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Review

A Review of the Latest Trends in Technical and Economic Aspects of EV Charging Management

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Abstract: The transition from internal combustion engines to electric vehicles (EVs) has received significant attention and investment due to its potential in reducing greenhouse gas emissions. The integration of EVs into electric and transport systems presents both benefits and challenges in energy management. The scheduling of EV charging can alleviate congestion in the electric system and reduce waiting times for EV owners. The use of renewable energy sources (RESs) for EV charging and supporting the grid can help mitigate the uncertainty of these energy resources. Vehicle-to-grid (V2G) technology can be used as an alternative approach in the event of sudden high consumption of the grid. Additionally, cost minimization through large-scale coordinated planning is crucial for the future of e-mobility systems. This review paper focuses on the latest trends considering the various approaches and features in coordinated EV scheduling, as well as the influence of different stakeholders, categorized as single- and multiple-charging stations (CS) and aggregator levels. By implementing coordinated EV scheduling, various methods are presented to better manage the needs and satisfaction of EV owners as well as the profit of CS and the market trends of e-mobility systems. In this regard, EV charging strategies considering V2G, uncertainty evaluation of parameters, coordinated charging management, congestion of CSs and electrical lines, route mapping, and technical and economic aspects of the system hierarchy, including consumers, CSs and aggregators, are reviewed and discussed.

Keywords: electric vehicles; charging station; EV charging management; EV scheduling; V2G; stakeholders; distribution system

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1. Introduction

Electric vehicles (EVs) create potential for future energy systems by lowering the use of fossil fuels and greenhouse gases (GHG). The European Union's long-term goal to achieve a low-carbon economy [1] supports accessible charging frameworks and facilities, as well as strategies, for developing a green transportation system, which has led to extreme interest in renewable energy sources (RESs) in energy and e-mobility systems. EVs as a clean means of transportation have a significant impact on energy systems in both infrastructure and characteristics. EVs play key roles in the development of sustainable urban transport systems and offer various advantages, including reducing noise, improving local air quality, decreasing CO_2 due to higher efficiency compared to internal combustion engines, allowing grid integration of RESs, and reducing the dependence on fuels as the source of energy. In [2], mitigating CO_2, as well as efficient use of RESs, is surveyed, while the impact of different stakeholders' objectives is considered.

1.1. Charging Station Congestion Evaluation

One of the innovative applications of RESs is utilizing these resources in charging EVs. Authors of [3] modelled a dynamic pricing scheme for RES generation in charging stations (CSs) and a decision mechanism for EVs to find the best location for charging based on congestion and traffic, as well as the price of electricity. Moreover, flowing numerous EVs to the CSs in the crowded areas near city centers results in traffic congestion at CSs. However, increasing the number of EVs requires suitable infrastructure, locating the best charging spots to build CSs [4] and providing enough facilities [5]. In this regard, building new CSs requires evaluating several aspects including charging prices, locations, and capacities in strategic planning. Authors of [6] proved that considering a series of existing CSs' profit and loss, while running new CSs, makes the final optimal scenario different. Operational and investment costs from the owner's perspective and the convenience of EV owners shall be considered in a competitive environment. From another perspective, transitioning from fuel-powered to electrified transportation systems results in a massive number of EVs charging randomly. In city centers during peak hours, energy management strategies are needed to effectively balance demand and supply. By growing the EV industry with more and more EVs in the market and consequently on roads, their charging patterns give rise to congestion in the electrical grid [7]. From the point of view of the uncertainty of RESs and network load, the importance of balancing the electricity and power demand is remarkable [8,9]. This helps in changing consumers' behavior by motivating them to use their electrical devices in less busy times, which, by the revolution of EV home charging, positively impacts controlling the congestion of lines.

1.2. Power Transaction with Electrical Network

Power transactions include customer services by CSs and services provided by EVs into the grid, as well as charging infrastructure. The vehicle-to-grid mode (V2G) is described as a situation where an EV can inject electricity back into the grid through discharging mode. In this case, EVs can be discharged during the period of peak hours in the V2G mode and contribute to the security of supply. As a result, EV users have the advantage of selling electricity to the power grid when the electricity price is high. This can be estimated as being similar to the storage system in peak shaving [10]. Moreover, V2G can participate in valley filling and spinning reserve [11] and demand response [12]. Furthermore, increasing variability in power generation due to RES systems makes the storage capacity necessary. The adoption of EVs can also lead to the development of technologies related to RES. V2G technology enables EVs to store energy from RESs, such as solar and wind power, and then discharge that energy back to the grid during times of peak demand. This allows EVs to function as mobile energy storage systems, which can help to balance the grid and reduce the need for additional energy generation. In this regard, EVs can improve the stability of the grid. For example, EVs can be used as mobile energy storage systems, which can help to balance the grid by discharging electricity. In this regard, V2G technology creates the advantage of EVs to exchange electricity within the power grid and, in consequence, has a significant impact on the operation and management of power systems and the electricity market. However, careful planning and management of the energy system is necessary to ensure that the integration of EVs and renewable energy is efficient and environmentally sustainable [13–15].

1.3. EV Aggregators

EV aggregators manage and optimize the charging and discharging of large numbers of EV batteries. These companies utilize EV batteries to aggregate energy and provide services to the energy market or grid. EV aggregators offer demand response services, which involve adjusting the charging and discharging of EV batteries in response to changes in grid conditions or energy prices. This service helps to balance supply and demand by reducing or increasing the electricity from EV batteries. Moreover, EV aggregators provide frequency regulation services that result in grid stability. Furthermore, EV aggregators can sell energy stored in EV batteries to provide services to energy markets.

1.4. Uncertainty in EV Charging Management

The RES has the advantage of providing extra electricity capacity and creating more resilience to the system. However, due to their intermittent nature, these energy sources present challenges and inefficiencies in energy production. The fluctuating nature of RESs can create imbalances in the supply and demand of electricity. However, EVs can help to mitigate these issues by serving as mobile energy storage systems. The use of EVs as energy storage can help to increase the penetration of RESs in the electric grid. By allowing excess RESs' energy to be stored and used later, EVs can help to reduce the curtailment of these resources, which occurs when energy production exceeds demand, and the excess energy is not utilized. Researchers of [16] considered demand and supply balance by contributing to the electricity demand response while the comfort of customers is provided. From another side, the charging behavior of EV owners has a direct impact on the uncertainty of the integrated power and transportation network. In this regard, a suitable mechanism for modelling the stochastic nature of consumers' charging patterns [17] is vital. In [18], the authors declared that modelling a realistic and robust system cannot exist without considering the uncertainty of energy resources and electrical network load. The uncertain parameters, which are modelled in different articles, are shown in Figure 1.

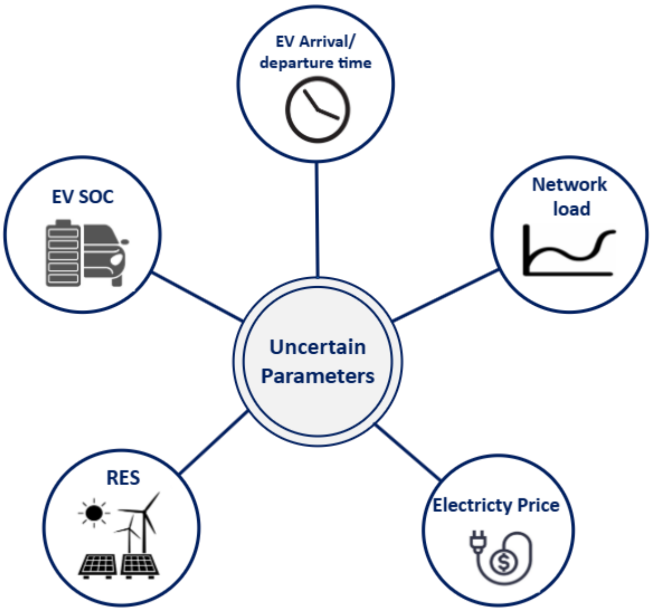

Figure 1. Uncertain parameters in integrated transportation & electrical system.

1.5. Coordinated vs. Uncoordinated Charging Management

Charging management of EVs in smart systems is not possible without proper management strategies. Uncoordinated EV charging is a situation when EVs can start charging immediately by the time they arrive at the CS. The uncoordinated charging of EVs through CSs connected to the distribution system (DS) could cause extra load and congestion to the system [19]. Coordinated charging, on the other hand, is an energy management approach in which the time and power of charging and discharging modes are optimized. Moreover, technical constraints of the electrical grid, EV battery requirements, and CS capacity are considered. To mitigate the negative impacts of uncontrolled charging of EVs, a system-constrained coordination method is proposed in [20]. In this research, the proposed management scheme helps in mitigating extra pressure on the grid as well as congestion and traffic of charging spots. Another coordinated EV charging/discharging is proposed in [21] in the format of a cooperative strategy in which EVs of a building can interact with each other in V2V mode and lower the consumption of the electrical grid, with the help of vehicle-to-load (V2L), minimizing the cost. The objective functions which are optimized through different coordinated management schemes in different research articles are shown in Figure 2.

