

A Review on Electric Vehicles Charging Strategies Concerning Actors Interests

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Abstract

Electric vehicles are becoming increasingly popular in societies and an important part of smart grids. Utility companies should be able to provide them with vital energy as they need electric energy instead of fuel, and this is where new challenges emerge in the network. In order to avoid causing utilities to incur additional energy and economic losses, researchers have proposed smart charging as a way to provide adequate energy to vehicles. When developing a charging schedule for a fleet of EVs, special considerations are made on variables such as energy, cost, and EVs mileage. In this review paper, the importance of EVs integration into smart grids is studied, and then different methods to develop EVs charging scheduling are investigated. These methods can vary from optimization algorithms to learning-based, and game theory-based approaches. Then, as the considered system consists of three main actors, including EV users, the utility operator, and aggregators, a systematic review is conducted on these actors, and objectives related to each one are analyzed. Finally, research gaps related to the problem are studied. Researchers can use this review to conduct further research on the integration of EVs into smart grids.

Keywords

deep learning, electric vehicle, smart grid, optimization, driver behavior, charging

1 Introduction

Today with global warming and raising the awareness of the vehicle users, the number of EVs is drastically increasing, and they will most likely replace traditional vehicles entirely in the future, or at least will soon dominate the market [1]. It is targeted for global EVs number to approach a 30% share by 2030 as we expect to see an exponential increase in the number every year [2]. For example, in Hungary, EVs' share was 1.9% in 2019, 50% more than its 2018 share, indicating a growing interest among casual users toward EVs. In some other European countries, the share is much higher. For example, the EVs market share has already reached 28.8% in Norway and 6.4% in the Netherlands. Also, while the number of EVs compared to conventional vehicles in China is 1.4%, many countries have targeted 100% EVs usage in a not-so-far future [3].

As stated in the literature, although EVs are beneficial to urban Society by reducing air pollution, their challenges must be understood and addressed to clear the path for electrification of such devices.

In Sabzi and Vajta [4], the challenges of EVs charging and the fact that they need additional electrical energy from the grid were analyzed, and we proposed three solutions to provide this energy, as follows:

- Expanding the transmission, distribution, and charging station infrastructure;
- Installing energy storage devices and renewable energy sources to help the grid;
- Smart charging strategies.

Moreover, we concluded that the third solution was the most optimum in the long run. Smart charging can be carried out to pursue several technical and financial objectives. Technical objectives include balancing load power, V2G scheme realization, V/f regulation, reducing losses. Financial objectives benefit the actors inside the market, including the utility operator, EV users, and aggregators. Furthermore, objectives can vary in a smart charging plan, from increasing the actors profits to time-saving and

milage optimization. This article considers the three main actors' objectives, and each one's role and interests in the market platform will be studied.

While the main contribution of this research is to provide a state-of-the-art review of the literature to researchers working on EVs integration and smart scheduling solutions, the rest of the paper is organized as follows: in Section 2, the optimization problem is stated and constraints related to each section are analyzed, in Section 3 a review on the most recent methods for EVs charging scheduling in smart grids is carried out. In Section 4, the actors with a significant role in the platform and their interests are studied, and several objective functions are presented. In Section 5, we introduce the research gaps, and finally, in Section 6, conclusions will be given.

2 Optimization problem statement and formulation

In many studies, the issue of EV charging has been considered as an optimization problem. In this case, an objective function is defined, which must be minimized or maximized subjected to the existing constraints. Therefore, in order to develop optimal EV scheduling strategies, the objective function and constraints should be formulated first. The main purpose of optimization is to find the location and time of charging for each vehicle so that the proposed method is optimal for both the driver and the network that improves the performance of the smart grid. In this way, if the drivers intend to charge the vehicle during peak hours, a discount can be offered to them to postpone the charging. In order to encourage drivers to charge their vehicles during off-peak hours, incentives should be made that can include lower charging costs.

In smart charging, unlike the conventional charging method, charging station operators, market operators and drivers are connected to cloud and have the ability to exchange information, monitor and manage the situation [5]. Therefore, another requirement for scheduling a charging program is a communication network that can exchange data on vehicle location, vehicle SoC rate, and driver preference for cost, time, location, and distance with the market operator or aggregator [6]. The aggregator can also send the desired results for charging to each driver by examining the information received from the drivers and the network constraints received from the distribution network operator and implementing the optimization method defined for the problem [7]. In this case, the charging schedule can be considered in real-time and the possibility of two-way communication between the network and EVs is established and EVs can work in both

V2G and G2V modes [8]. As a result, after each implementation of the optimization method, vehicles are prioritized and for those that are charged during peak load, drivers are required to pay more.

In order to define the optimization charging problem of EVs in the network, the objective function and the required constraints must be determined. Constraints are introduced to bound the solutions within the physical and user-specified limitations. In previous studies, two types of constraints have been proposed: network constraints and EVs constraints.

2.1 Network constraints

As the name implies, these constraints include keeping the parameters related to the stability and efficiency of the network within the defined allowable range. These parameters include voltage, power demand, losses, power quality, switching number of capacitors and on-load tap changer switching.

One of the main network constraints that have been considered in many papers is the distribution network voltage, for which the upper and lower limits of ± 10 or $\pm 5\%$ are usually considered and in a total of 24 hours, these limits must be observed. This constraint is defined as Eq. (1) [9]:

$$V^{\min} \leq V_k \leq V^{\max} \text{ for } k = 1, \dots, n, \quad (1)$$

where V^{\min} and V^{\max} denote the minimum and maximum allowable bus voltage range, respectively and k and n are the bus number and the total number of buses, respectively.

