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Review

Towards the Integration of Sustainable Transportation and Smart Grids: A Review on Electric Vehicles' Management

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Abstract: In this paper, a survey is presented on the use of optimization models for the integration of electric vehicles (EVs) and charging stations (CSs) in the energy system, paying particular attention both to planning problems (i.e., those problems related to long term decisions such as the siting and sizing of CSs), and operational management problems (i.e., the optimal scheduling of EVs in smart grids, microgrids and buildings taking into account vehicle-to-grid (V2G) capabilities). Moreover, specific attention was dedicated to decision problems that couple transportation and electrical networks, such as the energy demand assessment for a vehicle over a path and routing and charging decision problems for goods and people transportation. Finally, an effort was dedicated to highlighting the integration and the use of EVs in very recent regulation frameworks, with specific reference to the participation in the balancing market through the figure of an aggregator and the inclusion in the management of Energy Communities (ECs) and sustainable districts.

Keywords: electric vehicles; optimization; microgrid; optimal control; smart grid; planning

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1. Introduction

The increasing concern about environmental sustainability is pushing towards the electrification of the transportation sector, especially the road transport that is in Europe, which accounts for around 72% of total transport greenhouse gas (GHG) emissions [1]. Electric vehicles (EVs) can help in reducing CO_2 emissions as well as improving air quality and noise levels in urban areas. Therefore, EVs represent the best option for achieving significant decarbonization of the road sector if coupled with renewable energy sources (RESs). For the reasons mentioned above, national and local entities are boosting the EVs adoption, and a rapid increase in the EV number is expected shortly. Nevertheless, in addition to the barrier represented by the limited travel autonomy and the low number of available charging facilities, it should also be considered that a massive integration of EVs will present great challenges, especially to power distribution systems, where EVs will be connected most [2]. Indeed, EVs are additional loads whose uncontrolled charging process could increase the peak load, create undesired local congestions, degrade the power quality, intensify power losses, and cause voltage fluctuations. In particular, EVs can be used for Demand Response (DR) purposes through an aggregator in the energy market. DR can be applied at different spatial levels: a wide territory characterized by multiple districts and municipalities, energy communities, microgrids, and buildings. Generally, the actions that can be applied are related to the disconnection of the load from the grid or its significant reduction. In addition, in the case of EVs, there are specific technologies that increase the possibilities of flexibility, demand reduction, and shifting; in fact, Vehicle-to-Grid (V2G) and Vehicle-to-Home (V2H) technologies can provide power to the electrical grid and make the EV act as a storage system.

In this framework, different actions could be undertaken to mitigate possible problems related to CSs and EVs and enhance their spread. In particular, in this paper, attention is focused on the siting and sizing of CSs (i.e., planning), the optimal scheduling of EVs' charging, the routing, and charging of vehicles that transport goods and people, and the integration of EVs in the energy system for DR. These topics necessitate the integration of different networks (ICT, electrical, transportation/traffic) and different decision-makers (i.e., local prosumers, microgrid owners, aggregators, etc.). Figure 1 reports the main topics considered in this work and the associated interacting networks.

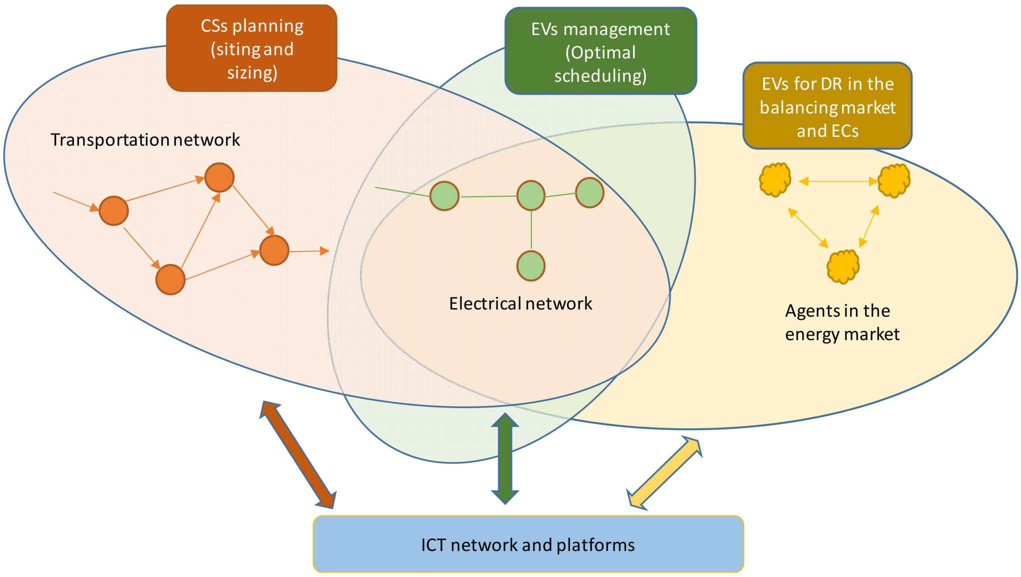

Figure 1. Considered topics and related networks.

The planning of CSs consists of the optimal sizing and siting of recharging technologies over territory. It must be treated multidisciplinary (i.e., considering traffic flows, territorial constraints, available technologies, distribution grid, etc.).

When all CSs are installed, it is necessary to optimally schedule the EVs' charging daily to minimize costs, satisfy users' needs, and respect deadlines. These kinds of problems refer to operational management, particularly optimal scheduling.

Additional difficulties are present when a user wants to make a trip between point A and point B. Reasons to be taken into account are explained in depth in [3]. They are mainly related to a limited battery capacity, the need for a longer stop to recharge the battery, the characteristics of the available infrastructure of charging stations, the intrinsic nonlinearities associated with the battery models, and the need to develop energy consumptions models over a path, etc. [4].

Finally, EVs and CSs can help the operations of the electrical grid thanks to the ability to transform from a distributed load that needs to be managed to a flexible load that can assist the electrical grid in emergencies. This can be performed by modulating and shifting the load and implementing V2G strategies. Thus, EVs can be used for DR purposes, interacting with an aggregator in the balancing market, or being included in ECs and sustainable districts in general [5].

Several surveys related to EVs and their integration into smart grids were carried out in the literature. However, the topics are different (and only partially overlapping) from the ones present in the proposed survey. Moreover, we aim to focus on optimization and control and integrating multidisciplinary competencies (i.e., smart grids, transportation, scheduling of resources, ICT). In the literature, some survey works are oriented toward charging–discharging strategies for EV aggregators and their impact on the grid [6,7]. They focus particularly on infrastructures already installed in the electrical grid, such as in [8,9], in which different decision architectures are discussed. In particular, it is highlighted that centralized control gives an overview of the complete system, but it is impracticable when the size of the system increases. Therefore, different decentralized controls are considered. In [10,11], different kinds of EVs, such as fuel cell hybrid electric vehicles and hybrid electric vehicles, are reviewed from a technological point of view. The authors also describe the effect of different control strategies and battery structural design and provide ideas for the life extension of different electric batteries. In [12], the current research on the charging functioning of electric vehicles, such as electric vehicle charging locations, is summarized.

Most of the papers describe different control techniques depending on the problem they face, such as the charging–discharging with different grid configurations or the scheduling and sizing of the EVs and CSs. These techniques range from Linear Programming to Artificial Intelligence techniques [13]. However, none of them reviews all the main issues (traffic, routing, smart grids, scheduling such as in manufacturing) that couple different networks and actors in the energy market.

