP	Maximize the social welfare	SOO	✓	Strict	—	Heuristic	Game theory; Group-strategy-proofness
Gkourtzounis et al. [30]	N/A	Maximize the number of served customers	SOO	—	N/A	—	Heuristic	EV sharing
Gong et al. [31]	IP	Maximize the total profit	SOO	—	N/A	—	Simulation	Charging pile and worker scheduling
Liu et al. [32]	CCP	Minimize the electricity cost	SOO	—	N/A	—	Genetic algorithm	Uncertainties in swapping demand and photovoltaic generation
Park et al. [33]	N/A	Minimize the total waiting time	SOO	—	Strict	—	Heuristic	Fuzzy logic
Yang [34]	IP	Maximize the utilization of power capability	SOO	—	N/A	—	CPLEX	Time-of-use price
Kurniawan et al. [35]	N/A	N/A	N/A	—	N/A	—	N/A	Measurement systems at distribution transformers
Liu and Ceder [36]	IP	Minimize the total number of EVs; Minimize the total number of chargers	MOO	—	N/A	—	Heuristic	Stationary battery charger; Public transit
Srithapon et al. [37]	N/A	Minimize the total cost	SOO	✓	N/A	—	Genetic algorithm	Energy arbitrage
Sun et al. [38]	NLP	Minimize the total cost	SOO	✓	N/A	—	Heuristic	Uncertainties in arrival time, departure time, and daily trip distance
Yao et al. [39]	MIP	Minimize the total cost	SOO	—	Strict	—	Heuristic	Heterogeneous fleet
Devendiran et al. [40]	N/A	Minimize the traveled distance, average waiting time, and energy	SOO	✓	N/A	—	Harris Hawks optimization	Prioritization of recharging stations
Kalakanti and Rao [41]	MIQCP	Minimize the sum of the time cost, charging expense, and the state-of-charge gap	SOO	✓	N/A	—	Firefly algorithm; Particle swarm optimization	Recharging speed
Qureshi et al. [42]	N/A	N/A	N/A	—	N/A	—	N/A	Communication with recharging stations
Wang et al. [43]	MINLP	Minimize the total cost	SOO	—	N/A	—	Column generation; Genetic algorithm	Public transit
Zdunek et al. [44]	IP	Minimize the number of switching operations	SOO	—	Strict	—	Frank–Wolfe algorithm	On-off scheduling

(*continued on next page*)

Table 4 (*continued*)

References	Formulation type	Model objectives	Optimization type	EV aggregation	Time windows	Use of renewable energy	Solution approaches	Notes/Major considerations
Wu et al. [45]	MIP	Minimize the recharging cost; Minimize the peak load	MOO	—	Strict	—	Heuristic	Time-of-use price

Notes: Formulation Type [CCP – Chance-Constrained Programming; IP – Integer Programming; MINLP – Mixed-Integer Non-Linear Programming; MIP – Mixed-Integer Programming; MIQCP – Mixed-Integer Quadratically Constrained Programming; NLP – Non-Linear Programming]; Optimization Type [SOO – Single-Objective Optimization; MOO – Multi-Objective Optimization].

4.2. EV scheduling with power grid considerations

The EV scheduling problem with power grid considerations explicitly incorporates various attributes of power grids and recharging stations (e.g., capacity of power grids and recharging stations, peak load restrictions for power grids and recharging stations). Each recharging station is generally associated with a capacity $\theta_i, i \in F'$ and a peak load restriction L. Then, the EV scheduling problem with power grid considerations can be mathematically formulated as follows:

EV Scheduling Problem with Power Grid Considerations (EVSP–PGC):

$$min \sum_{i \in V'_0, j \in V'_{N+1}} d_{ij} x_{ij} \quad (14)$$

Subject to:

$$x_{ii} = 0 \; \forall i \in V'_{0,N+1} \quad (15)$$

$$\sum_{j \in V'_{N+1}} x_{ij} = 1 \; \forall i \in V \quad (16)$$

$$\sum_{j \in V'_{N+1}} x_{ij} \leq 1 \; \forall i \in F' \quad (17)$$

$$\sum_{i \in V'_0} x_{ij} = \sum_{i \in V'_{N+1}} x_{ji} \; \forall j \in V' \quad (18)$$

$$\tau_i + (s_i + t_{ij}) x_{ij} - M(1 - x_{ij}) \leq \tau_j \; \forall i \in V_0, j \in V'_{N+1} \quad (19)$$

$$\tau_i + g(Q - y_i) + t_{ij} x_{ij} - M(1 - x_{ij}) \leq \tau_j \; \forall i \in F', j \in V'_{N+1} \quad (20)$$

$$e_i \leq \tau_i \leq l_i \; \forall i \in V'_{0,N+1} \quad (21)$$

$$u_j \leq u_i - q_i x_{ij} + C(1 - x_{ij}) \; \forall i \in V'_0, j \in V'_{N+1} \quad (22)$$

$$u_i \leq C \; \forall i \in V'_{0,N+1} \quad (23)$$

$$y_j \leq y_i - (h \cdot d_{ij}) x_{ij} + Q(1 - x_{ij}) \; \forall i \in V, j \in V'_{N+1} \quad (24)$$

$$y_j \leq Q - (h \cdot d_{ij}) x_{ij} \; \forall i \in F'_0, j \in V'_{N+1} \quad (25)$$

$$\sum_{i \in V'_{N+1}} x_{ij} \leq \theta_j \; \forall j \in F' \quad (26)$$

$$\sum_{i \in V'_{N+1}} x_{ij} \leq L \; \forall j \in F' \quad (27)$$

(*continued on next column*)

(*continued*)

$$x_{ij} \in \{0, 1\}, \tau_i, u_i, y_i \geq 0 \; \forall i \in V'_{0,N+1}, j \in V'_{0,N+1} \quad (28)$$

The objective function (14) of the EV scheduling problem with power grid considerations minimizes the total traveled distance. Constraint sets (15) through (25) incorporate some basic EV scheduling attributes, which are similar to the ones imposed in the **GEVSP** mathematical model. Constraint set (26) ensures that the capacity of any recharging station is not exceeded. Constraint set (27) ensures that the peak load restriction is not violated for any recharging station. Constraint set (28) specifies the attributes of the variables used in the **EVSP–PGC** mathematical model. Some typical EV routes for the EV scheduling problem with power grid considerations are shown in Fig. 6.

