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Electric vehicle fleet management in smart grids: a review of services, optimization and control aspects

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ABSTRACT

Electric vehicles can become integral parts of a smart grid, since they are capable of providing valuable services to power systems other than just consuming power. On the transmission system level, electric vehicles are regarded as an important means of balancing the intermittent renewable energy resources such as wind power. This is because electric vehicles can be used to absorb the energy during the period of high electricity penetration and feed the electricity back into the grid when the demand is high or in situations of insufficient electricity generation. However, on the distribution system level, the extra loads created by the increasing number of electric vehicles may have adverse impacts on grid. These factors bring new challenges to the power system operators. To coordinate the interests and solve the conflicts, electric vehicle fleet operators are proposed both by academics and industries. This paper presents a review and classification of methods for smart charging (including power to vehicle and vehicle-to-grid) of electric vehicles for fleet operators. The study firstly presents service relationships between fleet operators and other four actors in smart grids; then, modeling of battery dynamics and driving patterns of electric vehicles, charging and communications standards are introduced; after that, three control strategies and their commonly used algorithms are described; finally, conclusion and recommendations are made.

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1 Introduction

To achieve the European energy roadmap 2050 [1] "The EU is committed to reducing greenhouse gas (GHG) emissions to 80-95% below 1990 levels by 2050 in the context of necessary reductions by developed countries as a group". Carbon emission reduction target are also set up in other countries such as China, United States, and Korea. The corresponding influencing factors studies [2]–[6] show that power industry and transportations are the major contributing factors to CO_2 emission. For example, the power industry was responsible for around 30% of GHG in EU-27 in 2011. The second sector with more GHG emissions in 2011 were the transports with a share of 20.3% [7]. Thus, the decarbonisation of two main activities including power industry and transportations is required.

To reduce the GHG emissions, in power systems, renewable sources such as wind and solar power are widely adopted [8], [9]. In the transport sector, electric vehicles (EVs) are important means to assure the GHG emission reduction goals [4], [10]. However, the increasing investments in renewable power bring operational challenges into the power systems due to the intermittent resources. To cope with the new challenges, in smart grid [11], [12], EVs are commonly recognized as one solution in addition to their environmental benefits in the transport sector. They can be utilized to balance power fluctuations caused by the high penetration of intermittent renewable energy sources [13]. However, a large-scale integration of EVs also means new loads to electric utilities, and undesirable congestions and voltage problems may exist in the distribution network during the charging process [14]. All these factors bring new challenges to power system operators. As an outcome, smart charging solutions (including power to vehicle and vehicle-to-grid (V2G)) are needed in order to make EVs an asset to the smart grid rather than a merely traditional load.

Much research has been done to capture the benefits of electric vehicles as well as to address the conflicting challenges. It is concluded from the literature that a new business entity, namely an EV fleet operator (FO) has been widely proposed to exploit the new business opportunities by providing the multiple services of EVs to system operators. Alternative names for an EV FO are used such as EV virtual power plant, EV aggregator, EV charging service provider or EV service provider. The new entities [15], [16] could be independent or integrated in an existing business function of the energy supplier or distribution system operator (DSO).

In principle, three types of control strategies can be used by FOs when aiming at the objectives mentioned above, namely centralized control, decentralized control considering the distinctive market-based/transactive control and price control, respectively. Centralized control means that FOs directly schedule and control the charging of electric vehicles, while the transactive control and price control are usually implemented in a form of price signal, i.e. the individual EV optimizes the charging based on the electricity price information made available to them from FOs or from DSO. The key difference between transactive control and price control is the information exchange requirements, i.e., transactive control requires explicit responds from the individual EV while price control does not need such responds. More discussions regarding these three control methods will be presented in section 4. From the discussions [17], [18], it is generally accepted that for the centralized control the decisions are made on the system-level and therefore it can give better results such as ensuring the security of the power systems; however, the cost of communication infrastructure would be high for centralized charging. For the transactive control and price control, one of main advantages is the possibility to minimize the communications infrastructure cost [19], nevertheless, the solution may or may not be optimal, depending on the information sharing and the methods used to make the charging schedule.

The main content of this paper is to give a review and classification of the optimization and control strategies used for smart charging of EV fleets. Although the authors are aware of similar works [20]–[25] on reviewing smart charging of electric vehicles that are published recently, the research contributions of this study include: 1) a comprehensive summary of service relationships between fleet operators and other four actors in a smart grid context are presented; 2) three control strategies used by FOs including centralized control, transactive control, and price control are specifically distinguished and discussed; 3) mathematical modelling methods of the three control strategies are compared and evaluated. The aim of the present study is to provide a comprehensive understanding about EV fleet management

that allows commercial actors, e.g., EV FOs to exploit the service based electric vehicle aggregation and make the electric vehicles become integral parts of smart grids.

The remainder of the paper is organized as follows: the role and the service dependent aggregation of electric vehicle fleet operator are discussed in Section 2. Section 3 introduces the modelling of EV battery and driving pattern, charging and communication standards. Three control strategies including centralized control, transactive control and price control are described in Section 4. Commonly used algorithms in the centralized control, transactive control and price control of smart charging of EVs are presented in Section 5, 6 and 7, respectively. Section 8 concludes the paper with some suggestions for future research.

2 Service dependent aggregation and its facilitator fleet operator

In [26], Lopes *et al.* shortly summarized that a large deployment of EVs will involve the following studies: 1) Evaluation of the impacts that battery charging may have on power system operation; 2) Identification of adequate operational management and control strategies regarding batteries' charging periods; 3) Identification of the best strategies to be adopted in order to use preferentially renewable energy sources (RES) to charge EVs; 4) Assessment of the EV potential to participate in the provision of power system services, including reserves provision and power delivery. Following the summary in [26], this study starts by reviewing four kinds of control objectives of operational management of an EV fleet. Furthermore, it is possible to see these four control objectives as four types of services that can be offered by FOs to other actors in smart grids. In this section, the role of EV fleet operator is firstly discussed; then the relation between the fleet operators and other actors in a smart grid are described; next, four kinds of services which can be provided by fleet operators are introduced; at the end of this section, the relationship between these four kinds of services is analyzed.

2.1 Role of electric vehicle fleet operators

San Román *et al.* [16] proposed a regulatory framework for charging EVs where two electricity market agents, an EV charging manager and an EV aggregator/fleet operator are introduced. The EV charging manager is responsible to develop the charging infrastructure. The EV fleet operator is responsible for providing charging services to EV fleet and managing the EV fleet for other services provision. With respect to the feasibility of applying the fleet operator concept, Bessa and Matos [15] gave a literature review regarding the economic and technical management of an EV aggregation agent. The reviewed paper [15] is organized into three subject categories: electricity market, EV technical and economic issues; aggregation agent concept, role and business model, and algorithms for EV management as a load/resource.

It is observed that the role of each type of FO proposed various and the main difference lies in whether the FO has two functions or one function, i.e., some studies assumed that a FO is both a charging equipment supplier and charging service provider, others only refer fleet operator as the charging service provider. Although several differences exist in the details of the proposed FO concepts, they are assumed to achieve the same goals in this study, regardless the ownership of the charging equipment. These goals are:

- Guarantee driving needs of the EV owners with optimal management of EV charging;
- Provide peak power to the electric network from the V2G capability;
- Provide ancillary services to power system operators with optimal allocation of EV fleet resources.

2.2 Service relationships between fleet operators and other actors in a smart grid

Fig. 1 illustrates the relationships between fleet operators and other actors in a smart grid by showing the four services that FOs can provide to them.

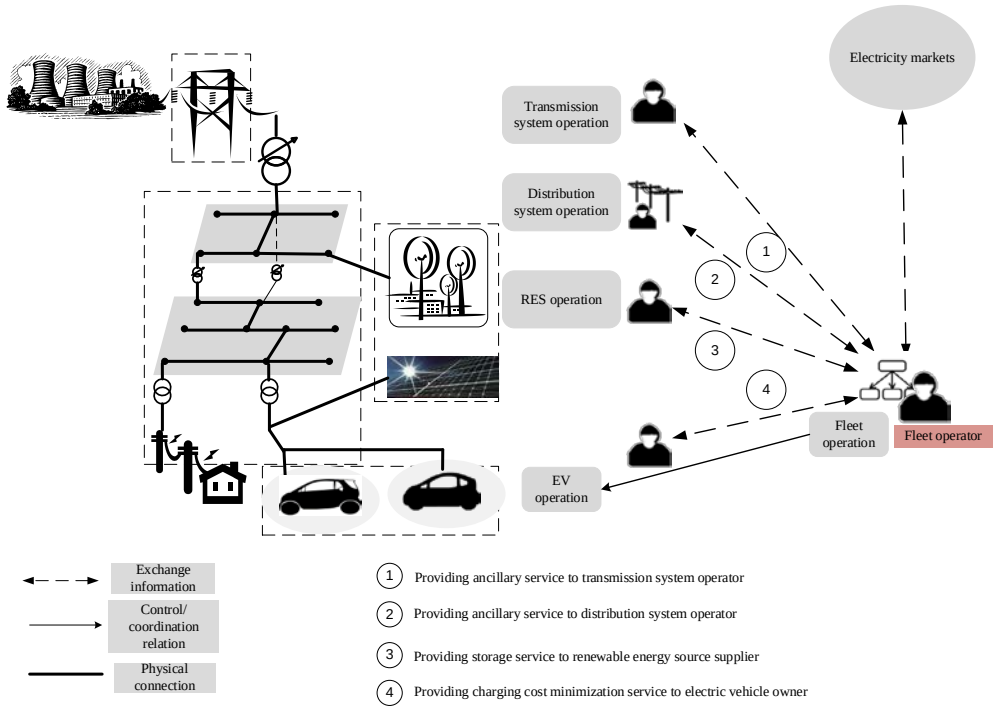

Fig. 1. The services relationships between fleet operator and other actors in a smart grid.

Note that the relationship between FOs and EVs is slightly more complex. From one perspective, FOs need to ensure the participation of EVs and then have the capability of providing services to other actors in the smart grid; from another perspective, FOs can provide service of energy trading to EVs such as helping the EV owner to save money. Therefore, FO may need to consider more factors rather than purely make profits when providing services to EVs.

2.2.1 Providing ancillary services to transmission system operator (TSO)

Ancillary services are needed to maintain the balance between the supply and demand so that a secure and reliable functioning of all power system is ensured [27]. The regulation down, regulation up, spinning reserve and non-spinning reserve are the most common services in the frequency control [27]. Regulation down and up, also referred as automatic generation control, has the purpose to fine-tune the frequency by matching supply and demand at any time that it is needed to respond within a minute or less. More specifically, regulation down and up are characterized by decreasing and increasing, respectively, the actual operation power level of a specific resource that participates in this service [27]. Spinning reserve corresponds to unloaded synchronized generation capacity that can quickly provide power to the network [27]. Non-spinning reserve is the portion of generation capacity that is capable of being synchronized and ramping to a specified load [27]. The regulation (up and down) is the service with the quickest response, the shortest duration, the shortest service availability and the highest price of the frequency regulation services. In terms of hierarchy for power system operators these services are categorized by: 1) regulation up and down; 2) spinning reserve; 3) non-spinning reserve. For this reason the regulation market contains the highest prices of all frequency service markets.