Thus, the main contribution of this paper is to present a survey on the use of optimization models for the integration of EVs and CSs in the energy and transportation systems paying particular attention to:

- Siting and sizing of CSs (i.e., planning), taking into account traffic, electrical grid, available software tools, and transportation networks;
- Optimal management of EVs' schedule in smart grids, polygeneration microgrids, buildings, etc.;
- Routing and charging of vehicles that transport goods and people;
- Integration of EVs in the energy market for demand response purposes.

This paper has relied on a number of current publications to support and substantiate the ideas spread throughout the paper. Figure 2 represents a classification by publisher and year of the articles cited in this survey. Moreover, the classification by topics is reported in Table 1.

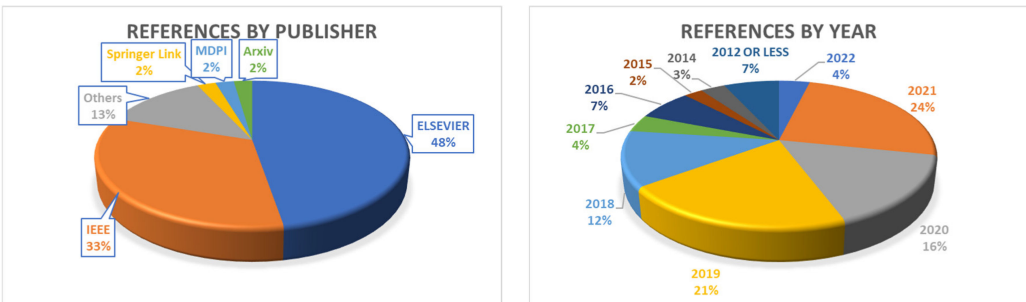

Figure 2. Classification of the articles structured by publisher and by year, respectively.

Table 1. References classified by topics.

Topics	Refs.
EVs' optimal scheduling in a smart grid	[14–46]
Charging stations planning	[47–63]
Routing and Charging	[64–86]
EVs in the energy market: Energy Communities	[87–96]
EVs in the energy market: Balancing Market	[97–105]
Distributed ICT architectures and multi-agent systems	[105–127]

The remainder of the paper is structured as follows. EVs' optimal scheduling in a smart grid is in Section 2. Section 3 is focused on charging station planning. Section 4 reviews different features of electric vehicle routing and charging problems. The capacity of the flexible load behavior, demand response, and multi-decision-maker optimization are presented in Section 5. Finally, conclusions and future challenges are discussed in Section 6.

2. EVs' Optimal Scheduling in a Smart Grid

In a scenario in which many vehicles may need a recharge, it is necessary to optimally schedule the operations to satisfy customers in terms of energy requests and desired readiness of the vehicle in terms of time. This is indeed a general class of decision problems related to limited resources (i.e., CSs) and processing requests (i.e., electric vehicles, energy demands) that are generally faced in the manufacturing system for the production and supply chain management. Moreover, since EVs can be a huge and intermittent load over the electrical grid and a resource to help manage the grid, they should be considered within a wider framework related to distribution grids, smart charging parks, microgrids, buildings, etc.

In this sub-section, the different aspects of EVs' optimal scheduling are presented and grouped in the following sets of problems:

- First of all, local private areas (microgrids, buildings, sustainable districts that own EVs) are considered, in which EVs are part of overall energy management. Within this framework, particular attention was devoted to the advantages and disadvantages of V2G services;
- Then, attention was focused on public areas (i.e., charging parks) and public transportation (electrical buses, car-sharing);
- Finally, it was discussed how optimization models can be used in practice using ICT platforms.

In the literature, the optimization models that regard the scheduling of EVs in local areas consider different issues such as the minimization of costs of the smart grid in which they are located, the minimization of carbon dioxide emissions, the integration of renewable energy sources, peak shaving and load shifting, etc. [14]. Usually, optimization problems are formalized in the discrete-time representation. For example, in [15], the aim of the model is to optimally schedule the EV charging in a smart grid while examining customers' dissatisfaction cost and by considering the EV demand as deferrable. The strategy proposed in [16] proves that if an orderly control is applied to the EV charging process, the system reliability is improved by reducing the peak and valley difference and the equivalent load fluctuation while satisfying the user's charging power demand. Zhaohao et al. [17] select the charging pricing as a tool for optimally coordinating the aggregator and EV charging stations and demonstrate that the total cost can be greatly reduced by applying the suggested model. Other approaches, such as in [18,19], are related to a discrete-event formalization, which offers the advantage of reducing the number of decision variables, though losing some details in the time domain representation. However, both discrete-time and discrete-event approaches offer the possibility to improve local energy utilization, reduce the need for investments in stationary batteries, provide demand response services and integrate EVs in the smart grid [20], and drastically reduce emissions when the system model couples EVs and renewables [21,22]. From an application point of view, a large number of articles are related to the optimal charging of EVs in buildings because, as assessed in [23], EVs can help in several issues such as demand response and cost minimization, but also for minimizing the net load variability and improving self-consumption. In fact, by considering that EVs can also act as mobile energy storage systems (ESS), one could mitigate the intermittent and uncontrollable nature of PV production and reduce the mismatch between production and consumption. This last-mentioned scheme is called vehicle-to-anything (V2X) and refers to technologies using the energy in EVs' batteries for any purpose outside the vehicles: indeed, this structure includes V2G, V2H, and vehicle-to-building V2B [24].

In the recent literature, many articles are related to V2X strategies that, if correctly managed, can perform ancillary services (such as regulation up and down, spinning reserve, and non-spinning reserve for frequency control [14]), contribute to lowering the electrical bill and bring economic profits to the EV or CS owners. The authors in [25] propose battery swapping stations as a solution to face the challenges related to V2G-based frequency regulation services, such as scalability, uncertainties of EV behavior, and communication delay; according to the results, the proposed strategy, based on the deep Q-learning network, can guarantee good profitability of the battery swapping station and handle the model uncertainties at the same time. The authors in [26] present a V2G operation designed to optimize the charging costs for EV owners while providing ancillary services to the grid; this can be achieved especially in on-peaks hours, thanks to the aggregator, which represents the intermediate link between grid operators and EVs. The vehicle-to-microgrid control framework is described in [27]; the proposed model aims at operating a commercial neighborhood as an independent electric unit through optimal voltage regulation and power-sharing. The results show that both economic and technical benefits are obtained. As previously mentioned, EVs can supply energy directly to a household via V2H. Ubaid et al. [28] show that the smart integration of EVs and ESSs in an optimal home power management configuration could further reduce the costs related to the energy supply and slow down the EV battery degradation process. As proved in [29], applying the V2H strategy, the energy stored in the vehicles' batteries is supplied to the house in those periods when the electricity price is higher: this leads to the minimization of the electricity bill. However, it must be said that there are also some drawbacks when using EVs for the regulation of the electrical grid. One main disadvantage is that performing V2X enhances the battery degradation; therefore, the energy delivery from the EV battery must be implemented only when strictly needed. The other one is related to uncertainties related to the calculation of energy requests of EVs and the efficiency of the batteries that strongly depends on the state of health and how it was used. In [30], in addition to a detailed review of the main EV control charging strategies (which are classified into scheduling, clustering, and forecasting), one can appreciate which are the main challenges of implementing them: EV load is unpredictable (EV drivers have uncertain behavior), EV owners may not cooperate out of commercial profit and privacy concerns, load demand varies with different EV models, the arrival and departure times are difficult to obtain, and there are several limitations in the communication systems. Amro et al. [31] develop a charging strategy where different customer behaviors are considered. To do that, they decompose the optimization problem into two sub-problems. A multi-objective optimization problem that considers several EV models is proposed in [32]; the results show that this broad-ranged problem can relieve local traffic jams, lower the EV number in charging stations, and diminish the waiting time for charging. The authors in [33] suggest a bi-objective optimization problem to satisfy the main stakeholders' interests (i.e., cost minimizations for the CS operator and a quick charging process for EV owners). In [34], the authors propose a real-time scoring system that should motivate EV owners to follow the cluster-based optimal scheduling for cost and battery degradation minimization which is planned the day ahead. The research developed in [35] concludes with the importance of V2H capability when no storage system is installed, moreover, this technology can avoid the necessity of installing a battery bank. A total of 25% of the total project cost was reduced with the methodology developed on the optimal design of electrification systems for isolated dwellings.

