Dynamic Pricing for Electric Vehicle Charging – A Survey

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Abstract

Dynamic pricing for electric vehicle charging can be beneficial for distribution system operators as well as for operators of public charging stations. Thus, it attracted many researchers and an increasing number of different approaches of dynamic pricing for EV charging can be found in the literature. This work aims at providing an overview and a categorization of the existing work in this growing field of research.

Keywords: dynamic pricing, electric vehicles, energy management, smart grid

1 Introduction

In recent years, the penetration of electric vehicles (EVs) significantly increased. In the year 2017, the sales of new EVs surpassed 1 million units and the global stock of electric passenger cars reached 3.1 million (an increase of 57% compared to 2016) [International Energy Agency, 2018]. It can be expected that the considerable grows of the EV penetration will continue in the next years.

The integration of the increasing number of EVs into the power grid is an open issue [Qian et al., 2011; van der Burgt et al., 2015]. The increasing and uncoordinated electrical load due to EV charging imposes significant challenges for the stable operation of the power grid. However, at the same time, there is the opportunity to make use of the EV's batteries in order to provide grid services, which can make the power grid even more stable and safe.

Another important requirement for the electrification of transport, besides the successful integration of the EVs into the power grid, is the availability of an adequate public EV charging infrastructure. The AFI (Alternative Fuels Infrastructure) directive of the European Union recommends a ratio of one publicly accessible charger per ten EVs [International Energy Agency, 2018]. If it is possible to operate public charging stations in a profitable way, then such an infrastructure or part of it could be deployed and operated by private sector stakeholders, like car manufacturers, oil companies or utility companies.

Controlled charging [Wang et al., 2016], also termed smart charging, is often seen as an important step towards a successful grid integration of EVs and a profitable operation of public EV charging stations. Different approaches for increasing the grid stability [Lopes et al., 2009; Waraich et al., 2013] and for increasing the profit of EV charging station operators [Rotering and Ilic, 2011] [Mehta et al., 2016] [Goebel and Jacobsen, 2016] [Naharudinsyah and Limmer, 2018] are proposed in the literature.

Besides controlled charging, dynamic pricing is a promising approach to overcome the challenges related to an increasing penetration of EVs. Dynamic pricing means, that the charging provider - which can be a distribution system operator or an operator/aggregator of public charging stations - dynamically adapts the price that has to be payed by the end users (the EV drivers) for charging their EVs. In this way, it is possible to react on changes in the operating conditions, for example, to increase the charging prices in periods of high electricity prices or of high energy production costs, respectively. A second and even more important advantage of dynamic pricing for EV charging is that it allows to increase the flexibility provided by the users or to make use of the users' flexibility in order to control their behavior or to guide them to a certain degree. Hereby, it is possible to achieve different benefits like reducing the energy production costs, increasing the stability of the power grid, increasing the user satisfaction, or reducing the operating costs of public charging stations.

Thus, dynamic pricing for EV charging attracted a lot of researchers and a lot of different approaches for dynamic pricing in the context of EV charging were proposed and published in recent years. The present work aims at providing an overview over existing work in this field of research. Different approaches for dynamic pricing for EV charging are reviewed and categorized according to their properties.

Dynamic pricing for EV charging can be seen as a special form of demand response. For an overview over demand response in general, the interested reader is referred to [Siano, 2014], [Deng et al., 2015], [Shariatzadeh et al., 2015], [Vardakas et al., 2015], and [Haider et al., 2016].

Furthermore, traditional time-of-use (TOU) rates are not covered in this work, since these rates only depend on time and are not dynamically adapted to changes in the operating conditions. More information to TOU rates can be found in [Zeng et al., 2008] and [Nicolson et al., 2018].

To the best of our knowledge, this is the first literature overview to dynamic pricing for EV charging.

2 Approaches for Dynamic Pricing for EV Charging

The different approaches for dynamic pricing for EV charging, which can be found in the literature, can be categorized regarding the following criteria:

- Type of pricing scheme (How do the prices look like?)
- Implementation of pricing scheme (How are the prices set?)
- Addressed flexibility (What is the purpose of the dynamic pricing?)