The operation of power system will benefit greatly from the introduction of EVs participation, namely in the electricity markets related to ancillary services. Moreover, the large integration of intermittent renewable sources will have more ancillary services requirements to maintain the power system balanced. Kempton and Tomic [28], [29] analyzed the potential of EVs in the ancillary service market and concluded that the participation in the regulation market appears to be one of the most promising application, because it can offer a substantial earning potential to EV owners. Dallinger *et al.* [30] proved the effectiveness to apply EVs in the frequency regulation and they could make an attractive alternative to the large generators with high prices. Rotering and Ilic [31] studied the participation of V2G in the ancillary service markets for the independent system operator of California. Based on this study, provision of regulating power substantially improves electric vehicle economics and the daily profits amount to 1.71$. Almeida *et al.* [32] proposes a novel primary frequency control technique for isolated systems

considering EVs penetration. Sortomme and El-Sharkawi [33] analyses the potential of V2G to participate in the regulation and spinning reserve based on the Electric Reliability Council of Texas market. The authors concluded that EVs can bring great benefits to the regulation and spinning reserve, but the battery life cycle represents a challenge to the viability for the application of V2G mode to the ancillary service market.

Overall, the above studies have pointed out that EVs can have a high contribution to the regulation and spinning reserve services, especially in the regulation up and down services. These services require a quick response from the resources (e.g. generators, demand response programs and EVs) that can be called for a few minutes. In addition, an adequate telecommunication infrastructure is required to support the ancillary services responding from the resources. Since EV batteries have characteristic of rapid responses, EVs are most appropriate for the regulation up and down. Additionally, the highest price offered in regulation up and down services can bring more profits for the EV owners. Regarding spinning reserve, it is also mentioned as a good service for EVs participation, but with lower revenue, higher duration and higher availability than regulation service. The spinning service requires that resources can have a synchronized reserve available to be called in a typical duration of minutes (e.g. 10 minutes) until 1 hour. With respect to the non-spinning reserve it is pointed out by the literature that EVs will not be suitable for this service due to its higher duration (e.g. hours) and lower prices. However, accelerated battery degradation might be the main challenge for a complete implementation of EVs participation in the ancillary services. Table 1 gives an overview of the literature by the different kind of frequency regulation services (regulation, spinning and non-spinning reserves).

Table 1. Characterization of the literature by the frequency regulation market

Service Name	*Short description*	*Expected asset in the market (e.g. Danish and European)*	*Reference*
Regulation up and down	A reserve that stabilizes the frequency in the matter of seconds of minutes.	Yes	[28], [29], [30], [31], [32], [33]
Spinning reserve	Release the primary reserve and restore the frequency to 50 Hz.	Yes	[28], [29], [33]
Non-spinning reserve	A manual reserve that releases the other two reserves.	No	N.A.

2.2.2 Providing ancillary services to distribution system operator (DSO)

Research indicates that uncontrollable charging of a large scale of EVs will bring some challenges to the distribution network. The challenges are related to peak power problem, grid congestion, power losses and voltage drop. Several studies evaluate the performance of the distribution network considering three types of strategies [20], [23]:

- Uncoordinated charging;
- Smart charging;
- Smart charging and discharging (i.e. bidirectional V2G).

An uncoordinated charging occurs when EVs connect to the distribution network and start immediately to charge until the batteries reach their capacity. The smart charging consists in an actor (e.g. DSO or EVs fleet operator) controlling the time and power of the EVs charging. The V2G control is similar to the smart charging and it has the capability of providing power to the grid.

Studies concerning the charging rate control of EVs and their effect on the distribution network are dated back to the early 1980s [34]. Heydt [34] argued that load management should be deployed to ease peak loading by the DSO, which is measured in term of load factor improvement. In 1993, Rahman and Shrestha [35] indicated that even low penetration levels of EVs can create new peak loads exceeding the natural peak if sufficient attention is not paid to distribute the charging load throughout the off-peak

periods. A penetration level of 20% is found to be the upper limit which could be managed by distributing the charging load. The literature points that without smart charging the power consumption on a local scale can lead to grid problems, such as unpleasant load peaks, line congestion and voltage limit violation. The studies [34], [35] examined mainly the impacts of EVs to the distribution system by adding the EV loading profile to the already existing load profile and evaluating the overall effect.

Recently, more parameters such as power losses, load levelling and grid congestion have been considered for supporting the integration of EVs in the distribution network. Sortomme *et al.* [36] proposed optimal charging algorithms to minimize the impacts of EVs charging in the distribution network in terms of power losses and load factor. Morais *et al.* [37] proposed a multi-objective optimization algorithm to evaluate the impact of EVs in the power demand considering the scheduling cost and load levelling as objectives functions of the proposed algorithm. In terms of voltage regulation, this objective is achieved by proper scheduling of the reactive power or by controlling the load demand in order to reduce the voltage drop. Wu *et al.* [38] examined the potential of a proper selection of current phase angle by EV charger in order to compensate capacitive and inductive reactive power. Leemput *et al.* [39] discussed the impact of the reactive support by EVs charging in a low-voltage residential distribution network. In [40], a methodology is proposed to deal with active and reactive management of a distribution network with EVs to improve the voltage profile while a minimum operation cost is achieved.

Most of the literature indicated that TSO has the responsibility with the ancillary services about frequency control (i.e. regulation, spinning and non-spinning reserve), DSO is responsible for the local voltage control and local congestion prevention. However, with the increasingly penetration of distributed resources, the DSO can have an important role in the frequency control in the future, especially in the regulation and spinning reserve [41]. In [42], it is presented the application of distributed generation to provide ancillary services to control the frequency. The FO could also participate in this service that the DSO will need in the future operation of the power system.

Currently, the ancillary services proposed in the literature that FO can provide to DSO are: 1) congestion prevention (i.e. reduce peak load and power losses); 2) voltage regulation. The literature is divided based on this classification as it is shown in Table 2. Nevertheless, in the future the FO can also be able to provide regulation for the frequency control under DSO supervision.

Table 2. Characterization of the literature by the ancillary services in the DSO

Service Name	*Short description*	*Expected asset in the market (e.g. Danish and European)*	*Reference*
Congestion prevention	Intelligent control of the charge and discharge of EVs in order to avoid grid congestion, minimize load peaks and reduce power losses.	Yes	[34], [35], [36], [37]
Voltage regulation	Intelligent control of the charge and discharge of EVs to improve the voltage profile avoiding the increase of voltage drops.	Yes	[26], [38], [39], [40]

2.2.3 Providing storage services to renewable energy source supplier (RES)

One of the main challenges for operating the power system with renewables sources such as wind and solar is related to their intermittent behavior that is influenced by the stochastic nature of their primary energy sources. Regarding this subject, EVs have been suggested as one of the most promising solutions for mitigating this intermittent behavior, compared with other solutions such as using centralized storage system or backup generation that represent a high capital cost to the power system operators. Basically, EVs can store the excess energy from renewables in their batteries that would otherwise be curtailed and wasted. EVs can use this stored energy for their daily driving, or in the case of EVs with V2G can also

supply this energy back to the network. The literature concerning this topic is focused more on the back-up of EVs to the wind than the solar energy [22], [24], [43].

Lund and Kempton [44] investigated the impact of using V2G technology to integrate the sustainable energy system. Two national energy systems are modelled; one for Denmark including combined heat and power (CHP), the other is a similarly sized country without CHP. The model (EnergyPLAN) integrates energy for electricity, transport and heat, includes hourly fluctuations in human needs and the environment (wind resource and weather-driven need for heat). The results indicated that adding EVs and V2G to these national energy systems allows integration of much higher levels of wind electricity, and also greatly reduces national CO_2 emissions. Bellekom *et al.* [45] investigated the impact of large scale EVs and wind integration in the Dutch power system. The study concludes that wind integration can increase from 4 GW (no EVs scenario) to 10 GW if there are around 1 million EVs connected to the network. Dallinger and Wietschel [46] examined the impact of EVs charging in the German electricity system with 50% share of renewables in 2030 (wind and solar) where the charging strategy is obtained through consumer price response. Furthermore, this study concluded that EVs can play an important role in mitigating the intermittent behavior of renewables, being stored in the EVs over more than 50% of the yearly excess renewable energy.

Saber and Venayagamoorthy [47] proposed a particle swarm optimization algorithm to handle the unit commitment of a power system considering a large penetration of renewables and EVs. The authors concluded that using the EVs with V2G in a smart grid concept will contribute to the minimization of cost and emissions in the unit commitment and to reduce the unbalance introduced in the operation of the intermittent renewables. Another study by the same authors [48] proposes a particle swarm optimization algorithm to solve the same optimization problem including uncertainties related to load consumption, renewables' generation power and number of EVs connected to the network. A probabilistic distribution is considered for each stochastic variable and then a few scenarios are generated and the optimization method solves the unit commitment for each different scenario. In addition, a mixed-integer linear programming algorithm is presented in [49] to deal with the resource scheduling in smart grid context considering a scenario with intensive penetration of renewables and EVs.

In terms of EVs integration with solar energy, Birnie [50] proposes the installation of photovoltaic (PV) panels to supply the daytime charging of EVs in a parking lot assuming New Jersey solar irradiation. The study concluded that the PV panels can meet the driving needs of the EV owners during the summer, but not in the winter. Zhang *et al.* [51] examined the integration of PV panel in collaboration with EVs and heat pumps in the Kansai Area of Japan. The authors concluded that it would be necessary to introduce 1 million EVs and 1 million heat pumps to reduce the excess of energy by 30% from a hypothetical scenario of 30 GW of solar capacity in the area.

Overall, the literature examines the extent of renewables integration, namely wind and PV energy, which EVs can accommodate in the power system in order to reduce CO_2 emissions. In general, these studies concluded that the connection of more EVs in the network and the control of their charging rate have the potential to increase the share of renewables in the power system and to mitigate the intermittence behavior of renewables. Besides, EVs with V2G can supply the excess of renewable energy previous stored in the batteries back to the network when power is needed, such as in periods of high demand and low renewable generation. Table 3 presents a classification of the literature related to this subject, in which the articles have been divided in studies related to renewable integration and storage device.