The previously mentioned literature is mainly focused on the control strategies for private electric vehicles. Nevertheless, public parking lots can be exploited as charging facilities if they are equipped with CSs. Potential applications for this operation mode include parking lots where vehicles are parked for quite a long time, such as office buildings, shopping malls, and airports. This could be a feasible solution for EV owners with technical and economic difficulties installing their own charging stations. If the parking time is higher than the time required for the charging process, the parked EVs can be handled according to a smart charging scheduling; the EVs must be managed to avoid grid overloading and, at the same time, meet EV owners' requirements. The fuzzy logic interference base algorithm proposed in [36] is applied to a parking lot and aims at satisfying EV users' requirements by avoiding grid overloading; according to the results, the proposed algorithm allows the management of the available power so efficiently that grid overloadings are reduced and more EVs are served. In [37], the authors apply V2B to a university building equipped with an EV parking lot to provide ancillary services (peak shaving and valley filling) by regulating the power consumption profile; by proving that the higher the number of parking spots is, the more effective the peak power consumption reduction is, as they demonstrate that the V2B combined with a parking lot is a feasible and good solution for reducing the power demand of a building. Control strategies can also be applied for cost minimization. Jiang et al. [38] developed a grey wolf-based real-time scheduling for EV charging operations in a parking lot where a PV and an ESS are also present with the final purpose of minimizing costs for the owners of the parking lot; the result shows that the adopted strategy also permits the increase in PV exploitation. The authors in [39] present a bi-level framework for the operational schedule of a smart distribution company (SDISCO) cooperating with a private parking lot owner; the two investigated levels aim at the cost minimization for the SDISCO and the parking lot owner. An additional level could be added representing the owner of the electric vehicles.

Additionally, as regards public transportation, a very specific application of the described approaches for controlling the EV charging process is the management of electric vehicle fleets, particularly electric buses (EBs). Indeed, increasing EBs use is another potential opportunity to reduce energy consumption and emissions related to the transportation sector. Moreover, enlarging the number of public vehicles concerning private ones could further help achieve the environmental targets. EV fleets operate differently compared to passenger vehicles, for example, their driving paths are fixed as well as the arrival and departure times. Moreover, the difficulty related to energy forecasting is reduced since aggregated parameters to represent energy and power constraints of the entire fleet should be employed when dealing with EV fleets [40]. The work in [41] provides a comprehensive survey of technical and management aspects related to electric buses. Xie et al. [42] show a real-time strategy that minimizes the overall cost by optimizing the velocity planning and battery depth of discharge to improve the battery state of health; according to the results, a far-sighed framework is the better than a short-sighed energy management approach. When speaking about electric vehicle fleets, one could also refer to the latest concept of car-sharing, which is a potential solution for fostering EVs diffusion despite the several aforementioned barriers. The work proposed in [43] aims at improving the EV exploitation while enhancing the battery lifespan through a management system applied to EVs in a mixed vehicle-type fleet; the results show that, besides intensifying the EV accessibility and improving the battery health, this approach also allows to increase e-carsharing profitability. The authors in [44] jointly optimize the infrastructure planning and the real-time managing of the fleet for a one-way electric vehicle sharing service in an urban area; they succeed in handling impactful spatial–temporal demand uncertainties thanks to a multi-stage stochastic approach and a demand-adaptive fleet operation strategy.

Finally, the last set of papers in the literature is devoted to developing ICT platforms that include the optimization problems mentioned above. Generally, these platforms are called energy management systems (EMSs) and building energy management systems (BEMSs), used for optimally managing microgrid or building operations. The authors in [45] design an EMS for minimizing the charging cost of EVs parked in a workplace parking lot that is fed by solar power; by forecasting the PV power production and optimally managing the power flows, the proposed EMS can reduce the power withdrawn from the grid and increase PV self-consumption. Thomas et al. [46] investigate how an EMS operates in a building if PV uncertainties are considered, and the stochastic behavior of an EV fleet with V2X capabilities is analyzed. According to the results, a stochastic approach is fundamental for significant cost reduction, and EVs are selected as the most promising technology to sell energy back to the grid. In the BEMS proposed in [47], which aims to feed the most critical loads in a building according to an importance ranking, the EVs are considered autonomously-moving batteries introducing dynamic uncertainties that the control system has to handle.

According to the inherent nature of the problem, new stochastic methods that includes various sources of uncertainty are proposed to consider charging demand for different tasks.

The work developed in [48] by Neragestani et al., works with different uncertainties to determine the optimal sizing implementation of a storage system for a fast-charging station. The proposed approach considers different types of vehicles in the fleet, the probability of daily mileage driven, and the probability of driving as a function of time instant to model the charging demand of a Plug-in Hybrid EV during a defined period. In [49] the model examined on an MG includes different RES such as PV, fuel cells, wind turbine, micro turbine and ESS, in which a new optimization procedure based on krill herd is proposed to deal with a smart charging strategy both in public charging stations and in residential communities.

3. Charging Station Planning

The planning of CSs must be treated in a multidisciplinary way because it is necessary to consider different aspects such as the charging and transportation demands in a specific area, the territorial constraints, distance and traffic conditions, drivers' behavior, the presence of specific areas that are more suitable for CSs location (such as commercial centers, industrial areas), population density and economic status, etc. There is not a general framework that considers all these aspects, but there are many papers that couple different areas of expertise to solve the problem of CSs planning.

In this section:

- Attention is firstly dedicated to existing review papers related to the optimal planning of charging stations, highlighting the main challenges;
- Then, optimization problems that include coupled transportation and power networks are described;
- Finally, the role of GIS (Geographic Information System) tools is highlighted.

Fundamental work in reviewing the CSs' planning is represented by [50]. In this paper, the authors analyze the studies published until 2019 regarding the planning of CSs. They conclude that there is an increasing trend in heuristic models to the detriment of exact methods. This is because exact optimization methods resulted in being not viable for real-world systems with multiple objectives to optimize and large complex datasets. Moreover, the most interesting conclusion about the CSs planning framework is that the impact on the electric distribution system is rarely considered, even if many studies warn about this lack. Another review paper published in the same period of [50] is [51]. This work focuses on the contemporary presence of distribution networks and traffic network constraints. Most of the papers analyzed in this review adopt a Particle Swarm Optimization (PSO), followed by Genetic Algorithms (GA), Ant Colony Optimization (ACO), and linear integer programming for optimal CSs placement. Among the possible mentioned future research, there is the definition of multi-objective optimization problems able to consider at the same time costs and waiting time, as well as reliability indexes of the networks. Another main lack in the literature is represented by the rare consideration of uncertainties in the transportation network.

