

Review

# Dynamic Pricing for Electric Vehicle Charging—A Literature Review

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**Abstract:** Time-varying pricing is seen as an appropriate means for unlocking the potential flexibility from electric vehicle users. This in turn facilitates the future integration of electric vehicles and renewable energy resources into the power grid. The most complex form of time-varying pricing is dynamic pricing. Its application to electric vehicle charging is receiving growing attention and an increasing number of different approaches 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. Furthermore, user studies and the modeling of user preferences via utility functions are discussed.

**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) [1]. In 2018, nearly 2 million new EVs were sold and the global stock increased to 5.1 million units (63% more than in 2017) [2]. The share of EVs is still small. Only five countries had an EV share higher than 1% in 2018 [2]. However, it can be expected that the considerable growth 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 [3,4]. 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 – especially if vehicle-to-grid (V2G) technology is employed [5–7]. V2G allows to feed energy from EVs back to the grid. As a result, the EVs are not just a shiftable load but also a distributed energy source. This can be used for the provisioning of services like frequency regulation or peak shaving. Furthermore, V2G can support the integration of renewable energy resources into the grid. The variability and uncertainty of wind and solar energy generation represents a challenge for the balancing of supply and demand [8]. Using V2G technology, EVs can be employed as an energy buffer in order to reduce peak loads as well as curtailment in wind- and solar-based systems [9].

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 [1]. 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. The profitable operation of charging stations can be supported by so called EV aggregators. An EV aggregator is an agent, which aggregates a large number of charging points and acts as a middleman between charging station operators or EV owners and the energy market. According to Reference [9], the viable trading

of EV power on the wholesale market requires the aggregation of at least around 500 charging points or EVs.

Smart charging [10], which allows the control of charging processes in a coordinated way, 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 towards increasing the grid stability [11,12] and the profit of EV charging station operators [13–15] are proposed in the literature. Smart charging could be also applied by individual users in order to reduce their charging costs [16–18]. Furthermore, it can be used for the purposes of minimizing distribution system losses [19], of reducing distribution network investment costs [20], of minimizing loss of life of transformers [21] and of peak shaving and valley filling [22].

Besides smart 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 charging stations—dynamically adapts the price, which has to be paid by the end users (the EV drivers) for charging their EVs. In this way, it is possible to react to changes in the operating conditions, for example, to increase the charging prices during periods of high electricity prices or 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 to a certain degree (see Section 3.4 for more details). Hereby, it is possible to achieve different benefits like reducing energy production costs, increasing the stability of the power grid, increasing user satisfaction or reducing the operating costs of public charging stations. The International Renewable Energy Agency considers smart charging and user incentives, like dynamic pricing, to be two key factors for unlocking the flexibility potential from EVs, which is required for a successful grid integration of EVs and renewable energy in the future [9]. Thus, dynamic pricing for EV charging attracted a lot of researchers and a lot of different approaches to dynamic pricing in the context of EV charging were proposed and published in recent years. The present work aims at providing an overview of existing work in this field of research. Different approaches to dynamic pricing for public and residential 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, which refers to a procedure that motivates end users to change their electricity consumption, in response to financial incentives. For an overview of demand response in general, the interested reader is referred to References [23–25]. 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 on TOU rates can be found in References [26,27].

Dynamic pricing approaches are already discussed in existing literature reviews of EV charging management [28–30]. In these works, different approaches to decentralized charging control based on price signals are reviewed. However, decentralized control is not the only possible application of dynamic pricing. Compared to existing works, the present literature review is not focused on charging control but on dynamic pricing strategies and discusses their different applications. Furthermore, the present work provides a review of utility functions, which are used in the literature on dynamic charging pricing in order to model user preferences. Moreover, user studies, which can reveal insights useful for a practical realization of dynamic pricing approaches, are discussed.

The rest of the paper is structured as follows: Section 2 provides a brief overview of the current situation regarding EV charging tariffs, taking the example of the United States. Section 3 describes and categorizes the different dynamic pricing approaches, which can be found in literature. Section 4 provides an overview of utility functions used in the context of dynamic charging prices. In Section 5, user studies are discussed and finally, Section 6 summarizes and discusses the work and its findings.

## 2. Tariffs for EV Charging in the United States

In order to provide an overview of the current practices regarding pricing for EV charging, this section discusses the actual situation in the United States. The U.S. were chosen as an example due to poor availability of information on other countries.

Home charging is billed according to the residential electricity tariff of the user. The majority of households in the U.S. have a single rate or flat rate electricity tariff with a constant price per kWh, independent of the time the energy is consumed [31]. In addition, there is often a fixed fee per billing period, which is independent of the energy consumption [32]. Some tariffs contain peak demand charges (in \$/kW), which are based on the peak electricity demand in the billing period. However, this is unusual for residential consumers [32]. Many utilities offer TOU tariffs. These tariffs commonly differ in peak, intermediate and off-peak periods [32]. Until recently, TOU tariffs were rarely adopted by residential consumers in the U.S. but they receive growing attention [33]. An increasing number of utilities offer special tariffs for EVs [34]. This can be, for example, TOU tariffs, which apply only to the EV charging, while the rest of the energy consumption is billed via a single rate tariff. This requires a separate energy meter in order to measure the EV charging load. Today, there are also programs with hourly real-time electricity prices [35]. Furthermore, there are pilot projects for V2G [34] and demand response [36] programs.