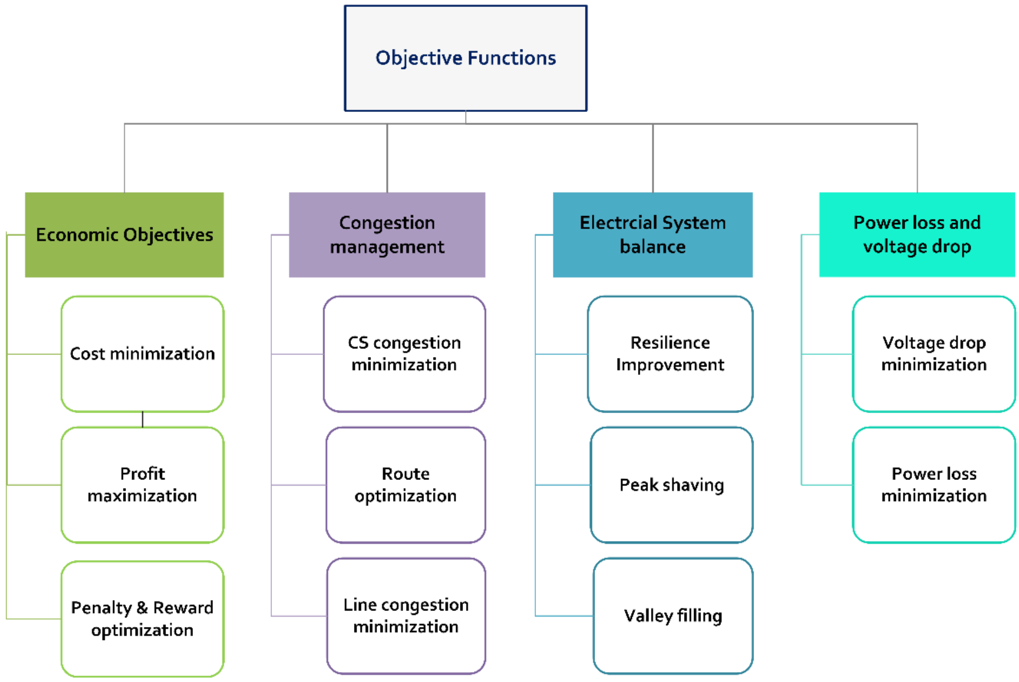

Figure 2. Objective functions in coordinated charging management.

From the multi-stakeholder's perspective in EV charging management, each one follows its profit. Two or more e-mobility stakeholders, including distribution system operators (DSO), CS operators (CSOs), EV owners, aggregators, and electricity market operators are considered in the reviewed papers. In this regard, optimal EV scheduling in multilevel stakeholder systems requires an efficient management scheme. Therefore, it is necessary to optimize the operation of CSs and coordinate management of electrical systems, while the satisfaction of customers in financial and time efficiency is met. In [22], the convenience of EV owners as the lowest level of stakeholders is evaluated. Power loss and voltage deviation of the grid and CS traffic management are surveyed through a fuzzy logic method. Moreover, it is essential to model the benefits of CSs to assess their economic viability, plan infrastructure development, and make policy decisions. By analysing factors such as the demand for charging, the cost of installation and operation, and the impact on the grid, stakeholders can make informed decisions about infrastructure development and investment to support the growth of the electric vehicle market and the development of a sustainable transportation system. In this regard, the price of electricity for charging electric vehicles is considered in a suitable scheme in CSs. From the perspective of coordinated EV scheduling, CS charging management can be categorized into three different decision-making schemes: centralized, decentralized, and hybrid. Centralized decision-making for EV charging is defined as control and management of charging/discharging EVs by a central operator or aggregator, which has the responsibility to receive the data from EVs and the electrical grid and arrange the scheduling. Additionally, the charging costs of EV owners besides the DS constraints is necessary [23]. The scheduling problem aims to minimize electricity costs of CSs and EV owners, controlling queues of EVs, minimizing their waiting time, avoiding charging in high consumption hours, etc. In [19], a centralized, coordinated EV charging in a grid-connected system framework is offered. Decentralized charging scheduling is developed in such a way that EV owners can communicate with the CSO by sending and receiving signals [24]. In this regard, cost and waiting time minimization and congestion avoidance in each CS is done through negotiation between

CSs and EVs in a distributed manner. Diagrams of centralized and decentralized EV scheduling are shown in Figure 3.

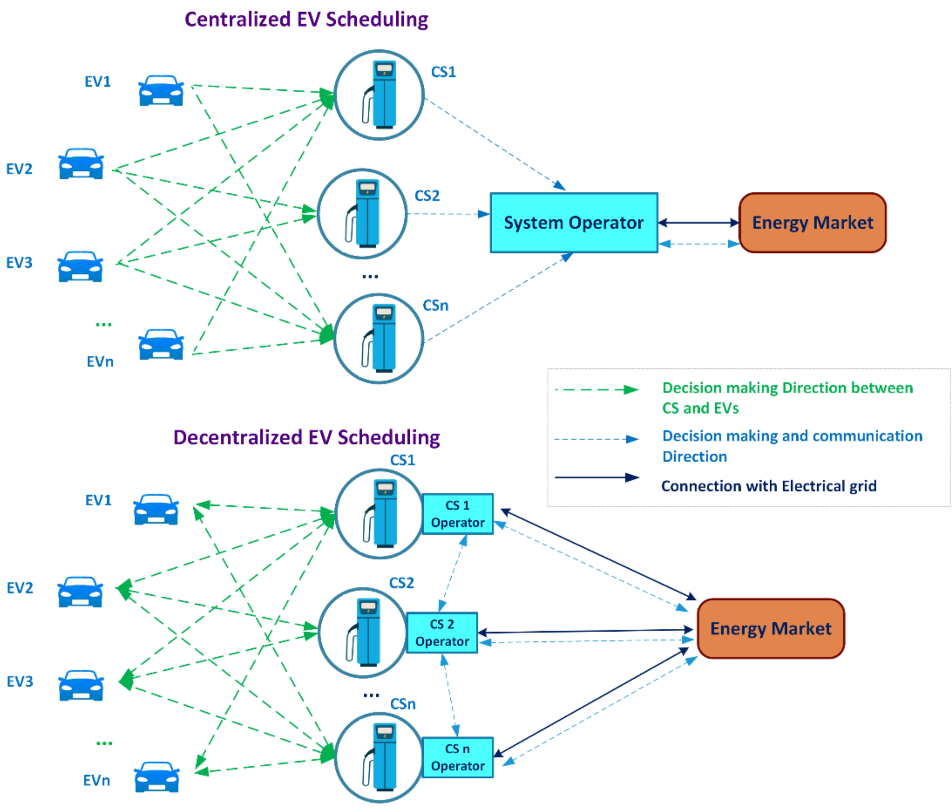

Figure 3. Diagram of centralized and decentralized decision making in an integrated electrical-transportation system.

Furthermore, to take advantage of both centralized and decentralized decision-making capabilities, a hybrid decision-making approach is applicable. In a hybrid controlling approach, both centralized and decentralized frameworks are modelled, in which the system consists of two levels (centralized level through a system operator and the decentralized level within a distributed management scheme).

This review paper is surveying recent publications in journals related to electrical and energy systems with the specialty of EV charging management. The aim is to investigate the latest trends in multi-stakeholders' hierarchy, considering technical and economic characteristics. Different techniques and methodologies, as well as controlling strategies of each modelling approach proposed in each paper, are discussed, and their motivations and limitations are categorized.

The main contributions of this review paper are as follows:

- Investigating communication levels of different stakeholders in multilevel decision making in single-CS, multiple-CS, and aggregator-based scheduling.
- Study of grid-connected EV charging challenges and benefits, as well as the uncertainty of parameters related to an interconnected electrical and transportation system.
- Reviewing coordinated charging scheduling approaches in each centralized, decentralized and hybrid EV scheduling schemes referred to in the reviewed papers.
- Surveying various optimal dispatch models and methods which are used in EV charging management.

The paper is organized as follows:

In Section 2, EV scheduling in a single-CS is reviewed in different parts. Section 3, surveys articles that focused on different approaches in EV charging management of multiple CSs. Section 4 describes aggregator-based EV charging scheduling. Sections 5 and 6 present a discussion and conclusion, respectively.

2. Single-CS EV Charging Scheduling

In recent years, the EV industry has grown, following the low carbon emission reduction policy worldwide. EVs bring various benefits to the transportation system, due to finite features of fossil fuels. However, the increasing number of EVs results in some challenges in an integrated electrical and transportation system: charging facilities offering services to EV owners with the least waiting time, growing congestion of lines due to the electricity consumption from the grid, increasing the use of RESs to lower the dependence of electricity from the upper grid, intermittency of RESs', as well as EVs', random behavior, arrangement, and operation inside a CS. Moreover, EV charging loads should not exceed the charging power capacity of each CS, while user satisfaction on receiving their minimum SOC is required. Therefore, managing a CS and, in other words, charging scheduling of EVs, is necessary to meet different stakeholders' benefits and requirements. In this regard, several research works investigated the charging scheduling of one or several EVs in a single CS from different technical and economical perspectives. The framework of a single CS system with different communication parts is shown in Figure 4.

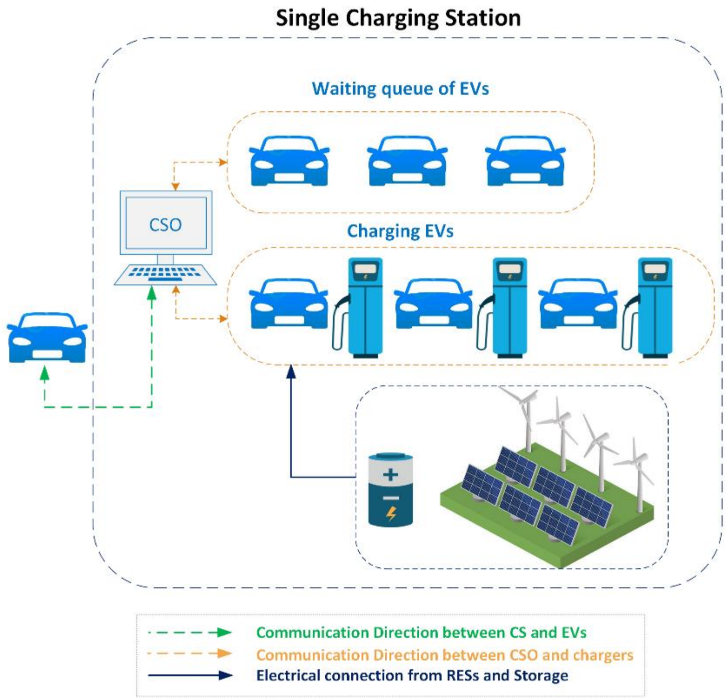

Figure 4. Diagram of a single CS electrical and communication connections.

