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Smart charging of electric vehicles considering photovoltaic power production and electricity consumption: A review

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ABSTRACT

Photovoltaics (PV) and electric vehicles (EVs) are two emerging technologies often considered as cornerstones in the energy and transportation systems of future sustainable cities. They both have to be integrated into the power systems and be operated together with already existing loads and generators and, often, into buildings, where they potentially impact the overall energy performance of the buildings. Thus, a high penetration of both PV and EVs poses new challenges. Understanding of the synergies between PV, EVs and existing electricity consumption is therefore required. Recent research has shown that smart charging of EVs could improve the synergy between PV, EVs and electricity consumption, leading to both technical and economic advantages. Considering the growing interest in this field, this review paper summarizes state-of-the-art studies of smart charging considering PV power production and electricity consumption. The main aspects of smart charging reviewed are objectives, configurations, algorithms and mathematical models. Various charging objectives, such as increasing PV utilization and reducing peak loads and charging cost, are reviewed in this paper. The different charging control configurations, i.e., centralized and distributed, along with various spatial configurations, e.g., houses and workplaces, are also discussed. After that, the commonly employed optimization techniques and rule-based algorithms for smart charging are reviewed. Further research should focus on finding optimal trade-offs between simplicity and performance of smart charging schemes in terms of control configuration, charging algorithms, as well as the inclusion of PV power and load forecast in order to make the schemes suitable for practical implementations.

1. Introduction

In the Paris agreement, most nations agreed to limit the global temperature increase to 2 °C above the pre-industrial level by 2030 [1]. In order to reach this target, the emissions from the transportation sector should be reduced, as they currently contribute to a quarter of the global greenhouse gas (GHG) emissions [2]. However, the emissions from the transportation sector have not improved in recent years compared to other sectors [3] and road transportation has been a significant source of GHG [4–6]. Electrification of road transportation is believed to be a promising solution to reduce the GHG emissions and has consequently been boosted in recent years [7]. The coupling of electric vehicles (EVs) with renewable electricity generation could play an important role in gradually improving the emission factor of the road transportation sector. In Refs. [8,9], it was shown that the well-to-wheel (WTW) emissions of an EV recharged from a mix with a large share of coal-based power generation is comparable to gasoline-based internal combustion engine vehicles (ICEVs), while recharged with a large share of electricity generated by solar or wind power installations, the WTW emissions of an EV could be close to zero. In another study [10], it was concluded that charging 50,000 EVs using renewable energy sources (RESs) could reduce the GHG emissions by up to 400 Mtons per year.

Awareness of GHG emissions and their effect on the environment have increased the adoption of both EVs and RES, such as photovoltaic (PV) power production [11,12]. In 2017, there were 3 million EVs on the roads worldwide, which is a 500% increase from

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2013. With an ambitious target of making EVs represent 30% of the global new personal vehicle sales by 2030, the number is expected to grow exponentially [7]. A significant growth is also taking place with PV. The total global installed PV capacity was around 400 GW as of 2017, producing around 600 TWh annually [13]. Moreover, this is expected to increase up to more than 1 TW in capacity and 1500 TWh in annual energy yield by 2023 [13].

However, the rise in EV and PV integration poses new challenges to power distribution grids. Current distribution grids have not been designed to host large volumes of intermittent distributed generation and uncontrolled EV charging [14]. Uncontrolled and uncoordinated EV charging might degrade the power grid performance and could lead to the collapse of existing power grid operation [15]. While for PV, high penetration of PV power leads to the so-called duck-curve [16] and overvoltage problems [17] due to mismatch between supply and demand. With noticeable increases in the penetration of both EVs and PV, power grids might need reinforcements in the near future in order to maintain operational performance which are costly and time inefficient [18].

On the individual building level, the introduction of the net zero energy building (NZEB) concept has increased building-applied renewable energy, especially PV [19]. In NZEBs, the annual energy use of the building should be matched by on-site renewable generation [20]. EVs can be considered as an extra load connected to the house; consequently, EV-PV synergy in buildings can help the buildings to reach the NZEB level [21]. However, PV power production is not always available when the electricity is needed. This leads to seasonal and diurnal mismatch between PV power production and electricity consumption which is not addressed in the NZEB concept since it mostly considers only the annual energy balance. A building with a PV system that provides as much energy as it uses in a year will not be able to avoid occasional shortage of self-produced electricity [20]. Adding on-site storage, i.e., batteries, has been one of the most common and effective solutions to overcome these load mismatch problems [22]. However, adding an on-site storage system can be costly and not economically feasible [22–24]. Besides on-site storage, demand side management (DSM) is also an efficient strategy to deal with such problems [22,25]. Even though impacts from DSM alone are more limited compared to the impacts from adding on-site storage, DSM is still a popular alternative [22,25]. This is especially true due to the high costs of storage systems [22–24].

Flexible loads are the pillars of DSM schemes. Compared to other electric appliances, EV charging load offers more flexibility. Based on a survey, vehicles are parked 22 h on average, with 16 h, on average, of uninterrupted or inactive parking [26]. This creates an opportunity to shift the charging load through smart charging control without violating the convenience of the users such as having a full battery by the time of departure in the morning. EV smart charging could be categorized as a specific type of DSM for EVs [27]. Smart charging on building level can improve load matching, thus increasing both the self-consumption and the self-sufficiency [21,28]. On the power grid level, smart charging can be used to reduce component loading, balance the load, and minimize voltage and frequency fluctuations [14], which improves the hosting capacity.

Given the potential for a massive integration of EVs and PV into the power system and built environment, it is interesting to review what solutions to the above challenges have been proposed in existing research on EV smart charging. Several recent papers have reviewed various aspects of EV smart charging and EV-PV-load interactions. Demand side management strategies for high self-consumption of PV power production have been discussed quite extensively in Ref. [22], but EVs are not the main focus and smart charging is not even considered. Thorough reviews on optimization methods for smart control of EV charging have been conducted in Refs. [29–33] with broader focuses, leaving only a little room for EV-PV-load interactions. In Ref. [27], the review of smart charging of EVs mainly focused on the control configuration of EV charging. In Ref. [34], EV charging from PV power is reviewed with the main focus on control architecture and components. EV charging interaction with PV power production has been reviewed to some extent in Refs. [21,35]. EV charging from the perspective of the smart grid is reviewed in Refs. [36,37]. However, detailed discussions on smart charging control strategy in Refs. [21,27,34–37] are very limited.

To the knowledge of the authors, there has not been any detailed review on charging control and coordination strategies with respect to PV power production and electricity consumption patterns. Smart charging of EVs can involve many factors and objectives, e.g., solar power production, wind power production, grid balancing, electricity pricing, etc. This paper limits the scope of the review to studies including PV power production and electricity consumption. In other words, smart charging studies that involve PV and electricity consumption profiles, especially with objectives or sub-objectives related to increasing PV power utilization and load balancing, will be discussed here. This paper also discusses spatio-temporal aspects of smart charging, which have rarely been reviewed previously.

The main contributions of this paper can be summarized as follows:

- A comprehensive discussion on the interaction between PV power production, electricity consumption and EVs and the role of smart charging within it is provided.
- A detailed discussion on various smart charging objectives involving PV power production and electricity consumption is provided.
- Two aspects of EV smart charging configuration are reviewed: control configuration (centralized/distributed) and spatial configuration (home, workplaces, charging stations, etc.).
- Various proposed mathematical models and control algorithms of smart charging are discussed in depth. Both optimization and rule-based approaches for smart charging used in recent works are presented along with the main results.
- Discussions, research gaps and recommendations for future work related to EV smart charging are also included.

Fig. 1 presents the overall contents of this paper. The rest of this paper is organized as follows. In Section 2, the interaction between PV, EV and electricity consumption is discussed. Sections 3–5 review smart charging objectives, configurations and mathematical models and control algorithms respectively. Section 6 presents the concluding discussions on several open issues and suggestions on future work for EV smart charging considering load and PV.

2. Interaction between PV, EV and electricity consumption

A general introduction to electricity consumption, PV power production and EV charging is provided in this section. The interaction between these three components, and how smart charging can contribute to improved synergies, are also presented and discussed.

Electricity consumption is defined by numerous variables, such as human and industrial activities, and spatio-temporal and climate conditions [19,38,39]. The electricity demand varies between cold and hot climates mainly due to heating, ventilation and air conditioning (HVAC) devices. Regardless, when it comes to the daily load shape, the pattern is strongly correlated with human activity [38]. Fig. 2 (a) shows a typical electricity demand profile on regional level, which clearly reveals the diurnal activity patterns [40–42].