Many public charging stations in the U.S. allow free charging [37]. For those, which do not, various pricing models exist [37–39]. Most of them use a time-based fee (usually \$/min), which might also apply for the time the EV is no longer charging. There are even charging stations with an idle fee, which is higher than the fee during charging. Besides time-based tariffs, there are also tariffs with a fee per kWh. However, this is not permitted in all U.S. states. Session-based billing with a fixed price per charging session is likewise common. At some charging stations, a session fee comes on top of the usage-based fees. A further pricing model in use is a monthly or annual fee, which allows arbitrary EV charging during the corresponding period or at least provides a discount on charging.

Electricity tariffs for operators of public charging stations in the U.S. have been analyzed by Muratori et al. [40]. Most commercial and industrial tariffs applicable to public EV charging have a TOU structure. About half of them include demand charges. Muratori et al. show that these demand charges can result in high energy costs, especially for fast charging stations with a low utilization.

## 3. Approaches to Dynamic Pricing for EV Charging

The different approaches to 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 from the user's point of view?)
- Implementation of pricing scheme (How are the prices set?)
- Addressed flexibility (What is the purpose of the dynamic pricing?)

Before the different types of dynamic pricing approaches and examples of them are discussed more in detail in Sections 3.2–3.4, some fundamental concepts and terms, which are frequently used in the literature on dynamic pricing for EV charging, are discussed in the following subsection.

### 3.1. Fundamentals

In many papers on dynamic pricing for EV charging, the preferences of users are modeled with the help of utilities. It is assumed that a user  $n$  gets a certain satisfaction from consuming a good  $x$ , which is expressed as utility  $U_n(x) \in \mathbb{R}$ . In the context of EV charging, the "good"  $x$  can be, for example, the amount of charged energy or the duration of the charging session. In works on dynamic pricing for EV charging, it is frequently assumed that users make decisions that maximize their profit, which is their utility minus their costs. That means, a user  $n$  chooses  $x$  so that  $U_n(x) - P_n(x)$  is maximized, where  $P_n(x)$  is the price, the user has to pay for  $x$ . Often, it is also assumed that users do not charge, if charging results in a negative profit for all possible values of  $x$ . In that sense, the utility  $U_n(x)$  can be

seen as the price, the user  $n$  is willing to pay for the good  $x$ . Examples of utility functions used in the literature on dynamic pricing for EV charging are discussed in Section 4.

The maximization of the social welfare is often considered as a goal of the dynamic pricing. The social welfare can be defined in different ways. In a number of works, it is defined as the sum of the users' profits (utilities minus the prices paid) and the charging provider's profit. In other works, the social welfare is considered to be equivalent to the utilities gained by the users or to the users' utilities minus the costs for energy production. Further on, some works assume that the social welfare is maximized if the social costs are minimized, which are usually defined as the costs related to the production of the energy required for charging.

Many works show that their proposed dynamic pricing strategies for EV charging are *incentive compatible*. A pricing strategy is incentive compatible if a user cannot gain an advantage by providing untrue information (e.g., regarding the preferred amount of energy or the preferred departure time). One can distinguish two types of incentive-compatibility: A pricing strategy is *Bayesian-Nash incentive compatible* if a user has no disadvantage from telling the truth if all other users reveal their true preferences. The stronger concept of *dominant-strategy incentive-compatibility* means that the benefit with truth-telling is guaranteed to be at least as high as the benefit with misreporting, regardless of the actions of other users.

### 3.2. 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.

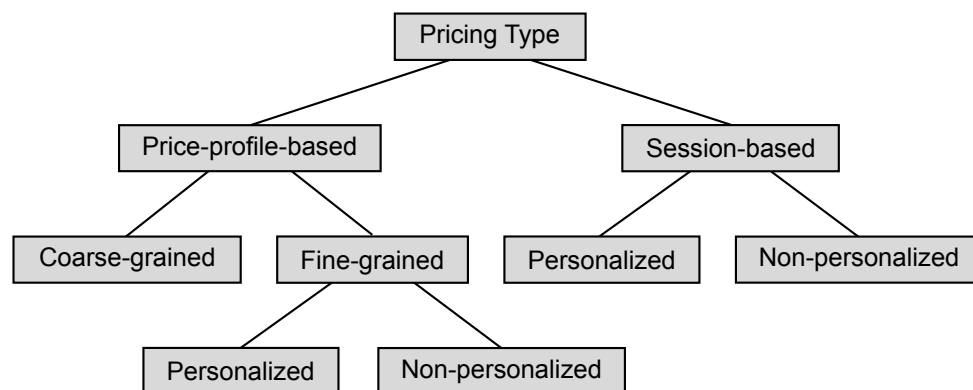


Figure 1. Categorization regarding pricing type.