In the following, the different types of dynamic pricing approaches and examples for them are discussed more in detail.

2.1 Pricing Type

The pricing type addresses how the prices are structured from the point of view of the users. The pricing types described in the existing literature can be categorized according Figure 1.

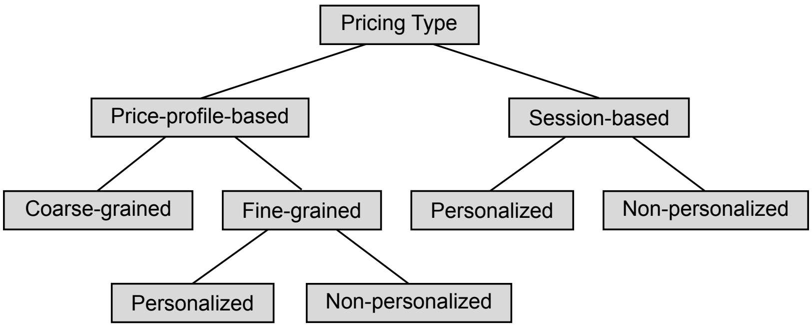

Figure 1: Categorization regarding pricing type.

Price-profile-based pricing sets different charging prices (usually per energy unit) for different time intervals. Most common in literature are fine-grained price profiles, which set an individual price for each scheduling interval (typically of a length between five minutes and one hour). However, some publications propose coarse-grained price profiles, which set a constant charging price for a longer period of time. This type of pricing is used in the work of Guo *et al.* [Guo et al., 2014b,a, 2016]. They investigate the setting of dynamic charging prices per energy unit for charging at a parking deck, where customers get a discount on the parking fee, if they charge their vehicle during parking. The charging price is fixed over 24 hours. The authors argue that such a flat price is an efficient way to build confidence between customers and the parking deck operator.

The fine-grained price profiles can be either personalized or non-personalized. The latter means that the charging price in a certain interval is the same for all users, while with a personalized price profile, different users can get different charging prices for the same interval. Soltani *et al.* [Soltani et al., 2015] describe for example the setting of personalized price profiles for multiple households (different price profiles are set for the different households) with the objectives of maximizing the charging provider's profit and keeping the electrical load under a certain limit. They propose the use of *conditional random fields* [Lafferty et al., 2001] in order to predict for each household, depending on the charging price, the probability that the household charges. The predictions are used as basis for setting the price profiles for the individual households. An example of non-personalized fine-grained price profiles can be found in [Lu et al., 2017]. In this work, an iterative process is described for setting energy prices for individual scheduling intervals with the objectives of maximizing the social welfare and of balancing demand and supply. It is assumed that an energy supplier acts as charging provider. In each interval, the energy supplier computes a charging capacity, which maximizes the energy supplier's profit, and announces a charging price per energy unit to the users, who decide on the amount of energy they want to charge in the interval based on the offered price. If the total amount of energy the users want to charge does not equal the charging capacity, the prices are updated (increased if the charging capacity is exceeded and otherwise decreased) and the procedure is repeated until it converges.

In **session-based pricing**, a user is presented with a total price for a complete charging session. So in contrast to price-profile-based pricing, the user gets no price information for individual intervals or subsections of the charging session. Like for fine-grained price profiles, personalized and non-personalized variants of session-based pricing can be found in literature. In the non-personalized variant, users get the same price if they request the same amount of energy to be charged in the same period of time. This type of pricing is for example used by Ban *et al.* [Ban et al., 2012]. Based on queueing theory, they set different prices for different spatially distributed charging stations with the goals of maximizing the throughput and minimizing the waiting time at the different charging stations. Prices at different charging stations might differ, but two users who arrive at the same time at the same charging station, get the same price for the complete charging session. The price is independent of the requested amount of energy. However, it is not stated whether it is considered that two users can have different energy requirements or not. An example of personalized session-based pricing can be found in [Bhattacharya et al., 2016]. Based on an auction (see also Section 2.2), prices for complete charging sessions are set with the objective of maximizing the social welfare. It is shown that (under certain conditions), the pricing mechanism is nearly incentive compatible in the sense that users can gain only small utility by untruthful declarations. Like for all auction-based pricing mechanisms, the prices are personalized - two users can get different prices although they start and end charging at the same time and charge the same amount of energy.