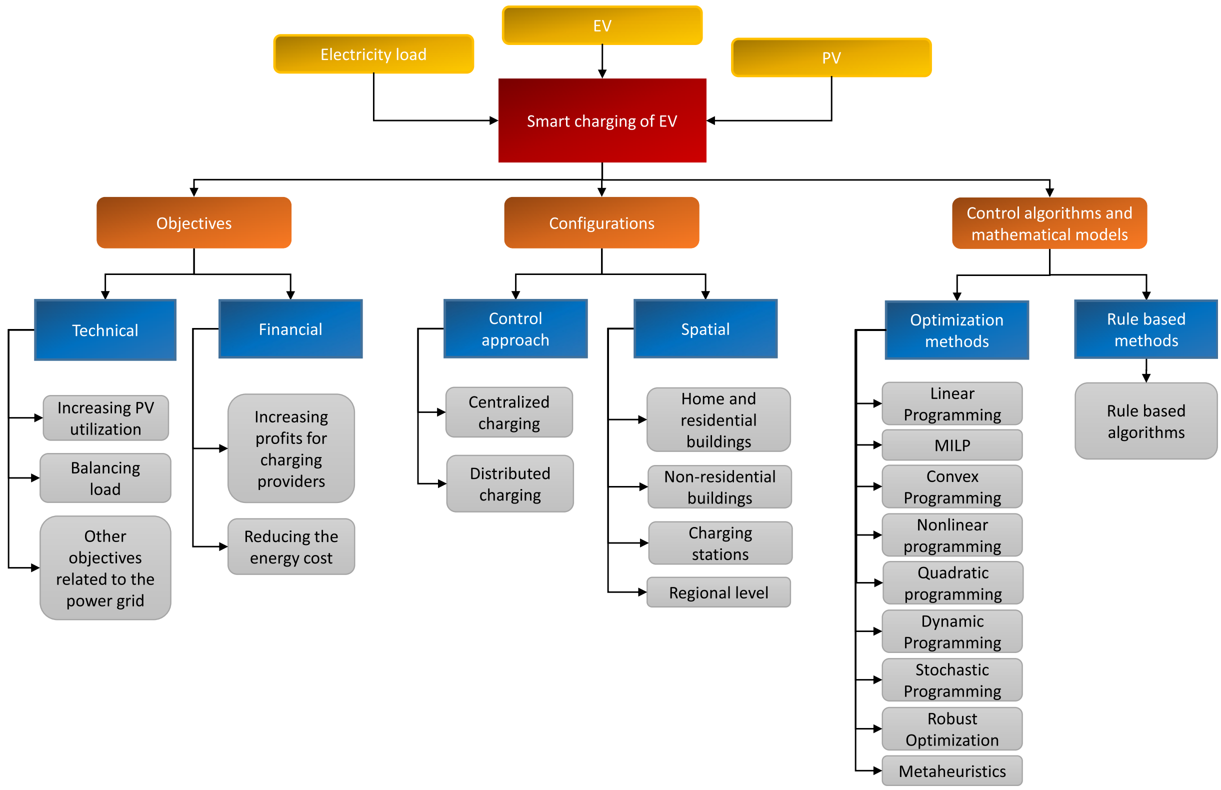

Fig. 1. Summary of the smart charging research reviewed in this study.

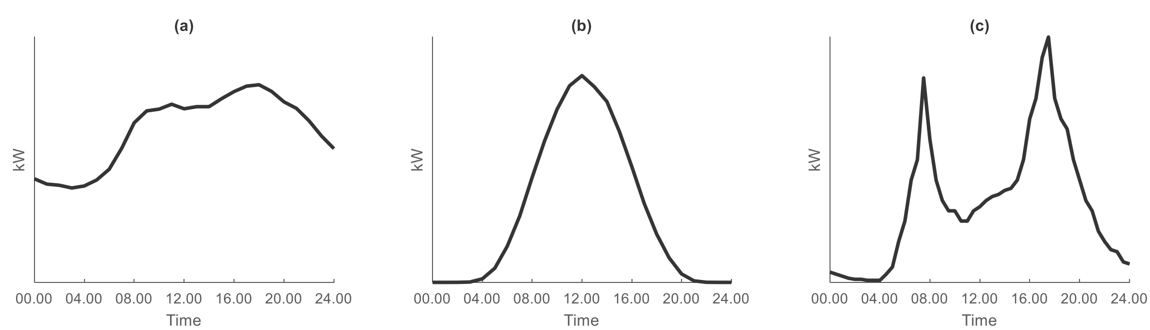

Fig. 2. (a) Electricity load profile in Sweden on a day in January 2019, obtained from Ref. [41], (b) Typical PV power production profile based on daily average solar global horizontal irradiance curve for Stockholm, obtained from Ref. [45], (c) Typical city scale EV charging load shape inspired by the model in Ref. [46].

PV systems convert incident solar irradiance into electric power. PV power production varies depending on location and orientation and depends directly on the apparent position of the sun in the sky [43]. Close to the equator, there is little seasonal variation in the number of daily sun hours and the irradiation follows a consistent diurnal pattern, while at high latitudes, the number of sun hours and the solar irradiation vary strongly between seasons. In addition to this deterministic pattern, cloudiness decreases the power generation [44]. Fig. 2 (b) illustrates a typical PV power production profile averaged over a year.

Uncontrolled EV charging profiles are defined by the daily mobility patterns or activity schedules of the vehicle users [47]. An illustration of the charging demand on city scale, which includes home charging, workplace charging and charging at other locations inspired by the work in Ref. [46] is shown in Fig. 2 (c). Results show that with the model in Ref. [46], the total load has two peaks, one between 06.00 and 10.00 due to charging at workplaces, and the other one between 16.00 and 20.00 due to home charging. The peaks of EV charging load coincide with periods of high electricity consumption. One reason for this is that with opportunistic charging (charging upon arrival), charging starts simultaneously with other human activities such as early morning workplace activities and evening activities at homes. Unfortunately, this is not the case with solar power production since the peaks are in the midday. Currently, many electric grids have low load factors or utilization factors due to high demand in the late afternoon and low demand from midnight to morning [14]. This will become worse with increasing uncontrolled EV charging load, which might lead to needs for grid reinforcement.

The future load curve is likely to experience drastic changes due to increasing amounts of PV generation and EV charging load [40]. Inspired by Refs. [17,48], Fig. 3 presents an example daily net-load curve in the residential distribution grid with large shares of PV and EVs. High PV penetration will create higher ramps in the

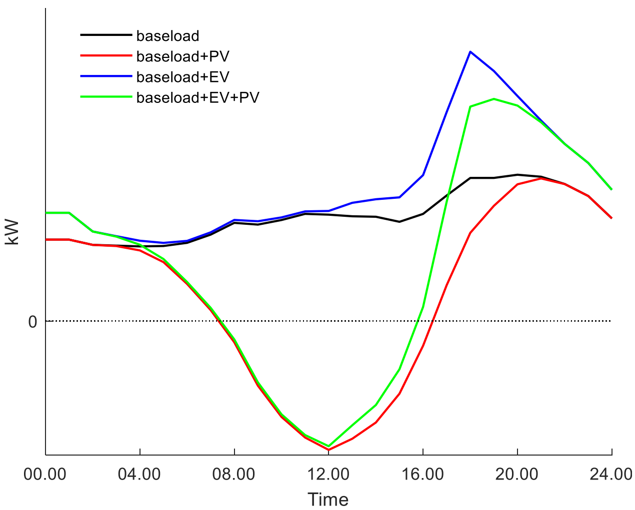

Fig. 3. Typical net load shapes in several scenarios in residential distribution grids inspired by Refs. [17,48].

morning and the evening, which is called a duck-curve [49]. The duck curve becomes more prominent with the addition of large scale of uncontrolled EV charging [21,50]. Hence, new strategies for managing power systems that can support the increase of PV and EVs might be needed in the future.

On the building level, increasing both self-sufficiency and self-consumption of buildings has been attractive to many stakeholders due to the increased demand for high performance NZEBs [20,22]. Different building types have different load profiles and EV charging profiles. In residential areas, for example, the occupancy fraction of EVs available during working hours (and peaks of solar power production) is relatively low, which implies that uncontrolled EV charging will not help increasing the PV power self-consumption [21]. In workplaces, the number of EVs parked could be high during high solar power production; however, the electricity consumption is also high. Hence, addition of uncontrolled EV charging might not help to increase PV power self-consumption.

The temporal flexibility of EVs due to long parking duration offers the opportunity for control and coordination of EV smart charging. Smart charging schemes enable EVs to interact better with PV and/or electricity consumption, for example by programming EVs to charge when the PV generation is high and not to charge when electricity consumption is high [21]. Improved interaction of EVs with PV and/or load will lead to several benefits. A study in Ref. [50] has shown that improved synergy of EV-PV-load reduces the negative impacts from the increase in EV charging load and PV power generation. Furthermore, vehicle-to-grid (V2G) offers additional opportunities in a smart charging scheme by including ancillary services to system operators such as frequency and voltage control [31,51].

Smart charging schemes have numerous opportunities and benefits, for example:

- Increasing PV utilization [19,52–58].
- Reducing peak loads [59–67].
- Balancing three-phase loads [68].
- Avoiding grid overloading issues [69–71].
- Avoiding voltage problems [72].
- Providing grid frequency regulation services [73–75].
- Reducing the grid losses [59,72,76–78].
- Reducing the charging cost [55–57,72,79–85].
- Increasing the profits for charging providers [52,86–90].