In the recent literature, technical papers regard the simultaneous optimal planning of CSs and distributed generation (DG) power units in distribution systems [52]. In [52], the authors use different approaches to model the EVs' load. Then, they evaluate the optimal site and size of fast CSs in the distribution grid, considering the uncertainty of the initial state-of-charge of the EVs with a Monte Carlo simulation. In the work presented in [53], a comprehensive optimization model for the sizing and siting of different renewable resources-based DG units, CSs, and storage units in a distribution system is presented. However, the most recent literature highlights that it is necessary to simultaneously consider the transportation and power networks. From the distribution grid point of view, CSs represent a large load that must be collocated somewhere so that they do not negatively affect the grid stability. From the transportation network point of view, the CSs must serve the largest number of users. CSs planning must also solve the issues from the driver's point of view; in fact, the uncertainty related to the availability of the CSs remains one of the main issues in the EVs' adoption.

A very popular approach is to integrate the choices of individual drivers to determine the distribution of the charging demand. A possible solution lies in the well-known User Equilibrium (UE) traffic assignment approach [54], which must be extended to where a certain amount of traffic is generated by EVs or mixed fleets. A primary method in which this approach is described is presented in [55]. The authors extend the UE principle to determine, besides the flow over the network links, the service requests from the drivers to the various service stations. UE traffic assignment influences the distribution of the energy demand and thus the planning of charging stations. Further work is represented by [56], where the authors present a bi-level decision architecture in which the electrical and the transportation networks are integrated. The UE traffic assignment conditions are derived by the lower level to assess the energy demand and to represent users' choices. The higher level presents the formalization of an optimization problem in which power losses and installation costs are minimized, while benefits are maximized. This model considers the UE conditions for the case of EVs and the electrical grid model (load flow equations, bounds over-voltage, apparent power, etc.). Another study in which UE conditions are considered is presented in [57]. Here, the authors coordinate charging with traveling behavior in a generalized network revealing the relationship between charging and traffic flow. Then, they present a Logit-type discrete choice model to formulate the Stochastic UE (SUE) and analyze the influence of road capacity and charging price on the flow distribution. In [58], the authors study the selection process and decision-making psychology of travelers' behavior for path selection and charging. This paper considers the difference in travel utility perception between the users of EVs and fuel vehicles, the time-varying traffic flow, and charging stations' service level and location. Then, the authors establish a two-level programming model to solve the problem of charging station site selection. The higher level is a system optimal model, and the goal is to minimize the travel time of the network. The lower-level model describes the randomness of charging and travel behaviors and the time-variability of departure time, establishes the dynamic user equilibrium model, and designs a heuristic algorithm. The authors present a numerical example in which they verify the validity of the presented model. In [59], attention is focused on calculating travel paths through a dynamic traffic flow simulation, which allows considering the real-time changing traffic conditions and minimizes costs (construction, operation, travel cost) for the optimal sizing and siting.

In [60], both the transportation network (TN) and the power distribution network (PDN) are considered; a comprehensive planning model is proposed, which determines the optimal expansion strategies for both TN and PDN, including sites and sizes of new charging stations, charging spots, TN lanes, and PDN lines. In TN, the authors considered an unconstrained traffic assignment model to capture the steady-state distribution of traffic flows explicitly. The proposed model is a mixed-integer linear programming (MILP) one, and the objective function includes construction costs of the CSs, EVs travel time, and expansion of both the networks (PDN and TN). According to the proposed numerical examples, the model returns an optimal solution in a reasonable computation time when considering moderately sized networks. In [61], a two-stage planning model for the CS placement problem is proposed. The goal of the first stage is to identify the candidate locations for the placement of charging stations by applying fuzzy logic, taking into account the distance between the nearest bus in the distribution network and a node in the road network, grid stability, and traffic intensity. Then, optimization is performed by adopting a multi-objective framework to select CS optimal locations, type, and the number. The authors propose a case study composed of two cases, a 25-node road network and an IEEE 32-bus distribution network, and a real network in Tianjin, China.

It is interesting to note that GISs are used as valuable tools in the decision process in literature. The authors in [62] present a GIS-based site selection model for decision-making in the investment planning process for smart cities. In particular, they focused on CSs in their case study, designing a GIS-based integrated site selection model for investment planning in the smart city concept. The authors apply Multi-Criteria Decision

Analysis (MCDA) techniques (typically used for criterion weights evaluation in GIS-based site selection models). The authors consider 15 criteria divided into three main groups: environmental/geographical, economic, and urbanity. Then, they generate a suitability map for CSs site selection in a real case scenario. In [63], a model for the location of a CS equipped with PV is presented. This model combines GIS with MCDA techniques. First, some suitable areas were selected through a GIS. Second, MCDA methods were used for further evaluation. Then, ranking the results of the MCDA techniques, the best areas were determined.

Moreover, through dual sensitivity analysis and comparative analysis, the authors proved the stability and reliability of the model. This study resulted in an interesting alternative in providing support for the layout of CSs (with PV) in an urban context. In [64], the authors address the urban environment's fast-charging station location problem. They formulate an optimization problem as a maximum coverage location problem (MCLP), considering existing petrol/fuel station locations as candidate locations.

The developed GIS-based platform is integrated with a linear-programming relaxation-based MCLP algorithm. In the case study, some real data are considered; in particular, population and highway traffic data are used as demand metrics to mimic vehicles on highways that need a recharge and drivers without dedicated chargers. The results show that the demand coverage is improved by more than 50% when compared to existing fast-charging stations if fast chargers are located in existing petrol stations. In [65], a novel framework is proposed to find the optimal location and size of public CSs, maximizing the benefit of the investment. This work considers that charging behaviors and urban land use have an impact on the income of CSs. An agent-based trip chain model is applied to represent the charging and travel patterns of EVs' owners, generating a charging demand which is assigned to each geographic cell according to the volume of traffic flow and the type of land use. Then, the maximization of the economic benefits of CSs is performed thanks to a MILP model that considers charging costs and revenues, system investment costs and land rental costs. A cell-based geographic partition method based on GIS is exploited to see how the land use influences the stochastic and dynamic nature of EV charging behaviors. This approach is then tested on a real case study in the Swedish city of Västerås. According to the results, the CS profitability is strongly affected by the served charging demand, the location, the drivers' charging behavior, and the service range of CS.

Moreover, the most significant factor impacting profitability is the charging price. In [66], the authors present a machine learning approach based on different classes of clustering solutions. The work is tested on two large datasets, including spatial data on households with EVs. The different clustering techniques result in the optimal siting of some CSs. As highlighted by the authors' future research could involve a probabilistic environment to deal with the traffic congestion scenario in the transportation network. Other applications of GIS can be found in [67], where the authors use available sources of GIS data to describe, in a quantitative way, the urban context of geographic locations of CSs. Their analysis aims to identify the most promising predictors for future analyses of the relationship between the characteristics of the charging stations' locations and performance indicators of stations. In the GIS-based framework, the main approach seems to be evaluating certain criteria weight which can be used to develop suitability maps. As described in [65] and [66], the coupling of more traditional approaches with GISs seems to be very effective since it can take advantage of the data analysis available through GISs, which can effectively determine the optimal planning.

4. Routing and Charging

This section surveys the literature on the Electric Vehicle Routing Problem (EVRP), which is an extension of the popular Vehicle Routing Problem (VRP). Interested readers can refer to [3] for a very recent survey on VRP and similar problems.

The EVRP aims to optimally route a fleet of EVs to provide a freight transportation service, considering the characteristics of the available infrastructure of CSs, the features of the battery, and the models of energy consumption rate (ECR). Figure 3 reports such a problem for a case in which there is a depot, multiple customers and different possible charging stations.