4.2.1. Description of the relevant studies

Khodayar et al. [97] examined a total of two operating modes of EVs, including consumer- and grid-controlled. Under the consumer-controlled operating mode, EVs extracted power from the grid, whereas under the grid-controlled operating mode, they stored and delivered energy to the power grid. An hourly power-generation scheduling model was proposed to minimize the hourly power supply cost. It was concluded that aggregation of EVs as a distributed and mobile demand/storage would decrease congestion in the grid and grid operational cost. Ortega-Vazquez et al. [98] discussed that EVs could draw out power from the system at low-demand periods and feed it to the system during peak periods. Such a function could be facilitated further by a player, named “EV aggregator”, which would act as an intermediary between EV fleets, power systems, and system components. Hence, the study developed an EV aggregation system and scheduling scheme to optimize EV services and recharge in order to improve power system efficiency. The study concluded that coordination over recharging schedules would improve the performance of the system. Zhang et al. [99] conceptualized a recharging station that included devices enabled with renewable energy generation. In addition, energy could be bought from power grids. The grid power price and the arrival of EVs were uncertain and modeled using the Markov processes. The stochastic mathematical model, which had the objective of minimizing the mean recharging demand queue length, was tackled with simulation.

Kumar et al. [100] classified coordinated recharge of EV batteries into two categories, including time-coordinated recharge and power-coordinated recharge. The study assessed the impacts of three priority criteria on coordinated recharge scheduling of EV batteries, namely battery state-of-charge, allotted time, and slack time. The necessity of the weighted priority criteria was demonstrated through simulations. Kamankesh et al. [101] applied Monte Carlo Simulation for a stochastic model involving microgrids, which included EVs, storage devices, and renewable energy sources. Smart charging as well as controlled and uncontrolled charging patterns were assessed, and the benefits of smart charging (e.g., cost reduction) were demonstrated. Luo et al. [102] deployed EVs to facilitate intelligent transportation systems within a smart grid, considering node voltage and load deviation. A

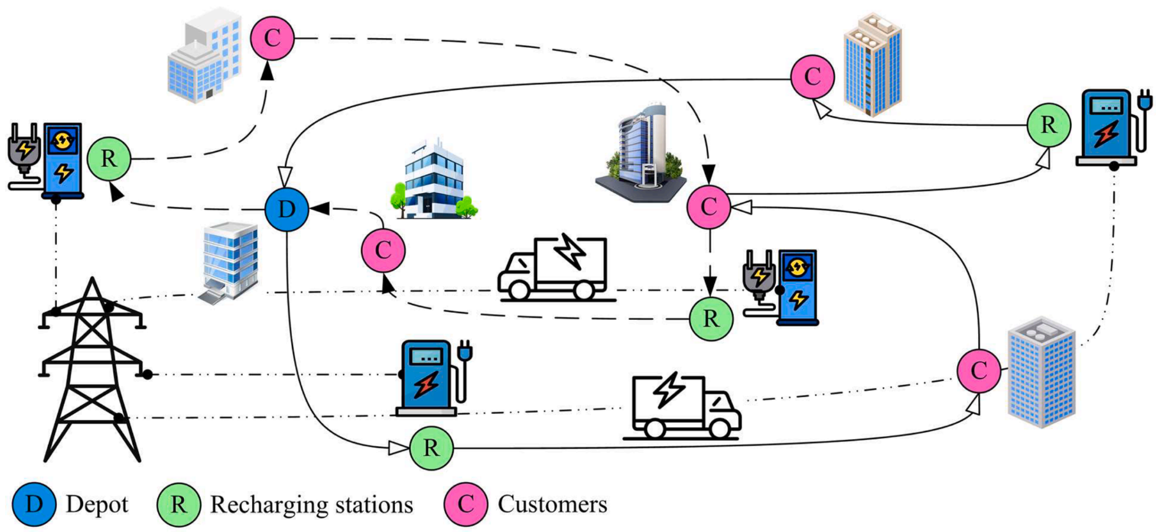

Fig. 6. EV scheduling problem with power grid considerations.

simulation platform was developed for large-scale EV deployment using the data for real-world charging scenarios. Grid and transportation system information were incorporated as well. Numerical experiments illustrated that the proposed methodology could improve grid system operation and transportation system efficiency.

Janjic et al. [103] tackled the EV scheduling problem for secondary fleet control. A multi-objective framework was defined with the objectives of minimizing the service waiting time, maximizing the revenues from secondary regulation, and maximizing the charging efficiency. The risk-taking attitude of decision makers was incorporated in the proposed framework, while vehicle usage was modeled as stochastic. For a small fleet of commercial EVs, the framework provided optimal schedules of grid connection of EVs. Li et al. [104] devised an online cost-sensitive EV energy load and supply algorithm for microgrids. The algorithm tackled a stochastic optimization problem that aimed to minimize the microgrid time-average cost. The algorithm applied the Lyapunov optimization technique to harvest renewable energy and battery recharge. Real data-driven numerical experiments indicated that the proposed algorithm was eco-friendlier and incurred less cost than other alternatives. Sassi and Oulamara [105] discussed that the EV scheduling and charging problem is NP-hard in nature. The study proposed a mixed-integer programming model to minimize the total recharge cost. Small-size instances were solved with CPLEX. However, heuristics were developed to solve large-size instances due to NP-hardness of the problem, whose efficiency was demonstrated through numerical experiments.

Maigha and Crow [106] performed multi-objective optimization with a total of three objective functions, including: (1) minimization of the battery degradation cost; (2) minimization of the customer charging-discharging cost; and (3) minimization of the deviation between instantaneous and average demand. An augmented ε-constraint method was used to perform three-objective optimization and two-objective optimization with the considered objective functions. A comparison with a weighted sum method established the superiority of the augmented ε-constraint method. Pal and Kumar [107] analyzed energy transfer between household users who possessed several assets, including EVs and other appliances. Vehicle-to-home and vehicle-to-neighbor energy transfers were allowed in addition to the vehicle-to-grid energy transfer. Then, a central controller was in charge of minimizing the total energy procurement cost of the residential demand response scheme. Simulation results demonstrated the validity of the proposed system. Sun et al. [108] treated the EV charging level as discrete, rather than continuous, as an attempt to realize a more realistic environment. The charging problem was disintegrated into two sub-problems, namely aggregate load profile attainment at the grid level and minimization of on-off switching at the individual charging level. Case studies confirmed the potential of the proposed methodology for real-world implementations.