One of the challenges in employing smart control is that PV generation, electricity load and mobility patterns are naturally variable. On an aggregated level, the variability decreases. In contrast, high variability exists on the individual level. Variability in the electricity load can be attributed to the occupancy and the activities of individuals. As regards PV power generation, the uncertainty can be attributed to weather related variability at the location [91]. Another source of variability, among different buildings in a specific area, can be attributed to cloud movements and shading patterns [92]. EV load uncertainties can be traced to the uncertainty in the variables representing the charging events, e.g., plug-in time and the state-of-charge (SOC). Probabilistic forecasting techniques are often employed to evaluate the uncertainty in the forecasted variables, e.g., future electric load. Such uncertainties can be then taken into account in smart charging schemes by using stochastic optimization techniques [15,79,83].

3. EV smart charging objectives

In this section, the main objectives of EV smart charging involving PV generation and electricity consumption are reviewed. The objectives discussed are both technical (increasing the PV power utilization, balancing the electricity load, objectives related to the power grid) and financial (reducing energy cost and increasing profits for charging service providers). Many of the objectives we review —to some extent— achieve other objectives as well. For example, when self-consumption of PV power increases, grid losses decrease, which in turn leads to a cost reduction. The charging algorithms could also have multi-objective formulations where decisions are taken in the presence of trade-offs between two or more objectives.

3.1. Technical objectives

Increasing PV power utilization

Since solar power is not a dispatchable power source, it has no flexibility to follow the dynamic of the load, resulting in a limited PV power utilization. Hence, controlling flexible loads will have to be used instead to increase the PV power utilization, especially if energy storage systems are missing or limited [22]. With smart charging, EVs become a flexible load that can be shifted in time and controlled, and thus possible to use for load matching purposes and increasing the PV power self-consumption. Smart charging with increasing PV power utilization as the main objective or one of the objectives has been studied in Refs. [19,52–58].

Balancing electricity load

Both electricity consumption and EV charging load are correlated with human activities. Therefore, it is likely that peak electricity consumption and charging demand coincide in case of uncontrolled charging [93]. With smart charging schemes, the electricity load could be balanced so that the differences between load peaks and valleys are reduced [59,68].

Load balancing with smart charging could be performed with off-peak charging or valley-filling charging. With off-peak charging, the EV charging is shifted to the hours when the electricity load is not at its peak. Off-peak charging was simulated in Refs. [66,67]. With valley-filling smart charging, not only the charging in the peak load period is avoided, but also the lowest power consumption period is filled, resulting in a flatter load curve. Valley-filling smart charging decreases system losses and increases the load factor [59]. With higher load factor, infrastructure reinforcement could be postponed [59]. Smart charging strategies with valley-filling objectives have been presented in Refs. [59–65]. The valley filling strategies could be extended to peak-shaving with bidirectional flow or V2G schemes. In this case, the battery of the EV is discharged to support the network during peak load periods, and then recharged during low load periods. This is possible since EVs are parked around 92–96% of the time [26,51].

Load balancing in a system with a high PV penetration is also challenging. In Ref. [68], it was shown that smart charging can be a solution to the problems if, instead of electricity load, net-electricity load (electricity load minus PV power production) is taken into account in the valley-filling smart charging. The scheme decreased the system power losses as a result of the increase of both the load factor and the PV power utilization.

Other objectives related to the power grid

High penetration of PV and uncontrolled EV charging can cause several problems for the power grid [17]. EV smart charging schemes can be used to potentially overcome these problems. In particular, if a V2G scheme is implemented, EVs can provide valuable services to the power grid other than just consuming the power [31,32,37,94].

Such smart charging objectives include providing frequency and voltage regulation, reducing grid losses, balancing an unbalanced 3-phase grid and avoiding overloading issues. Smart charging is used to provide grid frequency regulation in Refs. [73–75], avoid voltage problems in Ref. [72], reduce grid losses in Refs. [59,72,76–78], balance the phases in Ref. [68] and avoid grid overloading issues in Refs. [69–71].

3.2. Financial objectives

Many of the smart charging schemes are driven by financial objectives. Compared to smart charging with technical objectives, smart charging with financial objectives is more attractive for most EV users and charging service providers since it will benefit them directly [95]. Most of the smart charging schemes with financial objectives lead to a valley-filling type of charging, especially with distributed charging with nodal price scenario and centralized charging [37,96]. If local generation such as PV power exists in the system, smart charging with financial objectives will also lead to higher utilization of PV power.

Reducing energy cost

Smart charging with the objective to reduce the energy costs for charging will benefit the EV owners directly [36]. Thus, this type of smart charging is popular for EV owners. Smart charging schemes with the objective of reducing the energy costs involving photovoltaic systems have been studied and developed in Refs. [55–57,72,80–82]. Smart charging schemes with the objective of reducing the energy costs considering the electricity demand have been studied and developed in Refs. [79,83–85].

Even though having an EV could be more cost-efficient than having an ICEV [29], the charging cost could vary in a system with dynamic electricity prices. In this case, the energy cost during peak-hours is most likely higher than during off-peak hours. Charging in public places such as parking lots and charging stations could have various charging cost schemes such as hourly price, kWh price and subscription fee schemes [29].

Increasing profits for charging providers

One of the main interests of charging facilities and aggregators is maximizing the profits from the charging services [36]. Thus, minimizing operational costs and maximizing revenues are of importance. Smart charging to increase the profit for charging providers has been developed and studied in Refs. [52,86–90].

One of the strategies to increase the profits of the charging providers is to minimize the purchase of power from energy providers or electricity generators during high-price periods, i.e., peak-hours. Thus, smart charging with this objective often leads to a valley-filling type of charging [37]. Using renewable power such as solar power could also help the charging providers achieve their financial objectives [36]. The charging providers could also increase their revenues by participating in ancillary services and energy trading markets, especially with V2G schemes [31,32,51]. In this case, the charging providers could receive economic incentives by regulating the power flow from and to EV fleet batteries following the needs of power grid operators or energy traders. Several economic incentives for charging providers with this scheme were reviewed in Ref. [97].

3.3. Multi-objective formulations combining financial and technical objectives

Smart charging with a financial objective can result in a technical advantage, and vice versa. This occurs because the hourly electricity price often reflects technical limitations in the electricity grid. That being said, some recent sources employed multi-objective smart charging schemes. In Ref. [52], a smart charging scheme to increase both profits and PV self-consumption was developed. The proposed smart charging schemes in Refs. [55–57] were designed to both minimize the charging costs and maximize PV utilization. In Ref. [84], a smart charging scheme aiming to minimize both the peak loads and the charging costs were proposed. The smart charging proposed in Ref. [85] was employed to both balance a 3-phase grid and reduce the charging costs. In Ref. [72], a smart charging algorithm to reduce both charging cost and grid problems, such as grid losses and voltage fluctuations, was presented. The smart charging scheme in Ref. [98] has an objective of determining the optimal trade-off between minimizing charging cost and charging time. In Ref. [88], a smart charging scheme to find the optimal trade-off between maximizing the profits of the aggregator and maximizing the lifetime of a battery energy system storage (BESS) was proposed.

4. EV smart charging configurations

In this section, control configurations and spatial configurations of smart charging are reviewed. Control configurations define the level of the charging coordination, i.e., centralized or distributed control. Spatial configuration distinguishes between different types of charging locations and the temporal availability of the cars in the charging locations, i.e., houses, workplaces, charging stations, etc.

4.1. Control configuration

Smart charging of EVs can be divided, based on the control configuration, into two categories: centralized and distributed charging [27]. Further discussions on both configurations are presented in the following subsections.

Centralized control

In EV charging with centralized control, the charging time and rate of an EV fleet are decided by a central unit called aggregator. The aggregator gathers all the data related to the EV charging, such as battery state of charge (SoC), expected departure time, the locations of EVs and other charging requirements from the users to decide the charging schedule of the EVs [29]. The centralized smart charging approach was used in Ref. [52] to increase the PV utilization, in Ref. [63] to reduce the system peak loads, in Refs. [68,69,76,78] to avoid problems in the power grid, in Refs. [74,75] to provide frequency regulation services, in Refs. [79,81,84,85] to reduce the charging costs and in Refs.

[86,88–90] to increase the profits for aggregators.

This approach is more likely to reach an optimal charging strategy on the system level [70,99]. For example, to increase PV self-consumption and reduce the system peak load, it considers the aggregation of PV production and load in the whole system, not only in a single home or building. The centralized control approach will also improve the utilization of available network capacity. In addition, it enables the provision of ancillary services such as frequency and voltage control. Thus, higher system stakeholders such as power grid operators and aggregators are the ones who have the most interest to implement a centralized charging approach.

However, this charging strategy comes with several drawbacks and challenges. It requires a complex and expensive communication infrastructure, has a large amount of data to process and poses challenges concerning privacy of the users. The system also relies heavily on a central unit [27]. If the central unit collapses, then the whole smart charging scheme collapses [27,70].

Distributed control

Distributed or decentralized smart charging works on a disaggregated level, e.g., on the individual EV level, instead of being controlled by a central unit. However, it is common that the charging scheme depends on incentives, e.g., through a price signal, from a central unit. The distributed smart charging approach was used in Refs. [54,56,57] to increase the PV utilization, in Refs. [66,67] to avoid charging during the peak load hours, in Refs. [80,82,83] to reduce the charging costs.