2.2 Pricing Implementation

There are a lot of different approaches for setting the prices. However, all of them can be roughly categorized according Figure 2. Prices can be set either offline or online. **Offline approaches** set prices for a long planning

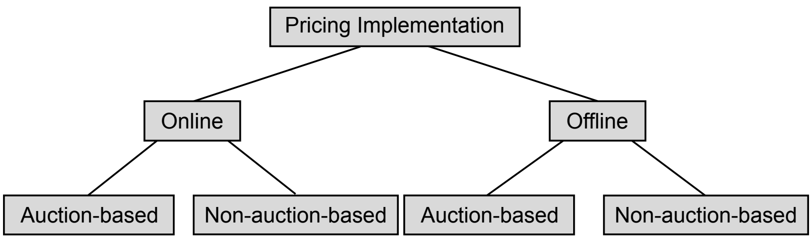

Figure 2: Categorization regarding pricing implementation.

horizon (e.g. 24 hours). They rely on the knowledge or at least a good prediction of the number of EVs that want to charge during the planning horizon and how much and when they want to charge. Some offline approaches, like [Ma et al., 2010] (see Section 2.3 for more details), require even an active contribution of all EVs or users in the setting of the prices. A special case of pricing is **auction-based pricing**. Here, each user specifies a maximum amount of energy to be charged, a deadline, and utilities dependent on the amount of charged energy. The utilities can be interpreted as bids in an auction, since they reflect the amounts of money, the user is willing to pay for a different amounts of energy. Dependent on the charging requirements and the utilities specified by the users, it is decided how much energy a user receives and how much he/she has to pay for it. An example of offline auction-based pricing is the already mentioned work of Bhattacharya *et al.* [Bhattacharya et al., 2016]. They propose adaptions of the *Vickrey-Clark-Groves* (VCG) auction mechanism, which requires the knowledge of charging demands over a planning horizon consisting of multiple scheduling intervals, in order to determine the amount of charged energy and the price (for the complete charging session) for each user with the objective of maximizing the social welfare. With the VCG mechanism, the price for a certain user u contains so called *opportunity costs*, which reflect the amount of utility, that the other users lose due to the participation of user u in the market. The VCG mechanism is incentive compatible, but it has the drawback that users have to specify full utility functions in the amount of charged energy, what they are usually not able to do. Bhattacharya *et al.* propose an adaption of the VCG mechanism, which requires users to specify utilities only for certain levels of charged energy and they show that their approach is nearly incentive compatible. The majority of pricing approaches is non-auction-based. For example, Wang *et al.* [Wang et al., 2015] set a fine-grained price profile for charging at a university campus charging site one day ahead. The prices are set with the objective of load shaping. This is done over a heuristic, which uses a prediction of the load curve on the next day.

Online pricing mechanisms do not rely on the knowledge of all charging demands during a longer planning horizon, either because they are myopic and plan only a short time period ahead or because the planning does not rely on knowledge of future charging demands. They can handle unexpected arrivals of new EVs, what makes them more suitable for a practical implementation than offline approaches. In the case of fine-grained price profiles (coarse-grained price profiles are set offline per se), an online approach sets in each interval the price for the next interval and does not plan further ahead or it computes a new price profile for multiple intervals ahead, when a new user arrives. Online approaches for session-based pricing compute a price for each EV, when it arrives. Like offline approaches, online approaches can be auction-based. An online auction mechanism with the objective of maximizing the social welfare is described by Gerding *et al.* [Gerding et al., 2011]. The approach determines in each interval based on utilities specified by the users, how a fixed amount of available energy is distributed among the plugged in EVs in the next interval. It is shown that it is necessary to occasionally leave a part of the available energy unallocated, even if there is demand, in order to make the approach incentive compatible. An example of a non-auction-based online approach is described by Kim *et al.* [Kim et al., 2017]. They assume a charging station where a price for the complete charging session is offered to each arriving user and a user can either accept the price and is placed in a waiting queue or he/she leaves the station. Additionally, they assume that the charging station operator has to pay a penalty if a waiting EV is not serviced within a certain time limit. For this scenario, they describe an approach for setting in each interval the prices for arriving EVs/users with the objective of maximizing the charging station operator's profit.