2.1. Congestion Management in a Single-CS System

From the point of view of congestion management in a single-CS system, both EV owners and the owners of CSs face different issues. For example, flowing a large number of EVs into one CS results in a long waiting time for EV charging and negatively impacts user satisfaction. On the other hand, the higher waiting time affects the CS because EV owners leave the charging spot in the queue traffic condition. In [25], these challenges are contributed to the research through a pricing scheme for a dual charging mode (AC and DC) capability. An optimal charging scheduling possibility is presented in this research, which helps in lowering the drop rate of EV charging and minimizing the waiting times. In [26], a heuristic fuzzy inference algorithm is used to minimize the objective of waiting time on a public CS. The research works focused on congestion of CS as well as other objectives are presented in Figure 5.

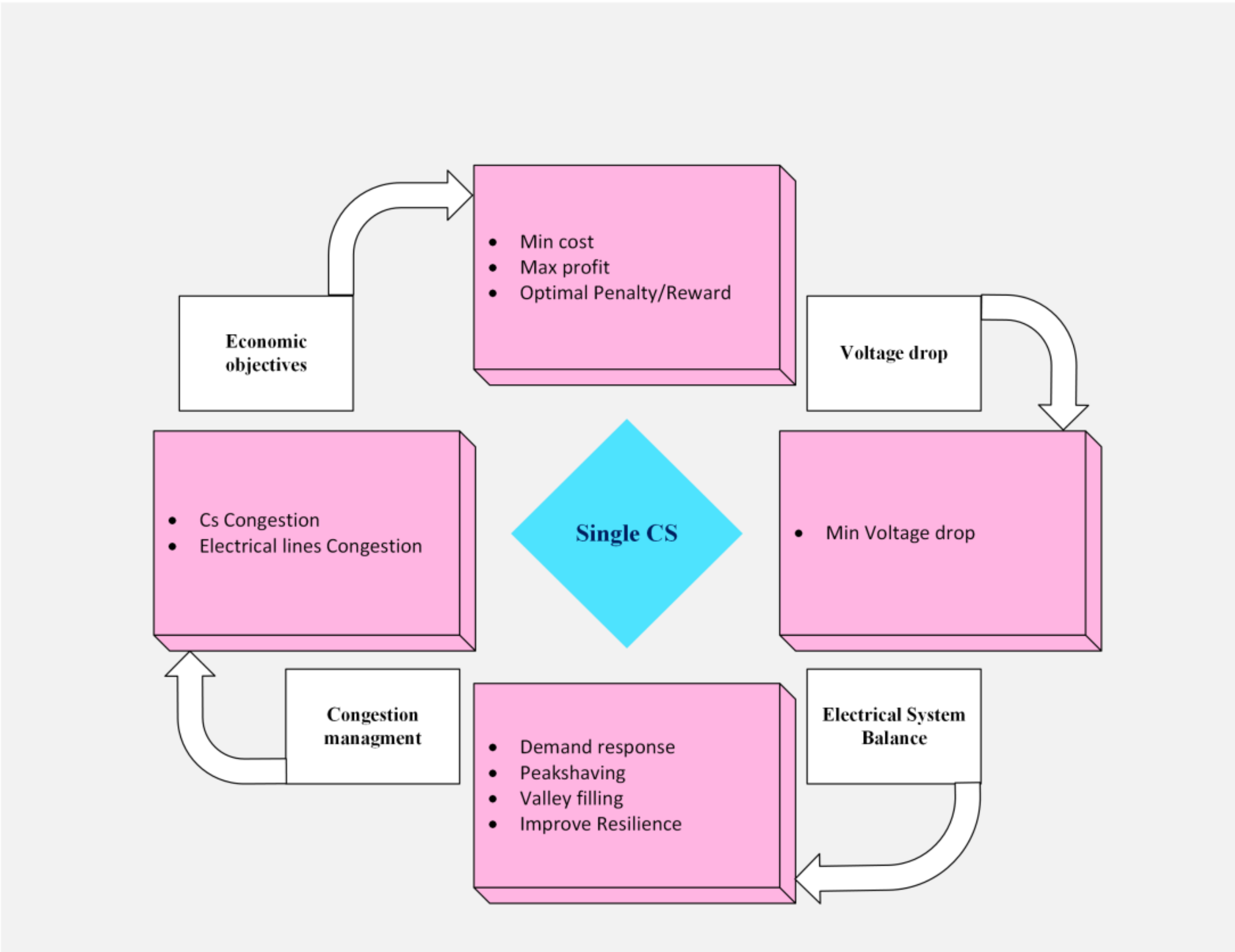

Figure 5. Single-CS network objectives categorized into techno-economic groups.

2.2. Modelling the Uncertainty of Parameters in a Single-CS System

To model the uncertainty of parameters, a bi-level programming model is presented in [16], when the interaction of the energy system and CS is modelled considering the probability of RESs (wind and PV). Moreover, EV scheduling is managed in the CS by the combination of fast charging (FC) and semi-FC chargers. Authors of [26] evaluated the uncertainty of EVs' behavior in a CS in which the charging management of EVs is done through fuzzy scenarios. From the perspective of the uncertainty of future EV demands, researchers in [27] introduced a scenario tree and benders decomposition method to solve the stochastic optimization problem. The idea of developing a multimode CS with PV support is also presented in [28], which focuses mostly on the modelling of uncertain parameters to maximize the overall system profit in optimistic and pessimistic scenarios. In [29], a two-stage stochastic scheme is proposed for charging management in a commercial PL, considering the uncertainty of electricity price, EV arrival and departure and charging demand. Another stochastic modelling based on the forecasting method and the stochastic model predictive scheme is applied in [30]. The aim is to optimize charging scheduling in a CS under the uncertainty of RES and electrical network loads. In [31], a chance-constrained linear programming (LP) approach under uncertainty of PV power and the network load is presented. In [32], the CSO acts as the responsible party between the DS and EVs to sell electricity under stochastic behavior of EV arrival and departure times through suitable strategies. Authors of [33] present an optimal grid-connected EV scheduling approach under uncertain EVs' behavior by different scenario evaluations. The uncertain parameters and methods used in the surveyed articles focused on a single CS are shown in Table 1 brief.

Table 1. Single-CS uncertainty of parameters and modelling/methods.

Number	Uncertainty				Uncertainty Modelling/Methods
	RES	EV Behavior	Electricity Price	Network Load	
[25]		√			Probabilistic method (Poisson point process)
[27]		√	√		Monte-Carlo and scenario tree
[32]		√			PEM
[16]	√				Probabilistic sequence discrete (Weibull and Beta distribution)
[28]	√	√	√		Interval modelling for PV and price- EV demand and charging time using Gaussian distribution and clustering method
[26]		√			Min-max aggregation method
[30]	√			√	Chance-constrained model predictive control
[34]		√			Probabilistic method (Poisson distribution)
[35]	√	√			Monte-Carlo method
[36]		√			Probabilistic method (Normal distribution)
[29]		√	√		price forecasting: ANN, Charging demand: exponential distribution, Arrival/departure: Poisson distribution
[31]	√			√	Monte-Carlo method
[33]		√			Probabilistic/Scenario-based modelling
[37]		√			Probabilistic/scenario-based (Normal distribution)
[38]	√	√			MDP—Fuzzy
[39]		√			SOC using lognormal distribution and arrival time using normal distribution
[40]		√			Probabilistic method (Scenario-based modelling)
[41]	√				Probabilistic method (normal distribution)
[42]	√			√	Robust chance-constraint

2.3. Electricity Exchange between EVs and the Grid in a Single-CS

In [16], EVs' positive impact on improving the flexibility of the system using demand response and discharging EVs as spinning reserve through a chance-constrained method is evaluated. In [31] a grid connected energy management system is developed in which an aggregator assigns strategies for trading electricity with an upper grid. Authors of [32] presented a joint interval-based algorithm for V2G and G2V management in a PL, from the perspective of the PL operator. Furthermore, a method of encouragement/punishment for EV owners is implemented to motivate EVs to discharge in peak hours. Another grid-connected approach is presented in [42], in which the overall system balance is considered as the main objective function. Different scenarios are implemented for the charging and discharging of EVs, considering incentivizing strategies for EV owners to contribute effectively in V2G. In [34], a centralized/decentralized scheme tries to optimize and manages the charging and discharging scheduling of EVs through V2G to give rewards to both EV owners and chargers. Researchers in [35] proposed a stochastic charging/discharging scheme through V2G mode by modelling the price of charging/discharging and the participation rate of EVs.

In [33], two objectives, including maximizing the profit of both CSs as responsible for V2G and G2V and EV owners' costs, are evaluated. In [37], a V2G capability in the discharge mode of grid-connected EVs in a PL is considered to improve the flexibility of the DS. In [38], a V2G mode for EVs is considered to exchange surplus EVs' power, offering the best price for EV participation. Researchers of [43] evaluated different case studies in G2V/V2G modes to improve the flexibility of the system in helping with valley filling and load flattening, while on the opposite side limiting V2G in peak shaving due to increasing the cost of battery degradation. Authors of [44] introduced an overload mitigation approach using V2G and investigated the scenarios that V2G cannot help with overloading conditions. However, the economic impact of valley filling and overload mitigation is not evaluated as well as the pricing mechanism in each scenario.