Using distributed control, the required information is processed in a distributed way, which reduces the communication infrastructure substantially. Since the charging control remains with the user, the distributed charging scheme has a higher user acceptance and overcomes the privacy problems in the centralized control approach [14,29]. Furthermore, since the distributed control approach does not rely on a central unit, it is less vulnerable to system errors than the centralized charging approach is [14,29]. The PV self-consumption and load factor on the individual building level are increased effectively with this approach [21,27].

Since real-time insight into operating conditions at all points in the system is limited, the distributed charging approach might not result in an optimal result on the overall system level [70]. Distributed charging schemes could lead to congestion of lines and transformers as they lack information about the rest of the network [27]. Another problem may arise when a large number of EV users change their charging rate in response to a significant change in the price signal, leading to the so-called avalanche effect [14,29]. The avalanche effect and the congestion problems could be minimized by setting a price signal that varies within the system, which is known as a nodal price strategy [27]. Moreover, the distributed control approach will have less ability to provide ancillary services to the network compared to the centralized charging approach [27].

4.2. Spatial configuration

In this section, the spatial configuration and the temporal aspects of electric vehicle charging load relating to PV power production and electricity consumption are discussed. The number of EVs available at each location varies over time. Thus, the EV charging load profile is different in different locations, e.g., homes and workplaces. With solar power limited to daytime, it is preferable to have EVs parked and available during those hours, which is not always the case for certain locations. In Ref. [46], spatial uncontrolled charging load was classified into three states: home, work, and other places. Home charging peaks in the evening, work charging peaks in between morning and mid-day, while charging at other locations has lower power demand and fills the valley between the peaks of work charging and home charging. The aggregation of the charging loads leads to two charging peaks in the morning and evening, respectively.

Thus, smart charging strategies designed for particular locations are constrained by the parking periods of EVs in these locations [21]. The following sections discuss smart charging in residential buildings, non-residential buildings, charging stations and aggregated over larger areas, i.e., on a city or regional level.

Residential buildings

Most of the inactive or uninterrupted parking takes place in residential areas, at detached houses or residential building parking areas/garages [26]. Thus, the flexibility of EV charging is highest at residential buildings. Besides the flexibility, EV charging during inactive parking at the residential buildings also offers a convenience to the EV owners as the EVs will likely be fully charged in the morning before the first trip of the day [89]. Several smart charging schemes on the individual residential household level have been proposed in Refs. [19,61,82,83,100,101]. In Refs. [15,66,67,102] studies on home smart charging schemes from the perspective of the residential distribution grid were conducted.

Smart charging of EVs can be designed to fill the valley of the typical household load. From the perspective of the residential grid operators, this is one of the most relevant charging schemes as it will reduce grid losses and voltage fluctuations. However, most of the smart charging schemes at residential buildings have financial objectives as the users get direct benefits of such a scheme. By implementing the correct price signal, smart charging schemes with financial objectives can also serve the valley-filling objective [103]. In this case, smart charging at residential buildings could follow a dynamic electricity price and/or on-site power generation to achieve the financial objective while satisfying the system load valley-filling objective.

However, matching EV charging with on-site PV generation is limited by the low fraction of EVs parked at residential buildings during the day when the solar power production peaks [21,104]. On the other hand, the potential of household load valley filling is very high with EV smart charging as the fraction of EVs at residential buildings is closer to 100% when the load is at its valley in the night [104].

Non-residential buildings

Since most of the cars are not at home during daytime, they are either parked in non-residential buildings or being driven [104,105]. Thus, the potential of smart charging in non-residential buildings during these hours is high. Non-residential buildings include workplaces and commercial and public buildings. The benefits of smart charging in non-residential buildings can vary as the load profile could be different depending on the type of the building [39,106,107]. EV smart charging strategies for different buildings types have been proposed previously, e.g., for workplaces [19,52,72,86], commercial buildings [53,79], schools and universities [80,108]. In Ref. [106], an extensive study on the impacts of a smart charging strategy on 16 different types of buildings, from a small office to a hospital, was conducted. In contrast to smart charging at residential buildings, smart charging at non-residential buildings might benefit more from a combination with solar power production, since when building occupancy is high during daytime, the building energy demand is also high. Similar to the smart charging schemes at residential buildings, recent research shows that smart charging in non-residential building is mostly motivated by financial objectives of either building owners or users, which as mentioned earlier, are strongly correlated with technical objectives.

Charging stations

In contrast to residential buildings and non-residential buildings, a charging station as a single unit has a load curve that only depends on the EV charging load, and, hence, the mobility pattern of EV users. Smart charging and discharging schemes at charging stations are mostly motivated by financial objectives for their owners. With EV fleet management schemes at charging stations, EVs can provide better services such as ancillary service to TSO and DSO and energy storage services for renewable power producers, which increase the revenue of the charging stations [31]. Charging stations as services providers for load balancing and other ancillary services for nearby buildings or power grids with V2X (vehicle-to-anything) schemes such as V2G and V2B (vehicle-to-building) have been studied in Refs. [79,108,109].

Recently, equipping charging stations with PV systems has become more common as the coupling of the two technologies can improve technical, economic and environmental performance of EVs, such as reducing charging losses and WTW emissions [110]. Furthermore, the performance in these respects could be improved further with smart charging schemes [58]. Studies in Refs. [54,56,58,74,79,111,112] have shown that implementing smart charging control in charging stations equipped with PV systems increased PV utilization for EV charging.

Regional

On a higher system level, cities, islands or other regional levels where multiple residential buildings, non-residential buildings and charging stations are aggregated and assuming the charging infrastructure is available everywhere within the region, it can be seen that EVs are available anytime, except when being driven on the roads. Regardless centralized or in the form of numerous distributed schemes, smart charging on higher systems level will have various benefits. Analyzing higher system levels is necessary as the aggregation of EV charging load, electricity load and solar power creates different load profiles compared to the local scale. Aggregation itself could improve the energy performance of the systems since any PV power that is not wasted on a certain aggregated level adds to the self-consumption as shown in Ref. [113].

As stated before, aggregated uncontrolled EV charging load on city scale will have two peaks, one in the morning and one in the evening [46]. In the typical city-scale load profile, the peak of the EV charging load coincides with the high power consumption periods. Thus, EV smart charging on the higher system level might solve system problems such as peak load management which is indirectly correlated with emission problems [21,99]. Smart charging considering parameters on regional level was proposed in Refs. [64,70,74,78,99,114,115].

Recent research shows that most smart charging schemes at the regional level are motivated by technical objectives. This is reasonable since on regional level, the supply and the demand of the whole system must more or less be balanced all the time in order to maintain stable frequency. The objective could also be extended to assess regional energy system performance, such as emission performance, since EVs can interact not only with distributed PV systems, but also with regional and centralized power sources such as coal-fired, gas-fired, nuclear and wind power plants [99].

5. EV smart charging algorithms and mathematical models

Smart charging schemes can be programmed with optimization or rule-based algorithms to achieve certain objectives. The implementations could vary from real-time control to scheduled coordination problems. In this section, control algorithms and mathematical models for smart charging used in the cited references are discussed. These algorithms were classified into two categories based on problem formulations and solution methods: optimization methods and rule-based methods.

5.1. Optimization methods

Optimization is a method to find the best available solution for a certain mathematical problem. Optimization problems typically minimize or maximize a mathematical function called the objective function in a feasible set which is defined by some constraints on the variable [116]. A general mathematical optimization problem can be written as:

$$\text{minimize } f(x), \text{subject to } g(x) \leq \ b, \tag{1}$$

where x is the vector containing the variables to be optimized, f is the objective function to be minimized (could also be maximized), g is the equality or inequality constraint function, and b is a vector containing the boundaries or the limits of the constraint function.

In the application of smart charging of EVs, this method could be used to design a charging schedule that minimizes the charging cost, maximizes the use of renewable power for the EV charging, minimizes load variance, etc. The optimization method is one of the most common methods used for energy management systems (EMS) applications in general [117]. In contrast to heuristic methods, most mathematical optimization methods can guarantee optimal results for the formulated problems.

As mentioned earlier in Section 2, in order to implement an optimization method in energy management systems, including smart charging of EVs, some variables have to be estimated in advance. Some variables can indeed be known in advance and included in the problem formulation, such as day-ahead electricity prices. In some regions such as Central Europe, United Kingdom and Nordic countries [41,42], day-ahead and intraday electricity prices are available. This is not always the case for other variables such as PV generation and electricity consumption which have uncertain natures. Arrival and departure times of vehicles are also uncertain in reality. However, such uncertain variables could still be forecasted with several techniques, as reviewed in Refs. [118–120]. Several smart charging schemes in the reviewed papers included forecasting models and/or forecasted variables in the formulation of the optimization problem to make the studies more realistic. A probabilistic forecast was used in Refs. [15,79,83,98,101], while a deterministic forecast was used in Refs. [52,64,65,71,80,88]. Other studies reviewed in this paper assumed that the uncertain variables are perfectly forecasted by using historical data or modeled data as input and focus solely on the optimization algorithm performance as a benchmark for comparison with other charging algorithms or uncontrolled charging methods.