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. [41–43]. 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 for 24 h. 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. [44] describe, for example, the setting of personalized price profiles for multiple households with EVs (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. It is assumed that in each time interval the households decide based on the prices, whether they charge their EVs or not

and that different households react differently to prices. Soltani et al. propose the use of *conditional random fields* [45] in order to predict for each household the probability that it charges for a given price. The predictions are used as a basis for setting the price profiles for the individual households. An example of non-personalized fine-grained price profiles can be found in Reference [46]. In this work, an iterative process is described, which sets 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 its 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. [47]. Based on queuing 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 Reference [48]. Based on an auction (see also Section 3.3), 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.

### 3.3. Pricing Implementation

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

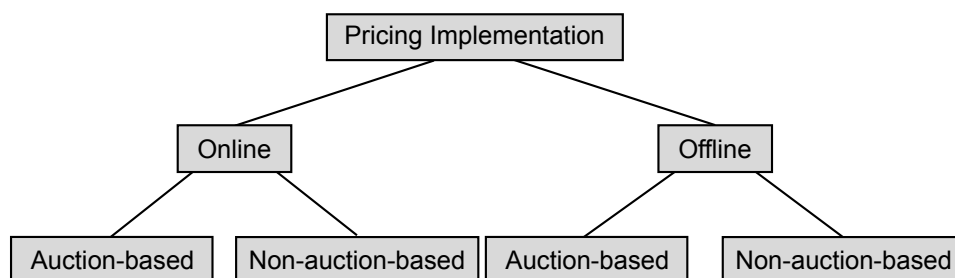


Figure 2. Categorization regarding pricing implementation.

Offline approaches set prices for a long planning horizon (e.g., 24 h). 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 Reference [49] (see Section 3.4 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 departure time and utilities the user gains by different amounts 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 different amounts of energy. Depending on the charging requirements and the utilities specified by the users, it is decided how much energy each user receives and how much he/she has to pay for it. An example of offline auction-based pricing can be found in the already mentioned work of Bhattacharya et al. [48]. They propose extensions of the *Vickrey-Clark-Groves* (VCG) auction mechanism. This mechanism 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  $n$  contains so called *opportunity costs*, which reflect the amount of utility, that the other users lose due to the participation of user  $n$  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, which they are usually unable to do. Bhattacharya et al. propose an extension 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 are non-auction-based. For example, Wang et al. [50] 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 with the help of a heuristic, which uses a prediction of the load curve of 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, which 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 to 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. [51]. Based on utilities specified by the users, the approach determines in each interval, how a fixed amount of available energy is distributed among the users 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. [52]. 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 to set in each interval the prices for arriving EVs/users with the objective of maximizing the charging station operator's profit.

### 3.4. 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. For example, users are often flexible in the charging duration. They do not always require to charge their EVs as fast as possible, because they park over a longer period. This fact can be used by an intelligent charging control, for example, to shift the charging load into off-peak hours. However, it requires that users communicate their flexibility in the charging duration. With the help of dynamic pricing approaches, users can be encouraged to reveal their full flexibility. Besides the flexibility in the charging duration, other flexibilities can be addressed. The existing approaches to dynamic pricing for EV charging address one or more flexibilities of those shown in Figure 3.

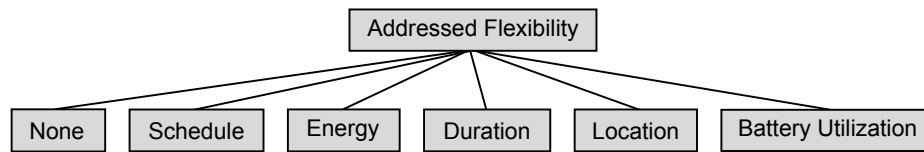


Figure 3. Categorization regarding addressed flexibility.

#### 3.4.1. No 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. [41] 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 in advance) charging requirements of customers under the assumption that these charging requirements are not affected by the charging price. Another dynamic pricing approach, which does not consider user flexibilities is described by Wang et al. [53]. They assume that the charging provider offers a charging price to an arriving user and that the user makes a counter-offer. Then, the charging provider updates the initial offer and so on until a price is found, which satisfies the charging provider as well as the user, or a maximum number of iterations is reached and consequently the negotiation fails.