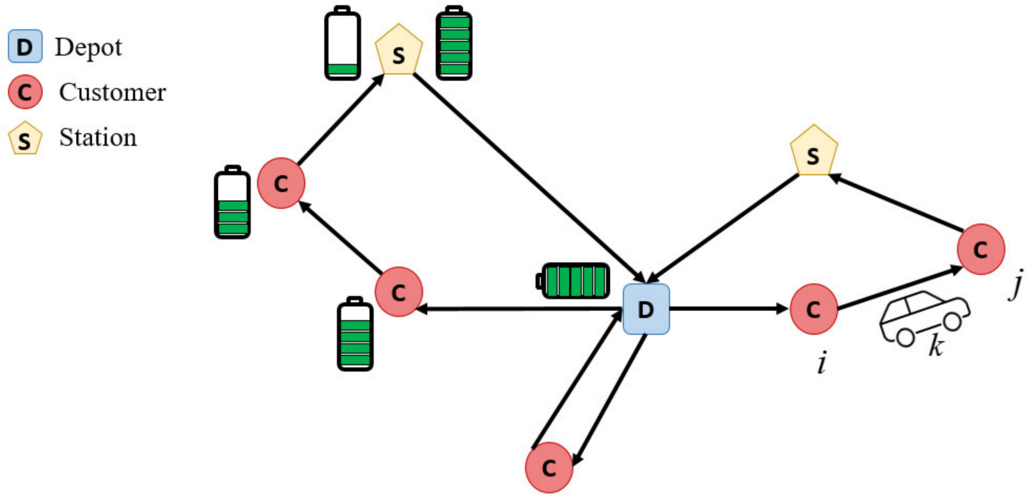

Figure 3. The routing and charging decision problem.

The concepts underlining the EVRP are introduced in three different works [68–70]. The problem is formulated as a MILP on a complete direct graph. The set of vertices includes the depot, the customers, and possibly the stations. Note that the two critical aspects characterizing this variation of the VRP are the limited driving range of vehicles (and thus their need to recharge to complete trips) and the low spread of CSs on the territory. The Green VRP, first defined in [68], considers the need to refuel alternative fuel vehicles, not specifically electric, thus allowing detours at a set of stations. Electric vehicles are first considered in [69], but recharge is only allowed at the customers' nodes. The first paper to introduce the EVRP considering specific nodes for CSs is [70], where customers are also characterized by time windows (ERVP-TW).

One of the main issues of the EVRP is that, differently from the customer nodes, each CS may be optionally visited but also visited more than once. Two possible modeling solutions were designed: cloning the CSs in the network, which is the most widespread solution in the literature, or adopting a cloneless model based on the so-called recharging paths. The introduction of CSs' clones allows to extend to EVRP the classic routing constraints of VRP easily; however, it is critical to determine the minimum number of copies to avoid an excessive growth in the number of variables. On the other hand, cloneless models require additional variables and constraints that are not always easy to be defined. Additional features that were modeled for the CSs concern the possibility to recharge partially (i.e., to use only the energy needed for routing, thus decreasing costs), to have different charging modes (in terms of technologies and power levels) with different capacities (which can be power o time-dependent [71]), and battery swapping stations [72].

In the literature on EVRP, several papers were published that address different features. Interesting contributions regarding the CS modeling are given by [73–80]. The work in [73] formulates the EVRP, including partial recharges and multiple recharging technologies, then solves this problem by several heuristic approaches. Partial recharges are also addressed in [74], where the authors propose a variable neighborhood search (VNS) metaheuristic. This approach is extended in [75] through a novel three-steps metaheuristic able to outperform the previously proposed method. An exact procedure based on a branch-price-and-cut algorithm for the EVRP considering full/partial recharges at CSs is presented in [76]. Partial recharges are also allowed in [77,78], where an adaptive large neighborhood search (ALNS) algorithm and a granular Tabu Search approach are introduced, respectively, for solving the EVRP. In particular, in [78], the considered EVRP consists of pickup and delivery freight transportation. A mixed fleet VRP with TW is faced in [79], where the size of a fleet including both EVs and traditional vehicles should be determined, as well as the routing, allowing both full and partial recharges/refuels. The authors propose a branch-and-price approach and an ALNS metaheuristic. In the same research stream that assumes a mixed fleet, an iterated local search algorithm is exploited in [80] to minimize the pollution emissions due to the traditional vehicles.

Another peculiar characteristic of the introduction of EVs in routing problems is related to the battery functioning pattern. All the papers mentioned above assume a battery's linear discharge and recharge function. Different models, considered more realistic, can instead be found in [81–86]. The first contribution that introduces a nonlinear charging model for the EV battery is [81]. In [82], the authors propose a novel arc-based state of charge modeling; in particular, they introduce a cloneless MIP model based on a recharging path. They also develop an exact labeling algorithm to find the optimal routing solutions. A variant of the EVRP with a nonlinear charging function is solved by a multi-start heuristic in [83], considering the possible sharing of CSs. A mixed-integer programming (MIP) formulation for the ERVP-TW that adopts a linearization method for a nonlinear charging function is given in [84]. In [85], a branch-and-price algorithm is presented to minimize the total travel and charging times without approximation of the charging time function. Finally, a multi-depot EVRP with a nonlinear charging function and capacity constraints is considered in [86], proposing a genetic algorithm to minimize the driving times, the number of recharging stops, and the time spent to recharge.

A third peculiar aspect characterizing EVRP is the model of the ECR. The work presented in [4] first considers realistic features, such as the carried load and the vehicle speed, in the ECR model; in particular, the vehicle speed is assumed to depend on the arc but constant, with a simpler linear energy cost function. A nonlinear formulation of the EVRP is given in [87], considering constant but arc-dependent vehicle speeds, with the objective of minimizing the energy consumption. In [88], the authors proposed an ant colony optimization algorithm for the EVRP, including some new real factors in the ECR model, such as the gradient of the road and the discharge and the recuperation phase of the electric drive. In [89], the energy consumption uncertainties are addressed, including endogenous and exogenous factors (such as weather and traffic), solving the problem using a large neighborhood search-based heuristic approach. Finally, a MIP model for the EVRP-TW with a realistic ECR is introduced in [90], assuming time-of-use energy prices; in addition, the ECR model includes contributions on the energy consumption due to the carried load, the terrain gradient, the number of starts and stops, and the speed of the vehicles on the arcs that can vary in a given discrete set of values.

5. EVs in the Energy Market: Demand Response and Multi Decision-Maker Optimization

In the previous sections, it was shown that EVs represent a huge distributed load that the electrical grid should manage but that, at the same time, are flexible loads that can help the electrical grid in emergency situations (by shifting the demand, providing energy storage, and providing power through V2G capabilities).

In this section, attention is focused on the role of EVs in the newest regulation frameworks related to smart grids, which have introduced the presence of new actors such as aggregators in the energy balancing market and Energy Communities (ECs).

Specifically, an aggregator is an entity in charge of interacting with the Transmission System Operator (TSO) to reduce a load of a portion of territory through the coordination of different prosumers and users. The remuneration drives decisions from the TSO to reduce loads, the avoidance of local users' dissatisfaction, and the incentives to provide to customers.

ECs are the consequence of a new regulatory framework that allows different users/prosumers to sell and share energy among them to promote auto-consumption and renewables use and minimize costs.