Amamra and Marco [109] envisioned a bidirectional EV scheduling system, where EV users connected their vehicles to the grid with frequency and voltage regulation. Along with recharging requirements, the day-ahead scheduling system addressed a number of EV scheduling aspects, such as regulation charge, battery state-of-charge, battery degradation cost, plug-in time, and others. Extensive simulation showed that through the EV-to-grid technology, frequency provision and voltage support were possible while decreasing EV recharge costs. Chung et al. [110] attempted to obtain a consensus between recharging stations and EV owners. The recharging stations aimed to minimize the recharge cost, while the EV owners were focused on maximizing the user convenience level. An online centralized algorithm was developed to obtain Pareto-optimal solutions. Moreover, a low-complexity solution algorithm was proposed to substitute the online centralized algorithm. The reduction of charging cost and time was demonstrated by numerical experiments. Sharma and Jain [111] proposed a scheduling scheme, which featured time-of-use price-based recharge strategies. The scheduling scheme also acknowledged peak recharge times in order to avoid system overloads. Under the proposed scheme, the EV aggregator obtained more profit due to extensive flexibility available to EV users, as compared to unregulated recharge schedules.

Zhou et al. [112] studied the EV recharge scheduling under a utility company with a number of recharging stations. Game theory was applied so as to minimize the electricity cost of the utility company and to maximize the payoff at the recharging stations. A mathematical model with low computational complexity was developed, and a heuristic equipped with the MATLAB CVX tool was used for solution. Simulation results illustrated that compared to a state-of-the-art scheduling methodology, the proposed methodology significantly improved peak-to-average ratio, charging cost, and payoff. Aliasghari et al. [113] stated that EV aggregators acted as a facilitating agent between EV owners and the grid. The study prepared a robust optimization model using the information gap decision theory in order to address various uncertainties in the battery state-of-charge along with arrival and departure times. Simulation results implied that opportunistic and robust scheduling methods could be employed to maximize the profit of EV aggregators. Koufakis et al. [114] planned the EV recharge scheduling at a recharging station that procured energy from renewable energy sources. An offline algorithm was developed to minimize the total recharging cost for the station. Furthermore, an online algorithm was devised, which aimed to predict renewable energy generation, and its low execution time was shown through numerical experiments.

Liang et al. [115] conducted concurrent EV rebalancing, order dispatching, and recharge scheduling for a large fleet of EVs. Deep reinforcement learning was applied to obtain a near-optimal solution for the partially observable Markov decision process. Near-optimality of the obtained solutions was demonstrated through a tabular method. Rasheed et al. [116] asserted that price-based load management programs could alter the costs of EV scheduling. In this regard, as a means to minimize the total EV charging cost with the overall goal of obtaining energy system stability, a multi-region energy price estimation methodology was proposed that took into account the distinct power consumption patterns of each region. Furthermore, the general peaks in the power distribution system were minimized. Improved fair cost distribution as well as high user satisfaction were illustrated by the proposed methodology. Xie et al. [117] proposed an EV scheduling scheme for an EV-sharing company that owned EVs and parking lots. Under the presented scheme, passengers hired and drove EVs from one parking lot to another. Even though EVs were shared between many passengers, EV tracking was not required, as the spatial transport of energy was captured. Case studies implied that the proposed model could reduce peaking and fill valleys without compromising the profit.

Ban et al. [118] examined a system with multiple nanogrids that could swap EV batteries with fully charged batteries. A mathematical formulation was presented, and a heuristic solution methodology was developed, which was inspired by the Genetic Algorithm and the Exhaustive Method. It was concluded that the proposed battery swapping–charging system had significant merit in exploring energy trading, business models, and market mechanisms. Das et al. [119] stated that an EV required several hours for a full recharge. Moreover, the itinerary of an EV could affect its recharge requirements. Thus, a scheduling scheme for EV recharge was proposed along with considerations of recharging station assignments to EVs. Uncertainties in driving cycles were tackled with the 2 m point estimation method. The Wilcoxon Signed rank test and Quade test confirmed the robustness of the proposed methodology. Jin and Xu [120] incorporated stochastic electricity charge and renewable energy production within a dynamic programming formulation. A nodal multi-target characterization was established to mitigate dimensionality. Based on the conducted numerical experiments, such a characterization was revealed to be optimal. Li et al. [121] attempted to incorporate renewable energy generation uncertainties while performing a flexible demand response in EV recharge. A bi-level model was proposed to achieve user satisfaction and to obtain a balance between energy supply and demand. In particular, a demand response system was developed with a dynamic pricing scheme and was shown to be effective.

Wu and Chen [122] presented a distributed EV scheduling framework, where EV aggregators made bids to indicate their recharging requirements. On another level, EV aggregators and distribution system operators negotiated strategies for a tradeoff between economic benefits from EV recharge and distribution system stability. Numerical experiments demonstrated the effectiveness of the proposed framework. Xu et al. [123] applied blockchain and 5G technologies to develop an intelligent EV dispatching model for a distributed energy grid. Smart contracts were used for data storage as a means to protect historic data. Dynamic scheduling along with optimization of multi-vehicle line blocking were performed. Comprehensive simulation experiments revealed that the proposed system could perform blocking/unblocking of the Internet of Vehicles in a quick manner. Wu et al. [124] discussed that electric buses had to deal with a number of issues, such as extensive recharging times, peak load risk, peak time tariffs, and others. Hence, the study formulated a bi-objective optimization model to minimize the peak load and operational cost of a public transit system, considering the aforementioned issues. A Branch-and-Price algorithm was developed to obtain exact solutions for the time-expanded network model. Results indicated that the proposed algorithm significantly outperformed an off-the-shelf algorithm in peak load leveling and cost savings. Several other studies have assessed EV scheduling while incorporating power grid considerations [81,82,125–165].