Another constraint is defined as the line to neutral voltage deviation and its upper limit is usually determined by the utilities is defined as Eq. (2) [10]:

$$\Delta V(t, k) = |V(t, k) - 1| \leq \Delta V_{\max}, \quad (2)$$

where ΔV_{\max} is the maximum allowable deviation.

For voltage, there is a constraint called the three-phase voltage unbalance factor, and similar to the previous constraint, its maximum allowable value is set by the utility and is defined as Eq. (3) [11]:

$$VUF(t, k) = \frac{|V^-(t, k)|}{|V^+(t, k)|} \leq VUF_{\max}, \quad (3)$$

where VUF is voltage unbalance factor and V^- and V^+ are negative sequence and positive sequence of voltage, respectively. These two values can be determined using Fortescue transformation technique.

Another effective constraint in solving the optimization problem is the amount of power demand. As expressed in

Eq. (4), for each power system, the power must be kept in a threshold at any given time [12]:

$$\sum P_{\Delta t, k} \leq D_{\max}^{\text{total}}. \quad (4)$$

In Eq. (4) Δt is the time interval within 24 hours, P is the total consumption and D is the maximum allowed demand for the grid.

Power losses in the network are a constraint that should not exceed the maximum defined limit [13]. The formulation of these criteria is as Eq. (5):

$$\sum_t P_{\text{loss}} \leq P_{\text{loss_max}}, \quad (5)$$

where t is time, and $P_{\text{loss_max}}$ is the maximum allowable loss in the grid.

Furthermore, losses in the network are calculated as follows [14]:

$$P_{\text{loss}} = P_{\Delta t, (k, k+1)}^{\text{loss}} = R_{k, k+1} \left(|V_{k+1} - V_k| |y_{k, k+1}| \right)^2. \quad (6)$$

where $P_{\Delta t, (k, k+1)}^{\text{loss}}$ is the power loss in time interval Δt and between buses k and $k+1$ and V_k is the voltage of bus k . In this equation, $R_{k, k+1}$ and $y_{k, k+1}$ are resistance and admittance of line section between buses k and $k+1$, respectively.

Another important parameter is the power quality in the network, which is checked for THD, and THD in the network should not exceed the allowable THD. Here, THD is defined for voltage as Eq. (7) [9]:

$$\text{THD}_{v_i} = \left[\left(\sum_{h \neq 1}^H |V_i^h|^2 \right)^{\frac{1}{2}} / |V_i^1| \right] \times 100\%, \leq \text{THD}_v^{\text{max}}, \quad (7)$$

where, V^h is the voltage harmonic and h is the order of harmonic in voltage. THD can be defined for the current in the network as well.

There are capacitors in the network in both the feeders and the secondary buses to compensate reactive power and resolve voltage deviation issues. There is a limitation to switch the capacitors in feeders and these capacitors can only be switched on or off once a day. But secondary buses capacitors can be switched on more than once. However, the maximum allowable switching of capacitors on the secondary buses can be considered as another constraint and it has an important effect on reducing losses in the network. This constraint is defined as Eq. (8) [10]:

$$\sum_{t=1}^{24} (C_{s,t} \otimes C_{s,t-1}) \leq C_{sm}, \quad (8)$$

where $C_{s,t}$ is the status of the capacitor, and C_{sm} is the maximum allowable number of switching for capacitor s in a day.

An OLTC consists of an open load tap changer that is used in areas where there is an interruption in the power supply due to an unacceptable tap change. The ratio of the number of turns can be changed without breaking the circuit. However, because of higher maintenance costs and reduction of life expectancy the daily number of switching operation is limited by a constraint [15]. This constraint is defined as Eq. (9):

$$\sum_{t=1}^L |Tap_t - Tap_{t-1}| \leq Tap_{\max}, \quad (9)$$

where L is the number of load levels in a day. The maximum number of allowable switching operations of OLTC is 30 times a day [16].

2.2 Electric vehicles constraints

Each electric vehicle has specifications that affect the charging process, and in order to optimize the charging procedure, these constraints must be taken into consideration to provide an optimal charging program for each vehicle. These constraints are related to SoC, charging and discharging rates and charging time. Also, there is a maximum value for battery capacity [17]. The SoC constraint is defined as Eq. (10):

$$\text{SoC}_{\min} \leq \text{SoC}(t) \leq \beta(t), \quad (10)$$

where, β is the battery capacity of each EV.

In Eq. (10), as an upper limit, SoC_{req} can be considered instead of β and it is defined as the requested maximum charge set by the customer.

For each electric vehicle, the charge and discharge rates are defined as positive and negative power, respectively. The lower and upper bounds are defined as Eq. (11) [18]:

$$p_{\max}^{\text{discharge}} \leq p_n(t) \leq p_{\max}^{\text{charge}}, \quad (11)$$

where $p_{\max}^{\text{discharge}}$ is maximum V2G capacity, p_{\max}^{charge} is maximum charging rate and $p_n(t)$ is the charging/discharging rate in time slot t . If V2G mode is not possible for an electric vehicle, in fact the vehicle will not have a discharge rate and $p_{\max}^{\text{discharge}}$ will be considered as zero.

If EV provides some services for the network, the discharge rate cannot be greater than the battery capacity, because it can deliver maximum power that have been already stored in the battery. The formulation for this constraint is defined as Eq. (12) [19]:

$$d_{V2G}^t \leq \beta(t), \quad (12)$$

where, d_{V2G}^t is the discharge power in V2G mode at time t and β is the battery capacity.