Table 3. Characterization of the literature by the RES service

Service Name	*Short description*	*Expected asset in the market*	*Reference*

		(e.g. Danish and European)	
Renewable Integration	Evaluate the share of renewables that is possible to have in the power system with a large scale of EVs.	Yes	[44], [45], [50], [51]
Storage device	Large mobile storage capacity to mitigate the intermittent behavior of renewables.	Yes	[46], [47], [48], [49]

2.2.4 Providing charging cost minimization service to electric vehicle owner

In the above sections, research has been presented concerning the impact of EVs on other actors, namely TSO, DSO and RES supplier. This subsection presents literature considering EV's impact on the FO and EV owners. In order to stimulate active participation in smart charging management and to reduce the initial investments with the purchase of EVs, it is noted that the proposed works related to optimization and control of charging and discharging of electric vehicles should be aware of the fact of sharing profits from the FO with the EVs owners. It is assumed in [52] that the EV fleet operator manages the electricity market participation of an EV fleet and presents a framework for optimal charging of the EVs. The result illustrated that the electricity bills of charging the EVs are reduced. In addition, the electricity price of the day-ahead spot market, the regulation market and the driving patterns of the EV fleet are usually assumed to be known by the fleet operator, who is assumed to be the price-taker in the electricity market. However, Kristoffersen *et al.* [53] also investigated the possibilities of EV management where the FO has a significant market share and can affect electricity prices by changing the load through charging and discharging.

Besides studying the optimal charging from an EV fleet perspective, research in [31] shows how dynamic programming can be used by the individual EV controller to make an optimal charging schedule taking into account the electricity market price. In [33], [54], a strategy is presented for an EV aggregator to participate in the spot and regulation market. The V2G service can bring benefits to the EV owners because it can reduce the cost that owners had with the charging of their vehicles. However, the literature point out major concerns for the V2G concept [21]: 1) additional investments for enabling the bidirectional power flow, 2) advanced communication and smart metering and 3) high degradation of battery because of repeated cycling in comparison with the scenario of smart charging. It is expected in the near future, more FOs can exist in the market that provide services to the EVs to control and optimize their charging. Additionally, it is also expected that the concerns about V2G can be solved enabling the FO to offer V2G services for the electricity markets. Table 4 presents a classification of the literature related to this subject, in which the articles have been divided in studies related to charging management and charging and discharging management.

Table 4. Characterization of the literature by the EV owner service

Service Name	*Short description*	*Expected asset in the market (e.g. Danish and European)*	*Reference*
Charging management	Charging management aiming at lower cost.	Yes	[31], [52], [53]
Charging and discharging management	Charging and discharging management aiming at maximum profit.	Yes	[33], [54]

2.2.5 Analysis of the control objectives of fleet operator's smart charging

Several questions naturally arises after reviewing the four main services (described in 2.2.1 to 2.2.4) that FO can provide to other actors, e.g., whether conflicting interests exist between different services, whether some services can be integrated, and what are the relationships between these four main services. It is observed that multi-services research is already performed in several studies, however a sys-

tematic way of understanding the relationships between the described services is missing. Johannsson *et al.* in [55] presented a scheme to deal with these relationships based on a prioritized list. The potential conflicts between different actors (i.e. FO, TSO and DSO) appear when two actors need to use EVs for conflicting services, such as a service activated by an actor can cause a negative influence to other actors' management.

The authors in [55] present two examples concerning conflicting interests between actors. One of these examples is about how the frequency control can be in conflict with peak-shaving. In the example, the TSO control the frequency by activating a contracted aggregator. Then the aggregator responds by increasing the aggregated consumption of its consumers, e.g., EVs. However, the aggregator's positive response can cause overload in local areas, and the DSO must execute a service of congestion prevention to control this overload. If the aggregator attends the peak-shaving incident, the TSO may require another solution to maintain the frequency under control. However, if the aggregator ignores the peak-shaving alert, the local area that is managed by the DSO would be overloaded and more equipment would be damaged, such as power transformers and lines [55].

The authors in [55] proposed a prioritized service list for handling potential conflicts. The list includes: 1) Emergency actions (TSO); 2) Alert actions (TSO/DSO); 3) Local voltage control (DSO); 4) Peak-shaving (DSO); 5) Voltage support (TSO); 6) Mvar bands (DSO); 7) Frequency control; 8) Other ancillary services (TSO); 9) Imbalance issues (Aggregator, e.g. FO); 10) Power quality. This list should be used for helping different actors' management when causing a negative influence to other actors. In a case of two conflicting services, the main purpose is a service with higher priority will be activated instead of the other one. In order to incorporate the list in the management of the actors, the authors presented the behavior description that defines the behavior of a given resource for a specific service.

3 Smart charging infrastructure and modeling of EV battery dynamics and driving pattern

When designing the control strategies that aim at providing different services described in the previous section, many aspects should be taken in consideration namely the battery modelling, the charging and communication standards and finally the charging requirements of the users according to their driving profiles. In this section a general overview of these four aspects is presented.

3.1 Battery modeling

The increase of efficiency of batteries is one of the most important challenges in the EVs industry. Several battery technologies including Pb-acid battery, Ni CD battery, Ni-MH battery, Li-ion battery, and Li-polymer battery are available in the market, each one with different characteristics meaning different advantages and disadvantages. Three main characteristics of batteries including the energy efficiency, the energy density and the power density are studies in [56].

In general, there are two ways of modelling the charging characteristics of an EV battery. One is a model for an individual battery pack, another is aggregated or cell based model. For simplicity, most of the studies considered EV as a battery pack when investigating the optimal charging and discharging problem. Currently, most battery-modeling research [57], [58] focus on three types of studies:

- The first and most commonly used model is termed as a performance or a charge model and focuses on modelling the state of charge of the battery, which is the single most important property in system assessments;
- The second type of model is the voltage model, which is employed to model the terminal voltage, so that it can be used in more detailed modelling of the battery management system and in more detailed calculation of the losses in the battery;
- The third type of model is the lifetime model used for assessing the impact of a particular operating scheme on the expected lifetime of the battery.

3.2 Charging Standards

In the last decade, standards related to EVs were proposed from different principles. In general, IEC 62196 are adopted in Europe. The IEC 62196-1 is based on IEC 61851 defining four charging modes:

- Mode 1: AC slow charging from a household socket-outlet. Mode 1 charging is the most common option for electric vehicles due to the use of traditional house/industrial socket-outlet [56], [59]. Mode 1 charging is now only considered as the main mode for small vehicles such as two wheelers [59].

- Mode 2: slow charging from a household-type socket-outlet with an in-cable protection device in AC. Mode 2 also allows the use of traditional house/industrial socket-outlet. However, this charging mode, provides additional protection by adding an in-cable control box with a control pilot conductor between the electric vehicle and the plug or control box [56], [59];

- Mode 3: slow or fast charging using a specific EV socket-outlet with control and protection function installed in AC. Mode 3 requires a dedicated connection between the EVs and the charging station [56], [59];

- Mode 4: fast charging using an external charger in DC. Two sub-modes of operation are considered for this mode, namely, the DC level 1 (voltage lower than 500 V, current lower than 80 A, power at 40 kW) and the DC Level 2 (voltage lower than 500 V, current lower than 200 A, power at 100 kW) [56], [59].

It is important to mention that in charging Mode 1, there is no communication between the EVs and the charging point through the connection system. In Mode 2 and 3, a control pilot communication can be included allowing the control of the charging rate. In charging Mode 4, it is mainly used for the fast charging. A communication system is included in charging Mode 4 that allows battery charging management. In addition, in Mode 2, 3, and 4, wireless communication systems can be used to communicate with electric vehicles and control the charge and discharge process.

Concerning the type of connectors, the IEC 62196-2 proposes different types based on other standards the SAE J1772-2009 (Type 1) or the VDE-AR-E 2623-2-2 (Type 2). The type 3 is also fixed, but is not yet completely defined. Concerning the fast charging, the 62196-3 defines the DC fast charging plugs to be used in Mode 4, namely the CHAdeMO and the combined charging systems.

In U.S. the charging standards are defined by the Society of Automotive Engineers (SAE) in SAEJ1772. The recognized types of plug are similar to IEC 62196, but SAE has selected the J1772 combo plug as the standard. This plug allows both AC and DC charging using the same plug. The SAEJ1772-2011 defines six charging levels, three in AC and three in DC [21]. The AC Level 1 is practically applied at home environments while the AC Level 2 is suitable for public and commercial areas. The DC-fast charging levels (DC Level 1–3) are more adapted to public use.

In China, the EVs charging standards are defined in GB/T 20234-2011. According to this standard, EVs charging can be made in AC using the Mode 2 and 3 defined in IEC 62196. However, this use is limited to a single phase system allowing a maximum current of 16 A. The DC fast charging is also available considering a specific connector that allows a maximum voltage of 750V and 125/250A [60]. The fast charging uses the CATARC (China Automotive Technology and Research Center) protocol. In Japan, the CHAdeMO specifications are used as a standard [61].

3.3 Communications Standards

In order to illustrate how the charging and discharging schedule is implemented, this subsection discusses the relevant communication standards for integrating EVs into power grids. It is noted that the purpose of this section is to provide the relevant/widely used communication standard that can support EV smart charging rather than comparing the various communication standards. The IEC standards illustrated in Fig. 2 is recommended in [62]. The objectives of the study [62] is to realize a standardized communication interface between the vehicle and the grid. The standardization will make it possible for EV users to have easy access to EV charging equipment (EVSE) and related services throughout Europe. EVSE refers to all devices installed for delivering power from the electrical supply point to the EV and this charging equipment will support smart charging functions. The decision of the charging can be made on the EV level or on the FOs level. The IEC 15118 is the most recommended communication standard [62], and is demonstrated in details in [63], by the sequence diagram of a charging process between the EVSE and the EVs.

The IEC 61850 is recommended for the communication between the EVSE and the FOs [63]. In [64], the use of the smart metering infrastructure to transmit the information concerning the EVs charging state using the multiple access control protocol is proposed. According to [65], the protocol SAE J2836/3TM, published in January 2013, allows the coordination of both distributed energy resources and electric vehicles including the V2G capability (control the charge and discharge process). The information exchange with the EV was derived from the IEC/TR 61850-90-8 from February 2013. In [66], two other promising protocols to be used in the communication between charging stations and the system operators and/or aggregators, namely Open Charge Point Protocol (OCPP) and Hubject's Open Intercharge Protocol (OICP) are analyzed.

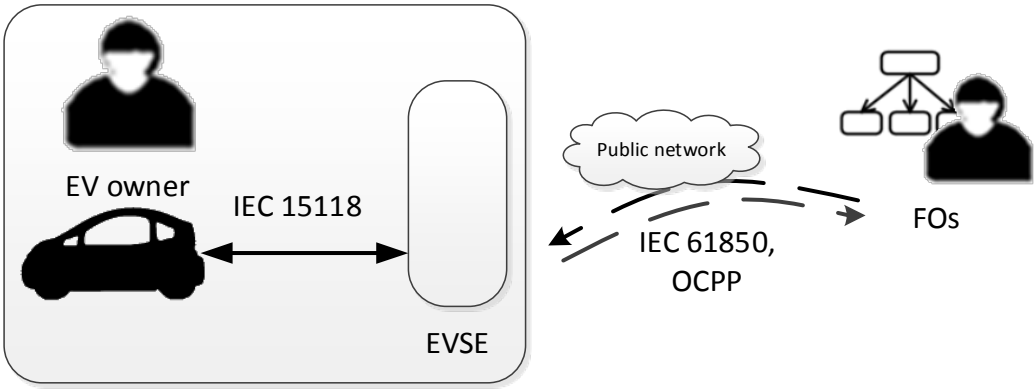

Fig. 2. *Relevant ICT standards support the EV smart charging in the context of smart grids.*

3.4 Driving pattern

The modeling of driving pattern can be divided into two main aspects:

- Use of EVs, in other words, a typical user's daily driving activities;
- Location of EVs when charging and how many of them will be charged at a time.