An overview of various mathematical optimization methods used for smart charging of EVs, involving either PV generation, electricity consumption or both are given in the following sections. In addition, specific objectives and their constraints are also discussed. The summary of studies on smart charging that use optimization methods, their specific objectives and common parameters in objective functions and constraints is presented in Table 1.

Linear programming

In linear programming (LP), the objective function and the constraints must be linear [116]. A general LP problem can be written as:

Table 1
Summary of the studies related to EV smart charging using optimization methods sorted according to optimization method.

Author & Year	Smart Charging Objectives	Optimization method	Parameters in objective functions and constraints[a]							Pr	Implementation or simulation setup	Tools used	Major Results
			PV	EL	EC	GC	NC	BP	t				
Richardson et al., 2012 [69]	Maximizing the number of EVs charged while avoiding distribution grid issues	LP		✓		✓	✓	✓			Test network: a LV distribution grid in Dublin	unknown	Battery SOC reached 99.9% on average after charging without grid infrastructure upgrade
Sundström et al., 2012 [71]	Maximizing the power delivered to the EVs while avoiding overload issues	LP		✓	✓	✓		✓			Simulated based on a grid in Danish island of Bornholm	IBM ILOG CPLEX	The charging demand was fulfilled without overloading the grid
Richardson et al., 2012 [70]	Maximizing the power delivered to the EVs while avoiding overload issues	LP & QP		✓		✓	✓	✓			Test network: a LV distribution grid in Dublin	MATLAB, digsilent	EV load (energy) could be increased to 50% of the baseload with controlled charging (both centralized and distributed) without grid upgrade compared to only 10% of the base, load with uncontrolled charging.
Ioakimidis et al., 2018 [108]	Peak load shaving and load valley filling	LP		✓			✓	✓	✓		Simulated based on the data collected at University of Deusto (UD) in Spain	MATLAB	The building peak power consumption is reduced 4–10% depending on the number of parking cars.
Sortomme et al., 2011 [59]	Maximizing the load factor and minimizing the load variance	LP & QP		✓		✓	✓				Simulated in 9-bus and 18-bus distribution test systems	CVX and MATLAB	Losses decreased by 5–30% depending on scenarios
van der Meer et al., 2018 [52]	Maximizing profits and maximizing PV utilizations	MILP	✓		✓		✓	✓	✓	✓	Electricity market and PV data from the Netherlands	IBM ILOG CPLEX	Charging cost reduction: up to 118% for one point charging, 427% for two point charging, thus, turning cost into profits. PV self-consumption increase: 10–20%
Ivanova et al., 2018 [89]	Minimizing the charging cost	MILP	✓	✓	✓		✓	✓	✓		Market and PV data in Victoria, British Columbia, Canada	MATLAB, IBM ILOG CPLEX	Charging cost reduction: 14–96% depending on season
Wi., 2013 [80]	Minimizing the charging cost	MILP	✓	✓	✓			✓	✓	✓	A building prototype in Korea	Self-developed software	Charging cost reduction: 6–15% compared to benchmark method
Mouli et al., 2017 [86]	Minimizing the total net cost and maximizing charging providers' revenue	MILP	✓		✓		✓	✓	✓	✓	Market and PV data in Austin, Texas	LPsolve	Charging cost reduction 32–650% compared to immediate and average rate charging policy
Franco et al., 2015 [85]	Minimizing the charging cost and balancing the load	MILP		✓	✓	✓		✓	✓		IEEE PES Distribution Test Feeders, 34-bus Feeder	AMPL and IBM ILOG CPLEX	The simulated grid with 15% unbalanced EV load had 15% less energy cost compared to the simulated grid with 40% unbalanced EV load
Kuang et al., 2017 [106]	Minimizing the total net cost of each type of building	MILP	✓	✓	✓		✓	✓	✓		Simulated on a system with a building and a charging station with PV, battery, combined heat-and-power plant based on Chicago condition	CPLEX studio	Among the compared building categories, warehouse buildings benefit the most with 17% cost saving, while secondary school benefits the least with only 4.41% cost saving
Wu et al., 2017 [82]	Minimizing the charging cost	CP	✓	✓	✓			✓	✓		Data from a single-family home in California, US	CVX MATLAB	Vehicle-to-home (V2H) or bi-directional operation has 2.6% lower total net cost compared to home-to-vehicle (H2V) or uni-directional operation
Gan et al., 2013 [62]	Minimizing the load variance	CP		✓				✓	✓		Based on residential household load profiles in Southern California	unknown	Flatter household load curves
Ma et al., 2013 [60]	Minimizing the load variance	CP		✓			✓	✓	✓		Data from Midwest Independent System Operator, US	unknown	The proposed decentralized method was proved to be convergent to the Nash equilibrium quickly and the result indicated that the proposed method could be an alternative to centralized control, which requires much more communication
Eldeeb et al., 2018 [88]	Maximizing profits of the aggregator & minimizing the loss of BESS lifetime	NLP	✓		✓			✓	✓	✓	Simulation based on real existing 1.2 MW PV station in Tudela, Spain	GAMS and BARON	Multi-objective case: 10% more revenues compared to the case of minimizing BESS capacity degradation only, 0.015% less BESS capacity degradation compared to the case of maximizing revenue only
Clement et al., 2009 [15]	Minimizing the residential grid losses	QP		✓		✓	✓	✓	✓		IEEE PES Distribution Test Feeders, 34-bus Feeder	unknown	The losses compared to the total power consumption is lower around 0.5% in controlled charging scheme compared to in uncontrolled charging scheme.

Table 1 (*continued*)

Author & Year	Smart Charging Objectives	Optimization method	Parameters in objective functions and constraints[a]							Pr	Implementation or simulation setup	Tools used	Major Results
			PV	EL	EC	GC	NC	BP	t				
Weckx et al., 2015 [68]	Minimizing the peak load and the load variance	QP	✓	✓				✓			A typical Belgian LV network with PV output measured at KU Leuven	IBM ILOG CPLEX	Grid losses reduction: 28% (as a result of three phase balancing and load variance minimization)
Mets et al., 2012 [114]	Minimizing the peak load and the load variance	QP		✓				✓	✓		A 3-phase Belgian LV network with 63 households	unknown	Peak reduction: QP: 70%; variability reduction: QP: 65%
Cai et al., 2018 [78]	Minimizing the power exchange between the microgrid and the upstream distribution system	QP	✓	✓		✓	✓	✓			An example microgrid with PV, wind, gas turbine generation and EV load	unknown	Network loss reduction compared to direct charging scheme: 25% for optimal charging without V2G, 28% for optimal charging with V2G
Jian et al., 2013 [61]	Minimizing the load variance	QP		✓			✓	✓	✓		Simulation based on a typical household with 2 EVs	unknown	V2G scenarios reduce the load variance more but they also increase losses
Zhang et al., 2014 [98]	Minimizing the mean waiting time of charging based on renewable power generation	SP - CP	✓		✓		✓	✓		✓	Unknown	unknown	The trade-off between charging cost and charging queue length is obtained. For example, in one of the scenarios, both charging queue could be reduced to more than 50% compared to the cheapest case, and the cost could be reduced to more than 70% in the shortest queue case.
Clement et al., 2009 [15]	Minimizing the residential grid losses	SP - QP		✓		✓	✓	✓	✓	✓	IEEE PES Distribution Test Feeders, 34-bus Feeder	unknown	Smart charging scheme with SP and probabilistic forecast has 0.002%–0.01% difference of power losses to the total load compared to the scheme with perfect forecast
Wu et al., 2018 [83]	Minimizing the net cost	SP - DP		✓	✓	✓		✓	✓	✓	Simulation based on travel pattern and electricity market in US	unknown	Compared to controlled G2V, controlled V2G reduces the cost by around 70%. V2H reduces the cost around 30%
Wu et al., 2016 [101]	Minimizing the net cost	SP - DP	✓	✓	✓	✓		✓	✓	✓	Simulation based on travel pattern and electricity market in US	unknown	The costs with optimal control for Tesla Model and Nissan Leaf are 493.6% and 175.89% less than those without the optimal control, respectively.
Quddus et al. [79],	Minimizing the net cost of both collaborators: buildings and charging stations	SP - MILP	✓	✓	✓					✓	Self-developed set-up with commercial buildings and charging stations and power grid. Electricity cost based on US market	CPLEX and SAA	Cost savings 6–24%
Wei et al., 2016 [81]	Minimizing the charging cost of each EV user	RO - CP	✓	✓	✓		✓	✓	✓	✓	Based on EVs and charging type in Japan, US and China	IBM ILOG CPLEX	Large EV charging management problem with individual economic objectives was solved
Yao et al., 2017 [73]	Frequency regulation	RO		✓	✓	✓		✓	✓		Simulated with historical data from Pennsylvania Jersey Maryland Interconnection (PJM), California, New York	unknown	The EVs can improve their revenue if they participate in the frequency regulation program under the performance-based compensation scheme
Liu et al., 2014 [64]	Minimizing the net-load variance	GA	✓	✓	✓		✓		✓	✓	An example city with 1 milion cars	MATLAB	Flatter net-load curve is achieved
Mehboob et al. [63],	Minimizing the system peak load	GA		✓		✓	✓	✓			IEEE 13 node test feeder	MATLAB, OpenDSS	System peak load does not increase with 90% penetration level of coordinated PEV charging.
Hosseini et al., 2018 [84]	Minimizing the fuel cost of PHEV, and reducing the peak load and the distance of peak and valley	PSO, ICA, Teaching-learning		✓	✓	✓	✓	✓			Unknown	unknown	For the particular problem, ICA gives better result on peak demand distance and peak load reduction
Celli et al., 2012 [77]	Minimizing power losses	PSO		✓	✓	✓	✓	✓	✓		Scenario based on residential area with 1 MW demand and 200 EVs	MATLAB	Peak load and losses reduction around 10% and 3% respectively
Liu et al., 2015 [53]	Improve PV self-consumption and reduce the impact on the power grid	PSO	✓	✓			✓	✓	✓		An example of commercial building microgrids	MATLAB	Peak power reduction and PV self-consumption increase
Wang et al., 2013 [65]	Valley filling	ACO		✓		✓	✓	✓	✓	✓	Simulation based on data from the electric realibility council of Texas	unknown	With 500 EVs in the system, the peak valley difference decreased from 505 kW to 127 kW