A battery constraint related to time of charge is proposed in Eq. (13) [20]:

$$t_{dep-i} - t > d_{char-i}, \quad (13)$$

where t_{dep-i} is the expected departure time of EV $_i$, t is the current time, and d_{char-i} is the duration needed for the EV $_i$ to be charged at full power to its expected SoC [20]. Therefore, based on this constraint, the scheduling should be such that the battery has enough time to be fully charged.

2.3 Objective function

An objective function is the function whose value is intended to be minimized (costs) or maximized (profits) through the optimization process and based on a set of constraints and the relationship between one or more decision variables. Depending on the goal of optimization, different objective functions can be defined including price cost, total energy cost, power loss, emission, deviation, V2G revenue, aggregator revenue, transformer overload and etc.

According to the researches, most of the papers have specified the objective function based on minimizing the total cost of the power demand, the general form of which is as Eq. (14) [21]:

$$\sum_{t=1}^T k_c P_{\Delta t}^{\text{Demand}}, \quad (14)$$

where, k_c is the cost per MWh of generation at time interval Δt based on the price of purchasing or producing the energy and $P_{\Delta t}^{\text{Demand}}$ is the power demand in time interval Δt .

In other articles, only power losses are defined as an objective function [12, 13, 15].

$$\sum_{t=1}^T P_{\Delta t}^{\text{loss}} \quad (15)$$

With regard to the wishes of the aggregator, a specific objective function will be defined and also constraints will be provided according to the existing actors in the grid and their limitations and parameters and the allowable range that were discussed in Section 4. In the end, the objective function should be maximized or minimized subjected to the constraints of the problem.

3 EVs charging scheduling methods

In a simple plan of smart charging, the demand is distributed across different time slots during the day or week, or a different charging station is proposed to drivers. Therefore, incentives like compelling prices can be used to encourage off-peak charging. In order to do this, EVs, charge stations,

and utility providers need to keep in constant communication to adjust prices or restrict the chargings according to grid usage patterns and the needs of consumers.

As stated, in smart charging, the aggregator offers different charging proposals to drivers, trying to improve one or more of the system characteristics. Following approaches have been suggested in the literature for EVs charging scheduling with respect to the formulated EVs charging problem:

- Mathematical optimization methods;
- Meta-heuristic and Heuristic optimization methods;
- Learning-based methods;
- Game-theory based methods.

While the first two methods are different solvers that could be used for the same problem, depending on the designer's creativity and preferences, the learning-based methods are used in a wide range of solutions, for example, predicting drivers behavior in chargings. On the other hand, game theory-based methods have been mostly used for EVs routing and finding the best combination of EVs (as agents) to be charged at a specific time and location.

3.1 Mathematical optimization

In this case, a mathematical model of the problem is developed. Although this method is straightforward, calculations can become complicated and more time-consuming; therefore, only one or two parameters can be optimized. Nevertheless, mathematical optimization methods are widely used to solve the EVs charging coordination problem. For example, in [22], investigating the impact of EVs charging on a residential distribution grid is the primary goal, and a quadratic optimization model and a dynamic programming technique have been used to solve the EVs charging coordination problem. These two methods presented similar results with the same computational time, achieving an acceptable accuracy. While [23, 24] use the MILP method to solve the EVs charging coordination problem, in [25], MILP has been employed for charging coordination in addition to DGs. The model built in [25] also features operational constraints, including voltage and current constraints. Moreover, a MILP approach that minimizes the total daily cost due to EVs charging is proposed in [23].

Xu et al. in [26] presented a decentralized charging method based on augmented Lagrangian and compared it with the centralized charging method. In the proposed method, drivers have the opportunity to select their

charging program locally, in which the high cost of communication in the centralized method is eliminated, and the volume of calculations is reduced. This method maximizes the aggregator's revenue while maintaining the distribution network's constraints.

In addition to smart charging, linear programming methods are mostly used for the optimal placement of charging stations. For example, to cost-effectively place electric EVs charging stations at bus stops, the programming relaxation algorithm is used to resolve the problem in [27], and a complex combinatorial problem is formulated in [28, 29] as an optimization problem to determine the minimal number of strategically selected charging stations.

3.2 Heuristic and meta-heuristic optimization

In the optimization process, one selects input values from a range of permitted values and then calculates the true value of the function. In the case of EVs charging optimization, the maximization can be conducted for the profit earned by utility or aggregator, or the minimization can be applied for the energy costs paid by drivers. Speed is typically more important than accuracy or optimality when using a heuristic method. Some of the most well-known heuristic methods used in EVs charging optimization are SVM, Tabu Search, and GA. Meta-heuristic algorithms are more efficient than traditional algorithms, which are inspired by nature. For example, in [30], PSO was used to optimize the problem of coordinated charging of EVs. The charging model includes OPF, statistical specifications of EVs, degree of satisfaction of EV drivers, and power grid cost. The proposed method significantly reduces power grid operation costs and satisfies the drivers.

In [31], a real-time charging method for EVs using energy storage systems and photovoltaic systems is proposed. For this purpose, GWO and IBGWO methods have been used to solve the problem, and the objective function was defined as cost minimization. The results prove that the IBGWO is highly effective in solving the problem, reducing operating costs, and improving PV operation.

In [32], the EVs charging optimization is presented by considering energy arbitrage and the distribution network cost. The cost function is defined based on peak demand, power losses, and transformer aging in the distribution network, and the genetic algorithm is used for optimization. In this paper, data from the city of Udon Thani in Thailand is used as a case study. This method has reduced the transformer peak load, power losses, and energy arbitrage losses. In another work [33], the authors used a

centralized GA to optimize the charge of EVs. They also analyzed the ToU rate to find a scenario with the least cost to the customer and the network. On the other hand, considering that the shape of the load curve remains constant, the authors concluded that the algorithm achieved statistically similar results within each run.