2.3 Addressed Flexibility

As already outlined, a benefit of dynamic pricing for EV charging is that it can help to increase the flexibility provided by the users or to make use of the flexibility of users in order to guide them to a certain degree. There are different flexibilities, which can be addressed. The existing approaches for dynamic pricing for EV charging address one or more flexibilities of those shown in Figure 3.

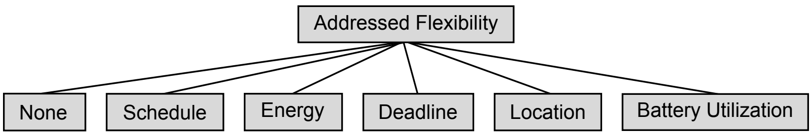

Figure 3: Categorization regarding addressed flexibility.

Some approaches address **no flexibility**. They just adapt prices to changes in the operating conditions without assuming reactions of users to changes in the prices. For example, Guo *et al.* [Guo et al., 2014b] compute a minimum value to which the price for charging on a parking deck has to be set in order to compensate the operating costs arising from fulfilling the (known) charging requirements of customers under the assumption that these charging requirements are not affected by the charging price.

Other approaches address the flexibility of users in the **charging schedule**. Users usually do not care how their EVs are charged exactly as long as they get their required energy when they need it. This is the basis of controlled charging. Through a central control it is possible to coordinate charging schedules of multiple EVs. However, a central control is not always applicable. An alternative to a central control is distributed control with coordination over price signals. This is described by different authors for the use case of controlling EV charging with the objective of filling the valley of a certain base load. One of the first who described such an approach are Ma *et al.* [Ma et al., 2010]. They propose an iterative approach for the distributed control: The charging provider sends fine-grained price profiles to multiple EVs, which optimize their own charging schedules w.r.t. their charging costs. The schedules are sent back to the provider, who adapts the prices and sends them back to the EVs, which optimize their charging schedules according to the new prices and so on. The charging price for an EV in a certain interval is the sum of two terms: A price per charged energy unit, which depends on the total load in the interval, and a penalty term, which depends on the deviation of the EV's charging power from the average charging power. The penalty is required for the convergence of the approach. It is shown that the approach is guaranteed to converge to an optimal valley filling charging schedule for the case of EVs with homogeneous requirements (same start and end times of charging, energy requirements, and maximum charging powers). Because of the penalty term in the prices, an EV might has to pay something for an interval although it is not charged in that interval. However, for homogeneous EVs, the penalty converges to zero. Gan *et al.* [Gan et al., 2011] propose an adaption of the approach from Ma *et al.*, which converges also for non-homogeneous EVs to an optimal solution. It also uses a penalty term in the prices, which converges to zero. Ghavami *et al.* [Ghavami et al., 2013] propose another adaption. They build the penalty term into the price per energy unit, which results in non-linear energy prices. Analogous to the penalty terms used in the other approaches, these non-linear prices can result in costs for intervals in which an EV is not charged. In Ghavami and Kar [2014], Ghavami and Kar extend the approach from [Ghavami et al., 2013] in order to deal with uncertainties in the charging demands of users.