2.4. Coordinated Charging Management in a Single CS

Coordinated charging management of EVs, as an important approach compared to uncoordinated EV charging, has been noted in various research articles. Authors of [45] proposed an algorithm to control the charging scheduling of EVs in an FC PL. In [25], both short-term EV scheduling and long-term profit of parking lot (PL) owners are evaluated, considering the least-rejected demand of EV owners. Authors of [16] proposed a joint optimization function, combining total operation costs of the multi-energy system and CS operation through a dynamic pricing scheme. In [46], a binary integer programming mechanism is used to optimize the use of PV in charging EVs in a single charging station and using a controlling protocol and a reservation mobile application to consider the impact of EV owners on charging management of the charging station. Furthermore, among controlling EV scheduling methods in coordinated management, several papers focused on either centralized or decentralized charging management. However, each of these two approaches has some capabilities and limitations. The centralized EV scheduling has the advantage of low complexity modelling in comparison with a decentralized control strategy. Figure 5 shows each objectives' category of the research works referred to in this article. For example articles [29–31] and [35–44,46] considered minimum cost while [32–35], focused on maximum profit of the charging station as objectives. References [31–34,36,46] presented methodologies for optimal penalty/reward of EV charging/discharging. Likewise, minimum voltage drop was studied in [37] and [44]. Authors of [16,29,45,47] considered demand response, while [39,40] and [44,45] focused on peak shaving and valley filling. Improving the resilience aspects was proposed in [39] while [25,26,37] addressed congestion management issues.

The centralized EV scheduling takes place through a central controller directly on charging management inside the CSs or PLs. For example, in [42], a PL owning several chargers in a commercial enterprise is modelled under the management of a central controller. Different scenarios of charge/discharge are considered, while EVs and PV energy stored in the battery and utility grid is used to feed the electric load of the commercial. A centralized bi-level programming approach using an ESS is presented in [48], while the CS is assisted by both a grid-connected and self-consumption system. Authors of [26] focused on the minimum waiting time of EVs to maximize the serviceability in a single CS. A comparison between coordinated management under the time of use pricing and uncoordinated charging is implemented in [43]. In this research, a centralized EV scheduling system is developed to minimize the charging costs of EVs considering battery degradation. In [35], centralized, coordinated management is done using the admission mechanism for accepting EVs in the CS, while ESS is used as a storage for RESs (wind and PV). Researchers in [36] proposed a centralized, coordinated charging model for an EV fleet fed by both PV and the grid. In this research, different charging management models considering winter and summer variations are implemented. The strategy of trading off between peak shaving and improving resilience is presented as supporting future outages in [39]. In this research, ESS charge/discharge is used in an FCS providing this capability while the total operation cost of the CS is minimized. In [16,40], an online charging scheduling is implemented to optimize total charging cost and peak load under a robust analysis of future EVs forecasting. The decentralized EV scheduling approach, on the other hand, has proficiency in the security of consumers charging information and gives them the possibility to communicate with the CS on their charging needs and preferences. In [49], a decentralized EV scheduling algorithm based on multi-agent cooperation has been proposed for a CS connected to the DS. In this regard, coordination between several EVs is arranged through communications and EVs will get charged according to their urgency. Another decentralized charging scheduling is presented in [50], when each EV can contribute to overload mitigation through a CS demand-response framework. In this research, EVs communicate with each other and the CSO, and the ones who are willing to contribute shift their charge schedule to other time intervals. A deep reinforcement learning approach is introduced in [38], in which charging and discharging scenarios are managed in a decentralized way under the random behavior of EVs in a solar PL. However, in some research works, both control strategies (centralized and decentralized) are evaluated. In the centralized EV scheduling each charger in the CS decides which EV to get the charging preference under time-of-use electricity pricing, while in the decentralized approach each charger as an agent observes the EV states [34]. Table 2 shows the different methods of the centralized, decentralized and hybrid schemes used in the surveyed single-CS articles. The focus on the charging coordinated management in single CSs is on centralized approaches based on latest research trends. Moreover, mathematical approaches and heuristic methods are used mostly as solvers in optimization problems.

Table 2. Single-CS network optimization modelling/methods.

Number	Coordinated Management	Optimization Model/Method
[25]	Centralized	Convex Optimization/CVX toolbox in MATLAB
[27]		Stochastic Dual Dynamic Programming/Bender's decomposition, Gurobi solver in MATLAB
[48]		MINLP/KKT, converted to MILP using McCormick relaxation and Big-M method, CPLEX solver in MATLAB
[28]		MILP and QP/Robust optimal scheduling algorithm using Gurobi solver in MATLAB
[29]		Approximate dynamic programming, big-bang-big-crunch algorithm
[42]		Heuristic algorithm
[26]		Fuzzy Integer LP/Heuristic Fuzzy
[30]		Grey wolf Optimization, Chance-constraints model predictive control
[31]		Chance constraint LP/LP software in MATLAB (i.e., linprog)
[36]		NLP/WORHP solver in MATLAB
[35]		Convex optimization/solvers in MATLAB toolbox
[43]		MIP and QP/Augment Epsilon-constrained technique
[33]		PSO Algorithm
[37]		Mixed real and binary vector/PSO algorithm
[44]		GA algorithm
[39]		LP/CPLEX in Visual Studio
[40]		Greedy algorithm and max flow algorithm (Fold-Fulkerson)
[41]		Political optimization algorithm
[34]	Centralized & decentralized	Reinforcement learning
[47]	Decentralized	MILP/Big-M method and CPLEX, BARON
[16]		MILP/Sequence operation theory Chance-constrained/CPLEX
[49]		A multi-agent-based cooperative algorithm—Graph theory
[50]		Non-cooperative game theory/KKT, distributed consensus algorithms
[38]	Hybrid	Agent-based deep reinforcement learning and fuzzy logic

3. Multiple-CS EV Scheduling

By spreading the number of EVs on the road, several challenges might happen in a transportation system:

- The availability of CSs in different parts of cities;
- The price of electricity;

- The use of RES to contribute to charging EVs;
- Avoiding DS line congestion and congestion of CSs in high traffic areas;
- Choosing charging spots location time and cost efficiently.

In this regard, several research papers surveyed the charging scheduling of multiple CSs from different technical and economic aspects and presented strategies to handle smart energy system management. The framework of an integrated electrical and transportation system is shown in Figure 6.

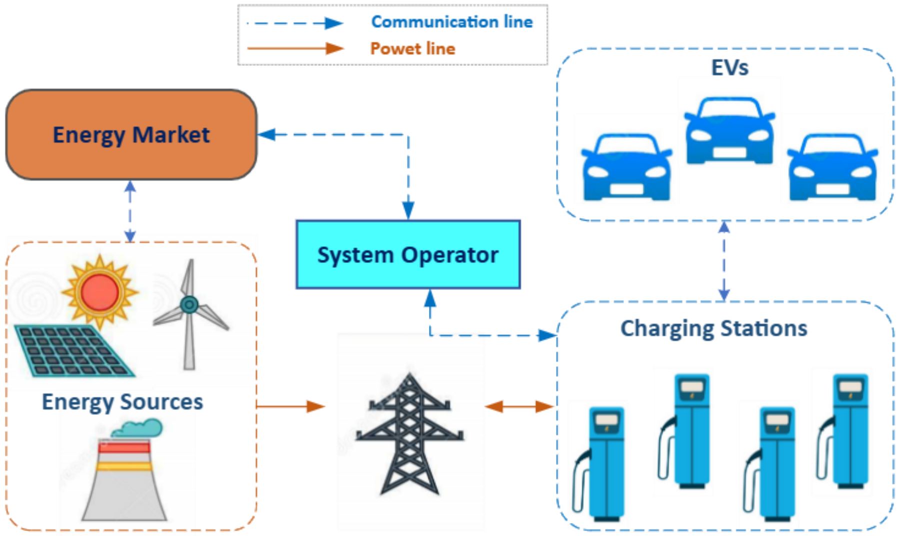

Figure 6. Integrated electrical and transportation system considering multiple-CS system.

3.1. Route Planning and Congestion Management in a Multiple-CS System

From the point of view of minimizing waiting time and congestion in CSs, authors of [51] proposed a hybrid energy management algorithm combining heuristic methods for large-scale systems. In [52], an EV-optimal routing is modelled to guide owners to the best charging location to minimize charging costs. Researchers of [53] developed a Stackelberg game model for real-time interaction of EVs and CSs. The focus of this research is to decide the best route considering charging service fees. Moreover, traffic and queue waiting time for each CS are considered in the objective function. Authors of [14] presented a model that helps in linearizing the nonlinearity of charging-load congestion in CSs with RES. A hybrid decomposition algorithm is developed to minimize the CS congestion on an hourly basis. An incentive pricing strategy is proposed in [54] to motivate EVs to choose higher capacity CSs for charging. In this research, a suitable function is modelled to help EV owners in choosing charging spots based on distance, price, and capacity. An optimal route-travel scheduling is implemented in [55] to minimize the traffic condition of EVs. In [56], the CSO is trying to optimize social welfare under an optimal routing plan for each EV. In [57], a dynamic programming algorithm is used to model the shortest path for EVs to reach a suitable CS for charging. To evaluate energy management of multiple CSs under uncertainty of the parameters, authors of [51,58,59] modelled EV arrival time using the Poisson distribution. In [60], a Monte Carlo method is applied for modelling uncertain EV parameters, such as EVs' arrival and departure time and the location of the charge. In [61], a Markov decision process (MDP) is used to model the uncertainty of EV charging navigation without knowing the transition probability, while charging prices and waiting time probabilities are modelled using a normal distribution. Authors of [62] used an interval-based analysis for modelling the uncertainty of RES. In [57], a model for the probability of EV charging based on time-of-use pricing is proposed. Moreover, the Monte Carlo method is used to model the traffic of EVs and their trip time and distance. Researchers in [63] introduced an analytical method called "spherical simplex unscented transformation" to model the RES generation, network load, and PL charging load demand uncertainties. In [64], robust optimization is applied to deal with the stochastic behavior of wind and solar. The uncertain parameters and methods used in the surveyed articles focused on multiple CSs are shown in Table 3 briefly.

Table 3. Uncertainty of the parameters in a multiple-CS system.