#### 3.4.2. Flexibility in the Schedule

Other approaches address the flexibility of users in the charging schedule. It can be assumed that users usually do not care much 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 via 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. [49]. They propose an iterative approach to distributed control: The charging provider sends fine-grained price profiles to multiple EVs, which optimize their own charging schedules with respect to 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 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 have 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. [54] propose a modification of the approach of 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. [55] propose another modification. 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 Reference [56], Ghavami and Kar extend the approach from Reference [55] in order to deal with uncertainties in the charging demands of users. A further work, which describes the usage of dynamic prices for EV charging scheduling with the purpose of valley filling, is the work of Zhang and Chen [57]. They also propose the setting of a price profile, where the charging price in a time interval depends on the total load in that interval. Based on these prices, the charging of the EVs is scheduled in a centralized way. Hu et al. [58] and Xydas et al. [59] propose online pricing schemes for valley filling. A price profile is computed analogously to the previously

described works with the difference that only the charging load from currently plugged in EVs is considered in the setting of the prices. When a new EV arrives, it computes a charging profile based on the prices and submits it to the charging provider. Then the prices are updated.

O'Connell et al. [60] propose the use of so called *locational marginal pricing (LMP)* in order to avoid power grid congestion. In this approach, different price profiles are set for different nodes/buses of the distribution grid based on a day-ahead prediction of charging demands. The prices are set in a way that cost-optimal charging schedules result in a minimum grid congestion and they can be decomposed into two components: marginal generation costs and congestion costs. The marginal generation costs are based on (predicted) day-ahead energy market prices. A very similar approach based on LMP is proposed by Li et al. [61]. Dallinger and Wietschel [62] describe an analogous pricing scheme, where charging prices consist of marginal costs and a grid fee, which is proportional to the utilization of the transformers of the power grid. Tan and Wang [63] propose a pricing scheme denoted as *reliability-differentiated pricing*. Here, the prices contain a component, which reflects potential costs resulting from transformer overloads. This should encourage customers to schedule the charging of their EVs in a way, which enhances system reliability. Yang et al. [64] describe the coordination of the charging load of a fleet of electric taxis with the help of dynamic pricing. They assume that in each time interval a taxi either charges or drives and that the probability of charging depends on the price. Based on this assumption, an iterative online approach for setting the prices with the objective of load shaping is described.

Xi and Sioshansi [65] assume a system with multiple distributed generators (DGs) and propose the use of price signals in order to coordinate EV charging with the operation of the DGs. The work of Clairand et al. [66] describes the use of dynamic pricing with the purpose of balancing energy consumption and renewable energy production. At the beginning of each day a system operator computes an EV charging price profile for the day based on a forecast of the energy demand and renewable production during the day. The prices are low in time intervals for which the renewable production is expected to exceed the demand and in other time intervals the prices are higher. Based on the prices set by the system operator, an EV aggregator manages the charging of the EVs.

Subramanian and Das [67] propose the use of dynamic pricing in order to reduce the costs of energy purchased in the energy market. They assume a system operator who provides energy to multiple EV aggregators and who purchases this energy in the day-ahead and real-time energy market. Furthermore, it is assumed that the system operator sets charging prices and that the EV aggregators schedule the charging of their EVs based on these prices. The prices are set in an online approach in a way that the costs arising to the EVs are minimized while the system operator's revenue is kept neutral (no loss and no profit).

### 3.4.3. Flexibility in the Energy Amount

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 the help of dynamic pricing.

For example, Han et al. [68] 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 concave utility functions in the amount of charged energy and that they optimize their own charging schedules with respect to 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. [69] propose an alternative offline approach to 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 a Stackelberg game in which the charging provider acts as the 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. [70] also assume users, who optimize their charging schedules and their amount of charged energy with respect to 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 to 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  $\alpha$ , which can be seen as a measure for the concavity of the users' utility functions. In References [71–74], further approaches to dynamic pricing, which address the amount of charged energy, are described.

#### 3.4.4. Flexibility in the Charging Duration

It is reasonable to assume that users often have a certain flexibility in the charging duration. Thus, with the help of dynamic pricing schemes, it might be possible to stimulate users to allow a longer charging duration.

This was proposed in 2012 by Bitar and Low [75] under the term *deadline differentiated pricing*. The deadline refers to the point in time, the requested amount of energy should be charged—the later the deadline, the longer the charging duration. 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 (with respect to 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 [76]. They propose an offline approach to 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 regarding the charging providers profit. In Reference [77], 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).

Based on a preliminary version [78], Bitar and Xu [79] extend the work from Reference [75] and propose an offline approach to setting the prices offered for the different deadlines. They show that the approach, in combination with the earliest-deadline-first charging scheduling strategy is (dominant-strategy) 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 can not really make their decisions based on a menu of price-deadline-pairs.

Limmer and Rodemann [80] propose an online approach to 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 with respect to 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 Reference [81], 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 [82,83] 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.

Bayram et al. [84] describe the setting of a discount offered to users to defer their (uncontrolled) charging sessions by one time interval. The discount is set in an online approach based on queueing theory with the objectives of maximizing the charging providers profit and of keeping the probability that users have to be blocked due to a shortage of charging points under an acceptable level.