The flexibility in the amount of **charged energy** is a further flexibility, which can be addressed by dynamic pricing approaches. Users might have a certain preferred amount of energy they want to charge – probably mostly a full charge of the battery is preferred. However, it can be assumed, that users are also satisfied if the amount of charged energy slightly deviates from the preferred amount. Hence, it might be possible to influence the amount of energy charged by the users, with help of dynamic pricing. For example, Han *et al.* [Han et al., 2012] propose a dynamic pricing approach which addresses the flexibility of customers of a public charging station in the amount of charged energy. They assume that there are two types of customers: cooperative ones and selfish ones. The cooperative customers allow the central control of the charging of their EVs, while selfish customers do not. The charging price per energy unit is fixed for cooperative customers, but selfish customers pay according to a fine-grained price profile. It is assumed that selfish customers have (basically) convex utility functions in the amount of charged energy and that they optimize their own charging schedules w.r.t. maximizing their utilities minus their charging costs. Thus, with increasing prices in the price profile, the total amount of energy charged by the selfish customers decreases. Han *et al.* propose an offline approach based on bi-level optimization to set the price profiles for the selfish customers in order to maximize the profit of the charging station operator under the assumption that the charging station buys energy for real-time electricity prices. Tushar *et al.* [Tushar et al., 2012] propose an alternative offline approach for the setting of the price profiles for a scenario very similar to that assumed by Han *et al.*. They formulate the problem of setting optimal price profiles as Stackelberg game in which the charging provider acts as leader who sets in each iteration prices with the goal to maximize his/her profit and the users act as followers who adapt their charging schedules according to the prices and their utility functions. Anshelevich *et al.* [Anshelevich et al., 2017] also assume users who optimize their charging schedules and their amount of charged energy w.r.t. their utilities minus the charging costs. However, in contrast to Han *et al.* and Tushar *et al.*, they do not focus solely on the charging provider's profit, but investigate the setting of price profiles with the goal to achieve a reasonable tradeoff between social welfare and the charging provider's profit. They propose an offline approach for the setting of the prices, which yields under certain assumptions, like concave utility functions of users, a nearly optimal profit for the charging provider and simultaneously a nearly optimal social welfare. The proposed algorithm for the setting of prices makes use of a parameter α, which can be seen as a measure for the concavity of the users' utility functions.

It is reasonable to assume that users often have a certain flexibility in the charging time or the **charging deadline**. Thus, it might be possible to stimulate users to provide more time for charging by offering them a better price for charging by a later deadline. This was proposed in 2012 by Bitar and Low [Bitar and Low, 2012] under the term *deadline differentiated pricing*. Users are offered a menu of different prices (per energy unit) for charging by different deadlines from which they can select. It is assumed that each user has a utility function in the charging deadline and that he/she selects a deadline based on her/his utility function and the offered prices. Furthermore, it is assumed that the charging provider can obtain a part of the energy required for charging for free from renewable energy resources and that the rest of the required energy has to be purchased for a fixed electricity price per energy unit. Bitar and Low propose a policy for the offline scheduling of the charging of the users' EVs called *earliest-deadline-first*. They show that under certain conditions, like certain forms of user utilities, this policy results in a *competitive equilibrium*. That means that the deadlines, that are optimal for the users (in the sense of their utility functions), are also optimal (w.r.t. the profit) for the charging provider. However, in this work, Bitar and Low do not state a strategy for the setting of the prices offered to the users. Such a strategy is proposed by Salah and Flath [Salah and Flath, 2016]. They propose an offline approach for the setting of price offers for different deadlines based on stochastic optimization, which accounts for uncertainties in the charging requirements of users during the planning horizon. However, they do not evaluate the approach in simulations. In [Salah et al., 2016], Salah *et al.* evaluate a deterministic version of the optimization without consideration of uncertainties (it is assumed that all charging requirements during the planning horizon are known in advance). In [Bitar and Xu, 2017], Bitar and Xu extend the work from [Bitar and Low, 2012] and propose an offline approach for setting the prices offered for the different deadlines. They show, that the approach, in combination with the earliest-deadline-first charging scheduling strategy is incentive compatible. However, the approach requires that users specify their charging deadlines before the corresponding prices are computed and submitted to the users. Consequently, with this approach users cannot really make their decisions based on a menu of price-deadline-pairs. Limmer and Rodemann [Limmer and Rodemann, 2017] propose an online approach for the setting of the price offers (per charging session), which employs robust evolutionary optimization in order to deal with uncertainties in the users' utility functions. Furthermore, they do not only consider the profit of the charging provider, but also the user satisfaction. They propose the use of a multi-objective evolutionary algorithm for the optimization of the price offers w.r.t. the objectives of maximizing the profit of the charging provider, minimizing the number of users, who decline charging because the prices are higher than their utilities, and minimizing the number of users, who have to be rejected because all charging points are occupied. In [Limmer and Dietrich, 2018], Limmer and Dietrich use an analogous approach to optimize the price offers with consideration of the charging provider's profit and the fairness of the offered prices. Ghosh and Aggarwal [Ghosh and Aggarwal, 2017, 2018] extend the idea of deadline differentiated pricing and propose to offer a menu of different prices (per charging session) for different pairs of deadlines and amounts of energy to be charged. Thus, they propose to address both, flexibility in the charged energy and flexibility in the deadline. They describe an online strategy for the setting of the price offers in the menu with the objective of maximizing the profit of the charging station operator and with consideration of uncertainties in the user utilities. The strategy is based on a heuristic.