[a] PV = PV power production, EL = electricity load/demand, EC = electricity cost, GC = grid characteristics, i.e., voltage, current, etc., NC = number of cars, BP = EV battery parameters, i.e., state-of-charge, maximum/minimum charging/discharging rates, t = arrival and departure times, Pr = prediction/forecast variable and/or model included.

$$\begin{aligned} \text{minimize} \quad & c^T x, \\ \text{subject to} \quad & Ax \le b, \\ & x \ge 0, \end{aligned} \tag{2}$$

where x is the vector containing the optimization variables, A is a coefficient matrix, and b and c are vectors.

In several occasions, some linearization techniques, modifications or simplifications are needed in order to solve the problem in an LP environment. For example, in Ref. [71], the original objective function, min $|x|$, was non-linear. Therefore, it was represented by the linear function, $x^+ + x^-$, with additional constraints that $x^+ \ge 0$, $x^- \ge 0$ and $x^+ \cdot x^- \ge 0$. In the end, the problem can be solved in an LP environment.

The LP approach was used in Refs. [69–71] mainly to limit the maximum power that can be drawn from the grid to charge EVs while considering the constraints on the capacity of the distribution grid. In these papers, real electricity consumption data were used as input to one of the constraints. In Ref. [108], the LP approach was used in a V2B scheme between a parking lot and a nearby building for the building peak load shaving and valley filling, with constraints on un upper limit on the power flow.

Mixed-integer linear programming

Mixed-integer linear programming (MILP) is one variant of LP in which some or all of the variables are restricted to be integers [121]. The use of MILP techniques is necessary when binary or integer variables are included within the optimization problem. For example, in smart charging schemes, EV states of charging, discharging and driving can be represented with binary values [122]. Similar to the LP approach, linearization techniques might be needed for problems with variables that are non-linear in reality. For example, the optimization problem in Ref. [85] originally had non-linear functions for the objective and the constraints such as active and reactive power flows, voltage and current magnitudes. However, they were linearized using a piecewise linearization method in order to employ a MILP formulation. Piecewise linearization methods are frequently used in optimization problems to convert nonlinear problems to linear ones, so that they can be solved in an LP or a MILP environment [123]. An extensive review on piecewise linearization methods was presented in Ref. [123].

The MILP approach was used in Refs. [52,79,80,85,86,89,106]. In Ref. [52], a centralized energy management system with PV power forecasts to optimally charge EVs at the workplace based on a MILP formulation was developed. The reason for using MILP instead of generic LP is that it is not common to charge more than one car with different charging powers at the same charging point. A similar work was also conducted in Ref. [86] with the addition of V2G and offering of energy reserves to the market. The objective in both papers was to minimize the total net cost of EV charging with several technical constraints such as the constraints on PV system size and electricity transferred to and from the grid.

In Ref. [106], MILP was used for cost-saving controlled EV charging and compared the benefits for different building types. In Ref. [80], an EV charging scheduling algorithm for individual buildings based on MILP combined with forecasts of both PV generation and electricity consumption in order to minimize the energy purchase cost was proposed. In Ref. [89] MILP was also used to minimize the charging costs considering PV generation and electricity consumption. The study, however, relied on historical data instead of forecasts. A similar objective function and MILP formulation were used in Ref. [85] but the study did not include the PV power production.

Convex programming

A convex optimization problem is an optimization problem in which the objective function, constraints and feasible sets are convex [124]. A convex optimization problem can be solved by convex programming (CP) [124]. A CP problem can be written as:

$$\text{minimize} \quad f_0(x), \ \text{subject to} \quad f_i(x) \le b_i, \quad i = 1, \dots, m, \tag{3}$$

where functions $f_0, \dots, f_m : \mathbf{R}^n \to \mathbf{R}$ are convex, i.e., satisfy

$$f_i(\alpha x + \beta y) \le \alpha f_i(x) + \beta f_i(y),$$

for all $x,\ y \in \mathbf{R}^n$ and all $\alpha, \beta \in \mathbf{R}$ with $\alpha + \beta = 1,\ \alpha \ge 0,\ \beta \ge 0$ [124]. With a convex objective and a convex region, there is only one optimal solution which is the global optimum.

LP and quadratic programming (QP) are two particular types of convex programming. The main challenge of this approach is formulating the problem as a convex optimization problem [29]. Advanced convex formulations of smart charging problems were made in Ref. [60,62] with objectives to minimize the load variance, in Ref. [81] with an objective to minimize the charging cost and in Ref. [98] with an objective to minimize the charging waiting time. Once the problem is made convex, it can be solved with a least-square or a linear programming approach [124]. The study in Ref. [82] employed the method of converting, approximating or simplifying an original non-convex problem to represent a non-convex problem as a convex one. The authors were then able to use a convex programming approach to find the optimal solution. In Ref. [82], the original formulation problem for optimal EV charging contained non-convex constraints, e.g., the efficiency function, which were transformed into convex functions. The objective of the paper was to minimize the net cost, which indirectly minimizes the load variance and maximizes the PV utilization, subject to constraints regarding the home power balance, grid limits, and the PEV and home batteries.

Nonlinear programming

In nonlinear programming (NLP), there is at least one nonlinear function, which could be the objective function and/or the constraints [116]. NLP formulations are generally more difficult to optimize than LP formulations [125]. Hence, nonlinear functions are usually linearized and solved in an LP environment, as done in Refs. [71,85]. A nonlinear approach was used in Ref. [88] to solve a multi-objective optimization problem. The objectives of the problem were to maximize both the profits of the aggregator and the lifetime of the BESS. Constraints regarding the grid and the parameters of BESS and EV batteries were included in the study. In this case, a nonlinear programming approach was needed because the BESS characteristics were nonlinear.

Quadratic programming

Quadratic programming (QP) is a particular type of nonlinear programming, in which the objective function is quadratic and is subject to linear constraints [116]. Since the quadratic function is convex, and the constraints are linear, it is easier to solve a QP problem than other types of NLP [116]. A general QP problem can be written as:

$$\text{minimize} \quad \frac{1}{2} x^T Q x + c^T x, \ \text{subject to} \quad Ax \le b, \tag{4}$$

where x is the vector containing the optimization variables, Q is a symmetric matrix, A is a matrix, and b and c are vectors.

In Ref. [15], the QP approach was used to minimize residential distribution grid losses subject to constraints related to the grid and

EV battery parameters. EV charging using the QP approach was studied in Ref. [68] for load-balancing in 3-phase distribution grid with PV systems. The constraints of the scheme were the power flow limits from each phase to the EVs. In Ref. [78], the QP approach was used to minimize the energy imported for EV charging from upstreams in the distribution systems which means maximizing the utilization of local power production including PV. In Ref. [114], the QP approach was used to reduce the peak load and the load variability with constraints related to EV battery parameters.

Dynamic programming

In dynamic programming (DP), a complicated optimization problem is divided into simpler sub-problems. Each solution of the sub-problem is indexed and stored in the memory so that it can later be used to solve these kind of sub-problems. Hence, DP could reduce the computation time for solving particular problems [29]. A stochastic DP approach was used in Refs. [83,101] to minimize the charging cost, which indirectly minimized the load variance. The constraints in the smart charging schemes in these papers were related to grid power and EV batteries.

Stochastic programming

Stochastic programming (SP) is a mathematical optimization framework which considers uncertainty within its variables [126]. The probability distribution functions of some of the variables is taken into account in such a framework. However, since a continuous probability distribution function is defined along the real line, such an approach would yield infinitely many possible values and, consequently, infinitely many solutions. In order to reduce the computational burden, a common approach is to draw random samples that collectively represent the probability distribution. Each of these samples yields an optimal solution, after which a probability distribution of optimal solutions can be obtained. Common practice is the so-called sample approximation approach (SAA), in which the mean of the obtained probability distribution is considered as the optimal strategy in expectation [127]. Another common approach to include forecast uncertainty is through so-called chance constraints. A chance constraint is defined by its probability level, which is the probability of exceeding the constraint. In case the forecast error is assumed to be Gaussian and independent, it is possible to calculate the deterministic equivalent of the chance constraint and significantly increase the computation time. However, it is rarely the case that the independence assumption of forecast errors holds [128]. The problem formulation in the stochastic programming could be linear, non-linear, convex or non-convex.