Kristoffersen *et al.* [53] investigated a method to construct driving patterns from the historic data in Denmark. By clustering survey data of the vehicle fleet in Western Denmark (January 2006-December 2007), a representative driving pattern for each vehicle user are constructed. Shahidinejad *et al.* [67] developed a daily duty cycle which provides a complete data set for optimization of energy requirements of users. This information can also be used to analyze the impact of EVs' daytime charging on the electric utility grid, which may create a peak demand. Normally, intra city or short-term driving patterns are largely predictable due to fixed working hours and fixed business schedules and routes of EV owners. In [68], a simulation tool is proposed allowing the generation of driving profiles for a large number of EVs considering a set of probabilities and EVs characteristics like the percentage of vehicles in movement, batteries efficiency, trips distances, vehicles class distribution, etc.

A more detailed analysis of driving patterns is performed in [69], considering that the environmental, economic and technical factors which influences the driving patterns of EV owners. Technical factors include: the number of EVs being charged (EV penetration trend), the availability of charging infrastructure, charging voltage and current levels, charging time, battery technology, battery life time and capacity. An analysis of real EVs driving behaviors is performed in [70]. The results indicated that the use of EVs has changed the daily routines of 36% of the participants leading to a significant reduction both in energy consumption and in greenhouse gas emissions.

4 Control strategies of fleet operator

In this section, the focus is the control strategies of fleet operators, i.e., how the FO optimally schedules and controls the EVs according to the specified objectives, such as the aforementioned four kinds of services (described in 2.2.1 to 2.2.4). Three control strategies are presented in this section: centralized control, transactive control and price control. Centralized control means that FOs directly schedule and control the charging of electric vehicles [52]. Transactive control [71] is a form of market-based control

method that has been adopted by the GridWise Architecture Council [72]. The purpose of transactive control is to reach equilibriums by using a scalable, distributed mechanism via exchanging information concerning generation, loads, constraints and responsive assets over dynamic, real-time forecasting periods using economic incentive signal. PowerMatcher[1] [73] is a good example of using transactive control for supply and demand matching in electricity networks. Transactive control usually requires two way communications, e.g., exchange of the price and power schedule information. Price control [74], [75], instead uses one way communication and applies broadcasting of price signal with a regular updated frequency to the demand side resources. An overview and comparison of the three control methods is presented in Fig. 3.

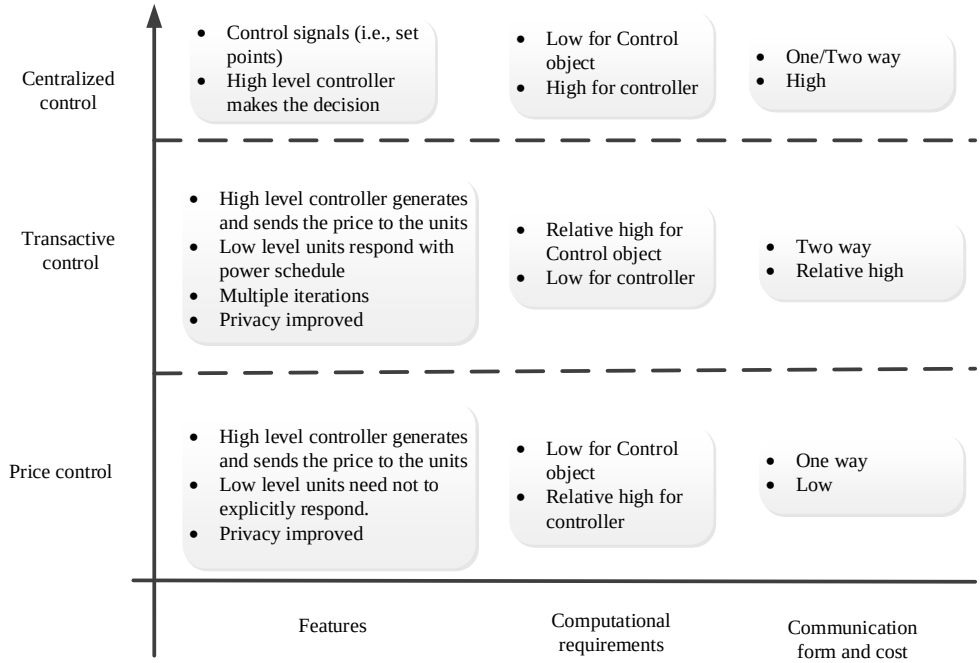

Fig. 3. Overview of Control strategies.

4.1 Centralized control of electric vehicle fleet operator

In this control strategy, the FO will centralize all the relevant information from the aggregated EVs, as it is shown in Fig. 4. The FO will require four inputs, i.e. the model of the EV battery and the EV driving patterns, the grid constraints and the electricity price to make a proper charging control of EVs.

[1] http://www.powermatcher.net

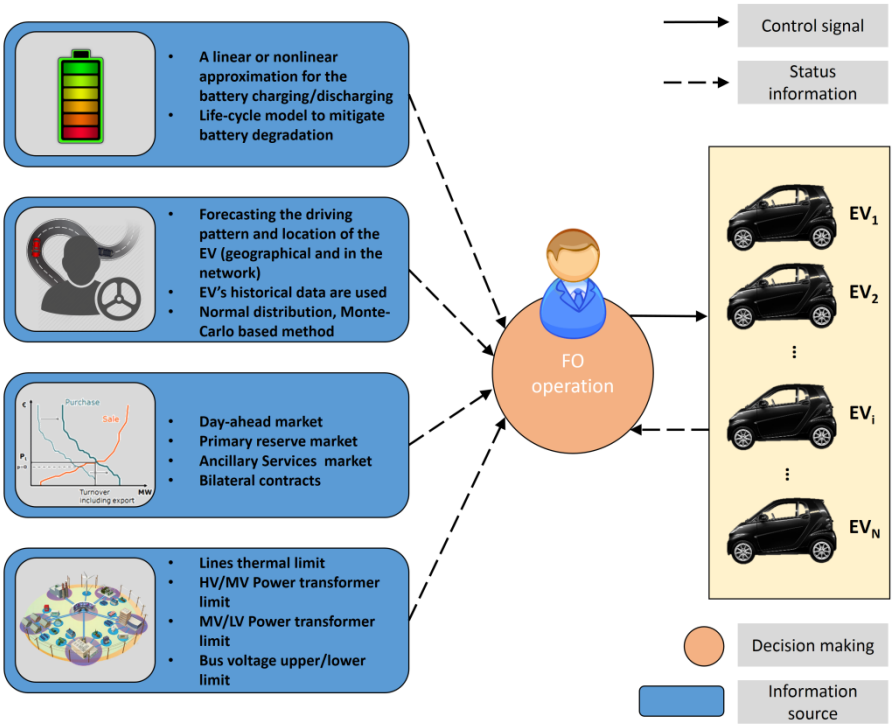

Fig. 4. Primary inputs and output of EV FO in a centralized control strategy.

4.2 Transactive control of electric vehicle fleet operator

The information flow in transactive charging control is presented in Fig. 5. Note that the goal of the FO is implicit in the figure. The key point of this figure is to show the two way information exchanging in term of power schedule and price. The basic idea of transactive control application in EV charging control is that EVs update their charging profiles independently given the price signal from the FO until equilibriums are achieved. In the transactive control, the EVs charging schedule is a result of the information exchanging between FO and EVs and thus it is not a purely decision of the EV owner.

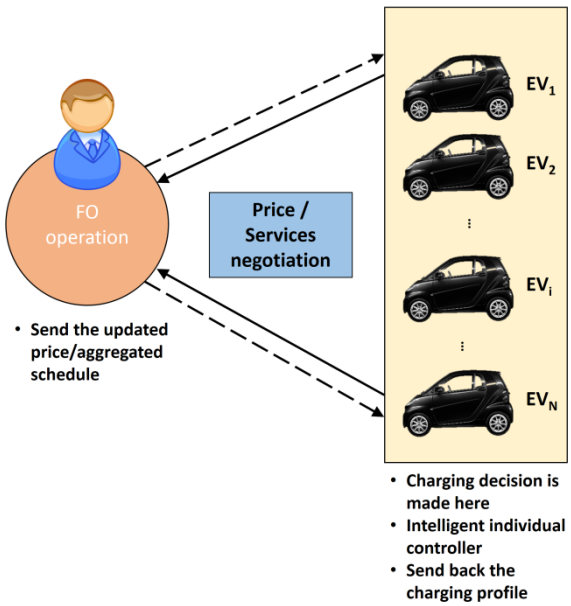

Fig. 5. Information flow between the FO and the EVs in a transactive control strategy.

4.3 Price control of electric vehicle fleet operator

The price control is another method that can be adopted by the FO, as it is shown in Fig. 6. This control method requires forecast of EV users' response to the prices sent by the FO. The price signal can be designed as time-of-use price or dynamic prices.

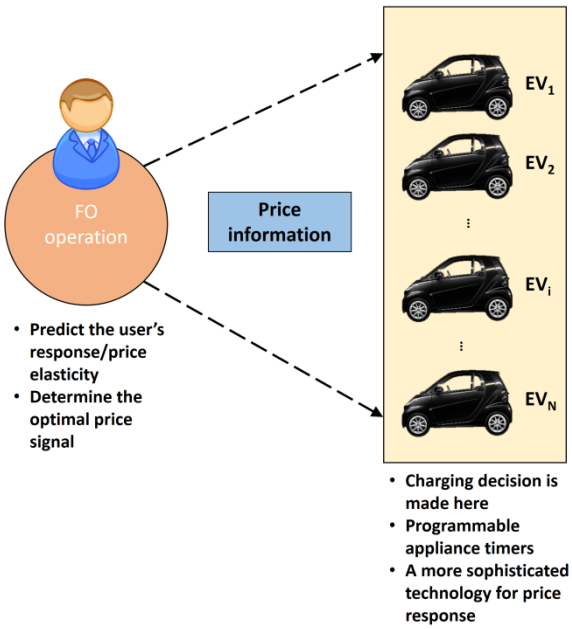

Fig. 6. Information flow between the FO and the EVs in a price based control strategy.

4.4 Discussion on integrating the control strategies

Although most research assume either centralized control or decentralized control including transactive control and price control architecture, this is indeed an important decision which should be taken in the earlier stage. From our perspective, three issues shall be investigated:

- Depending on the aggregation objectives presented in section 2.2, e.g., different objectives have different requirement on EVs in term of response time;
- Depending on the EV consumer's participation. Some consumers do not like their EVs to be controlled by FOs. Under such circumstance, transactive control and price control are suitable methods;
- Depending on the business model, e.g., whether the economic benefits of optimal charging of EVs can justify the cost of communication infrastructure in all control cases.