Number	Uncertainty				Uncertainty Modelling/Methods
	RES	EV Behavior	Electricity Price	Network Load	
[52]	√	√			Scenario-based modelling
[53]		√			Mixed logit model/Monte Carlo method
[54]	√		√	√	Normal distribution/Monte Carlo method
[55]	√		√		Scenario-based modelling
[57]		√			Poisson distribution for EV behavior, Normal distribution for charging time/Monte Carlo
[58]		√			Probabilistic method (Poisson process)
[59]		√			Probabilistic method (Poisson arrival process)
[60]		√			Normal distribution/Monte Carlo method
[61]		√	√		MDP
[62]	√	√			Interval based modelling
[63]	√	√		√	Normal distribution (EV behavior)/Spherical simplex unscented transformation (RES, Net load)
[64]	√				Robust optimization method
[65]		√			MDP
[66]		√			Probabilistic method (Weibull distribution)
[67]		√			Robust optimization based on interval forecasting
[68]		√		√	Robust Optimization
[69]	√	√			Lyapunov drift-plus-penalty
[70]		√			Probabilistic method (Normal distribution)
[71]		√			Scenario-based modelling combined with forecasting
[72]		√	√	√	PEM method
[73]		√			Poisson distribution/Monte Carlo method
[74]			√		Robust Optimization
[75]	√	√		√	Scenario based modelling

3.2. Modelling the Uncertainty in EV Charging/Discharging Management

To evaluate energy management of multiple CSs under uncertainty of the parameters, authors of [51,58,59] modelled EV arrival time using a Poisson distribution. In [60], a Monte Carlo method is applied for modelling uncertain EV parameters such as EVs' arrival and departure time and the location of the charge. In [61], an MDP is used to model the uncertainty of EV charging navigation without knowing the transition probability, while charging prices and waiting time probabilities are modelled using a normal distribution. Authors of [62] used an interval-based analysis for modelling the uncertainty of RES. In [57], a model for the probability of EV charging based on time-of-use pricing is proposed. Moreover, the Monte Carlo method is used to model the traffic of EVs and their trip time and distance. Researchers in [63] introduced an analytical method called "spherical simplex unscented transformation" to model the RES generation, network load, and PL charging load demand uncertainties. In [64], robust optimization is applied to deal with the stochastic behavior of wind and solar. In [55], the stochastic behavior of vehicle traffic, electricity price, and RES are modelled via multiple scenarios. The uncertain parameters and methods used in the surveyed articles focused on multiple CSs are shown in Table 3 briefly.

3.3. V2G Capability of EVs in an Integrated Electrical-Transportation System

In [76], the V2G option is given as an alternative to EV owners based on the price of electricity they are offered. In this research, the profit of EV owners in charging/discharging is optimized, and V2G is implemented through an EV aggregator. Researchers of [60] focused on the peak shaving and valley filling approach in implementing V2G to improve the flexibility of the system through a proposed algorithm. In [77], a hybrid clustering combining K-means and canopy clustering methods is used to apply V2G for each group of EVs by each recommended CS to improve EVs' welfare and credit on participation. In this research, the total cost of EVs and grid in response to V2G are evaluated in the second stage. An extra V2G trip is modelled in [78], where each EV can decide to choose an alternative discharging option according to the price.

In this research, an EV aggregator takes the responsibility to sell the electricity in V2G mode to the wholesale market. Authors of [68] introduced a central aggregation V2G model to mitigate voltage and frequency deviations of the grid in the smart grid. In [63], the V2G approach is implemented from the point of view of PL profit optimization when the flexibility of DS is improved. A time-expanded V2G modelling is presented in [79]. In this research, EV owners can minimize their costs by gaining revenue from discharging electricity to the grid in a joint route-scheduling framework. In [70], a V2G approach is considered as a support to improve distribution system flexibility by peak shaving and valley filling impact on the system load curve.

3.4. Optimal Dispatch of an Integrated Power-Transportation System

Regarding the coordinated management in multiple CSs in comparison with uncoordinated charging, several research works proved that coordinated strategies prevent technical system issues while optimizing different stakeholders' benefits. In this regard, EV scheduling from the perspective of different stakeholders' objectives for both the technical and economic aspects is evaluated in the recent research papers. In [53], a pricing strategy for every CS in each location is modelled to respond to EVs' charging requests. The objective of the research works focused on multiple CSs referred to in this article are presented in Figure 7. In this regard, [55–58,71–73,77,79–84], for example, evaluated minimum cost and [52–57,63,64,78,81,82,85] focused on maximum profit of the charging station. Authors of [61,77,81,82] presented methodologies for optimal penalty/reward of EV charging/discharging. Improvement of voltage drops and power losses were given focus in [66,68,71–73,83], while refs. [60,65,70], incorporated energy users' engagement in their studies in forms of demand response actions. Articles [57,63,70] studied improved loading of the network in terms of peak shaving and valley filling; [14,60,65] contributed to resilience improvement aspects. Authors of [51,54,56,61,83] focused on minimum waiting time while [55–57,61,78,79,82] considered route optimization related to congestion management of charging stations.

Moreover, several articles have presented coordinated scheduling in CSs located in different regions in a centralized, decentralized, or hybrid manner. A centralized EV energy management scheme is presented in [56] through a pricing-routing mechanism. In [54], DSO, as a central coordinator, optimizes the expected profit of selling electricity to EV owners, considering power system constraints in which the power loss caused by EV charging is considered in the calculations. A centralized EV scheduling model is presented in [68], when the central aggregator is responsible for coordinating EVs' arrival and departure hierarchy, as well as the operation of CSs. Moreover, in this research, the benefit of aggregators and EV owners in regulating voltage and frequency is evaluated. In [63], a Stackelberg game approach is proposed to coordinate DSO operational costs and PL profit optimization in the form of a bi-level programming. In [55], a coordination strategy is presented in which several EVs are controlled utilizing an aggregator, while all CSs are managed with a central operator. In this research, optimization is done considering the marginal price of conventional generators in an iterative, while the revenue of CSs is optimized. Researchers of [65] proposed reinforcement learning-based coordinated management of CSs when a coordinating agent interacts with the system and acts accordingly. In [64], asymmetric Nash bargaining is implemented to model an incentive mechanism for EVs to participate in DS resilient restoration. Furthermore, in this research, two DS restoration strategies are presented, when one is without EVs and the other under an EV payment model considering degradation and time costs. A joint route-mapping and scheduling scheme for EVs with central control of a server is presented in [79]. The efficiency of the proposed joint function scenario over the uncoordinated charging/discharging scheduling is surveyed and proved in this research. Researchers of [70] proposed a centralized, coordinated EV scheduling controlled by two types of operators, CSOs and central coordinators, enabling demand response and load variation. In this regard, the CSO is responsible for modelling charging possibilities by taking driving information from EVs while a central coordinator does the optimal scheduling.

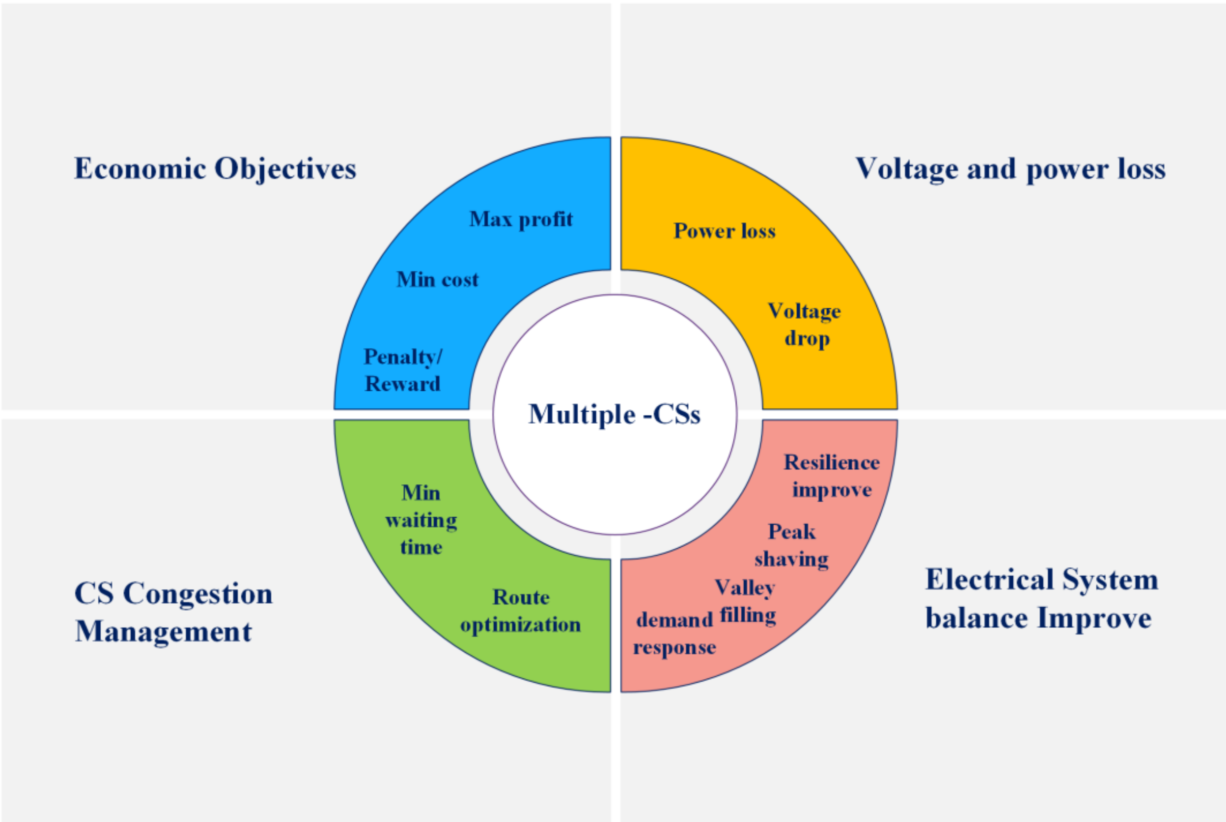

Figure 7. Multiple-CS systems electrical and economic objectives.