4.2.2. Summary of studies

A detailed summary of findings for the reviewed studies on EV scheduling with power grid considerations is provided in Table 5. The review of the selected studies on EV scheduling with power grid considerations revealed that a substantial number of the reviewed studies formulated mixed-integer programs with the objective of minimizing the total cost. Some other objective functions were considered in the state of the art as well, including minimization in the EV priority variance, minimization of the service time, maximization of the total revenue, maximization of the charging efficiency, minimization of the battery degradation, maximization of the payoffs at recharging stations, maximization of the total welfare, and minimization of the peak load. Furthermore, it was found that a substantial number of the reviewed studies employed EV aggregators, but did not impose time windows and/or consider the use of renewable energy. Moreover, heuristic algorithms were found to be common methods for the optimization models formulated for the EV scheduling with power grid considerations.

4.2.3. Future research needs

- The power system and infrastructure needed to recharge EVs require a consistent approach (e.g., universal code). Such an approach should be investigated by the future research [67,137].
- The requirements of EV owners need a better balance with that of power grids [4,18,145]. The future studies should focus more on the development of holistic approaches that incorporate the requirements of EV owners and power grids.
- Basic deterministic models may be inaccurate to model various grid parameters, such as power supply. Hence, robust optimization models would be more suitable for such modeling and should be explored more in the following years [82,132].
- Several studies that addressed the EV scheduling with power grid considerations have used coupled constraints. The Lagrangian Multiplier Method could be useful in relaxing coupled constraints [8,97,138].
- Sophisticated modeling techniques (e.g., machine learning) could be employed by the future research to better capture the deviation variance of power grids [10,28,153].
- Real-world scenarios may involve variables that are sensitive to time. Dynamic programming could be instrumental in capturing those variables [22,120,124,125,154].
- Some of the latest mathematical models have treated EV aggregators as distributed generators or large load consumers. It has resulted in increased computational complexity, and the deployment of more efficient solution algorithms would be necessary for this type of mathematical models [10,157].
- Incorporation of traffic factors (e.g., congestion, wait times) would make EV scheduling models with power grid considerations more accurate [41,124,151].

4.3. EV scheduling with environmental considerations

The EV scheduling problem with environmental considerations assesses the environmental impacts of EVs, such as emissions of greenhouse and non-greenhouse gases (e.g., carbon oxides, nitrogen oxides, sulphur oxides). The main source of emissions from EV use is EV charging. EVs may be connected to the grid for charging, and energy generation for EV charging may cause emissions. The time during which charging is scheduled and the region where charging occurs may impact the amount of emissions [166]. Energy produced for low-demand hours may be less expensive but more emission intense. As such, higher CO_2 emissions may occur from charging EVs during nighttime. For some

Table 5
Summary of findings: studies on EV scheduling with power grid considerations.

References	Formulation type	Model objectives	Optimization type	EV aggregation	Time windows	Use of renewable energy	Solution approaches	Notes/Major considerations
Khodayar et al. [97]	MINLP	Minimize the total cost	SOO	✓	N/A	✓	Heuristic	EV operations controlled by consumers and power grid
Ortega-Vazquez et al. [98]	MIP	Minimize the total cost	SOO	✓	N/A	—	N/A	Coordination among the power system operator and the EV aggregator
Zhang et al. [99]	N/A	Minimize the mean queue length	SOO	—	N/A	✓	Simulation	Uncertainties in the grid power price and EV arrival
Kumar et al. [100]	N/A	Minimize the variance in EV priority	SOO	—	Soft	—	Heuristic	Impact of priority criteria
Kamankesh et al. [101]	MIP	Minimize the total cost	SOO	—	Strict	✓	Heuristic	Microgrids
Luo et al. [102]	N/A	N/A	N/A	—	N/A	—	N/A	Node voltage; Load deviation
Janjic et al. [103]	MINLP	Minimize the service waiting time; Maximize the revenues from secondary regulation; Maximize the charging efficiency	MOO	✓	N/A	—	Genetic algorithm	Secondary frequency control
Li et al. [104]	N/A	Minimize the total cost	SOO	—	N/A	✓	Heuristic	Online dynamic optimization
Sassi and Oulamara [105]	MIP	Maximize the total traveled distance; Minimize the total recharge cost	MOO	—	N/A	—	CPLEX; Heuristic	Complexity analysis
Maigha and Crow [106]	MIP; MIQCP	Minimize the battery degradation cost; Minimize the customer charging-discharging cost; Minimize the deviation between instantaneous and average demand	MOO	✓	N/A	—	CPLEX; GUROBI; ε-constraint method	Conflicting system and customer objectives
Pal and Kumar [107]	MIP	Minimize the total energy procurement cost	SOO	—	Strict	—	CVX	Residential demand response
Sun et al. [108]	LP	Minimize the number of on-off switching	SOO	✓	N/A	—	Heuristic	Discrete charging levels
Amamra and Marco [109]	NLP	Minimize the battery degradation cost; Maximize the total revenue	HO	✓	N/A	—	Heuristic	Voltage regulation; Frequency regulation
Chung et al. [110]	N/A	Minimize the recharging cost; Maximize the user convenience level	MOO	✓	Strict	—	Heuristic	Consensus between recharging stations and EV owners
Sharma and Jain [111]	MINLP	Minimize the recharging cost; Maximize the total profit	MOO	✓	N/A	—	IPOPT	Time-of-use pricing
Zhou et al. [112]	N/A	Maximize the total electricity cost; Maximize the payoff at recharging stations	HO	✓	Strict	✓	CVX	Game theory; Uncertainty in EV arrival and renewable energy generation
Aliasghari et al. [113]	MINLP	Maximize the total profit	SOO	✓	N/A	—	Heuristic	Uncertainties in arrival time, departure time, and initial state-of-charge
Koufakis et al. [114]	MIP	Minimize the total recharging cost	SOO	✓	N/A	✓	Heuristic	Prediction of renewable energy generation
Liang et al. [115]	IP	Maximize the total welfare	SOO	—	N/A	—	Deep reinforcement learning	EV sharing
Rasheed et al. [116]	LP	Minimize the total cost	SOO	✓	N/A	—	Genetic algorithm	Multi-region EV charging
Xie et al. [117]	MIP	Maximize the total profit	SOO	✓	N/A	—	Heuristic	EV sharing
Ban et al. [118]	MIP	Minimize the total cost	SOO	—	Strict	✓	Heuristic	Nanogrids
Das et al. [119]	IP	Minimize the total cost	SOO	—	N/A	—	Heuristic	Uncertainties in driving cycle
Jin and Xu [120]	N/A	Maximize the sum of the negative stage cost and the entropy of the policy	SOO	—	Strict	✓	Heuristic	Actor-critic approach