The authors in [76], [77] compared the centralized control and decentralized control method when using them to make an plan for optimal delivery of energy to EVs as well as avoiding grid congestions. They outlined the advantages and disadvantages of both strategies, mainly from the communication perspective. However, more research is needed to evaluate how the choice of control strategy influences the overall performance and engineering requirements (e.g. information, communication and computation requirements).

When implementing different control strategies of smart charging of EVs, especially transactive control method, it is recommended that multi-agents system based technology is very suitable to design a coordinated and collaborative system for a smart charging network of EVs. In multi-agent systems, different interests of various actors shown in Fig. 1 can be presented and coordinated by using smart charging method. By using multi-agent systems technology, it is possible to model the optimization and the control occurring in the smart charging of EVs.

5 Mathematical modeling and control algorithms: centralized control of fleet operator

In this section, the algorithms often used in the centralized control are presented. Linear programming, quadratic programming, dynamic programming, mixed-integer linear and non-linear programming, stochastic programming, robust optimization, heuristic optimization and model predictive control will be discussed through an extensive literature review. Further, a qualitative comparison among the nine types of algorithms will be presented at the end of this section.

5.1 Linear programming

Sundstrom and Binding [78], used linear approximation to characterize the state of charge of a battery and formulated the charging process of an EV fleet into a linear programming (LP) based optimization problem:

$$\min t_s c^T P_b \tag{1}$$

Subject to

$$\begin{cases} A_s P_b \geq b_s \\ A_g P_b \geq b_g \\ A_b P_b \geq b_b \\ b_l \leq P_b \leq b_u \end{cases} \tag{2}$$

With the time slot t_s, price vector c, the charging power P_b (decision variable), the stopover inequality constraints (A_s, b_s), the generation inequality constraints (A_g, b_g), the battery inequality constraints (A_b, b_b), and the upper and lower power bounds (b_u, b_l). The solution of this linear optimization problem is the optimal charging profile that minimize the charging cost of EV fleet [78].

5.2 Quadratic programming

A nonlinear approximation (quadratic formulation (QP)) of the battery charging model is studied in [78]. The results showed that the number of constraints and calculation time are higher and they increases faster with a growing fleet in the quadratic formulation than in the linear formulation. An example is conducted for comparison and the result indicated that calculating time using the quadratic formulation is 819 times the calculation time using the linear formulation [78]. But the result difference does not justify the benefits of using quadratic formulation. Recently, linear and non-linear programming algorithms applied to renewable energy are summarized and compared in [79]. In [80], Clement-Nyns *et al.* formulated the power losses problem caused by large penetration of EVs in the grid into a sequential quadratic optimization problem. The charging power obtained by the quadratic programming cannot be larger than the maximum power of the charger P_{max}. The batteries must be fully charged at the end of cycle, so the energy which flows to the batteries must be equal to the capacity of the batteries C_{max}. x_n is zero if there is no EV connected and is one if there is an EV connected at node *n*. The above problem specification can be represented as follows:

$$\min \sum_{t=1}^{t_{max}} \sum_{l=1}^{lines} R_l . I_{l,t}^2 \tag{3}$$

Subject to

$$\begin{cases} \forall t, \forall n \in \{nodes\}: 0 \leq P_{n,t} \leq P_{max} \\ \forall n \in \{nodes\}: \sum_{t=1}^{t_{max}} P_{n,t} . \Delta t . x_n = C_{max} \\ x_n \in 0,1 \end{cases} \tag{4}$$

where R_l represents the resistance of line l, $I_{l,t}$ is the current in line l in period t, $P_{n,t}$ is the active power of EVs charge in the bus n in period t, P_{max} is the maximum charge rate and C_{max} represents the battery capacity. Finally the charging control is imposed by the binary variable x_n.

The quadratic programming techniques are applied using both deterministic and stochastic methods [80]. The input variables in both cases are the daily/hourly load profile. In the deterministic case, the load profiles are static. In the stochastic case, the load profile are transformed into probability density functions, which means the fixed input parameters are converted into random input variables with normal distributions assumed at each node. The details of stochastic case are presented in section 5.6.

5.3 Dynamic programming

Dynamic programming (DP) is widely used for different purposes in electric vehicle smart charging problem. In this study, the work in [31] is introduced where the purpose is to minimize charging cost by participating in regulation market. Firstly, a specific control strategy π is denoted by

$$\pi = \{u_0, u_1, \dots u_k, \dots, u_{N-1}\} \tag{5}$$

where u_k is the control variable for time k that denotes a dimensionless and discrete representation of P_k. P_k corresponds to the purchased power. The total cost of a whole charging sequence, J^π is calculated as:

$$J_0^\pi(x_0) = J_N(x_N) + \sum_{k=1}^{N-1} l_k(x_k, u_k, k) \tag{6}$$

J^N means cost of the final step, $l_k(x_k, u_k, k)$ denotes the cost-to-go for all other steps, N denotes the total number of time intervals, x_k is the state variable of the battery. The objective is to find the optimal control variables that can minimize the total cost. The detailed mathematic formulation of cost of final step and cost-to-go are not presented here. The purpose of the function used for calculation of cost of final step is to ensure that the battery is fully recharged before the first trip of the following morning. For the function of cost-to-go, the electricity price, regulation-up price and regulation-down price are considered.

This is a classical dynamic programming formulation and the optimal trajectory is calculated starting with the cost of the last state and going backwards through time until the first state's optimal cost $J_0^\pi(x_0)$ is given by the algorithm. Concerning the computing time of dynamic programming, the results in [80] show that the difference of the charging profiles for the QP and DP technique are negligible, however, due to heavier storage requirements of the DP technique compared to the QP technique, hence, the computational time for DP technique is longer.

5.4 Mixed-Integer Linear Programming

The use of mixed-integer linear programming (MILP) techniques is necessary when binary/integer variables are introduced in the problem. Several components in power systems have discrete characteristics, such as capacitor banks, transformer tap changers and thermal generators [81]. In electric vehicles charging problem, the binary variables can be used to determine the EV state namely: charge, discharge, and driving [82]. In [83], MILP is used to determine the impact of EVs in a power systems with high penetration of wind generation and demand response programs. In [84], MILP is proposed to determine the optimal EVs charging in unbalance distribution networks.

The most used optimization techniques to solve MILP are branch-and-bound, cutting-plane and branch-and-cut methods [85]. Branch-and-bound is the most widely used method for solving MILP [85]. The method consist of an implicit enumeration of candidate solutions to the MILP problem (forming a tree), and then each branch of the tree is explored and checked against a bound of the optimal solution. If the branch cannot find a better solution than the best one found so far (or bound), the branch will be no more explored. Each candidate solution is obtained by solving a relaxed sub-problem of the original MILP problem (by relaxing the integer conditions), and each branch contains additional constraints that limits the range of the integer variables. These additional constraints will help to obtain new candidate solutions with integer values in these integer variables. On the other hand, the cutting-plane method

iteratively solves the non-integer version of the MILP problem by including linear inequalities (or termed as cuts) to dictate that the integer variables assume integer values [85]. Currently, the branch-and-cut is the best choice to solve the MILP, it follows the same procedure as branch-and-bound and meanwhile incorporating the cutting-plane method [85]. This incorporation helps the branch-and-cut technique improving the computational performance (CPU time and memory) when compared with the branch-and-bound. Additionally, the branch-and-cut can incorporate relaxation and decomposition methods (e.g. Lagrangian Relaxation and Bender's Decomposition) to deal with large MILP problems.

To demonstrate the formulation of MILP problem, the example of section 5.2 is used, considering the EV maximum and minimum charging/discharging limits in each bus. Besides, EVs can only charge or discharge in each time period at same bus. Additionally, the objective should be a linear one, such as the energy cost (1) presented in section 5.1. In MILP formulation, the constraints (4) presented in section 5.2 should be adapted, in which the binary variables are introduced as following:

$$\begin{cases} \forall t, \forall n \in \{nodes\}: x_{c,t}.P_{min} \leq P_{c,t} \leq x_{c,t}.P_{max} \\ \forall t, \forall n \in \{nodes\}: x_{d,t}.P_{min} \leq P_{d,t} \leq x_{d,t}.P_{max} \\ \forall t, \forall n \in \{nodes\}: x_{c,t} + x_{d,t} \leq 1 \\ \forall n \in \{nodes\}: \sum_{t=1}^{t_{max}} \left(P_{c,t}+P_{d,t}\right).\Delta t = C_{max} \\ x_n \in 0,1 \end{cases} \tag{7}$$

In that case, the P_{min} has been defined as zero for the charging and discharging process, but in this new formulation the charging power $P_{c,t}$ and the discharging power $P_{d,t}$ can be 0 or assume a value between the minimum and maximum. The binary variables $x_{c,t}$ and $x_{d,t}$ have been introduced to determine when (time period) the EVs are charging or discharging.

5.5 Mixed-Integer Non-Linear Programming

The mixed-integer non-linear programming (MINLP) is used in the EVs scheduling mainly when other distributed resources are considered due to their non-linear operation characteristics, and when it is necessary to introduce the network technical constraints such as the lines thermal limits and the bus voltage operation boundaries [86]. The objective functions can be technical or economic taking into account the power losses [87], the operation costs [82], the load balancing [37], the voltages profiles [88], the greenhouse gas emissions [48] among others.

The introduction of the network constraints require the determination of the power flows in the network through its DC or AC models. The AC model is the main challenge due to its complex formulation of the Kirchhoff's law for determining the active and reactive balance in each bus, that can be formulated as:

$$P_{Gi(t)} - P_{Di(t)} = G_{ii} \times V_{i(t)}^2 + V_{i(t)} \times \sum_{j \in L^i} V_{j(t)} \times \left(G_{ij} \cos\theta_{ij(t)} + B_{ij} \sin\theta_{ij(t)}\right) \tag{8}$$

$$\begin{gathered} Q_{Gi(t)} - Q_{Di(t)} = V_{i(t)} \times \sum_{j \in L^i} V_{j(t)} \times \left(G_{ij} \sin\theta_{ij(t)} - B_{ij} \cos\theta_{ij(t)}\right) - B_{ii} \times V_{i(t)}^2 \\ \forall\, t \in \{1, \dots, T\}\,; i \in \{1, \dots, N_B\}\,;\ \theta_{ij(t)} = \theta_{j(t)} - \theta_{j(t)} \end{gathered} \tag{9}$$

where $V_{i(t)}$ and $\theta_{i(t)}$ are the voltage magnitude and angle in each bus *i* and in each period *t*, respectively. The lines characteristics are represented by the variables B_{ij}, and G_{ij} (imaginary and real parts of the admittance matrix corresponding to the *i* row and *j* column). Finally, generated power from different resources are represented by $P_{Gi(t)}$ and $Q_{Gi(t)}$ and the consumption power including loads and storage systems charge (EVs and storage systems) are represented by the $P_{Di(t)}$ and $Q_{Di(t)}$. Additionally, the MINLP formulation includes the same integer variables that are used in MILP.