Fan [85,86] proposes the setting of price profiles based on congestion pricing. The price per energy unit in an interval increases with an increasing total charging load in that interval. It is assumed that all users want to fully charge their EVs and that they adapt their charging rates based on the charging prices and a willingness to pay parameter. Users with a higher willingness to pay parameter choose a higher charging rate and thus have a shorter charging duration than users with a lower willingness to pay parameter. Liu et al. [87] describe a pricing scheme with different charging price profiles for different buses of a power distribution system. They assume that based on the prices, users choose between different alternatives for the charging power (and consequently for the charging duration). They propose a strategy for the setting of the prices with the target to minimize power distribution losses. In Reference [88], Limmer and Rodemann investigate the setting of prices for different charging deadlines with the objectives of maximizing the charging provider's profit and minimizing the peak load.

#### 3.4.5. Flexibility in the Location

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. [89], 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 the 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 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. [90] 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 to 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 the help of linear regression. In Reference [91], 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. [47], 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. Wong and Alizadeh [92] describe the setting of dynamic charging prices at different locations with the goal to minimize not only the waiting times at the charging stations but also the travel times of the users. However, they do not consider that the travel time depends on the traffic flow and that the setting of the prices might have an influence on the traffic. Further approaches on dynamic pricing with the purpose of controlling the location where users charge can be found in References [93–95].

#### 3.4.6. Flexibility in the Battery Utilization

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. [96] describe such a pricing scheme for charging stations with bidirectional charging capability. They assume that the charging provider purchases energy at 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 to 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 to the setting of the price profile works as follows: First, the charging provider sets the charging prices equivalent to the real-time electricity prices and submits them to the users. The users/EVs optimize their own charging (and discharging) schedule with respect to 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 Reference [97], Ghosh and Aggarwal describe the integration of the battery usage in the price menus from Reference [82] (see also Section 3.4.4). Thus, users get different price offers for different

deadlines, different amounts of charged energy and different battery utilization. Wu et al. [98] investigate from a game theoretical point of view the control of the charging and discharging behavior of a fleet of EVs by an aggregator via dynamic prices in order to provide frequency regulation services to the grid. In the investigated scenario, the charging requirements and battery levels of the EVs are not taken into account. Gharesifard et al. [99] assume a more realistic scenario, where the users prefer fully charged batteries, if they are not incentivized for discharging.

#### 4. Utility Functions for EV Charging

As outlined in Section 3.1, the modeling of user preferences is often done with the help of utility functions. The right choice of a utility function is especially important for simulation experiments. The more realistic the used utility function is, the more meaningful are the experimental results. However, there is not the one generally accepted utility function. Instead, different utility functions can be found in literature. The present section provides an overview of utility functions used in works on dynamic pricing for EV charging.

Before the utility functions used in the literature are discussed, some discrepancies in terminology have to be addressed. It is common to assume that users act in a way that the following optimization problem is solved:

$$\max_x f(x, p) = g(x) - h(x, p), \quad (1)$$

where  $x$  is the good, which can be consumed (e.g., the amount of charged energy),  $p$  is the charging price (or a price vector) set by the charging provider,  $g(x)$  is the satisfaction the user gains by consuming  $x$  and  $h(x, p)$  is the amount of money the user has to pay for consuming  $x$  (e.g.  $h(x, p) = x \cdot p$ ). That means, it is assumed that a user chooses a good so that the satisfaction gained from the good minus the price that has to be paid for the good is maximized. Some authors term  $f(x, p)$  utility. This is, for example, the case in Reference [48], where  $g(x)$  is termed valuation. In Reference [76],  $g(x)$  is called gross utility and  $f(x, p)$  is termed net utility. Other works term  $g(x)$  utility and  $f(x, p)$  profit or surplus. This is the terminology followed in the present work. Thus, in the following discussion to utility functions, we are interested in the function  $g(x)$ , which models the user satisfaction independently of the charging prices.

The setting of charging prices is commonly done by solving an optimization problem of the following form:

$$\max_p \phi(\bar{x}, p) \quad (2)$$

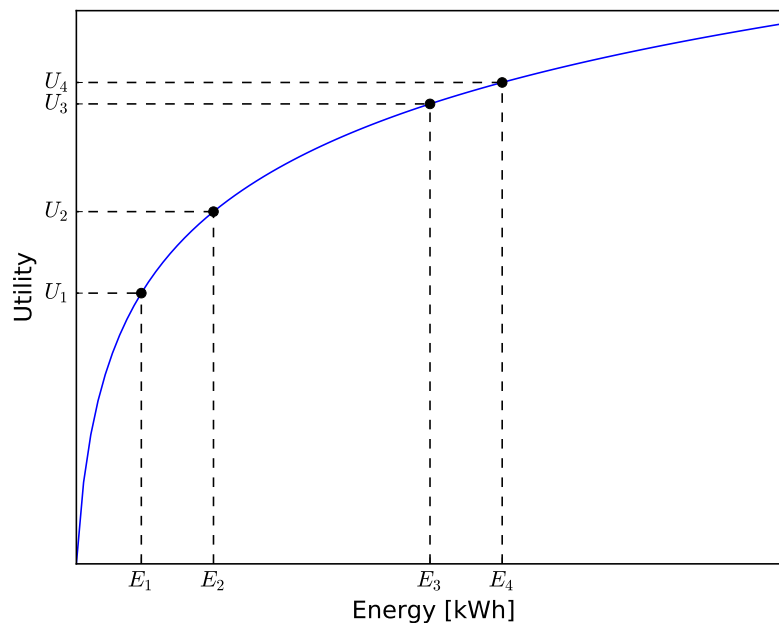
$$\text{s.t. } \bar{x} = \arg \max_x f(x, p), \quad (3)$$