(continued on next page)

Table 5 (*continued*)

References	Formulation type	Model objectives	Optimization type	EV aggregation	Time windows	Use of renewable energy	Solution approaches	Notes/Major considerations
Li et al. [121]	CCP	Minimize the community integrated energy system operational cost; Minimize the EV charging system operational cost	HO	—	N/A	✓	CPLEX	Flexible demand response
Wu and Chen [122]	QP	Minimize the total cost	SOO	✓	N/A	—	Heuristic	Transactive energy management
Xu et al. [123]	N/A	N/A	N/A	—	N/A	—	N/A	Data protection
Wu et al. [124]	MIP	Minimize the total operational cost; Minimize the peak load	MOO	—	Strict	—	Branch-and-price algorithm	Time-of-use price; Public transit

Notes: Formulation Type [CCP – Chance-Constrained Programming; IP – Integer Programming; LP – Linear Programming; MINLP – Mixed-Integer Non-Linear Programming; MIP – Mixed-Integer Programming; MIQCP – Mixed-Integer Quadratically Constrained Programming; NLP – Non-Linear Programming; QP – Quadratic Programming]; Optimization Type [SOO – Single-Objective Optimization; MOO – Multi-Objective Optimization; HO – Hierarchical Optimization].

regions in the United States (e.g., southwest region in the summer), energy generated during late hours may produce up to 65 % more CO_2 emissions as compared to peak periods [167]. Moreover, reinforcement of grids with EVs may emit greenhouse and non-greenhouse gases [168]. Let μ^{CO_x}, μ^{NO_x}, and μ^{SO_x} denote the amount of carbon oxides, nitrogen oxides, and sulphur oxides EVs typically emit per unit distance. Then, the EV scheduling problem with environmental considerations can be mathematically formulated as follows:

EV Scheduling Problem with Environmental Considerations (EVSP–EC):

$$min \sum_{i\in V_0^{'}, j\in V_{N+1}^{'}} d_{ij}\left(\mu^{CO_x}+\mu^{NO_x}+\mu^{SO_x}\right)x_{ij} \tag{29}$$

Subject to:

$$x_{ii}=0\ \forall i\in V_{0,N+1}^{'} \tag{30}$$

$$\sum_{j\in V_{N+1}^{'}} x_{ij}=1\ \forall i\in V \tag{31}$$

$$\sum_{j\in V_{N+1}^{'}} x_{ij}\le 1\ \forall i\in F^{'} \tag{32}$$

$$\sum_{i\in V_0^{'}} x_{ij}=\sum_{i\in V_{N+1}^{'}} x_{ji}\ \forall j\in V^{'} \tag{33}$$

$$\tau_i+\left(s_i+t_{ij}\right)x_{ij}-M\left(1-x_{ij}\right)\le\tau_j\ \forall i\in V_0, j\in V_{N+1}^{'} \tag{34}$$

$$\tau_i+g\left(Q-y_i\right)+t_{ij}x_{ij}-M\left(1-x_{ij}\right)\le\tau_j\ \forall i\in F^{'}, j\in V_{N+1}^{'} \tag{35}$$

$$e_i\le\tau_i\le l_i\ \forall i\in V_{0,N+1}^{'} \tag{36}$$

$$u_j\le u_i-q_ix_{ij}+C\left(1-x_{ij}\right)\ \forall i\in V_0^{'}, j\in V_{N+1}^{'} \tag{37}$$

$$u_i\le C\ \forall i\in V_{0,N+1}^{'} \tag{38}$$

$$y_j\le y_i-\left(h\cdot d_{ij}\right)x_{ij}+Q\left(1-x_{ij}\right)\ \forall i\in V, j\in V_{N+1}^{'} \tag{39}$$

$$y_j\le Q-\left(h\cdot d_{ij}\right)x_{ij}\ \forall i\in F_0^{'}, j\in V_{N+1}^{'} \tag{40}$$

$$x_{ij}\in\{0,1\},\tau_i,u_i,y_i\ge 0\ \forall i\in V_{0,N+1}^{'}, j\in V_{0,N+1}^{'} \tag{41}$$

The objective function (29) of the EV scheduling problem with environmental considerations minimizes the total emission from EV scheduling. Constraint sets (30) through (40) incorporate some basic EV scheduling attributes, which are similar to the ones imposed in the **GEVSP** mathematical model. Constraint set (41) specifies the attributes of the variables used in the **EVSP–EC** mathematical model. Some typical EV routes for the EV scheduling problem with environmental considerations are shown in Fig. 7.

4.3.1. *Description of the relevant studies*

Cardoso et al. [166] developed a flight aggregator model to address some limitations of the mathematical model developed by the Lawrence Berkley National Laboratory that prepared schedules for EVs as a resource of distributed energy. Specifically, simultaneous connections/disconnections between EVs, direct calculation of carbon dioxide emissions, and continuity in EV schedules were addressed. Numerical experiments suggested that energy costs were barely affected by uncertainties in driving schedules. Hoehne and Chester [167] discussed that cost reduction subsidies might be required for strategic EV scheduling as a means to persuade EV users or power generators. In order to reduce recharge-related emissions, EV users might need to change their recharge habits. EV users could find temporal and regional trends informative while estimating carbon dioxide emissions. Reddy et al. [168] integrated thermal units, renewable energy technology, and EVs for a smart grid and designed a binary version of the Fireworks Algorithm to solve the problem. The Fireworks Algorithm was employed for a scenario-based scheduling of the system, and significant savings in emissions and costs were recorded.