In general, the use of MINLP is suitable for problems with small number of EVs and other resources (small number of variables). For a large number of resources, the computational requirements and the execution time turn the use of this methodology inadequate for real application. But, the results obtained

are more exact and can takes into account more realistic models of the devices connected to the network. This means that the MINLP can be used in small cases to determine the errors of each approximation made by other techniques [82] or in real applications when a problem is restrict to a small area with few number of resources.

5.6 Stochastic programming

Most of the current researches [31], [78] assume that the load profiles, initial state of charge, driving pattern, grid conditions and electricity price are known and deterministic. However, this is certainly not the case in a realistic scenario. Therefore, there is a need to adopt stochastic approach to reduce the risks introduced by the uncertainties related to mentioned aspects. Recently, some articles [89], [80], [48] have been published with stochastic methodologies to deal with uncertainties in the EVs management.

A stochastic approach is considered in [80] when minimizing the power losses problem. A sample average approximation method [90] is applied to formulate the random inputs and the lower bound estimate principle is used to estimate the optimal value. It is noted that the model is the same as presented in equation (3) of this section (sub-section 5.2). The uncertainties of these parameters are formulated as probability density functions, in which the fixed input parameters are converted into random input variables with normal distributions assumed at each node. N independent samples of the random input variable ω^j, the daily load profile, are selected. Equation (10) gives the estimation for the stochastic optimum $\hat{v}_n$. The function $g(P_{n,t}, \omega^j)$ gives the power losses and $P_{n,t}$ is the power rate of the charger for all the EVs and time steps. $\hat{f}_N$ is a sample-average approximation of the objective of the stochastic programming problem:

$$\hat{v}_n = min\{\hat{f}_N(P_{n,t}) \equiv \frac{1}{N}\sum_{j=1}^{N} g\left(P_{n,t}, \omega^j\right)\} \tag{10}$$

The mean value of the power losses $E(\hat{v}_n)$, is a lower bound for the real optimal value of the stochastic programming problem, v^*,

$$E(\hat{v}_n) \leq v^* \tag{11}$$

$E(\hat{v}_n)$ can be estimated by generating M independent samples $\omega^{i,j}$ of the random input variable each of size N. The M optimization problems are performed where the nonlinear power flow equations are solved by using the backward-forward sweep method [91]. The optimal values of M samples constitute a normal distribution:

$$\hat{v}_n^j = min\left\{\hat{f}_N\left(P_{n,t}\right) \coloneqq \frac{1}{N}\sum_{i=1}^{N} g(P_{n,t}, \omega^{i,j})\right\}, j = 1, \dots, M. \tag{12}$$

$\hat{v}_n^j$ is the mean optimal value of the problem for each of the M samples. $L_{N,M}$ is an unbiased estimator of $E(\hat{v}_n)$. Simulations indicate that in this type of problem, the lower bound converges to the real optimal value when N is sufficiently high:

$$L_{N,M} = \frac{1}{M}\sum_{j=1}^{M} \hat{v}_N^j \tag{13}$$

A forecasted daily load file for the next 24 hours is required in the beginning, then the daily profile of the available set are varied by a normal distribution function. The standard deviation σ is determined in such a way that 99.7% of the samples change at maximum 5% or 25% of the average. In general, the simulation results indicated that the difference between the power losses of the stochastic and the deterministic optimum is rather small.

Other studies such as Fluhr *et al.* [92] uses Monte-Carlo method to generate the probability distributions of the travel paths for one week with the survey ”Mobility in Germany” (MIG), because the original data MIG only provide one day driving behavior; study in [93] uses normal distribution and Poisson distribution to investigate the probabilistic distribution of plug-in time and initial state of charge of EVs. A

fuzzy set model is used in [89] to deal with uncertainties related to electricity market prices and ancillary service deployment signals.

5.7 Robust optimization

Robust Optimization is other suitable method to handle the variables uncertainties [94]. The first step leading to robust optimization was given in 1950s. The main goal was to construct worst-case distributions for well-structured problem classes. The robust optimization came from the robust control community being initially proposed by [95]. But only in the last nineties it has been used in real problems and applications. The robust optimization considers that the uncertainties model is deterministic and set-based. One of the most important characteristics of robust optimization is that the obtained solution should be feasible for any realization of the uncertainty in a given set [94].

The robust optimization method can be used in power systems in several optimization problems due to the consideration of uncertainties in consumption, generation, market prices, and electric vehicles requirements [96]. For example, the adaptive robust optimization is used in [96] to solve the economic dispatch and in [97] to solve the security constrained unit commitment problem. In [98], [99], a robust optimization model is used to solve EV charge/discharge scheduling problem. In [98], both the electricity network and the transport sector constraints are considered in the model which is applied to the real case of Ontario, Canada, to determine Ontario's grid potential for supporting EVs for the planning horizon 2008-2025. In [99], the robust model also includes the distributed generation constraints.

Taking into account the use of robust optimization in a generic economic dispatch presented in [96], it is possible to divide the problem into two stages represented in the objective function

$$min_{p\geq 0,R,\Delta p(\Delta d)}\left(c_p^T P + c_R^T R + max_{\Delta d \epsilon D} c_\Delta^T \Delta p(\Delta d)\right) \tag{14}$$

In the first stage, the dispatch cost and the regulation capacity cost are considered. In the second stage, the worst case performance-based regulation cost is used. The variables P and R represent the energy dispatch decision and the regulation amount for automatic generation control (AGC) units presented in the first stage, respectively. The variable $\Delta p(\Delta d)$ represents the second-stage energy output from the regulation unit, which is adjustable to each demand realization $\bar{d} + \Delta d$, for $\Delta d \in D$, in which D represents uncertainty set. In the economic dispatch problem, the electric vehicles can be considered as a load in charge mode and as generator in discharge mode in the objective functions. The technical aspects of the EVs are considered in the constraints that subject to the objective functions.

5.8 Heuristic and meta-heuristic algorithms

One of the main problems of the EVs scheduling is its interdependency between periods. For instance, the energy stored in the battery in a certain period depends on the decisions applied in previous periods, such as charging/discharging power or energy spent in trips, and also on the decision applied in that period. Besides, a large-scale penetration of EVs can increase significantly the number of variables and consequently the execution time to find an optimal solution in an optimization problem. Considering the complexity, e.g., in [86], a deterministic technique (mixed-integer non-linear programming) is implemented to solve the day-ahead resource scheduling considering a penetration of 2000 EVs and this technique took around 28 hours to obtain the optimal solution. In this kind of problems, it is easily that a large number of variables and constraints is reached, such as 100,000 problem variables in [100]. This problem can be classified as a NP-hard problem [101]. The NP-hard problems include, no polynomial time algorithms, i.e. algorithms that need exponential computation time in the worst case to obtain the optimum solution [102].

The heuristics optimization algorithms intend to solve these problems obtaining a solution near to the optimal (not necessary the optimum) one in a convenient execution time. For example, in the previously mentioned study [86], the proposed meta-heuristic took around 18 minutes to find a solution with a difference close to the optimal one in 0.97%. In order to adapt the heuristics to real problems and to improve their performance, it is necessary to include some additional algorithms in some steps of the heuristics process that results in meta-heuristic algorithms.

An extended overview of the population-based meta-heuristic techniques is presented in [103]. Regarding the use of meta-heuristic in power systems, a review is presented in [104]. Recently, meta-heuristic

methods applied to renewable energy is reviewed in [102]. Thus, the following paragraphs intend to overview the application of some meta-heuristic techniques in the EVs charge and discharge scheduling.

In [100], a variant of PSO is proposed for solving the EVs charge and discharge process that minimizes the operation cost of electric vehicles. The main feature of the proposed method is the inclusion of a process to change the particles velocity in each iteration. Artificial bee colony (ABC) is used in [105] to optimize the management of distributed energy resources, including distributed generation, demand response and EVs. An ABC-based multi-objective algorithm is proposed in [106] to optimally determine the number, locations and sizes of the distributed generation and parking lots.

Genetic Algorithms (GA) is used in [107] to optimize the EVs charge scheduling that aims at minimize the operation costs while taking into account the network supply constraints. In [108], a modified GA algorithm is used to optimize the PHEVs charge patterns that consider multi objectives: 1) the total cost of fuel and electricity and 2) the total battery health degradation over a 24 hours period. The papers concluded that these two objectives are conflicting which resulting in a Pareto front optimal charge pattern.

Simulated annealing (SA) is proposed in [109] to schedule the EVs charging and in [110] to schedule the charge and discharge process, including the AC power flow constraints. One of the main disadvantages of SA is its dependency of the initial solution. Hence, in order to overcome this characteristic, a hybrid approach is proposed in [86] using an ant-colony optimization (ACO) algorithm to determine the initial solution that will be used by SA. The same authors [111] proposed two heuristics to obtain a good initial solution for the EVs and distributed generation, respectively. These heuristics presented an initial solution worse than the ACO in [86], however shown a much lower execution time than the ACO algorithm. Beyond the mentioned use of ACO to provide the initial solution to SA proposed in [86], a hybrid PSO and ACO algorithm is proposed in [112] to deal with short-term unit commitment problem with EVs considering different reliability limits.

5.9 Model Predictive Control

Model predictive control (MPC) is a control algorithm that optimizes a sequence of manipulated variable adjustments over a prediction horizon. The main advantage of MPC is the fact that it allows the current timeslot to be optimized; meanwhile it takes future timeslots in account. This is achieved by a finite time-horizon optimization, but only implementing the current timeslot. MPC has the ability to anticipate future events and can take control actions accordingly. The use of MPC in EVs smart charging is proposed in [113], considering the cost minimization objective function. The model takes into account the EV drivers' preferences, technical bounds on the control action (the charging rate is modeled as a semi-continuous variable) and both market and grid constraints. In [114], a MPC based power dispatch approach is proposed to minimize the operational cost while accommodating the PEV charging uncertainty. In [115] the economic MPC is used for electric vehicle charging planning. The model considered that the EVs can be used for both peak reduction and for ancillary services, by absorbing short term variations in the electricity production. According to the study, the use of proposed model can lead to 50-60% of savings when compared to uncontrolled charging. A two-stage hierarchical MPC model is proposed in [116]. On the upper level, the model considers the voltages deviations through the control of the generators. On the lower level, the model controls the EVs charging taking into account the driving requirements. The MPC method is also used in some experiments [117]. The experiences are made under the context of the “SMARTV2G” project and the focus is the implementation of a centralized demand side management using MPC control algorithm, which allows remote real time control of the charging stations considering the players preferences.

5.10 A summary of the presented algorithms with three types of criteria

In table 5, the information of the presented algorithms in terms of computation time, certainty of performance and applicability is summarized. The summary aggregates the comparisons described in the literatures in term of execution time and performance of the presented algorithms. The applicability of the presented algorithms is summarized from two perspectives.