From the point of view of decentralized, coordinated management, a multi-agent communication-based energy management scheme is presented in [85]. The goal of each CS is to maximize the number of charging scenarios while EV owners' strategy is to choose the specific CS to get service under an online and offline negotiation. Another multi-agent system is modelled in [81] combining local agents, CS aggregator, and global agent, in which the signalling and interactions are simulated using reinforcement learning in different hierarchies. In [80], first, real-time centralized energy management is done with the help of a central aggregator, and then a distributed algorithm using a method of low complexity distribution algorithm is presented. In this research, an EV aggregator takes the responsibility to sell the electricity in V2G mode to the wholesale market. In [67], a distributed multi-agent optimal scheduling is proposed through price negotiation of different agents including micro-grid agents, FCS agents, and the electrical grid. In this research, the possibility of EV changing their routes, generation costs, and electricity trading prices are considered, aiming to minimize total operation costs. Authors of [61] presented a deep reinforcement, learning EV charging-navigation strategy to optimize the cost of charging in CSs while minimizing driving times. However, in this research, the optimization problem is evaluated from the point of view of one EV owner. In [59], real-time charging management of EVs in a system of FCSs is modelled in a multi-agent framework. EV agents decide on the CS to charge, and CSs adjust their prices based on minimum waiting time and user welfare. A time-of-use pricing scheme is presented in [57] to optimize the CS profit, while the EV owner's strategy on choosing the least cost of charging and maximum welfare is modelled and evaluated. Authors of [66] proposed both centralized EV scheduling from the point of view of EV aggregators and distributed schemes based on bender's decomposition. In a distributed solution, a hierarchical multi-agent approach is presented to respect the privacy of the information of multiple levels in the system. Another decentralized coordinated scheduling/pricing model is offered in [83] to the coordinated transportation system and DS. The objective of this research is to minimize the operation cost under an AC optimal power flow and traffic delay of EVs. In [69], a distributed EV scheduling is presented to minimize the total cost from the perspective of a utility system, while the revenue of CSs is maximized through a game theory approach. In [67], a distributed EV scheduling system is presented to minimize the cost of thermal generators as well as minimize network power loss. Moreover, CS incentive-based modelling is implemented in this research. The use of hybrid-coordinated management in EV scheduling is proposed in [82], between several CSs when the scheduling problem is solved in three steps algorithms. The algorithms are among the electricity purchasing algorithm for each CS, finding the least distance for each EV and energy scheduling for CSs, respectively. Moreover, a reward function for maximizing CSs' revenue is modelled in this research. A hybrid approach is presented in [62] to coordinate the energy management of CSs and electrical distribution system in the electricity market. Researchers of [58] proposed a dual objective model for in-route EVs to minimize EVs' trip time to CSs, as well as charging costs as a hybrid-coordinated technique. Another hybrid-coordinated management of CSs and the EV aggregator is proposed in [52], when both real-time and day-ahead electricity pricing values are taken into account. In [76], a non-profit central cloud operator is considered to operate the charging management of a system through a hybrid framework. Table 4 shows the control strategies and optimization methods used in multiple-CS research papers. In multiple-CS systems, both decentralized and centralized approaches are used, mostly based on latest research trends. Moreover, different methods including mathematical, game theory and heuristic algorithms are developed in several research works to evaluate the coordinated charging management of multi-region systems.

Table 4. Coordinated management controlling optimization modelling/methods in a multiple-CS system.

Number	Coordinated Management	Optimization Model/Method
[56]	Centralized	Non-convex quadratic problem/An algorithm solution for hard capacity constraints
[54]		MILP/CPLEX in MATLAB
[68]		NLP/MATLAB toolbox
[64]		Mixed integer second-order cone model/GUROBI solver
[55]		MILP/CPLEX in MATLAB
[65]		Reinforcement learning
[79]		MINLP/K-shortest path problem combined Yen's algorithm—artificial intelligence-based algorithm
[70]		LP/MATLAB solvers (i.e., Linprog)
[72]		NLP/Chaotic Crow search algorithm
[14]		MINLP/Hybrid algorithm (Sample Average Approximation + Progressive Hedging algorithm)
[73]		NLP/CONOPT 3 solver in GAMS
[51]		PSO & Firefly algorithms
[63]	Centralized & decentralized	Stackelberg game MINLP/Strong duality theorem and KKT—Off-the-shelf solver for MILP
[66]		Multi agent system/Bender's decomposition, KNITRO solver in GAMS (NLP), fmincon solver MATLAB (LP)
[80]		Convex optimization/Interior points method, CVX
[71]		Non-Convex converted to convex with sec-order-conic/MPC method and differential evolution algorithm

Table 4. *Cont.*

Number	Coordinated Management	Optimization Model/Method
[78]	Decentralized	An iterative solution using Branch-and-Bound
[85]		ILP/IBM ILOG CPLEX
[81]		Reinforcement learning
[53]		Multi-agent Stackelberg game
[59]		Agent-based dynamic programming—multinomial logit model
[67]		Convex optimization/ADMM
[77]		MILP/Canopy+ k-means clustering -CPLEX in Python
[61]		MINLP/Big-M method and Deep Reinforcement Learning
[83]		Convex optimization, NLP/IPOPT solver for NLP optimal power flow -ADMM for coordinated pricing method for scheduling
[69]		Convex optimization/Nash equilibrium game theory and Lyapunov optimization using MATLAB toolbox CVX
[84]		Non-Convex converted to convex based on strong duality/ADMM
[74]		Mixed integer nonlinear programming/GAMS solver (MINLP)
[76]	Hybrid	SSA (heuristic method)
[58]		Convex optimization/Lagrangian method and KKT
[62]		Gisa pyramid construction and recurrent neural network
[82]		multi-agent reinforcement learning combined with online heuristic dispatching
[57]		Bilayer PSO
[75]		An iterative solution using Branch-and-Bound

4. Aggregator-Based EV Scheduling

With the increasing number of electric vehicles in the transportation system, the role of EV aggregators in commercial and residential PLs is essential. In this regard, EV charging scheduling, through aggregators in one layer and coordination between several aggregators in a two-layer coordination scheme, has been the topic of different research works. Figure 8 shows a framework of the charging scheduling system with aggregators.

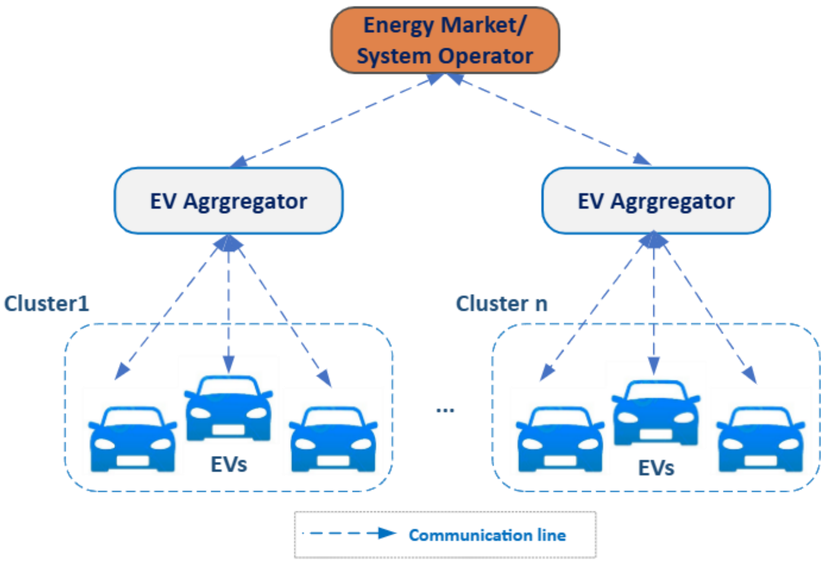

Figure 8. Aggregator-based EV coordinated scheduling scheme.

4.1. Grid-Connected EV Scheduling

EV owners can minimize their costs by gaining revenue from discharging electricity to the grid through the management of one or multi-layer aggregators. For example, in [86], a network of EVs participating in the energy and regulation market through V2G under a main aggregator's management is modelled. In this research, the optimal revenue is optimized considering the battery degradation of EVs. Authors of [87] modelled the worst case for the least trading electricity with the electricity market through V2G service as one lower stage objective in the multi-level optimization problem. In [88], both V2G and vehicle-to-vehicle (V2V) capabilities are considered in the optimization model under real-time electricity price, while a punishment/reward policy for EVs is defined. A DS network-constrained EV scheduling framework is proposed in [89], based on multi-agents in which V2G mode provides the active/reactive power injected from each charging point agent to the network. A V2G trading based on a hierarchical three-layer blockchain (data, operation, and transaction) is proposed in [90] using cellular automata technique to optimize the benefit of three stakeholders: EVs, aggregators, and grid, and minimizing grid load variation. Another blockchain based on controlled charging and discharging is presented in [91] from the aggregator perspective. In this research, several challenges, including low power quality, power loss and overloading, are discussed.

4.2. Uncertainty Involved in a System of EVs and Aggregators

The stochastic nature of RES in the DS and electricity market price can affect charging scheduling and energy management strategies. In this regard, EV aggregators, as the operators of EVs, are facing different system uncertainties as well as changeable EVs' traveling behavior. Regarding uncertainty of parameters, the authors of [92] developed a stochastic-based modelling scenario using the autoregressive moving average (ARMA) method for electricity market prices and a fuzzy system for wind farm uncertainty in power generation. Robust optimization is applied in [87] to model uncertain arrival time and demand of EVs. In [93], the uncertainty of EV behaviors is included in the optimization problem using stochastic programming, while robust optimization is applied to model the intermittency of locational marginal price. In [94], the information gap decision theory (IGDT) method is applied to model the uncertainty of RES and find the best decision in the robustness of the variables without knowing the probability density functions. Authors of [95] also developed an IGDT method to evaluate the uncertainty of electricity market price and a scenario-based stochastic method to model EV arrival, departure times, and SOC. The uncertain parameters and methods used in the surveyed articles focused on aggregator-based EV scheduling are shown in Table 5.

Table 5. Modelling/methods of uncertainty in a system with aggregators and EVs.