where the function  $\phi$  models the objective of the pricing approach, like for example, the charging provider's profit or the peak load reduction. Constraint (3) models the user response to prices according to Equation (1). The complete problem is a bi-level optimization. In the outer optimization the prices are optimized. In the inner optimization the user's decision based on the utility function and the prices is optimized.

##### 4.1. Utility Function in Energy

Many works employ utility functions in the amount of charged energy. It is usually assumed that the utility function is increasing and concave (Some works assume that the utility function is strictly increasing and/or strictly concave) [70,78,86,90,97,99]. The concavity of the function reflects the law of diminishing marginal utility. The *marginal utility* refers to the increase of the utility by consuming one more unit of a good after a certain number of units are already consumed. It is typically assumed that the marginal utility decreases with an increasing number of already consumed units. In the context of charged energy that means that, for example, a user gains more satisfaction from increasing the state of charge (SoC) of the battery from 50% to 60% than from 90% to 100%. This is reflected by a concave

utility function, as illustrated in Figure 4. The increase of energy from  $E_1$  to  $E_2$  results in a much higher gain in utility than the increase from  $E_3$  to  $E_4$ .



**Figure 4.** Illustration of diminishing marginal utility with concave utility function.

Often a quadratic function of the following form is used as utility function of a user  $n$  in the amount  $x$  of charged energy:

$$U_n(x) = -a_n x^2 + b_n x, \quad (4)$$

with (usually) user-specific parameters  $a_n$  and  $b_n$ . The function is exemplary shown as  $f_1$  in Figure 5. In Reference [90], such type of function is used to model the utility of a complete population of users. In Reference [69], the parameter  $b_n$  is assumed to be equivalent to the capacity of the EV battery and the parameter  $a_n$  is set to  $\frac{s_n}{2}$ , where  $s_n$  is called *satisfaction parameter*. Other works assume slight modifications of (4). For example, in Reference [82], it is assumed that a user  $n$  expects or desires a certain amount  $\hat{x}_n$  of energy and the following utility function is used:

$$U_n(x) = \begin{cases} -a_n x^2 + b_n x & , \text{if } x \leq \hat{x}_n \\ \frac{b_n^2}{4a_n} & , \text{otherwise} \end{cases} \quad (5)$$

where  $\hat{x}_n = b_n / (2a_n)$ . In Reference [68], the expected amount of energy is included in the utility function in the following way:

$$U_n(x) = -a_n \cdot (x - \hat{x}_n)^2 \quad (6)$$

with positive  $a_n$ . Thus, the utility is zero for  $x = \hat{x}_n$  and otherwise negative. That means that there is a negative effect on the utility not only by charging less energy than expected but also by charging more than expected. In Reference [46], a utility function in the charging power  $p_t$  (which is of course proportional to the charged energy) for a user  $n$  in an interval  $t$  is assumed, which is of the following form:

$$U_{n,t}(p_t) = -\frac{a_{n,t}}{2\hat{p}_{n,t}} p_t^2 + a_{n,t} p_t, \quad (7)$$

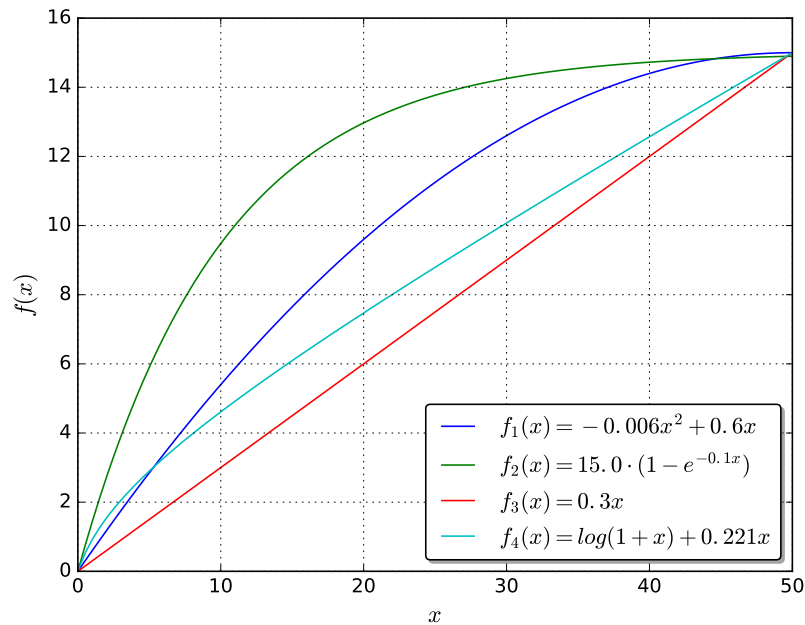
where  $\hat{p}_{n,t}$  is the maximum charging power. The parameter  $a_{n,t}$  is called *willingness-to-charge parameter*.