As mentioned earlier, most of the current research assumes that the variables involved in the optimization problem solving are deterministic. However, in practice this is generally not the case, and SP is able to reduce the risks by considering the uncertainty present in the variables. A study in Ref. [15] compared a smart charging scheme with SP and probabilistic load forecast to a scheme that used historical load data. SP was also used in Refs. [83,101] to minimize the charging cost and in Ref. [79] to minimize the overall system cost, both with constraints related to the grid and EV batteries.

Compared to deterministic optimization, stochastic optimization could provide more realistic results but the problem solving time can be much longer since more scenarios are considered [31].

Robust optimization

Robust optimization (RO) also deals with optimization problems involving uncertainty within their variables. It differs from SP in the uncertainty model formulation, which is not a probability distribution function but a deterministic set called the uncertainty set [126]. In RO, the focus is on the worst-case scenario while SP usually gives expected values from the optimization problem [129]. RO approaches for smart charging of EVs were used in Ref. [73] for a frequency regulation purpose and in Refs. [81,130] for cost minimization purposes. As in SP, the computation time in RO is longer than in deterministic optimization because more scenarios being considered [31]. Compared to SP, RO provides less optimum results, but is less complex to implement in real scenarios when it comes to solving problems in power systems [131].

Metaheuristic methods

Metaheuristics is a higher level strategy to find a sufficiently good solution to an optimization problem, especially when some information is not known [132]. Compared to convex mathematical optimization algorithms, metaheuristics do not guarantee a global optimal solution, but the computational process could be faster [132,133]. Since in many engineering optimization problems, including smart charging problems, the formulations are complex and nonlinear, metaheuristic methods could be good enough alternatives for solving otherwise computationally demanding problems [134]. Various metaheuristic algorithms have been proposed for smart charging of EVs involving either PV generation, electricity consumption or both.

Genetic algorithm:. A genetic algorithm (GA) is a metaheuristic algorithm inspired by the process of natural selection and commonly used to solve optimization problems by using equivalents of mutations, crossover and/or selection [135]. GA belongs to the larger class of evolutionary algorithms (EAs). In the application of EV smart charging, GA was used in Ref. [64] to optimally charge EVs, taking into account PV and wind power production. The objective of the smart charging in this case was to minimize the net-load variability of a region with constraints related to the power grid and the RES production [64]. GA was also used in Ref. [63] to minimize the peak load and avoid unnecessary reinforcement of an existing grid.

Imperialist competitive algorithm:. The imperialist competitive algorithm (ICA) is a metaheuristic algorithm for optimization problems, inspired by human social evolution, specifically imperialistic competition among humans and their empires [136]. Thus, ICA is a type of EA. ICA was used in Ref. [84] to define the charging schedule for plug-in hybrid electric vehicles with regards to the supply and demand of the power grid. In Ref. [84], ICA was also compared to particle swarm optimization (PSO) and outperformed it in terms of peak-valley minimization.

Particle swarm optimization:. Particle Swarm Optimization (PSO) is a swarm-intelligent metaheuristic method based on the idea of simulating the flight of bird flocks [132]. It solves optimization problems by having a population of candidate solutions called a particle swarm, which is moved iteratively so that an optimal or at least near-optimal solution to the problem can be found [132]. Smart charging of EVs using the PSO approach was studied in Ref. [84] to minimize the load variance subject to power flow limitations, in Ref. [53] to improve the PV self-consumption and reduce the impacts on the grid studied and in Ref. [77] to minimize the power losses, both with constraints related to the SoC and power flow of EV batteries.

Ant colony optimization:. Similar to PSO, ant colony optimization (ACO) is also a swarm-intelligent metaheuristic method [133]. The difference is that ACO is inspired by the behavior of real ants, which are able to find the shortest paths between food sources and their nest [133]. A study in Ref. [65] presented a smart charging scheme based on ACO for 500 EVs with an objective of load valley filling at the transformer level and constraints related to SoC of EV batteries and transformer capacity. In that paper, smart charging using ACO was also compared with the one using PSO. Results show that for the particular optimization problem in the paper, ACO has a shorter execution time and a lower load fluctuation.

5.2. Rule-based methods

A smart charging scheme with a rule-based method typically uses a simple problem solving approach instead of relying on a mathematical formulation that takes a long time to compute, hence being more practical. In many cases, the smart charging strategy only needs simple logical rules to react to new events, for example stopping charging when the load and the electricity price are high or charging when the PV production is high [20]. Compared to optimization methods, rule-based methods will not guarantee optimal or near-optimal solutions, but can achieve the immediate goal instantaneously while satisfying the rules or the constraints.

Various rule-based smart charging have been proposed in the recent years. Studies in Refs. [54,137,138] proposed smart charging algorithms based on real-time PV converter DC-link voltage sensing. In this case, the DC-link voltage value decides the operation mode and the power flow between PV systems, EVs and the power grid. Studies in Refs. [19,55–57,66,67] also applied various generic 'if-then' rule-based algorithms with some additional calculation of the parameters for the rules. In Refs. [66,67], the proposed algorithms prevented charging of EVs during peak hours unless the battery SoC of the EVs went below a predefined limit. Valley-filling smart charging with a heuristic rule-based approach was also studied in Ref. [76]. By applying certain rules, the valley-filling objective in Refs. [66,67,76] is achieved to some extent even though it is not optimal as in the optimization charging. In addition to the generic rule-based algorithm for smart charging application, fuzzy logic rules were used in Refs. [72,74] and queueing priority algorithms were used in Refs. [58,139]. Table 2 summarizes the studies on smart charging using rule-based algorithms, their specific objectives, and the parameters involved in the algorithms.

6. Concluding discussion

The challenges that are expected to arise from a rapid increase in the penetration of EVs and PV have driven attempts to find novel solutions. Smart charging of EVs is one such solution that has been proposed in recent power system research. The interaction of EVs and PV with existing electric load in power grids and with other electric appliances in buildings has been an emerging research topic along with evolving smart grid technologies and NZEBs. Concluding discussions in the three aspects on smart charging presented in this paper are included below. We also provide an analysis of the current trend of smart charging considering PV and load and suggest directions for future research.

6.1. Objectives

Smart charging schemes aim to fulfill various objectives. We also found synergies between many smart charging objectives; for example, maximizing self-consumption of PV power reduces charging cost. However, the interests differ between stakeholders. For charging service providers, the main common interest is to maximize profits from their services. For EV users, the cost-efficiency is the main common interest. For power grid operators, the major common goal is to have a long lifetime of their infrastructure. This also implies increasing the hosting capacity for RES and EVs with minimum grid reinforcements. Avoiding charging during peak hour periods and maximizing charging when there is a surplus power such as during peak solar production are two examples of smart charging schemes which can be of interest to the power grid operators. In order to achieve such objectives, the power grid operators could act as aggregators and control the EV charging by themselves, or use incentives to the charging service providers and EV users.

6.2. Configurations

The next topic which was discussed in this paper was smart charging configurations: control and spatial configurations. In terms of control configuration, both centralized and distributed charging have their own advantages and disadvantages. The distributed charging approach could be a good solution due to low communication requirements and privacy violations. However, at high penetration of both EVs and RES it could be better to implement centralized charging due to the instantaneous information availability. This will help optimizing the utilization of power grid capacity and renewable power on the system level. One issue is the necessity of an advanced communication infrastructure in case of the centralized approach. The spatio-temporal aspects of smart charging were also discussed. On the building level, such as houses and workplaces, the temporal flexibility of the EV charging is defined by the mobility behavior of the drivers, while on the higher system level, it can be said that the EVs are almost always available since on average they are parked for 22 h per day [26]. Smart charging at homes, non-residential buildings and charging stations are mostly motivated by financial objectives, since in these places the most important stakeholders are EV users, building owners and charging service providers. On the regional level, technical objectives related to the power grids or regional energy systems performance enhancements are more common.

6.3. Control algorithms and mathematical models

Various control algorithms and mathematical models have been proposed in recent research on smart charging. The proposed models can be categorized into two categories: optimization methods and rule based methods. Many smart charging studies focused on testing the algorithms and on potential studies, and thus rely on historical data instead of forecast data. Forecasting of future variables such as PV power production has been included in some studies, especially the studies that utilized optimization methods.

We found that each method has its advantages and disadvantages. Smart charging schemes with rule based algorithms are generally simpler and, thus, more practical to implement. However, these might not give optimal results. Smart charging schemes with convex optimization such as LP, MILP and QP excel in terms of finding optimal result, however the real problems sometimes include non-convex sets and functions which are difficult to solve. Thus, the challenges regard how to formulate the problems in convex environments, which is not always straightforward and realistic. Smart charging schemes with optimization methods are commonly more complex than the ones with rule-based algorithms and the execution or computation usually takes longer time. SP and RO can be used in optimization problems when taking into account the uncertain nature of PV and load. However, it can become more complex and computationally heavier and become less practical, especially for individual users. However, it might be necessary to include more probabilistic forecasts for central units such as aggregators and power grid operators. Metaheuristics could be a trade-off between the classical optimization approach and rule based algorithms in terms of simplicity and performance.