Number	**Uncertainty**				**Uncertainty Modelling/Methods**
	RES	**EV Behavior**	**Electricity Price**	**Network Load**	
[86]		√			Probabilistic method (Normal distribution)
[87]		√			Robust Optimization
[96]		√			Normal distribution/Monte-Carlo
[97]	√			√	Stochastic total sectoral load disaggregation
[24]		√			Probabilistic method (Normal distribution and lognormal)
[98]		√			MDP
[99]		√		√	Receding horizon optimization-based
[93]		√	√		Stochastic programming/Robust Optimization
[94]	√			√	IGDT
[100]		√			Normal distribution/Monte-Carlo
[95]		√	√		Normal distribution/Scenario-based stochastic and IGDT
[92]	√	√	√	√	Scenario-based modelling (ARMA, Adaptive-neuro-fuzzy-inference system, Normal distribution)
[101]			√		Robust Optimization

4.3. Energy Management in a System with One or Several Aggregators

From the point of view of controlling management approaches, both centralized and decentralized schemes are applied in a system with EVs and aggregators as operators of EV charging managing. For instance, in [74], a multi-level hierarchical optimization model is proposed in the condition of worst-case SOC through a central aggregator's decision-making. In [31], a centralized energy management algorithm for a CS is presented when an aggregator is responsible for the coordination of EV scheduling. In [78], an EV customer incentive pricing strategy is modelled to improve users' comfort as well as minimize their charging costs. In [96], a centralized coordinated EV scheduling through an aggregator is developed when a combination of valley filling/peak shaving and charging costs is considered as the objective function. In this research, two modes of FC and slow charging are chosen according to the urgency of each EV in a public CS. Researchers in [102] developed a centralized EV scheduling by modelling a two-stage hierarchical scheme considering charging priority for EVs. In this research, actual and predicted residential EV loads and non-EV loads consumed are modelled in the valley filling optimization strategy. Authors of [100] developed a coordinated EV charging scheduling scheme under the control of an aggregator and urgency indicator for both home charging and public charging. Authors of [75] introduced an algorithm for EV scheduling in the residential and commercial areas, each one controlled with one aggregator. In this research, the aggregator's responsibility is to optimize its own profit as well as provide demand response for DS and satisfy EV owners. Another demand response scheme through aggregators is implemented in [97] in a distributed game theory-based model. Moreover, in this research, financial benefits are optimized using an incentive price mechanism offered by each aggregator. Figure 9 shows corresponding objectives in an aggregator-based network. In this figure, for example articles [24,92,97] and [99] evaluated minimum cost and references [74,88,92–95] focused on maximum profit of the charging station. References [88,98] presented methodologies for optimal penalty/reward of EV charging/discharging. Minimum voltage drops and power losses were considered in [89,94,99,102,103]. Regarding the load management aspects, authors of [24,75,97,98] focused on demand response actions while [96,100,102,104,105] contributed to the peak shaving and valley filling.

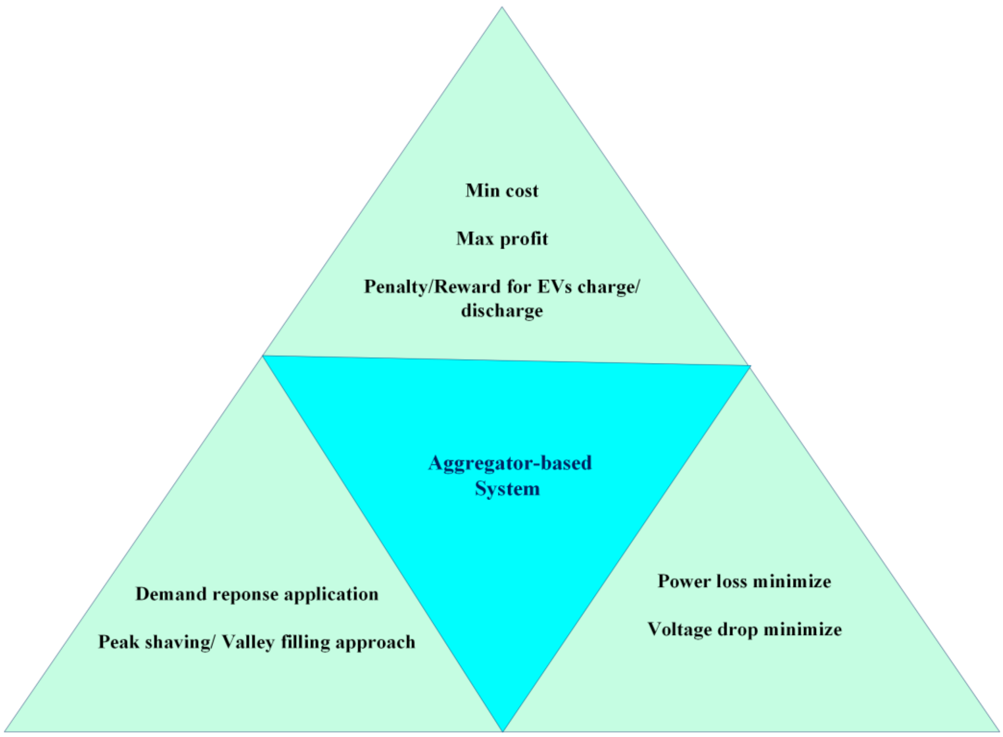

Figure 9. Technical and economic objectives in a system with Aggregators.

Another approach for coordinated charging under the control of an aggregator and operator is proposed in [106]. Energy management is implemented by designing an optimal model to minimize the dissatisfaction of EV owners, as well as calculating charging costs and discharging rewards. A single agent Q-learning approach is used for the day-ahead charging scheduling of an EV fleet. Additionally, in this research, non-scheduled EV charging is arranged on valley times at night. An aggregator-based charging/discharging coordination model is implemented in [99], considering network characteristics. In this regard, the voltage constraints are met in the optimization problem to alleviate DS under-voltage and over-voltage situations. Another two voltage-constrained centralized and decentralized frameworks are implemented in [103] to manage the charging scheduling of EV owners connected to the nodes of a DS in a residential area by mitigating voltage magnitude drop and load variation. In [89], a load variation minimization under an AC optimal power flow is developed through a multi-agent distributed EV scheduling including EVs agents, charging points agents, and charging clusters. From the point of view of electricity prices in the pool market, a risk-averse optimization framework is modelled in [92] for a three pool-market (day-ahead, regulation market, and balance market). In this research, EV scheduling is managed through an aggregator trying to minimize its costs, while the virtual power plant manages the coordination between the wind power plant and the aggregator. Another price-based EV scheduling is proposed in [24] through a decentralized and two centralized schemes, in a system with three different stakeholders (DSO, aggregator, and EVs). In this regard, pricing strategies and their cons and pros are evaluated for each centralized and decentralized aggregator-based system scenario. Another decentralized EV scheduling scheme (with the aim of valley filling) is presented in [104], on different EV groups managed by an aggregator. From the point of view of the aggregator's profit in coordination with an energy hub, a decentralized coordination scheme between an EV aggregator and an energy hub is developed in [93]. Another distributed coordinated management is implemented in [105] through bidirectional communications in different scenarios between EVs and aggregators in one layer and aggregator's coordination in another layer. In [95], a hybrid optimization method is used to maximize the aggregator's profit under risk-averse and risk-seeking strategies based on the forecasted price of electricity. Another hybrid algorithm is developed in [94], when the aggregator's revenue is optimized, and DS cost is minimized.

Moreover, in this article, CO_2 emission caused by conventional vehicles and power loss of electrical networks, as well as the use of DGs producing electricity, are minimized. Table 6 presents optimization methods applied in the surveyed aggregator-based EV scheduling. Furthermore, an aggregator-based system-centralized controlling method is used. Additionally, mathematical optimization modelling techniques are used mostly to solve EV charging coordination problem.

Table 6. Optimization modelling/methods of an aggregator-based system.

Number	Coordinated Management	Optimization Model/Method
[86]	Centralized	NLP/Generalized reduced gradient method
[87]		NLP converted to MILP using/CPLEX in Pyomo (Python)
[96]		MIP/(i.e., MATLAB solver intlinprog)
[88]		MILP/Intlingprog in MATLAB
[101]		PSO algorithm
[98]		Reinforcement learning
[99]		QP/CVXPY solver (i.e., CPLEX) in Python
[100]		CPLEX in MATLAB
[106]		QP/GUROBI in Python
[102]		Convex and quadratic/CVXOPT in Python
[92]		MIP/i.e., MATLAB solver intlinprog
[87]		MINLP solvers in GAMS (i.e., SBB, DICOPT2, etc.)
[31]		Chance-constrained, LP/LP solver in MATLAB (i.e., linprog)
[24]	Centralized & decentralized	The decentralized scenario is solved with the interior-point methodCentralized scenarios solved with: extended bi-level optimization and PSO
[104]		Game theory, Mixed discrete/Water filling-based algorithm
[103]		Shrunken primal-dual sub gradient algorithm

Table 6. *Cont.*

Number	Coordinated Management	Optimization Model/Method
[97]	Decentralized	Non-cooperative game/backward induction-based
[78]		An iterative solution using B&B
[93]		Mixed integer quadratic conic/ADMM
[89]		Multi-agent NLP/MIPS solver in Math power
[105]		MIQP/ADMM
[107]		Reinforcement learning
[94]	Hybrid	MINLP/e-constrain theory for converting multi-objective to the single objective problem–Grey wolf heuristic and PSO
[95]		MINLP solvers in GAMS (i.e., SBB, DICOPT2, etc.)