Not all works use a quadratic utility function in the energy (or power). Bhattacharya et al. [48] assume an exponential utility of user  $n$  in the amount  $x$  of charged energy:



$$U_n(x) = \kappa_n \cdot (1 - e^{-a_n x}), \quad (8)$$

with parameters  $\kappa_n$  and  $a_n$ . In simulation experiments, they set  $a_n = 0.1$  for all users and consider two types of users with  $\kappa_n = 15$  and  $\kappa_n = 12$ , respectively. The function is illustrated as  $f_2$  in Figure 5. The exponential utility function models a stronger diminishing of the marginal utility compared to the quadratic utility function.



**Figure 5.** Examples of a quadratic ( $f_1$ ), an exponential ( $f_2$ ), a linear ( $f_3$ ) and a logarithmic ( $f_4$ ) function.

Li et al. [74] use a linear utility function,

$$U_n(x) = a_n \cdot x + b_n, \quad (9)$$

with positive parameters  $a_n$  and  $b_n$ . The marginal utility is not diminishing with this type of utility function.

In Reference [78], piecewise linear utilities of the form

$$U_n(x) = R_n \cdot \min\{x, q_n\} \quad (10)$$

are assumed, where  $R_n$  is a user-specific parameter (which is equivalent to the marginal utility for  $x < q_n$ ) and  $q_n$  is the maximum energy demand of user  $n$ .

Ghariesifard et al. [99] assume a logarithmic utility function in the SoC  $l \in [0, 1]$ :

$$U_n(l) = u_n^1 \log(1+l) + u_n^2 l, \quad (11)$$

with user-specific parameters  $u_n^1, u_n^2 \in (0, 1]$ . As can be seen from  $f_4$  in Figure 5, the effect of diminishing marginal utility is comparatively small with this type of function.

Gerding et al. [51] assume in their experiments plug-in hybrid EVs and set the utility for a certain amount  $x$  of charged energy to the amount/cost of fuel that is saved compared to not charging  $x$ .

In Reference [76], it is assumed that the utility  $U_n(x)$  of user  $n$  is equal to the amount of money, the user would have to pay for the amount  $x$  of energy at an outside option (e.g., charging at home).

#### 4.2. Further Utility Functions

There are also utility functions in parameters other than the amount of charged energy in the literature on dynamic pricing for EV charging. An example are utility functions in the charging deadline or charging duration. Ghosh and Aggarwal [82] assume that a user  $n$  allows a certain maximum duration  $\hat{t}_n$  for charging and that the user's utility for a duration  $t$  is

$$U_n(t) = \frac{\max\{0, e^{(\hat{t}_n - t)} - 1\}}{e^{\hat{t}_n} - 1}. \quad (12)$$

Thus, the utility is zero for  $t \geq \hat{t}_n$  and otherwise it is greater zero. Limmer and Rodemann [80] assume that users can choose between charging as fast as possible or extending the charging duration by a number  $k$  of intervals. They use a linear function of the following form for the utility of a user  $n$  in  $k$ :

$$U_n(k) = \delta_n - \beta_n \cdot k, \quad (13)$$

with user specific parameters  $\delta_n$  and  $\beta_n$ .

In Reference [97], a utility function in the battery utilization  $B$  (in terms of the amount of energy, which is discharged and charged in addition to the requested amount of energy) is used. It is assumed that the utility (actually, it can be seen as disutility) of a user  $n$  in the battery utilization is linear:

$$U_n(B) = -\alpha B \quad (14)$$

with a positive parameter  $\alpha$ .

Kim et al. [52] assume different charging prices for different types of users and that users decide based on the price if they charge or if they leave the charging station. They do not consider utilities for individual users. Instead, they assume that for each user type  $m$  a representative user decides in each interval  $t$  how many of the arriving users of type  $m$  start charging. They use the following logarithmic utility function in the number  $n_{m,t}$  of users of type  $m$ , who start charging in interval  $t$ :

$$U_{m,t}(n_{m,t}) = \beta_{m,t} \log(1 + n_{m,t}), \quad (15)$$

with a parameter  $\beta_{m,t}$ , which depends on the user type and the interval.

Bayram et al. [93] propose the setting of different prices for a number  $S$  of locally distributed charging sites. They assume the following utility of a user  $n$  in a charging site  $s$ :

$$U_n(s) = -h(P_s) \cdot (p_s + c(d_{s,n}) + f(d_{s,n})), \quad (16)$$

where  $P_s$  is the blocking rate (the probability of being rejected because of congestion) of site  $s$ ,  $h$  is a function, modeling the disutility related to a high blocking rate,  $p_s$  is the charging price (per session) at site  $s$ ,  $d_{s,n}$  is the distance to site  $s$ ,  $c(d_{s,n})$  is the cost for driving to the site  $s$  and  $f(d_{s,n})$  is the dissatisfaction due to the time that has to be spent for driving to site  $s$ .