The users' flexibility in the **charging location** is another flexibility, which might be addressed by dynamic pricing approaches. This is commonly done with the purpose of balancing the usage or the electrical load over multiple charging sites. An example is the work of Flath *et al.* [Flath et al., 2014], which deals with the setting of charging prices for multiple locations (e.g., charging at home and charging at work) with the goal to reduce the peak loads arising at these locations. The basic idea is to shift the load not only temporally, but also spatially.

They propose to add a local component $p_{t,x}^{loc}$ to the price (per energy unit) for charging in interval t at location x. This local component of the price increases, the closer the (currently known) load at location x in interval t is to a prespecified load limit. In this way, price profiles for the different locations are constructed, which are offered to an arriving user, who plans the charging of his/her EV at the different locations ahead with goal to fulfill his/her charging demands and to minimize the charging costs. After a user submitted his/her charging profile to the charging provider, the prices are updated according to the new loads at the charging locations. Thus, a decision of a user might increase the prices offered to a later arriving users. The approach is evaluated in simulation experiments on the basis of real driving patterns. In the simulations, it is assumed that users plan their charging a complete week ahead. Luo *et al.* [Luo et al., 2016] also describe the setting of charging prices for a number of spatially separated charging sites. They assume that the charging provider purchases energy for real-time electricity prices, that a part of the required energy can be served by renewable resources and that a stationary battery can be used to buffer energy. Furthermore, they assume that users respond to prices at the different charging sites by not only shifting their charging demands temporally and spatially, but also by adapting their charging demands to the prices. Hence, they assume not only flexibility in the charging location, but also in the amount of charged energy. They describe an approach for the optimization of price profiles for the different locations based on dynamic programming with the objective of maximizing a weighted sum of i) the charging provider's profit, ii) the users' profit (which is the utility of users in the amount of charged energy), and iii) a (negated) penalty for the variance in the amount of purchased energy over the intervals of the planning horizon. The latter is taken into account, because high load fluctuations are considered to have a negative impact on the power grid stability. Luo *et al.* do not model the response of users to prices directly. Instead, they propose to estimate the amounts of energy charged in each interval and at each location with help of linear regression. In [Luo et al., 2018], the work is extended and the use of stochastic dynamic programming is proposed in order to deal with uncertainties in the renewable energy production, in the real-time electricity prices, and in the charging demands. In the already mentioned work of Ban *et al.* [Ban et al., 2012], different charging prices are set for different charging sites in order to maximize the throughput and to minimize the waiting times of users at the different charging sites.