The fuzzy control method models price uncertainty in the upstream grid to provide robust scheduling for charging EVs [34]. In [35], the authors proposed a new fuzzy charging strategy in which the price can be considered variable over time, and the nature of the problem is considered multi-constrained and multi-objective. This paper compares the proposed method with centralized charging and the conventional fuzzy method. The results prove the superiority of the proposed method.

Poursistani et al. [36] have proposed a method for modeling the load demand of EVs, which includes battery size, charge rates, and vehicle speeds. Then, to optimally charge the vehicles using the proposed model, they implemented the BGSA and concluded that this method positively affects the peak load shading.

In [37], the authors have used the AIS and tangent vector methods to charge EVs in the distribution network. Furthermore, they selected the IEEE 34-bus distribution system as a case study and concluded that these methods reduce losses and computational complexity after implementing the mentioned methods. In [38], the authors used the PSO to allocate energy to EVs in the charging process. The PSO uses previously stored data to solve the optimization problem, and if a change is made to the system, new data needs to be stored and used. They defined the objective function to maximize the average SoC. Moreover, they considered the algorithm's energy price, remaining battery capacity, and remaining charge time. They also used genetic algorithms to compare with the PSO method and concluded that PSO responds faster than GA.

In the following works, the authors intend to define the objective function as multi-objective, taking into account the minimization of the total charging time. In [39], the charging optimization of EVs has been done by using the fitness function to maximize the average SoC with 4 bio-inspired methods. These methods include PSO, GSA, accelerated PSO, and a hybrid version of PSO and GSA PSOGSA. The authors implemented these 4 methods for different charging scenarios for 50, 100, 300, 500, and 1000 EVs and compared the results in 5 critical parameters:

1. *Stopping criteria*: In all 4 methods, the algorithm introduces the final solution if this criterion is met.

2. *Convergence analysis*: Although there is a compromise between computation time and algorithm convergence, the combined PSOGSA algorithm converges with fewer iterations and performs better than other methods.
3. *Fitness value*: The combined PSOGSA method shows the best fitness value.
4. *Computation time*: Unlike other parameters, PSO and APSO perform better than the PSOGSA hybrid method and perform 100 iterations in less time.
5. *Robustness*: In this parameter, the PSOGSA hybrid method has the lowest standard deviation, showing the best robustness.

Arias et al. [40] have used 3 methods of Tabu Search, GRASP, and a new proposed HOA in order to optimize the coordinated charging process of EVs. The objective function in this paper is defined based on minimizing the total operating cost, and all three optimization methods offer reasonable solutions compared to uncoordinated charging. However, HOA has a higher advantage than the other two methods in providing better results. Furthermore, this paper shows that the charging process and network-related parameters such as voltage profiles, energy losses, etc., are improved by using DG sources.

3.3 Learning-based methods

Many papers in the literature have used LB methods for energy dispatching through VR and energy scheduling. For example, Alqahtani and Hu [41] developed a RL model for energy scheduling and routing of EVs while considering uncertainties in power supply and demand. LB methods are usually model-free, and therefore researchers have taken advantage of this in the process of EVs charging, which may depend on many dynamic parameters.

In ML methods, first, the trend and pattern among the data are determined by the learning process. Then, a model is obtained that predicts the exact behavior of a system's part. For example, in [42], an ML algorithm is used to predict the behavior of EV users in the charging process. The data used for learning are the time the vehicles stay in the charging stations and the energy consumption of each vehicle. The effectiveness of this algorithm has been validated by a 27% reduction in peak load, 10% load change, and 4% reduction in costs. Morsalin et al. [43] used an ANN decision-making system to predict energy demand and solve the charging coordination problem of EVs. They incorporate both V2G and G2V modes into

their work. Pilát [44] used a feed-forward NN and echo state network to solve the problem of charging EVs in a decentralized structure, and their results showed a reduction in prices for drivers.

Dang et al. [45] proposed a multi-dimensional dynamic charging method based on the Q-learning algorithm for charging EVs, where both V2G and G2V modes were considered. A reward table is created because the main parameter has been the ToU. The authors claimed that using this method would meet the requirements of EVs drivers and the distribution network at the same time. The disadvantage of this method is that if the dimensions of Table Q become large, the problem will be challenging to solve.

Some authors have implemented LB methods to solve optimization problems in the e-mobility environment. For example, in [46], the deep RL method has been used to quickly select the charging station and plan the EVs route to solve the charge optimization problem. The objective function is defined to minimize the charging time and cost of energy. While the data of the battery SoC, the location and direction of EVs, the number of parking lots, and the number of chargers were required, the results of their work showed that the proposed method achieved a near-optimal solution. Shi et al. [47] defined the objective function to minimize driver's waiting time, electricity costs, and vehicle operating costs. They used a decentralized learning method and a centralized decision-making process to solve the problem. The decentralized learning method consists of two parts that allow drivers to share their operational experiences and estimate the state-value function using the DNN model. The results of their work showed that the proposed method works appropriately in terms of cost reduction. In [48], the problem of charging EVs is modeled as the MDP, and its goal is to minimize the cost of charging in the long-term time horizon; furthermore, the SRL has been used to learn pricing patterns and solve the problem of charging optimization. The results of this work show a reduction in the costs imposed on the customer.

3.4 Game theory-based methods

The issue of EVs charging scheduling can be considered as a game. While the optimization-based methods aim at minimizing or maximizing a cost, GT-based methods try to find a suitable solution for actors. In the case of EVs charging, if drivers accept the proposed charging station or routing, the issue can be regarded as a Nash equilibrium strategy. In this case, the goal will be to find the best route to offer to the applicant driver; as a result, the complexity

is significantly reduced. Moreover, a maximum of 15% reduction in travel time is achieved, and therefore road traffic density and energy consumption are lowered [49].