Table 5. General comparison between the presented algorithms

Control algorithms	*Execution time*	*Certainty of Performance*	*Applicability in general*	*Applications to EV charging*
Linear programming Used in: [78].	Generally, it is the fastest one.	Results in [78] showed that the performance is excellent in term of finding the optimal solution.	1) The objective function is linear, and the set of constraints is specified using only linear equalities and inequalities. 2) Standard model, easy for implementation.	Minimize charging cost of EVs.
Quadratic programming Used in: [78], [80].	Ref. [78] showed that the calculation time using the QP is 819 times than the one using LP for a fleet of 50 vehicles.	Ref. [78] showed that the difference between using LP and QP is minor. Therefore, the benefit of using the QP does not justify the increase in computation time.	1) The objective function has quadratic terms, while the feasible set must be specified with linear equalities and inequalities. 2) Standard model, easy for implementation.	1) Minimize charging cost of EVs. 2) Minimize power losses of power systems.
Dynamic programming Used in: [31], [80].	Ref. [80] indicated that the computational time for DP is slower compared to QP.	Ref. [80] showed that the difference between the charging profile of using QP and DP is negligible, although the QP gave more accurate results.	1) Studies the case in which the optimization strategy is based on splitting the problem (EV charging schedule) into smaller sub-problems (multi-time slots). 2) No standard model, difficulty increases for complex problem. 3) Give global optimal result.	1) Minimize charging cost of EVs. 2) Minimize power losses of power systems. 3) Maximize profit of providing regulation services.
Mixed-integer Linear programming Used in: [81], [83]-[85].	The execution time depends substantially on the number of binary and integer variables.	The objective function is similar to the LP and QP problems when the same constraints are considered. However, the binary and integer variables can change significantly the operational limits.	1) Studies considering a short time to obtain the solution. 2) Model the discrete operation of some power components (e.g. capacitor banks). 3) Start-up and shut-down costs.	1) Minimize charging cost of EVs. 2) Minimize losses of power systems. 3) Maximize profit of providing regulation services.
Mixed-integer Non-linear programming Used in: [86]-[88].	Ref. [82] indicated that the computational time is highly dependent of the number of EVs. Other important aspect is if the problem considers the DC or the AC network model.	Ref. [82] shows that the operation cost increase due to the losses are considered in the model. The main advantage is the network technical constraints validation.	1) Studies considering the network technical constraints. 2) Tested in single and multi-objective functions. 3) Give global optimal result.	1) Minimize charging cost of EVs. 2) Minimize power losses of power systems. 3) Maximize profit of providing regulation services. 4) Load levelling.
Stochastic programming Used in: [80], [92], [93].	The computation time is longer generally because more scenarios are considered.	The simulation results in [80] indicated that the difference between the power losses of the stochastic and the deterministic optimum is rather small.	Studies the case in which some of the constraints or parameters (Load profile, driving pattern etc.) depend on random variables.	1) Minimize charging cost of EVs. 2) Minimize power losses of power systems. 3) Maximize profit of providing regulation services.
Robust Optimization Used in: [96]-[99].	As in stochastic optimization, the computation time is longer generally because more scenarios are considered.	According [96], the robust optimization is less complex to implement in real problems than the stochastic optimization. However, the stochastic optimization is more mature technique, tested	Studies the case in which some of the constraints or parameters (Load profile, driving pattern etc.) depend on random variables.	1) Minimize charging cost of EVs. 2) Minimize power losses of power systems. 3) Maximize profit of providing regulation services.

		to solve several problems.		
Heuristic and meta-heuristic optimization Used in: [86], [100]-[112].	The exaction time is lower when compared with other techniques. However depends a lot of the used technique and also the required results quality.	In [86] and [100], there is solved optimization problems with different scenarios and the meta-heuristic results presented a small error lower than 1% in comparison with the optimal solution.	1) Studies considering the network technical constraints. 2) Tested in single and multi-objective functions. 3) Tested in problems considering the uncertainties. 3) Use of several techniques and several hybrid methods. 4) Give a local optimal result.	1) Minimize charging cost of EVs. 2) Minimize power losses of power systems. 3) Maximize profit of providing regulation services. 4) Load levelling.
Model Predictive Control Used in: [113]–[117].	This technique presents a low execution time, therefore it is a suitable approach to be used as control method in near-real time operation.	In [113], the MPC method obtained excellent results in a rolling scheduling problem, considering different predictions in the method, such as EV drivers' preferences.	Method used for studies in scheduling and near-real time operation, considering some uncertain parameters.	1) Minimize charging cost of EVs. 2) Minimizing the network voltage deviations.

6 Mathematical modeling and control algorithms: transactive control of fleet operator

The following papers [52], [71], [118], [119]–[122], are selected to illustrate the transactive control's application in EV fleet management. In [52], transactive control method is applied to solve distribution network grid congestion between the distribution system operator and the electric vehicles fleet operators. Firstly, EV fleet operators formulate a cost function that reflects the charging power deviation from the scheduled charging power, e.g., in the form of a quadratic function:

$$\mu_{k,i} = C_{k,i}\left(\tilde{P}_{k,i} - P_{k,i}^{E}\right)^2 \tag{15}$$

where k is the index of EV fleet operator, i is the index of time slots. $\tilde{P}_{k,i}$ is the decision variable, $P_{k,i}^{E}$ is the scheduled charging power and it is the optimal charging schedule for EV FO. However, the sum of the charging schedule $P_{k,i}^{E}$ may bring operational challenge to DSO and thus it needs to be modified. The overall objective is to minimize the cost function of EV FOs with respect to the grid capacity constraints. The minimization is formulated as a Lagrange problem and solved iteratively using a decomposition algorithm. The Lagrange multipliers are interpreted as congestion price that coordinates the EV FO's charging profiles. Furthermore, the study is extended in [118] to solve the voltage band violations by introducing congestion prices on the buses level.

In [71], Ipakchi pointed that a higher penetration of distributed resources will require a greater attention to distribution congestion issues and a need for improved distribution automation and distribution management capabilities. A transactive control approach is proposed to solve the problems. In the example described in [71], a plug-in electric vehicle requests using 7.8 kWh of charging energy over the next two hours. This request can be presented as a demand transaction and sent to a demand-side management application operated by the utility distribution company. Knowing the transaction delivery point to which the car charger is connected to, this application will check the available capacity of the secondary distribution transformer, lateral and feeder circuits. Then it determines whether the additional load will impact the circuit reliability and cause any adverse phase imbalances. The demand-side management application will then schedule the charging for the requested time period. At the same time, the application may receive many more information such charging requests that have to be checked, and in aggregate they have to be coordinated with wholesale scheduling at substation supplying the feeders to ensure adequate supply. Each of these actions could be modelled as a transaction between a consumer system, a utility decision support system, distribution field equipment and supply scheduling system in an aggregate form.

Ma *et al.* [119] formulate a class of finite-horizon dynamic game (or a transactive control system) to optimally control the charging profile of a large-scale of electric vehicles. Within the game, the control objective is to minimize electricity generation costs by establishing an EV charging schedule that fills the overnight demand valley. Moreover, the paper establishes a sufficient condition under which the system converges to the unique Nash equilibrium. The key formulas are listed below:

$$x_{t+1}^n = x_t^n + \frac{\alpha^n}{\beta^n} u_t^n, t = 0, \dots, T-1 \tag{16}$$

where x^n is the state of charge of EV_n, $\alpha^n$and β^n means the charging efficiency and battery size of EV_n, and u^n represents the local control variable. The purpose of the study is to find the set of feasible full charging controls, which are described as follows:

$$\omega^n := \{u^n \equiv (u_0^n, \dots, u_{T-1}^n); s.t. u_t^n \geq 0, x_T^n = 1\} \tag{17}$$

where the final constraint on x_T^n requires that all EVs are fully charged by the end of the interval. The cost function of agent n, denoted by $J^n(u)$ is used as criteria and specified as:

$$J^n(u) := \sum_{t=0}^{T-1} \{p(r_t)u_t^n + \delta\left(u_t^n - avg(u_t)\right)^2\} \tag{18}$$

where each agent's optimal charging strategy must achieve a trade-off between the total electricity cost $p(r)u^n$ and the cost incurred in deviating from the average behavior of the EV population$\left(u^n - avg(u)\right)^2$. With these criteria and certain conditions, the theorem about the existence of the Nash equilibrium is presented in the paper [119]. The proposed algorithm ensures convergence to a flat, or optimally valley filling aggregate charging profile. In order to implement the transactive control system, an iterative algorithm for computing the unique Nash equilibrium is proposed which includes four steps: 1) The utility/fleet operator broadcast the forecast of base demand to all the EVs. 2) Each of the EVs proposes an optimal charging strategy that minimizes its charging cost with respect to a common aggregate EV demand broadcasted by the fleet operator. 3) The FO collects all the optimal charging strategies proposed by the individual EVs, and updates the aggregated EV demand to all EVs. 4) Repeat step 2) and 3) until the optimal strategies proposed by all EVs no longer change. Similar study is performed in [120] where Gan *et al.* further proved that transactive control based algorithm converges to optimal charging profiles, irrespective of the specifications of EVs, even with asynchronous computation. Besides, the authors also extended the algorithm to track a given load profile and to real-time implementation.

In [121], a scalable three-step approach for demand side management of EVs is presented. The three steps consist of aggregation, optimization and control. In the aggregation step, individual EV charging constraints are aggregated upwards. In the optimization step, the aggregated constraints are used for scalable computation of a collective charging plan, which minimizes costs for electricity supply. In the real-time control step, the calculated charging plan is used to create an incentive signal for all EVs, determined by transactive control method. These three steps are executed iteratively to cope with uncertainty and dynamism. The modeling method of the real-time control step is presented as follows:

1) The individual power constraints of an EV *i* at time *t=0* are represented in a demand vector ${}^iP^{dem}$, which contains all possible power values for charging the EV's battery. These power values vary between ${}^iP^{min}$ and ${}^iP^{max}$, and are specified by a self-defined piecewise linear function ${}^if_d$.

$${}^if_d = \begin{cases} P_{max}^i - \rho^r \left(\dfrac{P_{max}^i - P_{min}^i}{{}^i\rho_c^r}\right), & 0 \leq \rho^r < {}^i\rho_c^r \\ P_{min}^i, & {}^i\rho_{min}^r \leq \rho^r < \rho_{max}^r \end{cases} \tag{19}$$

$${}^iP^{dem} = \left\{ {}^iP_{\rho^r}^{dem} \mid {}^iP_{\rho^r}^{dem} = f_d(\rho^r), \forall \rho^r \in \{0, \dots, \rho_{max}^r\} \right\} \tag{20}$$

where ${}^{i}\rho_c^r$ the corner price of EV *i*, and the corner price of EV *i* is a heuristic which determines the slope of a demand function.

2) Based on the piecewise linear function ${}^{i}f_{\mathrm{d}}$ defined in (19), the FO uses the aggregate demand functions and the optimal charging decision obtained in optimization step, i.e., P_0 in the original paper to generate the equilibrium price ρ_{eq}^r.

3) This equilibrium price is sent to all EV agents. Upon receiving the signal, each EV agent will locally match ρ_{eq}^r in its own demand vector, which amounts to the individual charging power.