Bidirectional charging, which allows charging as well as discharging of batteries, can be employed for different applications, like peak load reduction or the provisioning of regulation market services. However, frequent charging and discharging of the battery of a user's EV damages the battery. Thus, the user should be compensated for using her/his EV's battery for bidirectional charging applications. This is the idea behind dynamic pricing schemes, which address the flexibility in the **battery utilization**. You *et al.* [You et al., 2016] describe such a pricing scheme for charging stations with bidirectional charging capability. They assume that the charging provider purchases energy for real-time electricity prices and that there is an upper bound for the power that can be drawn from the grid. Energy stored in the battery of one EV can be discharged and can be used to charge another EV. However, discharging a battery results in a certain battery loss - the financial costs resulting from the battery degradation due to discharging. It is assumed that the goal of the charging provider is to minimize the sum of the costs for purchasing energy and of the battery loss. You *et al.* describe an iterative approach for optimizing a price profile, where the prices are not only for charging but also for discharging (if an EV's battery is discharged in an interval, the user is compensated according to the charging price in that interval). The approach for the setting of the price profile works as follows: First, the charging provider sets the charging prices to the real-time electricity prices and submits them to the users. The users/EVs optimize their own charging (and discharging) schedule w.r.t. their costs, taking into account the battery losses arising from discharging and send the charging/discharging profiles to the charging provider. If these profiles result in a violation of the load limit or if in an interval more energy is discharged than charged, the prices are adapted via a gradient method and the procedure repeats until convergence. In [Ghosh and Aggarwal, 2016], Ghosh and Aggarwal describe the integration of the battery usage in the price menus from [Ghosh and Aggarwal, 2017]. Thus, users get different price offers for different deadlines, different amounts of charged energy and different battery utilization.

3 Summary and Discussion

Dynamic pricing for EV charging is of increasing interest, since it can help to solve issues related to grid integration of EVs and to the profitable operation of public EV charging stations. There is a growing number of publications, proposing different approaches for dynamic pricing for EV charging, which address different flexibilities of users. One of these flexibilities is the flexibility in the charging schedule. This can be utilized for distributed scheduling/control with help of dynamic pricing. However, the existing approaches are impractical since they require the users or EVs to optimize their own charging schedules in multiple iterations. Furthermore, at least for public charging stations, distributed control is usually not required since a centralized control can be employed. The flexibility in the battery utilization is another flexibility, which can be addressed by dynamic pricing schemes. However, an issue with this is that it is usually hard to determine or to estimate the damage of the battery resulting from a certain dis-/charging pattern. The flexibility in the charging location can be used to balance the number of users or the electrical load over multiple charging sites. This might be especially interesting for distribution system operators, who seek to ensure an adequate grid stability. Furthermore, the flexibilities in the amount of charged energy and in the charging time can be addressed. In the authors' opinion, these are the most promising ones for operators of public charging stations for increasing their profit. However, distribution system operators can take advantage of these flexibilities as well.

Many of the dynamic pricing approaches discussed in the present paper are offline approaches, which assume perfect knowledge of charging demands during the planning horizon. This makes them of questionable practical use. Analogously, several approaches assume that the preferences or utilities of users are known. For a practical realization, dynamic pricing approaches have to be robust regarding uncertainties in future charging patterns and the users' preferences or have to be able to explicitly deal with such uncertainties.

An open issue is the lack of field or user studies. It is not clear, how users respond to dynamic prices. For example, how much discount does a user expect for charging 10 kWhz less or giving 15 minutes more time for charging, than initially intended. Furthermore, it is not clear if a dynamic pricing scheme would be accepted by the users at all. A dynamic pricing scheme, especially with personalized prices, might be perceived as unfair. Additionally, users might be not willing or able to make decisions based on the charging price.

Another aspect, which requires more research is the question, how dynamic pricing for EV charging can be technologically realized. An adequate infrastructure is required, which decides on the prices and communicates them to the users. This also includes adequate user interfaces, which might be crucial for the user acceptance. In order to save the user the effort of negotiating prices, each time he/she is charging, a software agent could learn the preferences of the user and communicate with the charging facility on behalf of the user.

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