Usually, the aggregator plays a vital role in GT-based methods. As an example, Mediawathe and Smith [50] considered the competition between aggregators for charging EVs as a non-cooperative game. To minimize the total cost of charging energy, each aggregator determines the start time of charging EVs and the charging energy profile. They showed that using this strategy led to energy savings. Wang et al. [51] proposed the Stackelberg game modeling method for pricing aggregators and charging EVs. In this way, they defined two upper and lower levels for the price as:

- The upper level: the price of grid electricity;
- The lower level: the pricing mechanism of the aggregator.

The method to solve the problem is to maximize the profit of the aggregator and minimize the charging cost of each EV concerning prices. Game Nash equilibrium is calculated using quadratic programming.

Furthermore, [52] proposed a non-cooperative optimization for EVs charging scheduling using SG and MT. By expressing the EVs allocation problem as a matching algorithm, the authors first aim to balance the utilization ratio between charging stations and EVs employing MT. The authors claim that the Stackelberg equilibrium proves to be superior to the Nash equilibrium when considering the dynamics of energy demand and energy pricing.

4 Actors in an EV-integrated smart grid

In an EV-integrated smart grid, three actors are mainly involved in the charging operation, each with its own goals and interests, including utility operators, EV users and aggregators.

4.1 Utility operator

EVs should be supplied with continuous power from the grid at the desired time in dispersed locations; therefore, in only G2V mode and in unscheduled charging, they are not favorable for utility companies as utilities are desired to have a homogenous load profile; otherwise, they will face future issues imposed on the grid, such as local power shortages. The effect of EVs charging on load profile in transmission systems has been investigated in [53–56], and the effects of EVs charging stations on load profile in distribution systems have been investigated in [57, 58]. Also,

charging stations can imply several impacts on the grid's power quality, such as injecting harmonics and changing the grid's power factor [59, 60], which are out of the scope of this article. Table 1 summarizes the operational impacts of EVs charging in the grid, divided by energy-related and power quality issues.

4.1.1 Flattening the load profile

Flattening the load profile is the main interest of the utility operator. If the demand in different hours of the day is not controlled, there will be a risk of overloading transformers leading to equipment getting damaged. Also, by flattening the load on different buses, generators are not required to ramp up and ramp down sharply; furthermore, a more efficient steady-state operation will be achieved. For this purpose, EVs charging operation must be scheduled to fill up the valley and reduce the charging load in peak hours for flexible and motivated users. As shown in Fig. 1 [61], the effect of a fleet of EVs charging in a short period of the day on the grid is extreme, and the amount of demand in the hours between 6 AM and 4 PM is drastically increased, and the voltage drop is observed while adding renewable energies such as PVs into the grid will compensate the demand developed by the EVs up to certain level. As shown in Fig. 2, when EVs are aggregated

Table 1 The summary of EVs charging impacts on the grid

Impacts on power quality	Impacts on the energy-related matters
Harmonics	Inhomogeneous load profile
Sag/Swell	Transformer overloading
Flicker	
Notches	Shortage of energy
Voltage imbalance	Need for new electricity infrastructures

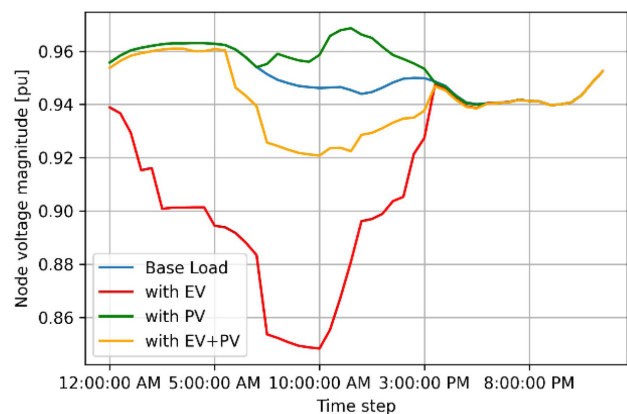


Fig. 1 Load curves in a residential distribution grid at different scenarios with and without EV and PV [61]

into a grid, the load forced on the grid is enlarged (highlighted in red) [62]. Fig. 2 shows 4 different cases, wherein in Fig. 2(a), the network is without EV, in Fig. 2(b) EVs are charged without any plan (called dumb charging), in Fig. 2(c) multiple tariffs are applied to the price of electricity, and in Fig. 2(d) smart charging is applied to the vehicles. As observed in Fig. 2(a), when EVs are not integrated into the grid the tension is at its lowest and there is just a minimal pressure on the grid that is distinguished by the red color. The highest tension is seen in Fig. 2(b), when dumb charging is applied and EVs are not controlled by the aggregators, and according to Fig. 2(c) using multiple tariffs does not help reduce this tension. However, using smart charging lower the tension on the electricity grid as the red color has been reduced in Fig. 2(d).

Furthermore, there are some methods to flatten the load profile in a grid, but minimizing the variance of the aggregate load profile is the most common method, as described in Eq. (16):

$$\min_{p_i(t)} \sum_{t=1}^T \left(D(t) + \sum_{i=1}^N p_i(t) \right)^2, \tag{16}$$

subject to, $\sum_{i=1}^T \eta_i p_i(t) \Delta_t = (s_i^{dep} - s_i^{arr}) b_i,$

$$p_i^{min} \leq p_i(t) \leq p_i^{max},$$

where $D(t)$ is non-EV load profile, N is the number of EVs whose charging is scheduled over the time slots T with lengths Δ_t , and s_i^{arr} , s_i^{dep} , b_i , p_i^{min} , p_i^{max} and η_i are SoC at arrival, SoC at departure, battery capacity, minimum charging power, maximum charging power and charging efficiency of the i^{th} vehicle, respectively.