Lu et al. [169] investigated a load dispatch model to optimize the pollutant treatment cost and operational cost of a microgrid. Moreover, the system's load variance was minimized to promote its stability. Different charging scenarios, including coordinated charging with and without distributed generations along with uncoordinated charging were analyzed, and coordinated charging was proven to be superior. Mohammadkhani et al. [170] tested thermal energy storages, EVs, and battery energy storage systems as a combined cooling, heating, and power unit for residential microgrids. A multi-objective optimization framework to minimize the emissions as well as the energy costs of such microgrids was formulated. Time-of-use power charges along with reducible loads were incorporated in the framework to facilitate a demand response program. A case study that was conducted as a part of the study illustrated the effectiveness of the proposed strategy. Ahmad and Sivasubramani [171] deliberated that there was a need for capacity increase of power grids, as the number of EVs connected to power grids was on the rise. In this connection, the study identified the EV fleet size a power grid could handle within a scheduling framework. It was

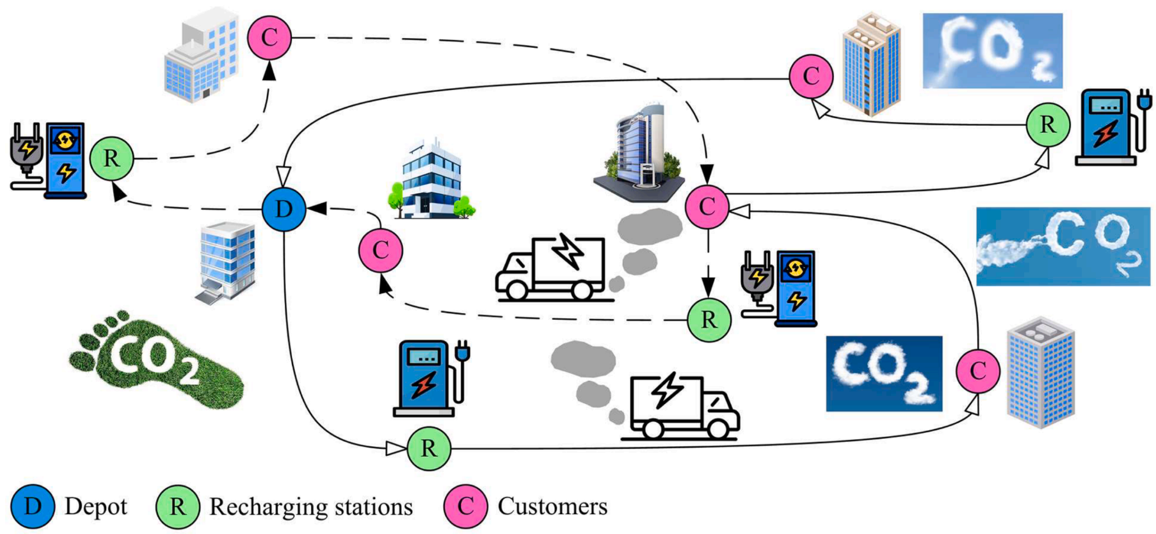

Fig. 7. EV scheduling problem with environmental considerations.

demonstrated that a vehicle-to-grid participation could substantially increase the fleet size handling capacity of a power grid.

Sadati et al. [172] formulated a bi-level optimization model to schedule the operations of a distribution company. Another market participant, namely EV parking lot owners, was considered in the model. The model aimed to maximize the total profit, however, at different levels for different market participants. The Fortuny-Amat and McCarl linearization as well as Karush–Kuhn–Tucker conditions were used in the study. Simulation results demonstrated that the distribution company owner made more profits by a critical peak pricing program as well as recharge schedule of EVs. Brinkel et al. [173] discussed that grid reinforcement could reduce EV charging costs or emissions; however, such an action would lead to other costs or emissions due to the grid reinforcement itself. In this regard, the study compared the costs and emissions due to grid reinforcement as opposed to its benefits in EV recharge (i.e., reduction in costs and emissions). Moreover, a tradeoff between minimization of various costs (e.g., electricity cost, battery degradation cost) and emissions due to EV recharge was analyzed. Numerical experiments revealed that the EV-to-grid framework obtained up to 32.4 % cost savings as compared to uncontrolled EV recharge while considering current transformer capacities. Das et al. [174] concurrently minimized carbon dioxide emissions along with battery degradation, energy cost, and grid interaction for an energy service. Frequency regulation was conducted as well for the multi-objective optimization framework, and it was demonstrated to be profitable for users.

Dixon et al. [175] performed the management of excess renewable energy throughout EV scheduling. In particular, a demand for excess renewable energy was created, which would have been curtailed otherwise. At the same time, the carbon dioxide emission from EV charge scheduling was minimized. Numerical experiments indicated that such a scheduling methodology could reduce carbon dioxide emissions by 30 %. Emrani-Rahaghi and Hashemi-Dezaki [176] assessed the uncertainties in renewable energy resources and electricity price for residential energy hubs. A probabilistic scenario-based model to optimize the daily operational cost was formulated and tackled with the K-Means Algorithm. The proposed methodology exhibited more substantial computational time savings than that of Monte Carlo Simulation-based methodologies. Luo et al. [177] analyzed the impact of the pollutant trading market on the operational cost of an energy hub model that involved an energy storage system and EVs. A scheduling scheme was proposed to obtain the minimum emission tax cost and purchase cost. It was demonstrated that the proposed methodology could meet the users' temperature condition requirements.

Morais et al. [178] designed an Elitist Nondominated Sorting Genetic Algorithm-II (NSGA-II) for a multi-objective variant of the EV scheduling problem, which had the objectives of minimizing the operational cost and greenhouse gas emissions. Numerical experiments clearly demonstrated the efficiency of the proposed solution methodology for the considered multi-objective decision problem. Rahman et al. [179] discussed that EVs could be treated as energy-storage tools, as they could be used for peak shaving or load shifting within a power grid. Hence, an EV scheduling scheme was developed to minimize the total energy consumption. Both deterministic and stochastic models were proposed, which employed quadratic programming and Monte Carlo Simulation, respectively. Based on the conducted numerical experiments, vehicle-to-grid feasibility was suggested by both of the models. Tu et al. [180] indicated that electricity generation could result in a significant quantity of upstream emissions. Hence, marginal greenhouse gas emissions were minimized within the scope of EV charge scheduling. A case study for the Greater Toronto and Hamilton Area (Canada) revealed that the proposed approach could reduce about 97 % of emissions as compared to that of conventional vehicles.