5. Discussion and Future Works

The future transportation system with an increasing number of electric vehicles will face several challenges in developing advanced charging infrastructure and efficient management schemes. An integrated electric and transport system needs to be robust to technical issues like congestion of electric lines caused by several EVs connected to DS nodes or other factors, such as RES uncertainty, network load changes, node voltages, and so on. Furthermore, from the point of view of economic benefits in a smart transportation system, each participant's costs and welfare shall be evaluated and well-defined. This review paper surveyed several research articles about charging coordination of EVs from the point of view of technical and economic aspects. Regarding coordinated EV charging management, different research works developed optimal models and controlling strategies to handle related technical and economic issues. Network-constrained systems in which active/reactive power, as well as the voltage of DS nodes, required to be checked by the system operator or coordinator, are modelled in several articles. Some of the researchers paid much attention to peak shaving or valley filling by modelling load variation function as the main objective. Additionally, demand response is still one of the interests of several research works by growing the EV industry. Handling the uncertainty caused by RES as substitute sources for fossil fuels is another issue that is evaluated, especially with CSs equipped with PV panels. In this regard, several reviewed articles assessed EV impact as mobile battery storage in handling different system issues:

- By V2G possibility, EVs can contribute to the security of supply and transfer electricity back to the grid or to other EVs through the V2V framework V2L, which lately has been considered lately.
- Contributing to demand response, valley filling and peak shaving by charging EVs in off-peak and discharging in peak loads, considering incentive/price-based mechanisms.
- The contribution of RES in charging electric vehicles during low consumption hours and the possibility of acting as a reserve to help the network during high consumption times.

The challenges related to an integrated electric transportation system reflected in this review paper can be categorized into technical and economic challenges.

5.1. Technical Challenges

- Voltage regulation in distribution networks, since EVs contribution to demand increase affect stability of the distribution network and result in voltage drop, while during lower charging demands, EVs provide support to the network by supplying energy back to the grid;
- Power loss of the electrical energy in the distribution network, since EVs can lead to an increase in power losses due to the additional load on the grid and the need to transmit power over longer distances to reach charging stations and improve the power loss by integrating electricity back to the grid in peak demand or grid instability;

- Power capacity and grid stability, since EV charging infrastructure requires large amounts of power, which can strain the electrical grid and result in instability;
- Congestion of electrical lines due to a large number of EVs charging at the same time, especially during peak hours, in which an efficient charging management of EVs in CSs and PLs can mitigate electrical lines overload created by EV charging;
- Scalability as a challenge due to the increase in the number of EVs on the roads and the lack of enough charging infrastructure, which leads to congestion in existing charging spots in city centres and requires an increase in charging infrastructure;
- Uncertainty of RES (such as wind and solar) generation as supporting resources in electricity supply: this intermittency can affect charging and discharging of EVs, while EVs can store the RES energy in batteries and discharge whenever needed;
- Stochastic behaviour of EV owners in travelling times, SOC, and arrival times which makes deterministic charging planning unreal;
- Battery degradation of EVs due to continuous charge/discharge scenarios in V2G on battery lifetime and contribution to the supply of electrical grid;
- Proper communication for efficient EV-grid management, which requires interoperability functions that enable seamless communication and data exchange between different EV stakeholders. This includes, but is not limited to, standardization of communication protocols, such as the open charge point protocol (OCPP—used for communication between charging stations and central management system), ISO 15118 (related to plug and charge functionality and allows for seamless authentication and payment for EV charging), and the combined charging system (CCS—used for communication between charging stations and central management system), and the implementation of interoperability functions that enable seamless authentication and payment for EV charging. By improving interoperability in the EV industry, EV-grid management can help to promote the growth and adoption of EVs, while also enhancing the overall user experience and convenience for EV owners.

5.2. Economic Challenges

- Assuring the profitability of existing CSs in providing charging facilities while meeting technical considerations and their costs on interaction with the electricity market;
- Charging costs and welfare of EVs as well as maximizing their benefits in the electricity market through participation in V2G mode;
- Aggregators' benefits on giving service to allocated EVs charging/discharging in an aggregator-based scheduling system;
- Efficient pricing strategies for CSs in real-time and short-time intervals;
- Costs on constructing new charging spots considering the revenues of existing ones;
- The high cost of installing and maintaining of CSs.

5.3. Future Challenges and Trends

There are still open issues regarding the management of EVs in the future transport system, according to recent research reviews on charging operation and management.

Convincing customers to participate in V2G by motivating strategies inside the CSs and modelling a real, all-inclusive pricing mechanism to cover the costs of battery degradation during its lifetime are the challenge of future transportation systems.

Additionally, an optimal smart operation platform inside the FCSs can be a strategy to manage charging and discharging EVs simultaneously and in a time efficient manner. Furthermore, coordination between CSs together, as well as charge coordination within each CS to enhance the competitive environment, is another topic for future research works. The need for reservation systems to manage EV charging is a trend that is still under evaluation. The rapid expansion of the EV market, the need for charging infrastructure, and the integration of RES require sustainable charging solutions. Advances in new technologies, such as smart charging and V2G, are other approaches among the trends of future electric transportation systems. The applicability of peer-to-peer energy trading through blockchain to apply for V2G in the future needs further research [108]. Moreover, internet of vehicles with the use of blockchain is another trend topic of future research works [109]. Future trends in charging station planning aim to improve accessibility and sustainability of EV charging infrastructure. From the perspective of a decentralized energy management strategy, modelling appropriate communication infrastructures between CSs and EVs while accessing online road traffic information, is a necessity. Moreover, evaluating applicable competitive strategies among CSs can help with reduced traffic in crowded areas in city centres. The capability of battery swapping in charging spots, as well as using near end-of-life EV batteries as storage devices to manage energy inside these CSs, can be another approach for future research. From the point of view of residential EV charging, modelling centralized aggregators that can manage PLs and coordinate them with the energy market is another approach to facilitate existing PLs with EV chargers, both technically and cost efficiently. Slow charging overnight can lower the risk of overloading the electrical system and yield the possibility of discharge management during nights to store in the ESS for use in peak times. The capability of V2V through inductive or instant charging inside the CSs is another interesting topic for future research works targeting EVs' coordinated charging schedules. The use of EVs in public transportation is another trend that helps to reduce the amount of pollution emitted by traditional fossil fuel-powered vehicles. This potential can significantly reduce emissions and improve the quality of air in cities, as battery technology and charging infrastructure can improve charging management of electric buses and trains. Overall, the management of CSs faces a complex set of challenges and requires ongoing research and innovation to support the growth of the EV market and the development of a sustainable transportation system.

From the point of view of future market mechanisms, EVs can participate in different electricity markets and ancillary services. For example, EVs can participate in energy markets by providing demand response services. This helps to balance the grid and reduces the need for additional power generation during peak hours. EVs can also participate in frequency regulation services by adjusting their charging rate in response to changes in grid frequency. EVs can be charged and discharged based on the drop or rise in frequency. EVs can also participate in capacity markets by providing capacity by using EVs to provide backup power during emergencies and discharge during peak hours to help with peak loads. EVs can also provide spinning reserve services by acting as a backup power source in case of unexpected grid disruptions.

Overall, EVs can participate in several electricity markets and ancillary services, providing a valuable resource for grid operators to manage supply and demand and maintain grid stability.

6. Conclusions

E-mobility is a green transportation technology, and along with RES, could help to follow the green transition policy. The importance of assessing the effects of the increasing number of EVs on roads and power grids and how to build appropriate facilities and smart charging management is undeniable. The purpose of this review article was to survey the latest research ideas on the coordinated management of EVs' charging/discharging in future integrated electricity and transportation systems and to find new trends in this field on which to focus. To be able to categorize more effectively, the surveyed articles were categorized into three main groups including single CS, multiple CSs, and aggregator-based scheduling. In each category, different challenges, approaches, and solution methods were discussed. Research works that focused on single CSs developed more centralized controlling methods over decentralized methods inside the CSs. In this category, economic aspects of different stakeholders were taken into account excessively, and penalty/reward mechanisms were modelled for EV owners. In multiple-CS scheduling, more attention was given to the convenience of EV owners, route optimization, and congestion of CSs, as well as the economic aspects of the stakeholders. Aggregator-based EV scheduling, on the other hand, focused more on electrical system balance, peak shaving, valley filling, and demand response, as well as economic efficiency. Moreover, FC was mostly modelled for public CSs and slow charging for residential or commercial PLs. However, some researchers proposed two charging modes within the CS to provide customers with both offers based on their preferences and conditions. The hybrid controlling approach is used in some of the articles to take advantage of two different approaches or methods in a combined scheme. In some papers, centralized scheduling of switching from FC to slow charging was also presented to manage critical conditions and avoid peak loads. The economic functions modelled in the papers were:

- The profit of CSs on giving service to EVs and discharging electricity to the upper grid and electricity market;
- Costs of EV on charging including battery degradation cost and peak-load charging;
- Aggregators' profits on charging management of EVs;
- Social welfare and convenience of EV owners;
- Cost allocated to system operation considering the operation of conventional generators, system operation costs, CS operation costs, etc;
- Investment costs for constructing new CSs and RES power plants as supply energy of CSs.

Finally, the overall purpose of this review article was to try to give a broad perspective on recent trends in the future of e-mobility systems. In addition, it intended to give a view to the ideas of continuing more research pathways in coordinated charging management of integrated electrical and transportation systems.

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Abbreviations

EV	Electric vehicles
RES	Renewable energy source
DG	Distributed generators
ESS	Energy storage system
V2V	Vehicle to vehicle
V2G	Vehicle to grid
V2L	Vehicle to load
G2V	Grid to vehicle
CS	Charging station
PL	Parking lot
DS	Distribution system
DSO	Distribution system operator
CSO	Charging station operator
MDP	Markov decision process
ANN	Artificial neural network
PSO	Particle swarm optimization
GA	Genetic algorithm
PEM	Point estimate method
LP	Linear programming
ILP	Integer linear programming

MILP	Mixed integer linear programming
NLP	Nonlinear programming
QP	quadratic programming
MIQP	Mixed integer quadratic programming
GAMS	General algebraic modelling system
MPC	Model predictive control
SSA	Salp swarm algorithm
ADMM	Alternating direction method of multipliers
IGDT	Information gap decision theory
SBB	Simple branch and bound
KKT	Karush–Kuhn–Tucker
SOC	State of charge
FC	Fast charge
FCS	Fast charging station
PV	photovoltaic

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