Figure 4 shows the main actors that manage DR in the balancing market: TSO, DSO, aggregator and local prosumers (charging parks, microgrids, buildings, and energy communities).

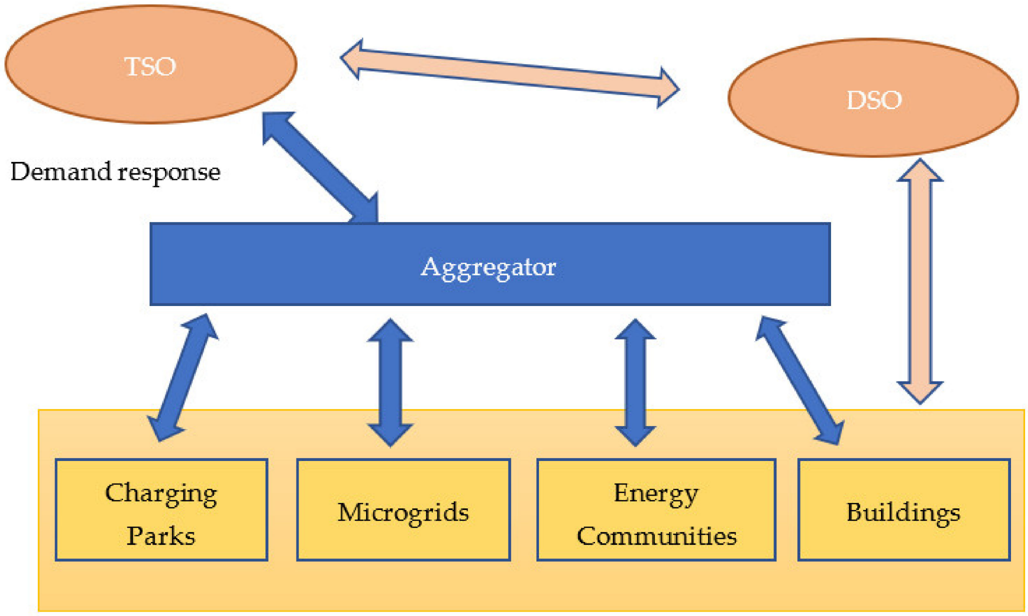

Figure 4. The framework of demand response.

5.1. Electric Vehicles in Energy Communities

An EC is a set of small or residential commercial agents, each of them acting as a prosumer and generally including shared generation (thermal and electric), flexible loads, and shared storage units, such as batteries [91]. EVs can be part of the EC and can act as storage or as a resource to be shared and charged. Nevertheless, EC definitions might vary from country to country. The EU Clean Energy Package recognizes certain categories of community energy initiatives as EC [92]: 'citizen energy communities' (i.e., only electrical energy and including production from fossil fuel) and 'renewable energy communities' (i.e., thermal and electrical energy only from renewables). ECs should allow citizens to participate in the energy system, encourage independence from the external grid, promote a fair sharing of benefits and costs among users by ensuring that no participant predominates over the others, and minimize costs, energy losses, and negative environmental impact. To this end, different approaches were introduced, such as distributed optimization [93] and Peer-to-Peer internal energy markets [94].

In the recent scientific literature, the article [95] provides a comprehensive review of market, regulatory and technological statuses to support the transition towards distributed cross-commodity energy management focusing on Germany and Finland. Since market structures will be more decentralized, the authors focus attention on the ICT tools and technologies that will allow the implementation of distributed architectures and integrated energy systems: Internet of Things (IoT), Artificial Intelligence, and blockchain. In fact, networked prosumers can negotiate and form smart contracts based on blockchain technology, IoT technologies are needed for real-time monitoring and control of DER, and AI technologies such as machine learning and automated decision-making, in turn, ensure optimal control of DER in different climate and temporal conditions. ECs should be the first step to developing smart energy municipalities [96], leading to many advantages such as costs reduction of the procurement of energy vectors, use of local resources and active participation of citizens, improvement of reliability and quality supply, electric load peak shaving, load shifting, etc. In particular, it is necessary for a multidisciplinary approach linking the technical conditions to the socio-economic systems of territorial planning. In [96], different real examples of smart ECs are reported in which EVs play an interesting role. As regards the EC field, the most advanced country in the world is Japan, and NEXT21 (Osaka, Japan) is a very interesting example, based on the concept of energy sharing, the end-users can exchange energy with each other, involving CHPs (Combined Heat and Power production plants), fuel cells, buildings, domestic hot water, absorption chillers, batteries, PV. The project of the smart energy city of Yokohama comprises an energy management system that integrates the Building Energy Management System for smart buildings, the Home Energy Management System for smart houses, and finally the Factory Energy Management System, which includes 2000 EVs, 4000 smart houses, and a photovoltaic system of 27,000 kW. The Toyota city project, aiming at cutting 20% of CO_2 emissions in the residential sector and 40% in the transport sector, includes the use of unused energy and heat in addition to electricity, the promotion of 3100 EVs and a certain number of V2G and V2H charging stations, and demand response at more than 70 homes. In the European context, the urban community in Nordhavn shows an integrated energy system characterized by heat pumps (HPs) and EVs. In Italy, the first EC is The Leaf Community Project (Ancona, Italy). Its structures and facilities are the following: Leaf mobility (electric vehicle), Leaf Working e-Lab (industrial building), Leaf House (building of six apartments), Leaf education (school), and Leaf Energy (five photovoltaic systems, two mini-hydro electric plants, ground source heat pump, condensing boiler, fuel cell, storage). It is important to note that storage systems such as batteries represent a key issue in ECs because they provide flexibility and facilitate the optimal management of local energy systems [97]. However, though battery storage has a significant impact on the total operational cost, the battery's lifetime reduces during charging and discharging cycles; this should be carefully considered in the overall EC management.

In the framework of ECs, many papers in the literature are focused on Peer-to-Peer (P2P) energy markets, which are particularly interesting when prosumers with production and storage capabilities are involved [94]. Such P2P markets rely on a consumer-centric and bottom-up perspective by allowing consumers to choose how they buy their electric energy freely. In [90], different kinds of these new P2P markets are reviewed: (i) full P2P market; (ii) community-based market; and (iii) hybrid P2P market, in which, depending on the degree of decentralization and topology, architectures can range from full P2P to hierarchical P2P. EVs can have a significant role in P2P frameworks. The paper in [98] proposes a fully decentralized algorithm based on a dual-consensus version of the alternating direction method of multipliers for smart buildings in considering multiple dynamic components such as heating, ventilation, air conditioning (HVAC), battery energy storage systems (BESS) and electric vehicles (EVs). EVs patterns are considered in selecting proper charging strategies, including immediate charging and smart charging. It is assumed that EV aggregators (EVA) have the responsibility to assemble the individual energy demands for overall management in smart buildings. EVA in the building can collect the specific EV information such as charging demand, arrival and departure times, maximal charging power, and driver preferences. In [99], EVs are pooled into forming virtual Local Electricity Markets (LEM), and it is investigated the impact of EVs' flexibility on the creation of virtual LEMs. The objective is to allow a set of EVs to trade electricity with other EVs or houses during their availability. In [100], it is assessed that P2P is expected to be particularly suitable to complement embedded PV generation and EVs. In particular, the authors simulate P2P energy sharing for a local microgrid of 50 households with community energy storage, PV and EVs (uni-directional EV chargers, chargers that can discharge EV battery energy to the home or the grid). According to the results, P2P trading with V2G can lead to an increase in shared energy, modest improvements to microgrid self-sufficiency, and improvements to household bills. However, the combination of P2P with V2H brings substantially greater advantages.