In [122], the auction based transactive control is applied to control the cluster of loads with the purpose of providing spinning reserves. Firstly, each device defines an utility function for the utilization of the electricity, e.g., the corner price model developed in [121] is applied for calculating a bid function of an EV. Then, in real-time operation, all the device agents send their bid to a concentrator agent or fleet operator agent. The concentrator agent sums up the bid functions of their zone and then sends the aggregate bid function to a unique auctioneer agent. Finally, the auctioneer agent will define the equilibrium price as the intersection of the aggregate bid functions and the supply bid function. After the equilibrium price is defined, it is sent back to all of the devices agents and the corresponding power of the device agents will be determined. The market clearing takes place every 15 minutes or can be made event-driven. Furthermore, the transactive control method is extended to cooperate in frequency reserve markets.

In summary, a key operational parameter used in transactive control is value (i.e., cost/utility functions in [52], [71], [118], [119]–[122]) and thereafter the equilibrium price can be discovered and the transaction can be executed. It is seen that iterative information exchange is required to reach equilibriums between the fleet operator and electric vehicles in [52], [118], [119], [120], while only one-time information exchange is required in [71], [121], [122] to reach the equilibrium. Furthermore, the modelling methods and algorithms to implement the transactive control for electric vehicles integration are summarized and compared in Table 6.

Table 6. General comparisons among the presented studies

References	***Modeling methods***	***Key features***	***Control/computing algorithms***	***Applications to EV charging***
[52] [118]	Convex optimization modeling.	A hierarchical control structure is proposed that includes DSO, FO, and EVs.	Dual decomposition algorithms.	1) Prevent distribution grid congestion. 2) Solve Voltage problem. 3) Minimize charging cost.
[71]	Auction based decision making.	Market platform is needed at the distribution system level.	Merit-order based method.	Prevent distribution grid congestion.
[119]	Non-cooperative game theory method.	The existence, uniqueness and optimality of the Nash equilibrium of the EV charging problems are studied.	A decentralized computational algorithm is developed to reach the convergence.	Minimize electricity cost.
[120]	Optimal control theory with convex function.	Compared with [119], it is proved that asynchronous computation can also converges to optimal charging profile.	A decentralized algorithm is proposed to iteratively solve the optimal control problem.	Aims for flat loading profile.
[121]	Piecewise linear cost function.	Iteration of the three-step approach is proposed to address the uncertainty of EV's charging plan.	Dynamic programming.	1) Minimize charging cost. 2) Prevent overloading problem.
[122]	Distributed utility maximization problem.	Devices can identify their value of the received energy using utility functions.	A general multi-agent framework is used.	Primary and Secondary Frequency control.

7 Mathematical modeling and control algorithms: price control of fleet operator

Price signal used in the price control ranges from time-of-use electricity rate/tariff [74], [123] to hourly varying prices [75], [124]. Shao *et al.* [74] focused on the development of demand response model for

residential customers with EV penetration that reflects customer behaviors in response to variable electricity prices. Nine types of residential customer loads are divided into three groups: critical, interruptible and deferrable loads. Of which, the deferrable load means it shuts down the equipment when price is higher than a pre-determined value, the load will be shifted to less-expensive hours. EV fits into the 'deferrable load' type. It is assumed that if the time-of-use price is increased by 100% from its corresponding flat rate, 20% customers are willing to shift or shed their non-critical load. For simplicity, the participation function is linear. Two EV penetration levels are studied consist of low penetration level and high penetration level. There is one EV for every five houses in the low penetration level and there are two EVs for every five houses in the high penetration scenario. With the time-of-use electricity rate, it is shown in the paper that the time-of-use rate helps reducing the peak load. Note that if the EV users use timing device to largely avoid the peak tariff and charge it in less-expensive hours, rebound effect [125], [126] may exists due to the time-of-use electricity tariff. As discussed in [127], since there is no inertia in EV charging process, the rebound comes faster and the peak value depends on the previously curtailment period and the size of curtailed energy. The problem can be solved by a well-designed time-of-use electricity tariff and diversified EV responsive strategies.

The relationship between EV charging behavior and time-of-use rates are specifically explored in [123] where suggestions are made for conducting a well-designed pricing experiment. The purpose of the experiment is to determine whether such rates help reducing future grid reliability problems as EV penetrate in the vehicle market. In [123], the EV user will charge the vehicle 25 times during the month based on assumptions of a monthly travel miles of 1,250 and each charge lasts four hours. Three types of time-of-use rates are used and each rate has three pricing periods: peak, mid-peak, and off-peak. In the simulation study, the authors developed a conditional logit model to get the choice probabilities of EV charging in presences of different time-of-use rates. The simulation results shown that a value of -0.80 will be needed to effectively eliminate peak time charging introduced by electric vehicles' charging and a value of -0.25 will be needed to eliminate half of the normal peak time charging load, after running simulations with a wide range of price elasticity.

Yu *et al.* [75] investigated the price elasticity of electricity consumers and these are also the important aspects in price control method. In [75], the marginal utility function of loads is realized by the following parametric stochastic process

$$r(t) = \begin{cases} \beta - \delta(t-\alpha), & \alpha \le t \le \alpha + \gamma; \\ 0, & otherwise. \end{cases} \tag{21}$$

where $\alpha, \beta, \gamma, \delta$ are random variables that describes the different characteristics of utility function, α stands for the time slot that a task is initially requested, which also reflects the task distribution, β is the initial marginal utility, which stands for the magnitude of the marginal utility, γ is the tolerable delay, which determines the maximum delay that a user can tolerate to finish a task, δ means the utility decay rate, which represents the cost of inconvenience by the delay.

Using the model, the scheduling of each individual task is now a random event whose probability distribution is controlled by the stochastic process $r(t)$. The aggregate demand curve can be estimated through expectation with respect to the distribution of $r(t)$. Note that some assumptions have been made in [75], such as the time period of the scheduling is divided into *T* time slots, there are total *M* individual tasks *m: m=1,…, M* of different appliances that are to be initialized by all the users within the scheduling period, and each task will consume x_m kWh. Furthermore, it is assumed that each task can be completed within one time slot; therefore, tasks that have duration longer than one time slot will be decomposed into multiple tasks that are considered independently.

Huang et al [124] proposed a distribution locational marginal pricing (DLMP) method through quadratic programming designed to alleviate congestions that might occur in a distribution network with high penetration of flexible demands such as electric vehicles and heat pumps. In the DLMP method, the DSO calculates dynamic tariffs and sends them to the fleet operators. The fleet operators make the optimal energy schedules for the flexible demands. It is proven in the study that the DLMP through quadratic programming modeling can ensure a unique marginal price for the FOs. Instead, DLMP through line-

ar programing modeling [128] might bring multiple solutions issue of the fleet operator optimization that may cause the congestion management by DLMP to fail. The case studies showed that DLMP helps alleviating congestion problem. It is also shown that the linear programming based modelling can lead the failure of the DLMP.

In summary, studies [74], [75], [123], [124] suggested that the electricity price can be properly designed to reduce the peak demand as EVs penetrate in the vehicle market. However, it is also noted in [74], [75], [123] that to which extent the properly designed price signal could assist in maintaining grid reliability will remain open until empirically tested EV owner's price responsiveness through experiment pilots are known. When investigating EV owner's price responsive behavior, decomposition methods [2]–[6] widely used in energy economics field can be applied to find the relation between EV's charging response and electricity price, state of charge, customer driving habits and reasons for buying the EV etc. Additionally, Table 7 depicts the information of the presented algorithms in terms of modeling methods, key features, price signal format and applications to EV charging. The presented algorithms are also summarized and compared in this table.

Table 7. General comparisons among the presented studies

Refer-er-ences	***Modeling methods***	***Key features***	***Price signal format***	***Applications to EV charging***
[74]	Three types of load shedding and shifting strategies are defined logically.	Household loads and EVs charging profile are studied.	Time-of-use tariff.	Reduce the peak demand.
[123]	Conditional logit model.	A social experiment is suggested to estimate the price response of EVs' charging.	Time-of-use tariff.	Avoid transformer overload.
[75]	1) Parametric utility model. 2) Stochastic expectation model.	Compared to [74], utility functions are developed for the three types loads: critical, interruptible and deferrable load.	Dynamic price signal.	Reduce the transformer overload.
[124]	Distribution locational marginal pricing method via QP.	It is discussed that compared with linear programming based DLMP formulation [128], QP based formulation ensures convergence to the DLMP.	Dynamic price signal.	Manage distribution network congestions.

8 Conclusion and recommendations

8.1 Conclusion

As a conclusion, it is learned from this study that centralized control, transactive control and price control show their pros and cons for management of an electric vehicle fleet. Centralized control offers best performance in controlling the EV fleet and therefore making better optimized charging profiles. For the centralized control, a linear programming based technique is recommended to characterize the optimal charging problem and generate the optimal charging schedule. In order to generate an optimal charging schedule, a forecasted electricity price and predicted EVs driving pattern are essential. Fortunately, they can be estimated by the commercial actors. Nevertheless, EV owners are encouraged to submit a provisional EV utilization plan for next day to the commercial actor for generating an optimal charging schedule. For the centralized control to become a success, more research is needed in setting up a collaborative business model which ensures the proper engagement of commercial actors and EV owners. Transactive control shows its advantages such as providing controllability of the EVs to the end-users and scalability of implementing the method in a large scale of electric vehicles. However, for the transactive control to become a success, some barriers needed to be resolved. For instance, an automated negotiation device which is not yet available needs to be mounted in the EV that performs the enabling function required in the transactive control. Price control is probably the most attractive way for the commercial actor to regulate the charging behavior of the EVs considering its easier implementation. It is especially effective in the case of decreasing the charging in the peak time for distribution system

operator or the case of increasing the load for transmission system operator. For the price control to become a success, more research is needed in price responsive models or price elasticity models to obtain satisfactory performance and grid reliability.

The following benefits of present study can be identified:

- The study outlines potential services that EV fleet operator could provide in a smart grid;
- The advantage and disadvantage of centralized, transactive control and price control are discussed, which gives a basis for comparing available methods for future developments;
- Details of the modelling method and algorithms of each control strategy are illustrated by showing the key formulas and compared in term of their performance, calculation time, communication and computation requirements etc.

8.2 Recommendations on future research directions in the area

Based on the discussions in the present study, future research directions are suggested as following:

- Coordinate the multi-objectives of smart charging of EVs

Recently, the trend in smart charging of EVs is to integrate the interests of EV owners, ancillary services required by the transmission system operator and the distribution system operator. This is because the conflict might exist in certain cases when involving electric vehicle flexibility which is explained in section 2.2.5.

- Real time EV fleet management

It should be observed and emphasized that the above discussion did not consider the real time operations, i.e., there is no continuous monitoring and assessment of the state of electric vehicle battery dynamics and therefore lack of the appropriate response in abnormal situations. This means that real time control method considering the dynamic behavior of EV fleet and power systems should be developed as well.

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