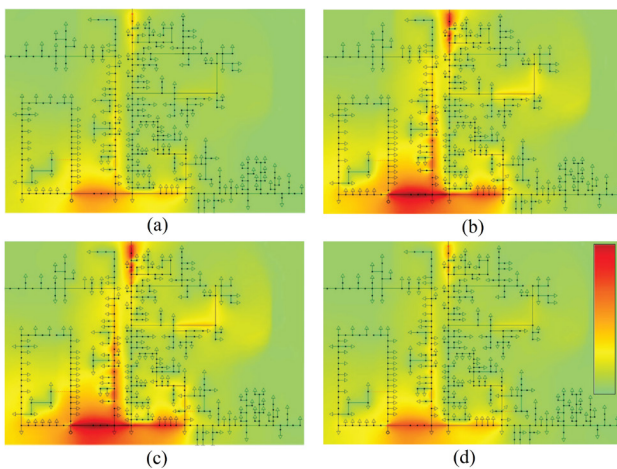


Fig. 2 Loading on a network resulting from different charging types in peak hour: (a) without EV; (b) dumb charging; (c) pricing with multiple tariffs; (d) smart charging [62]

Moreover, there are also economic-based methods whose aim is to fill up the valley in the demand curve while profiting the actors. In this case, the aggregator, or system's operator, receives observed signals from all participants and, together with the electricity's real-time price, develops a command signal containing the information on how profitable it is to charge a vehicle at a given time. This signal is then sent to the EV users, and they decide about the charging operation based on the price if they are price sensitive.

4.1.2 Maximizing the utility's revenue

Determining an electricity price by which both EV users and the utility operator's benefits are met is not an easy task; however, some articles have considered this matter. For example, Tushar et al. [63] presents a hierarchical model that determines the price of electricity which could optimize the profit of the EV users and revenue of the grid operator by selling energy. In this research, EVs first determine the amount of energy they want to buy from the grid and based on that; utility operators set a price that is made based on a trade-off between the revenue earned by the utility and money that EV users saved, therefore the solution is considered a game theory.

Also, some research has been carried out in the micro-grid framework. Misra et al. [64] presents a control framework with V2G and G2V modes. In this work, the charging price is set dynamically based on the supply-demand curve of microgrids. However, decisions about the charging operation are made by EV users in a multi-aspect decision-making operation.

In this research, gaining the most revenue for the utility is the second priority, as the aim is first to achieve the operational benefits, i.e., regulating load profile, as stated in Sub-subsection 4.1.1. However, by regulating the load, which leads to a minimized power loss, it is guaranteed that the utility's revenue is increased compared to the dumb charging scenario.

4.2 EV users

EVs' batteries have to be charged regularly (e.g., daily, weekly, etc.), which depends on multiple parameters, such as the driver's use case, the distance that an EV travels by one full charge, the path that driver takes, and etc. The amount of consumed energy directly affects the drivers and utility companies in terms of profit and energy management. If EVs consume energy without a smart schedule, called dumb charging as before [62], the optimization will

not be achieved, bringing more challenges to the utility company. So, from the drivers' perspective, a set of goals must be achieved, and several interests must be satisfied.

4.2.1 Minimizing the EVs charging costs

Electric consumer behavior plays a vital role in the market, especially when prices become dynamic. Zheng et al. [65] showed that people's price sensitivity is an important factor in using green energies. Also, some research has been conducted to answer this question "what share of EV users are willing to change the time or location of their charging with the changes in prices?" Sadeghianpourhamami et al. [66] measured the number of flexible drivers who are sensitive to price (or time and location) and set a price-based-incentive charging plan for them to reduce the pressure on the grid at peak hours.

EV users are the main actors influenced by the electricity price who are willing to adjust the charging time (and sometimes location) based on the price. In this way, the simplest way for charging price minimization of a set of vehicles in time horizon T would be as Eq. (17) [67]:

$$\min_{p(t)} \sum_{t=1}^T \sum_{i=1}^N c(t) p_i(t), \tag{17}$$

subject to,

$$p_i^{\min} \leq p_i(t) \leq p_i^{\max},$$

where $c(t)$ is the electricity price, considering the fact that RTP is a function of the instantaneous total demand and the charging power should be constrained between a minimum and a maximum value.

4.2.2 Shortening the distance traveled

With a higher number of charging stations and home-charging ability, shortening the distance traveled is not as significant as before; however, EV users prefer to travel a shorter distance to charge their vehicle in remote areas. Therefore, this factor can be included in the algorithm in special cases and concerning the location.

4.3 Aggregator

Generally, aggregators act as an interface between the utility operator and the end-users to achieve a goal for participants in the market. Their most usual responsibility is to achieve demand response while reducing the operational cost of the whole system. In a traditional definition, aggregators pay compensation to end-users, allowing them to control their consumption [68]. They mainly represent the

end-users and negotiate with the grid operator on behalf of the users to improve the efficiency of the operation.