Alabi et al. [4] devised a day-ahead scheduling framework for a virtual powerplant that involved EVs. Specifically, a hybrid inexact scheduling scheme was proposed, which used the robust cardinal uncertainty set method to address uncertainties in energy demand. Furthermore, the Latin hypercube sampling method was employed to quantify the proposed system's intermittency. It was shown that robust control parameters, EV parameters, charging station standards, as well as multi-energy demand and generation could deliver a multi-flexible performance. Habeeb et al. [181] examined a direct current nanogrid system to integrate the EV recharging infrastructure with demand response initiatives, renewable energy sources, as well as energy storage facilities. A scheduling scheme for the examined nanogrid was developed. Moreover, a specific stochastic framework was designed for fast recharging stations. The significance of demand response initiatives on the retailer's profit was suggested by numerical experiments. Mansour-Saatloo et al. [182] assessed a microgrid, which used a combination of power, heat, and hydrogen. Hydrogen-based recharging stations were used for EV parking lots, fuel cells, as well as hydrogen vehicles. The proposed microgrid could interact with both hydrogen and electricity markets. Empirical results demonstrated that the proposed model could reduce operational costs by 76.35 % while handling uncertainties efficiently.

Yin and Ming [183] designed a multi-objective Particle Swarm Optimization algorithm, which employed reverse learning, competitive learning, and local search, in order to schedule EVs for charge and discharge. The study undertook several objectives, including the minimum operational cost, pollution, peak valley difference, node voltage offset rate, grid loss, and charging cost. Numerical experiments revealed that the algorithm could effectively achieve the anticipated objectives.

Zeynali et al. [184] investigated the integrated scheduling of EVs and wind farm for a day-ahead wholesale market, considering cost and emission objectives. A bi-level nonlinear model was proposed, which was later linearized with semi-integer variables. K-means clustering was

Table 6
Summary of findings: studies on EV scheduling with environmental considerations.

References	Formulation type	Model objectives	Optimization type	EV aggregation	Time windows	Use of renewable energy	Solution approaches	Notes/Major considerations
Cardoso et al. [166]	MIP	Minimize the total cost	SOO	✓	N/A	—	CPLEX	Distributed energy resource
Hoehne and Chester [167]	N/A	Minimize the total emission	SOO	—	N/A	—	N/A	Regional electricity reliability
Reddy et al. [168]	MIP	Minimize the total cost; Minimize the total emission	MOO	—	N/A	✓	Fireworks algorithm	Incorporation of thermal units, renewable energy, and EVs
Lu et al. [169]	N/A	Minimize the operational cost; Minimize the pollutant treatment cost; Minimize the load variance	MOO	—	N/A	✓	Particle swarm optimization	Stochastic EV access
Mohammadkhani et al. [170]	MIP	Minimize the total cost; Minimize the total emission	MOO	—	Soft	—	Augmented ε-constraint method	Combined cooling, heating, and power
Ahmad and Sivasubramani [171]	QP	Minimize the total running cost	SOO	—	N/A	—	Heuristic	Fleet size determination
Sadati et al. [172]	MINLP	Maximize the profit of the distribution company; Maximize the profit of the parking lot	HO	—	N/A	✓	N/A	Uncertainties in renewable energy resources
Brinkel et al. [173]	MINLP	Minimize the total cost; Minimize the total emission	MOO	✓	N/A	—	ε-constraint method	Emission tradeoff; Grid reinforcement
Das et al. [174]	NLP	Minimize the energy cost; Minimize the battery degradation; Minimize the grid net exchange; Minimize the total emission	MOO	—	Soft	✓	Heuristic	Frequency regulation
Dixon et al. [175]	MIP	Minimize the total cost	SOO	✓	Soft	✓	CPLEX	Excess renewable energy management
Emrani-Rahaghi and Hashemi-Dezaki [176]	N/A	Minimize the daily operational cost	SOO	—	N/A	✓	K-means algorithm	Uncertainties in renewable energy resources and electricity price
Luo et al. [177]	MIP	Minimize the total cost	SOO	—	N/A	—	GUROBI	Emission tradeoff
Morais et al. [178]	MINLP	Minimize the total cost; Minimize the total emission	MOO	✓	N/A	—	Elitist NSGA-II	Elitist strategy
Rahman et al. [179]	QP	Minimize the total power consumption	SOO	✓	Strict	✓	N/A	Load leveling; Peak shaving
Tu et al. [180]	IP	Minimize the total emission	SOO	—	N/A	—	Heuristic	Marginal greenhouse gas emissions
Alabi et al. [4]	MIP	Minimize the total scheduling cost, curtailment, and fuzzified economy cost	MOO	✓	N/A	✓	GUROBI	Hybrid inexact optimal scheduling
Habeeb et al. [181]	MINLP	Maximize the total profit	SOO	—	Strict	✓	Heuristic	DC nanogrids
Mansour-Saatloo et al. [182]	MIP	Maximize the robustness function for wind; Maximize the robustness function for photovoltaic power	MOO	—	N/A	✓	Augmented ε-constraint method	Combined hydrogen, heat, and power microgrid; Hydrogen-based recharging stations
Yin and Ming [183]	N/A	Minimize the operational cost; Minimize the total emission; Minimize the peak valley difference; Minimize the node voltage offset rate; Minimize the grid loss; Minimize the recharging cost	MOO	—	N/A	✓	Particle swarm optimization	Competitive learning, reverse learning, and local search
Zeynali et al. [184]	MIP	Minimize the total cost; Minimize the total emission	HO	—	N/A	✓	CPLEX	Uncertainties in arrival time, departure time, and traveled distance

Notes: Formulation Type [IP – Integer Programming; MINLP – Mixed-Integer Non-Linear Programming; MIP – Mixed-Integer Programming; NLP – Non-Linear Programming; QP – Quadratic Programming]; Optimization Type [SOO – Single-Objective Optimization; MOO – Multi-Objective Optimization; HO – Hierarchical Optimization].

employed to obtain five EV fleets. Furthermore, robust optimization sets were used to model wind power. Extensive simulation demonstrated that the proposed methodology delivered 40 % emission reduction and 4.4 % locational marginal price manipulation. Several other studies have assessed EV scheduling while incorporating environmental considerations [185–195].