5.2. Electric Vehicles in Balancing Market through an Aggregator

Regarding the balancing market driven by an aggregator, the Peer-to-Peer mechanism is replaced by decision architectures. One arbiter/broker (i.e., the aggregator) receives information from local users/prosumers and is responsible for coordinating the overall load reduction. These market structures are helpful both for providing economic advantages to the market participants and helping the distribution's grid manager alleviate the pressure over the grid of distributed and intermitted load and productions. EVs represent a huge and intermittent load over the territory. However, at the same time, they can provide flexibility (through load shifting, energy storage, and V2G capabilities). Thus they can be used as a user/prosumer coordinated by an aggregator to participate in DR programs [5]. In this framework, the growing number of new electric vehicles seems to be a real challenge, expected to be 60% of the total vehicles sold by 2030 and 100% by 2050 [101]. There are two ways, i.e., direct or indirect, to achieve and incentivize DR to consumers. Indirect DR programs try to change the behavior of the loads through different methods of rewards; the use of different periods in which the price of electricity changes and incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is at risk. In the latter case, there are DR programs such as the Special Case Resource (SRC) program or the Day-Ahead Demand Response Program (DADRP) promoted by New York Independent System Operator [102]. SRC provides an upfront payment for capacity, a payment for load reductions when dispatched, and it may include penalties for non-compliance with capacity obligations. DADRP allows participants to submit load reduction bids in the Day-Ahead Market, where they compete with generators.

Interestingly, attention to load management was promoted in the U.S. by the rise of air conditioning that caused short load peaks. Among the U.S., there was a real increase in the number of entities offering DR programs, from 126 in 2006 to 274 in 2008, an increase of 117% [103]. Direct DR programs happen when the aggregator or the distribution system operator adjusts the demand profile at its own decision, directly disconnecting the consumer's equipment, who are notified at short notice. Participants in the program are compensated for their participation with a bill credit or discount. In other cases, participating customers are rewarded with money based directly on the amount of load reduction during critical conditions.

Most of the works in the recent scientific literature on DR include V2G technology. They are focused on deciding when and how frequently to charge or discharge the battery using optimization models. For example, Saber et al. in [104] propose a Particle Swarm Optimization, a kind of evolutionary algorithm, to solve V2G of car parks; this technique was demonstrated to solve complex constrained optimization reliably and accurately. In particular, V2G and EVs are included in an overall Unit Commitment decision problem. A multi-objective function minimizes costs (including fuel cost, start-up cost, and shut-down cost of a thermal device) to efficiently schedule on/off states of the available system resources. In [105], an aggregator using a combined portfolio with direct and indirect techniques of DR is proposed. The main problem here is to select a balanced combination of DR contracts to achieve the best results. For this purpose, it is proposed that each contract's selection and weight are defined by three different criteria: higher profit to the aggregator, higher utility for the end-user, and higher reduction in electricity consumption. The work in [106] also applies the combination of two types of demand response for EVA, which avoids the limits of choosing a single type of DR. Incentive-based demand response is used to improve the total effect of demand response, while the price-based demand response forces unwilling users to participate in the program. EVA is the entity that provides charging facilities to a group of EVs and acts as an intermediary between the distribution system operator and EVs owners to solve techno-economic problems in the operation and control of the electrical grid [107]. Aggregators must sign an agreement with EVs user indicating remuneration, the method of charging or discharging, limits on power production and reduction, etc. Contreras-Ocana et al. in [108] develop a decentralized framework to jointly schedule loads in a commercial building and the charging behavior of an EV fleet. Huang et al. [109] use a Building Integrated Energy System (BIES), a combination of on-site or DG technologies with thermally activated technologies to provide users with different energy sources, such as heating, cooling, and electricity.

5.3. The Role of Distributed ICT Architectures and Multi-Agent Systems

The framework presented in the previous sub-sections happens to have multi-objective and multi-decision maker optimization models applied to large-scale case studies. An effective technique to solve such decision problems is to use distributed ICT systems (i.e., a system whose components on different networked computers can communicate and coordinate their action to achieve a more complex common goal) governed by multi-agent, distributed, and hierarchical optimization. In fact, dividing the problem into several sub-problems makes them simpler because the computation for a single entity would be more burdensome and arduous. This distributed system is known as Multiagent System (MAS); it is used in different applications, such as distributed logistics, unmanned aerial vehicles, autonomous driving, or network packet routing [110]. MASs are composed of multiple interacting intelligent agents. An agent is essentially a unit characterized by being able to interact with its environment and with other agents. They also can make decisions on their own. This structure is shown in Figure 5. The three distinct parts allow the agent to take information from its environment and act on it, exchange information with other agents, and the Decision-Making Unit. ICT systems based on MAS should be coupled with optimization methods to solve sub-decision problems while guaranteeing optimal solutions. This is particularly interesting in graph-based networks in which a node of the network is unavailable for faults, natural disasters, or malicious attacks. Another way the agent can decide is based on optimization methods coupled with Reinforcement Learning techniques, and the most common algorithm used is Q-Learning [111].

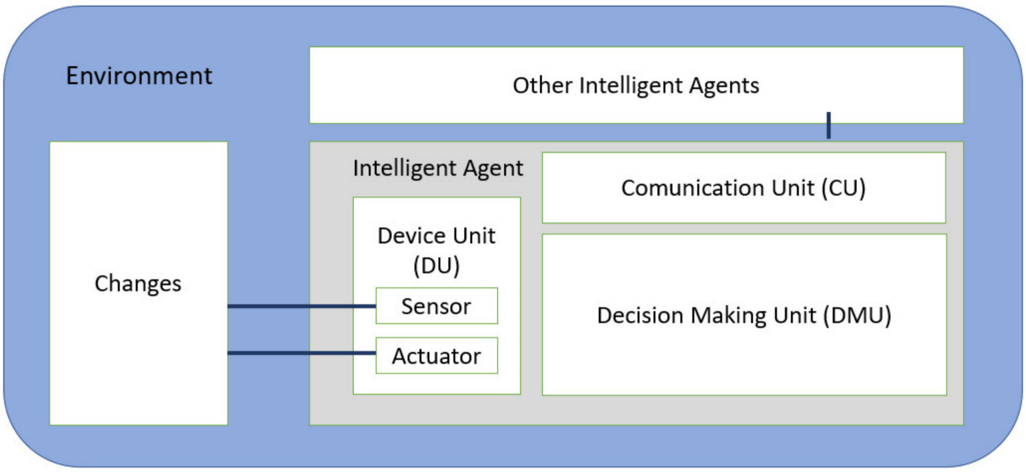

Figure 5. Structure of an agent.