Table 2
Summary of the studies related to EV smart charging using rule-based algorithms.

Author & Year	Smart Charging Objectives	Schemes	Parameters involved in the algorithms[a]							Pr	Implementation or simulation setup	Tools used	Major Results
			PV	EL	EC	GC	NC	BP	t				
Hamilton et al., 2010 [137]	Increasing the overall power transfer efficiency from PV array to PHEV or grid	Rules based on PV converter voltage sensing	✓			✓					Based on the conditions of a PHEV carport charging station in Florida	PSPICE	Around 4% increase in the PV transfer efficiency
Goli et al., 2012, 2014 [54,138]	Minimizing the use of energy from the grid and maximizing the use of PV power to charge the EV	Rules based on PV converter DC-link voltage sensing	✓			✓		✓			Simulated in MATLAB environment, implemented in the laboratory in Texas	MATLAB/Simulink, PID controller	Successful implementation of the algorithm on laboratory scale
Barone et al., 2019 [19]	Increasing PV utilization in the buildings	Rules based on PV systems availability and building energy demands	✓	✓			✓	✓	✓	✓	Simulation based on a system with an office with building-integrated PV and a two-floor house in the weather zone of Naples, Italy	MATLAB, DETECt 2.3	PV self-consumption increased by around 3.5−6.6 MWh/year. Energy saving increased by around 45−77%
Turker et al., 2012 [66]	Avoiding charging in the peak hours while satisfying the charging demand before departure time	Rules based on SOC, peak load hour		✓			✓	✓	✓		Tested with 1000 different daily load profiles in France	unknown	SOC of 100% was achieved for all PHEVs at the departure time while avoiding charging during the peak hours
Turker et al., 2013 [67]	Avoiding charging in the peak hours while satisfying the charging demand before departure time	Rules based on SOC, peak load hour		✓		✓	✓	✓	✓		Simulation based on a grid with 96 houses in France	MATLAB	For the particular case study, limiting the charging power to 800 W at any time, was better for the voltage plan than preventing the charging during the defined peak hours.
Mousavi et al., 2016 [76]	Valley filling and minimizing the distribution losses	Rules based for shifting the charging time		✓		✓	✓	✓			LV residential distribution system in a suburban area in Dublin	digSilent	Compared to the uncontrolled scenario, losses reduced by 13−43% depending on the EV penetration ratio
Chen et al., 2017 [90]	Enabling the PV charging station to both participate in the ancillary service of the smart grid and satisfy the EV users	Rules based on EV battery energy bound and PV production. The focus is to utilize the ability of solid state transformer (SST)	✓			✓	✓		✓		Simulation based on data from National Renewable Energy Laboratory (NREL) with 60 cars plus laboratory-scale experiment	MATLAB/Simulink	Results show that the revenue of regulation of Solid state transformer (SST) based PVCS is doubled compared to that of a conventional PVCS. Smart charging had 93% charging completeness in SST based PVCS compared to 64% in conventional PVCS
Bhatti et al., 2016 [55]	Minimizing the charging cost, maximizing PV utilization and increasing the revenue of PV systems	Rules based on EV battery SoC, PV power production, energy storage capacity and levelized cost of energy (LCOE) of power sources	✓		✓	✓	✓	✓			Implementation in a remote grid in the Maldives	unknown	Around 58% reduction of charging cost, and 100% reduction of diesel generator dependency
Bhatti et al., 2017, 2018 [56,57]	Minimizing the charging cost, maximizing PV utilization and increasing revenue of PV systems	Rules based on EV battery SoC, PV power production, energy storage capacity and LCOE of power sources	✓		✓	✓	✓	✓			Simulation based on solar data for California from NREL, 150 cars and local LCOE	unknown	The charging cost reduced by 20−33% and the EV load power reduced by 32%
Mohamed et al., 2014 [72]	Reducing the charging cost, voltage problems and grid losses.	Real time energy management based on fuzzy logic with considerations of SoC, PV, local load and charging cost	✓	✓	✓		✓	✓		✓	Standard IEEE 69-bus system	MATLAB, digSilent	Flatter load curve, reduction of charging cost and improvement in the voltage profile and the system losses

(*continued on next page*)

Table 2 (*continued*)

Author & Year	Smart Charging Objectives	Schemes	Parameters involved in the algorithms[a] PV	EL	EC	GC	NC	BP	t	Pr	Implementation or simulation setup	Tools used	Major Results
Falahati et al., 2016 [74]	Grid frequency control	Fuzzy controller	✓	✓		✓	✓				Modified IEEE 39-bus system with PV and EV load	MATLAB/Simulink	The maximum and grid frequency deviation decreased by 22–45% compared to dumb charging. The RMS grid frequency deviation decreased by around 60% compared to PI controller with ICA optimization
Zhou et al., 2013 [139]	Reducing charging delay time by creating queueing and priority rules	Weighted fair queuing (WQF) priority based on supply and demand ratio		✓			✓		✓	✓	simulation set up for 3000 vehicles in a medium city in the US	MATLAB	Around 2% lower fraction of delay compared to first come first serve algorithm
Zhang et al., 2016 [58]	Increasing solar to vehicle (S2V) ratio	Queueing algorithm, priority sharing, and priority round robin	✓				✓	✓			Study case in University of California Los Angeles	WINSmartEVT, EVSmartPlug	S2V ratio for both priority sharing and priority round robin are increased to 1 compared to 0.54 ratio in the scenario without the algorithm

[a] PV = PV power production, EL = electricity load/demand, EC = electricity cost, GC = grid characteristics, i.e., voltage, current, etc., NC = number of cars, t = arrival and departure time. BC = EV battery parameters, i.e., state-of-charge, maximum/minimum charging/discharging rates, Pr = prediction/forecast variable and/or model included.

Metaheuristic methods do not rely on convex mathematical formulations as classical optimization approaches do, but it is not as simple as rule-based algorithms either. Metaheuristics methods could also be used to solve optimization problems with uncertainty variables.

Forecasts play a major role in smart charging schemes that consider the uncertain nature of PV generation and load. However, we found that there are still very few studies that assess the effects of forecast performance on smart charging performance; in other words, how the performance of smart charging schemes with benchmark forecasts such as deterministic and persistence forecast differ to ones with advanced probabilistic forecasts or perfect forecast. If the smart charging performance does not differ significantly, then the simpler forecast is more practical. This also relates to what optimization framework, either deterministic or stochastic optimization, should be used for different conditions. Stochastic optimization might be more accurate in finding optimal conditions for problems involving high uncertainty. However, the drawback is that it is computationally heavier than employing deterministic optimization. Thus, stochastic optimization might not be necessary in regions with lower variability conditions, e.g., areas which are almost always sunny during daytime, whereas stochastic optimization might be needed in regions where the conditions are highly variable.

6.4. Overall analysis and suggestion for future research

Our analysis shows that it is challenging to find optimal smart charging strategies that combine simplicity, reliability and execution time, which are among the important aspects for practical smart charging. The practical feasibility should be assessed to make smart charging fit for physical implementation. Research on optimal smart charging set-ups in order to fulfill interests of each stakeholder should be further explored. Distributed charging with nodal price schemes could be a trade-off between fully distributed and centralized charging schemes. This scheme can also help both the charging service providers and the EV users to fulfill their common financial interests. It can also help stakeholders on a higher system level achieve technical objectives such as system load valley filling and avoiding power system overloading. Hence, designing regional nodal price models based on spatial PV generation, electricity consumption and mobility could be a prospective solution of interest to such stakeholders. In nodal price schemes, the central units still have to do proper forecasting and more complex optimization, since they require system-level optimum. The users will need to only execute simpler smart charging schemes that only consider local level optimum.

In addition to the things discussed above, it would be interesting to assess the impact of smart charging schemes considering PV and load in different geographical locations. As solar irradiance varies strongly with the latitude, occupancy and mobility patterns in different countries could also be different. Further studies should evaluate EV smart charging schemes in different latitudes, different climates and for different occupancy patterns.

To sum up, the following aspects need to be further investigated:

- Further research on finding optimal trade-offs between simplicity and performance for the practical implementation of smart charging schemes, in terms of control configuration and charging algorithms. More comparison studies with respect to these aspects should be made.
- Further research on the inclusion of forecasts to deal with the uncertainty of PV power production, electricity consumption and user mobility in smart charging schemes and also finding

optimal trade-offs between forecast performance and simplicity in order to make the smart charging scheme practically viable.
- Further research on nodal price scheme methodologies for EV charging. It should consider not only spatial PV power production and electricity consumption but also mobility patterns since EVs move between different locations. The charging place categorization should be taken into account.
- Further research on impacts of smart charging of EVs including PV and load in different countries at different latitudes, and with different climate and mobility behavior. This in order to assess the importance of smart charging schemes, including their forecast techniques, in different geographical locations.

Declaration of competing interest

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

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