4.3.2. Summary of studies

A detailed summary of findings for the reviewed studies on EV scheduling with environmental considerations is provided in Table 6. The review of the selected studies on EV scheduling with environmental considerations revealed that a substantial number of the reviewed studies formulated mixed-integer programs with the objective of minimizing the total cost and/or minimizing the total emission. Some other objective functions were considered in the state of the art as well, including minimization of the total operational cost, minimization of the pollutant treatment cost, minimization of the load variance, maximization of the total profit, minimization of the battery degradation, minimization of the grid net exchange, minimization of the peak valley difference, and minimization of the total grid loss. Furthermore, the majority of the reviewed studies did not employ EV aggregators and did not enforce any time windows. However, the use of renewable energy sources was considered in a significant number of the reviewed studies. Moreover, metaheuristic and heuristic algorithms were determined to be popular methods for the optimization models formulated for the EV scheduling with environmental considerations.

4.3.3. Future research needs

- EV users, manufacturers, and promoters of solutions for sustainable transportation must explore practical methods to effectively capture emissions produced by EVs as compared to emissions produced by conventional vehicles [180].
- Minimization of the total cost of EV scheduling can result in a higher emission of greenhouse gases. Therefore, a tradeoff between cost minimization and emission minimization should be conducted by the future studies on EV scheduling with environmental considerations [168,170,173,178,184].
- A number of studies have used historic data regarding carbon intensity and curtailment. However, these parameters change with time, space, and other attributes. Therefore, specific analyses of carbon intensity and curtailment should be performed in a more comprehensive way [174,175].
- Uses of various renewable energy sources (e.g., hydropower, solar, wind) and their impacts on EV batteries could be researched by the future studies on EV scheduling with environmental considerations [153,169]. Moreover, variability in the availability of renewable energy may be an interesting research topic as well [153,171,176].
- Distributed storage, heating, and demand side response of renewable energy sources for EV charge scheduling should allow achieving a more decarbonized environment [170,182].
- Environmental and economic impacts of power grid reinforcements, considering dynamic power markets, may be investigated in depth in the following years [173,174].
- The COVID-19 pandemic substantially affected different industrial and public sectors across the globe [196–200] Due to the reduction of daily activities, a significant reduction in greenhouse gas and non-greenhouse gas emissions has been observed. The pandemic impacts on the EV markets and EV environmental performance could be investigated in the future studies.
- Methods to facilitate better education of recharging-related EV emissions should be assessed to promote smarter recharging practices in different communities around the world [167].

5. Conclusions

EVs can be perceived as a means to achieve carbon reduction, energy efficiency, and sustainable development of the transportation industry. A number of nations have announced policies to promote the deployment of EVs, especially in the last decade. However, EV deployment should be conducted in a planned manner, as EVs have some limitations that still have to be addressed (e.g., limited driving range, refueling capacity, carrying capacity). Innovative models and solution algorithms for the EV scheduling problem can be an effective approach to overcome such limitations, as they addresses these limitations while optimizing the paths and timetables of EVs. The present literature survey reviewed an assortment of studies, which assessed the EV scheduling problem. The studies related to communications between electric vehicles (e.g., coordination between vehicles and prioritization for recharging) and communications between electric vehicles and infrastructure (e.g., charging stations) were directly captured by the survey as well. The reviewed studies were classified into three categories, namely general EV scheduling, EV scheduling with power grid considerations, and EV scheduling with environmental considerations. A detailed description of the relevant studies was provided mainly focusing on the adopted formulation types, model objectives, problem-specific properties, solution approaches, and major considerations. Furthermore, a summary of findings and future research needs were provided for each of the study categories.

After a structured review of the collected literature, it was found that the collected studies proposed a variety of mathematical formulations, which comprise linear programming, non-linear programming, integer programming, mixed-integer programming, mixed-integer non-linear programming, and other formulations. However, the mixed-integer programming formulations were found to be the most common among the EV scheduling studies. The total cost minimization was typically adopted as the objective function of the proposed mathematical formulations. A substantial number of the reviewed studies on EV scheduling with environmental considerations also aimed to minimize the total emission. The mathematical models of the reviewed studies captured certain other objective functions as well, such as minimization of the total tardiness, minimization of the completion time, maximization of the number of completed tasks, maximization of the total profit, and minimization of the total waiting time. Single-objective optimization models were found to be more popular in the EV scheduling studies as compared to multi-objective and hierarchical optimization models.

In order to solve the proposed mathematical models, several solution approaches were used, comprising heuristics, metaheuristics (e.g., Genetic Algorithm, Particle Swarm Optimization, Variable Neighborhood Search, Artificial Bee Colony), exact optimization approaches (e.g., GUROBI, CPLEX, IPOPT), and other approaches. Metaheuristic and heuristic algorithms were identified to be the most common solution methods for the EV scheduling optimization models. As for problem-specific characteristics, the majority of the studies did not employ EV aggregators, enforce time windows, or use renewable energy. Moreover, a wide range of considerations were incorporated within the reviewed studies (e.g., heterogeneous fleets, time-of-use prices, various uncertainties pertaining to EV schedules).

There are several areas where the present literature survey could be expanded. First, EV infrastructure investments could be investigated in detail to ensure the sustainable development and deployment of EVs in the following years. Different types of EV infrastructure investments should be evaluated based on consultations and interviews with the relevant stakeholders. Second, the opportunities for effective cost management schemes for vehicle-to-grid systems, which account for customer privacy, should receive more attention in the following years. Third, a wireless power transfer can be an economically and environmentally efficient option for EV recharging [201–203]. Hence, it should be explored more by the future studies. Fourth, the number of autonomous vehicles increases every year, and the next generation vehicles are expected to be not only electric but autonomous as well. However, autonomous vehicles face certain deployment challenges, including development costs, user adoption, safety and security issues, and operational challenges [204–208]. These challenges should be addressed in the following years to ensure the successful and timely development of new generation electric and autonomous vehicles. Fifth, several countries have started using renewable energy for EV deployment. Incentive policies for the adoption of renewable energy sources should be studied more in depth to ensure their wide implementation by EV users. Sixth, the most popular EV routing models (e.g., [209–214]) can be studied more in depth in order to develop new and more efficient formulations for different variants of the EV scheduling problem. Seventh, more advanced algorithms should be developed and evaluated for the EV scheduling models, such as the Beetle Antennae Search Optimizer, Simulated-Annealing-based Bees Algorithm, different variations of the Grey Wolf Optimizer, and others [215–217].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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