Ahrarinouri et al., in [112] use this technology in an individual home in which one of the agents controls the State of Charge (SOC) of a vehicle battery. It charges and discharges according to the needs of the rest of the agents implemented at home, and the battery is used as an ESS. The majority of the works present in the literature apply a multi-objective function to charge EVs at the optimal time, trying to maximize the battery level at the moment of use and minimize the total cost of the energy and transformers' overloads [113]. The application of an agent for each EV allows each one to select the best time to charge or discharge. At the same time, they are learning how their own decisions affect other agents, and a collaborative policy is built. It is important to establish and build the corresponding infrastructures to facilitate EVs deployment in the real world, such as CSs. In [114], the authors use photovoltaic power generation and ESS. An important consideration in the management of CS is the optimization method for optimal performance and infrastructure planning. In [115], Silva et al., propose a MAS in which EVs are agents and act based on local information and communication. Local information is based on battery level, transformed load, and energy price. Maintaining communication allows the agent to observe how its behavior affects other agents. This allows the agents to decide if collaborate in a coordinated way or, on the other side, act with selfish behavior. Its architecture is based on evaluating the reward both for selfish and collaborative approaches. A cooperation criterion then chooses the best action and applies it in the next step. It is possible to create different architectures with these agents: centralized, decentralized and mixed [116]. The high flexibility of this technology makes it possible to create a complex communication network among them. Nizami et al. [117] propose three types of agents in their structure with different functions: grid agents, EVs agents, and EVs' aggregator agents. The EV agent is responsible for the charging or discharging of the EV. It generates flexible offers that are sent to the aggregator agent. Aggregator agents are, in this case, located at a grid congestion point to coordinate the EVs in their cluster. The grid agent is assigned to a regional distribution system operator, manages the low voltage grid, and is responsible for monitoring grid conditions. This grid agent notifies EVs' aggregators in its area of local grid constraints, such as the maximum supply capacity of congestion points. Decentralized control is defined for each EV agent at the lower level, while another centralized entity (aggregator agent) coordinates EVs agents.

It is evident from the literature that centralized approaches often perform poorly due to the large-scale nature of the underlying applications. Moreover, centralized approaches do not allow the plug-and-play ability, struggle to adapt to changing conditions at every timescale, and do not incentivize third-party investors who may not wish to make their detailed device parameters and costs available to the central controller. Various distributed optimization approaches (many that employ regularization) were developed to make these large-scale optimization problems more manageable [118,119]. These decentralized approaches solve the original centralized optimization formulation by: (i) properly allocating the computational burden of optimizing the problem's variables amongst different processing units, (ii) exploiting parallel or sequential computation to speed up iteration convergence, and (iii) ensuring that all processing units agree on coupling variables so that the distributed solution matches that of the original global solution. The main trade-off of these distributed methods with their centralized relatives is generally higher iteration complexity due to the added responsibility of coordinating the coupling variables [120]. A popular method that enabled a distributed implementation of dual decomposition is ADMM (alternating direction method of multipliers), introduced into the optimization literature in [121], wherein a distributed architecture is employed to compute primal variables with a centralized solver retained for the update of dual variables. More recently, a fully distributed implementation of ADMM was carried out in [122,123]. In terms of state of the art in distributed optimization, a large amount of literature exists, where papers [119,124], are some of the key examples. Taking as a reference the popular ADMM considered in [125], several papers, such as [123,126], have tried to accelerate convergence in ADMM by considering the Nesterov's [127] and the Heavy Ball methods [128]. In [126,129], other approaches for achieving accelerated convergence are examined using second-order methods and adaptive techniques for adjusting the penalty parameter. Other methods imply a parallel solver with a matrix-splitting technique and a distributed quasi-Newton method. In contrast to the above-mentioned papers, paper [130] presents a PAC approach, including elements that increase the algorithm convergence speed and enhance privacy in the exchange of primal and dual variables. Moreover, in a more recent paper [131], the authors propose a new distributed optimization algorithm, NST-PAC, is proposed ensuring the privacy of information exchange, with Nesterovs' acceleration-based iterations that lead to a fast solution.

6. Conclusions and Future Challenges

In this paper, attention is focused on the use of optimization models for EVs, with specific reference to planning problems (siting and sizing of CSs), optimal scheduling problems (for EV charging in buildings and smart grids, in public charging parks) both for public and private EVs, charging ad routing decision problems, and EVs' integration in ECs and the energy market for DR purposes through an aggregator. The different decision problems were described in connection with the literature, paying particular attention to optimization problems developed in the context of very recent regulations and the use of the most recent technologies. Several surveys related to EVs and their integration into smart grids were carried out in the literature. However, the topics are different from those present in the proposed survey. Moreover, we aim to focus on optimization and control and integrating multidisciplinary competencies (i.e., smart grids, transportation, scheduling of resources, ICT). Overall, the four different considered macro-areas (planning, scheduling, charging and routing, integration in the energy market) highlight the necessity of developing approaches (and integrated systems) based on digitalization, automation and green technologies. This is indeed in line with recent regulation that supports the digital and ecological transition. Moreover, it can be seen that there is a necessity to develop tools for a wide range of application areas and integrate multi-disciplinary expertise.

As regards the optimal scheduling of EVs, it is necessary to jointly manage EVs, production systems, storage and loads, taking into account new technologies (such as V2G) and the constraints of the electrical grid. Moreover, there is the exigency to find algorithms to be implemented in the field for CSs in smart charging parks. Future developments regard the development of fast algorithms to solve optimization problems and of the inclusion of EVs' scheduling in current Energy Management Systems.

As regards the optimal planning of CSs, it is clear that an interdisciplinary approach is fundamental. In particular, it is necessary to consider both transportation and electrical networks together with territorial characteristics and users' behavior.

Routing and charging optimization problems are NP-Hard and more difficult to solve than the classical VRP. Thus, the main challenge is to define fast solution methods. Moreover, the model of energy consumption is here crucial in order to determine the energy demand and the optimal route.

Finally, EVs can be seen as an actor in the energy balancing market participating in actions of demand response. Indeed, these are decision problems that involve multiple actors, multiple objectives, and privacy requirements and the main challenge is to define new distributed optimization approaches that can guarantee a fast solution and improve the resiliency of the electrical grid.

Author Contributions: The survey paper was organized by dividing effort among the different sections: V.C. and R.M. are responsible for the part relating to optimal scheduling, while L.P. and R.M. dedicated effort to the planning of CSs. G.F. and M.P. wrote the charging and routing part, while M.R. and D.F.V. wrote the last section. All authors participated in the other parts of the paper. All authors have read and agreed to the published version of the manuscript.

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Abbreviations

Acronym	Description
ACO	Ant Colony Optimization
ADMM	Alternating Direction Method of Multipliers
ALNS	Adaptive Large Neighborhood Search
BEMS	Building Energy Management System
BIES	Building Integrated Energy System
CHP	Combined Heat and Power
CS	Charging Station
DADRP	Day-Ahead Demand Response Program
DER	Distributed Energy Resources
DG	Distributed Generation
DR	Demand Response

EB	Electric Bus
EC	Energy Communitiy
ECR	Energy Consumption Rate
EMS	Energy Management System
ESS	Energy Storage Systems
EV	Electric Vehicle
EVA	Evs Aggregator
EVRP	Electric Vehicle Routing Problem
GA	Genetic Algorithms
GHG	Greenhouse Gas
GIS	Geographic Information System
HVAC	Heating, Ventilation, Air Conditioning
ICT	Information Communication Technology
IoT	Internet of Things
LEM	Local Electricity Markets
MAS	Multiagent System
MCDA	Multi-Criteria Decision Analysis
MCLP	Maximum Coverage Location Problem
MILP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
P2P	Peer-to-Peer
PAC	Proximal Atomic Coordination
PDN	Power Distribution Network
PV	Photovoltaic
RES	Renewable Energy Sources
SDISCO	Smart Distribution Company
SOC	State of Charge
SRC	Special Case Resource
SUE	Stochastic User Equilibrium
TN	Transportation Network
TSO	Transmission System Operator
TW	Time Window
UE	User Equilibrium
V2B	Vehicle-to-Building
V2G	Vehicle-to-Grid
V2H	Vehicle-to-Home
V2X	Vehicle-to-Anything
VNS	Variable Neighborhood Search
VRP	Vehicle Routing Problem

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