In the case of EV fleet charging, the aggregator's role can benefit utility operators, EV users, and the aggregator itself. In a market where each EV attempt to charge on its own, the optimal point seems impossible to achieve; therefore, the concept of the aggregator is introduced to consider all possibilities for every participant and different parameters of the system such as electricity price, SoC of each EV, required energy, load profile, etc. Hence, aggregators propose some offers regarding the charging time (or/and location) to the EVs to achieve the optimal point. The aggregator can consider the charging pattern of an EV and decide that if the charging process is moved to another time of the day, it will be financially beneficial for the EV user and operationally beneficial for the utility company. Fig. 3 demonstrates the role of aggregator in a market framework with EVs fleet. As seen, the aggregator is connected with EVs and utility operators through data lines, while EVs are directly connected to utility in terms of energy flow. An important parameter is the aggregator's profit, which is computed as the revenue earned from the utility minus the compensation aggregator pays to the end-users, EV drivers in our case.

In [68], although the residential load is considered, the cost function that aims to maximize the aggregator's net profit is introduced as Eq. (18), where the first part of the equation is the amount of reward paid to the aggregator from utility and the second part is the money aggregator pays to users as an incentive or compensation:

$$\max_{p_j} \lambda_j \Delta_c(p_j, P_{-j}) - \sum_{i \in T} p_{ji} d_{ji}(p_j), \tag{18}$$

subject to $p_{ji} \geq 0 \quad \forall t \in T$.

where λ_j is the reward to aggregator j , Δ_c is the demand response gain, p_j is the aggregator j net profit and d_j is the demand pattern from aggregator j .

Furthermore, in some articles, aggregators regulate the load and meet the demand with adequate energy supplied by the utility. In [69], the aggregator acts as a day ahead price predictor, and its profit is calculated as the revenue minus costs, as stated before, with revenue and price as:

$$\text{Revenue} = \sum_{t=1}^H [E_p(t) * FR], \tag{19}$$

$$\text{Cost} = \sum_{t=1}^H [P_p(t) * E_{sch}(t)], \tag{20}$$

where Ep and Pp are day-ahead predicted load and day-ahead predicted price in MW and \$/MWh, respectively.

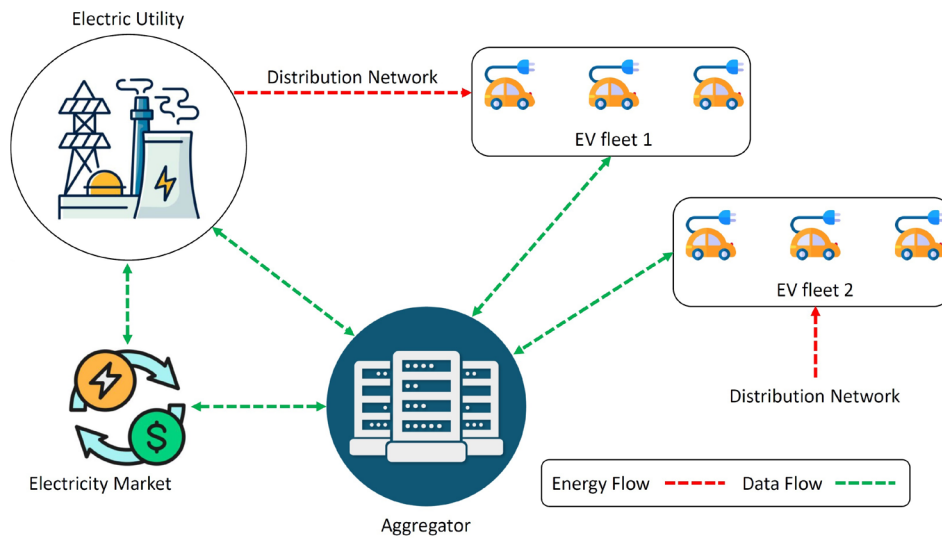


Fig. 3 Market framework with the aggregator

FR is flat rate of electricity price, P_p is predicted price and E_{sch} is the day ahead scheduled power.

Fig. 4 shows the actors in the market with corresponding data and objectives related to each one.

5 Research gaps

Driver behavior is the main source of uncertainty affecting the charging process and energy consumption that has not been properly considered in past studies. As human decision-making is involved, it is highly recommended to create a practical approach for forecasting EVs demand to ensure intelligent EVs energy management in an e-mobility environment. It is crucial to estimate the EVs charging load (time and place) to develop a demand response pattern that can be used in the algorithm. Therefore, an AI algorithm can be used to estimate the EV users' behavior with clustering

methods such as k-means clustering or DBSCAN in future research. To achieve this, one must find out which specific habits and demographic attributes of EV owners directly affect the charging process. For example, we know from the results presented in [70] that age and gender directly affect the route choice of EV. Also, it is known that younger EV users tend to charge the vehicles at lower SoCs while older users usually go to charging stations with a higher level of SoC. Additionally, a categorization of the specific vehicles regarding the parameters mentioned in Fig. 4 can be helpful in developing a more accurate charging schedule for EVs. Some of these parameters include arrival time, stay time, departure time, charging duration, etc. This kind of algorithm can specify which EVs are flexible and which percentage of EV owners can change their charging pattern through offers made by the aggregator.

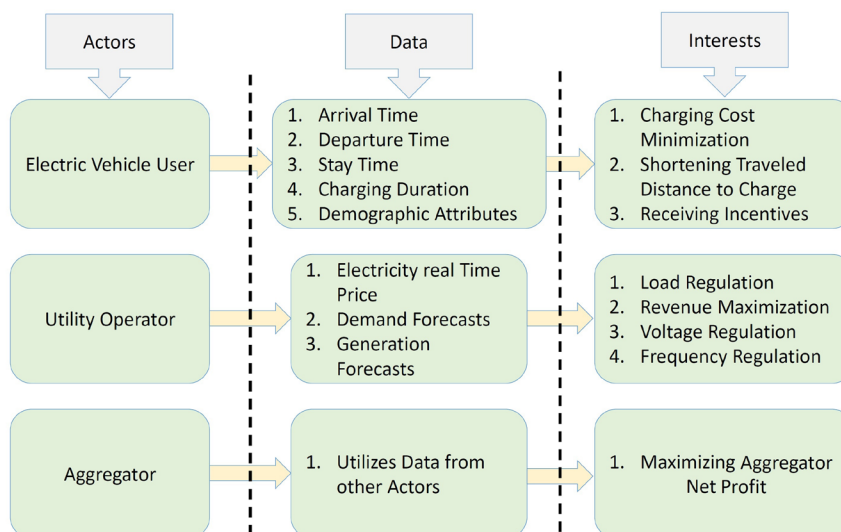


Fig. 4 Actors and related data and interests

Furthermore, a global optimization model like in Fig. 5 is suggested for future research to meet the interests of all actors. Of course, optimizing such a system seems impossible or very difficult as there are conflicts between different actors' interests, but combining DL in the first stage with the optimization in the last stage can achieve at least partial global optimization. As seen, the system consists of three main actors, including utility in the upper level, EV users in the lower level, and aggregators between them. The aim can be to meet the defined goals, which can differ based on the application and actors' interests.

The utility, as described before, has several interests, such as flattening the load profile and increasing its revenue. As said in Section 4, flattening the load profile has a higher priority, and then the focus can be made on the financial aspect of the problem's constraints are not violated. On the next level aggregator considers every actor's interests. Aggregators have a crucial role, and they should see EV users and utility benefits simultaneously. The aggregator can be a physical corporation or just a software unit for programming the problem. On the level of EVs, the aim is to minimize the charging cost and let the EV users participate in the market and receive incentives for their participation in DSM.

6 Conclusions

Considering how imperative it is for a greener future to integrate EVs into electricity grids, we investigated the importance of EVs integration in this study. It is well established that EVs are the main players in the future transportation sector, so we need to consider their impact on the

electricity grid. Consequently, we examined the effects of EVs on the grid with regard to energy and power quality. Some solutions have been proposed to address the challenges imposed on the generation section, including using local energy storage or decentralized generation, expanding current infrastructures, and utilizing smart charging. It was noted that smart charging might be the most practical and viable solution for these challenges. EVs smart charging is a broad concept, which can be considered a game theory problem or an optimization algorithm that minimizes the amount of energy delivered to EVs. It is beneficial in one way or another for certain aspects of the system to implement smart charging. So, four different approaches to smart charging were described, including mathematical optimization techniques such as MILP, heuristic and non-heuristic optimization methods, game theory-based methods, and learning-based methods.

Moreover, since the main actors in the framework are EV users, the utility operator, and the aggregator, then we studied the role of each one in the grid. We investigated the interests of each of them. We suggested that future studies should examine the role of EV users, whose demographic attributes and individual behavior may directly affect aspects of energy consumption and charging, such as charging station choice and route choice. Additionally, we suggested a market framework to solve the scheduling problem. As seen in Fig. 5, in the first level, drivers' behavior and demographic attributes must be considered and processed by a deep learning method and combined with data of other actors; an algorithm would be developed to create the charging plan on the last level.

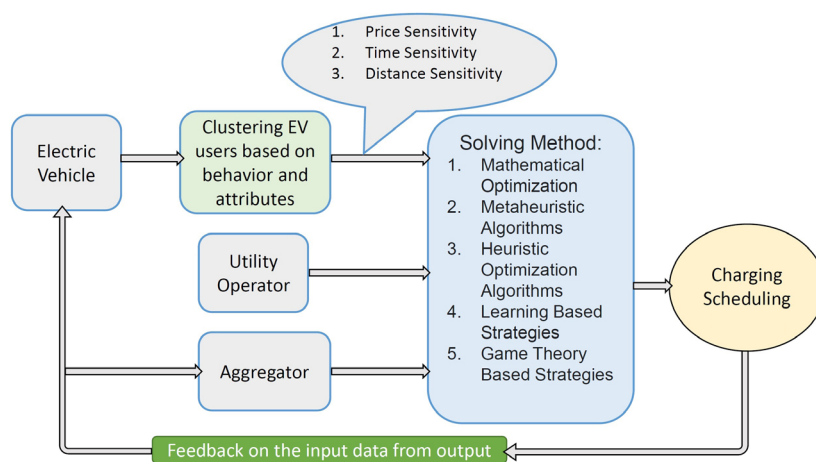


Fig. 5 A suggested global optimization for future research

Abbreviations

AIS	Artificial immune systems	MDP	Markov decision process
BGSA	Binary gravitational search algorithm	MILP	Mixed-integer linear programming
DG	Distributed generation	ML	Machine learning
DR	Demand response	MT	Matching theory
DSM	Demand-side management	NN	Neural network
DNN	Deep neural network	OPF	Optimal power flow
EV	Electric vehicle	OLTC	On-Load Tap Changing Transformer
G2V	Grid to Vehicle	PSO	Particle swarm optimization
GA	Genetic algorithm	PSO-GSA	Hybrid version of PSO and GSA
GRASP	Greedy randomized adaptive search procedure	RL	Reinforcement learning
GSA	Gravitational search algorithm	RTP	Real-time pricing
GT	Game theory	SG	Stackberger game
GWO	Grey wolf optimization	SoC	State of Charge
HOA	Hybrid optimization algorithm	SRL	Sarsa reinforcement learning
IBGWO	Improved binary grey wolf optimization	SVM	Support vector machine
LB	Learning-based	THD	Total Harmonic Distortion
DBSCAN	Density-based spatial clustering of applications with noise	ToU	Time of use
		V2G	Vehicle to grid
		VR	Vehicle routing

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