## 5. User Studies

As outlined in the previous section, user preferences are usually modeled through utility functions. A question is, how realistic such functions are. How do EV drivers respond to dynamic prices in reality and is this adequately reflected by the utility functions used in the literature? Another question is how external factors influence the user preferences. Such factors can be, for example, the time of day or the location of the charging facility. Furthermore, it is not clear if a dynamic pricing scheme would be accepted by the users at all. Unfortunately, there is a lack of user studies, which fully answer these questions. However, there exists literature, providing helpful starting points.

There are several studies to charging behavior without consideration of the impact of pricing. Such studies can provide insights into the users' flexibility that can be theoretically exploited through dynamic pricing schemes. For example, based on data from public charging stations in the Netherlands, Wolbertus et al. [100] investigate the impact of factors, like the start time, the day of the week or the parking pressure, on the connection times of EVs. From the observed factors, they identify the start time as the factor with the highest influence on the connection time. Another example is the work of Sadeghianpourhamami et al. [101], who also analyze charging data collected in the Netherlands. They investigate the flexibility of users in terms of charging duration and charged energy and how much of this flexibility can be exploited for the two applications load flattening and load balancing.

There are also some studies of charging behavior, which take pricing into account. Motoaki and Shirk [102] investigate how a flat-rate tariff (\$5 per charging session) influences the charging behavior at public fast charging stations compared to free charging. The study is based on data collected in the U.S. in 2013. The study comes to the result that the flat-rate prices cause users to charge longer (lower start SoC and higher end SoC) compared to free charging and that this decreases the usage efficiency of the charging stations, since the charging power diminishes with a SoC near to the maximum. Francfort [103] describes the effect of the introduction of a fee based on connect time at public charging stations in the context of a field study in the U.S. It was observed that the introduction of the fee did not reduce the number of charging sessions but did reduce the connection times. Sun et al. [104] study the effect of dynamic electricity prices on the recharging behavior of plug-in hybrid EV drivers at home based on data recorded in Japan. They conclude that the dynamic prices are an efficient measure to encourage users to shift their charging times.

Most studies, which consider variable prices for charging are based on user surveys (also referred as *stated choice studies*). Wen et al. [105] investigate based on a user survey, which factors, including the charging price, influence whether users charge or not when they have the possibility to charge. They identify three classes: Users of the first class (about 20% of the respondents) charge for higher prices only if necessary. Users of the second class (about 60% of the respondents) are also price sensitive, but consider additional factors like the charging speed in their decisions. The third class is not price sensitive and charges in nearly all situations. Parsons et al. [106] investigate user preferences regarding V2G contracts and the willingness to purchase EVs with V2G functionality. They assume contracts, which incentivize users of EVs for providing V2G services. The contracts require users to keep their EVs plugged in for a certain minimum number of hours per day. Furthermore, the contracts guarantee that the charging state of the EVs always allows a certain minimum driving range. With the help of a user survey, it is investigated, which monetary incentives are required in order to make such contracts attractive for users. The authors conclude that high incentives are required, because users perceive high inconvenience related to V2G contract requirements. They suggest to allow provisioning of V2G services on a pay-as-you-go basis in order to reduce inconvenience. Wolbertus and Gerzon [107] investigate via a user survey whether public charging stations can be operated more efficiently if drivers have to pay a fee for occupying the charging stations after the EV is fully charged. They conclude that most respondents of the survey would react to such a fee and would move their vehicle after charging but that respondents who experience a high parking pressure at home are less likely to react. A further study based on a user survey is described by Jabeen et al. [108]. They investigate user preferences regarding charging at home, at work and in public with consideration of prices. They conclude that users are in general very sensitive to the charging price. Daina et al. [109] investigate in a stated choice experiment charging behavior with considering not only flexibility in the charging patterns, but also in the driving patterns. Respondents are presented with a planned tour (consisting of trips and activities) and are asked to choose from different alternatives for charging (different energy amounts, charging durations and prices) before the tour and from alternatives for adapting the schedule of the tour. An interesting result is that many users prefer longer charging durations as long as the planned tour has not to be delayed. Furthermore, they conclude that there is a large heterogeneity in user preferences. They state that this can be exploited by charging providers,

who can “extract flexibility from those [drivers] more inclined to longer effective charging times without incentives”.

Besides the actual pricing scheme, the interface to the user can be expected to have a critical impact on the efficiency of dynamic pricing. Stein et al. [110] investigate the influence of the complexity of a user interface for auction-based dynamic pricing for EV charging on the behavior of users. For this purpose, they developed an online game where users make virtual bids for charged energy. They come to the conclusion that compared to a complex interface, which allows users to select all possible options, a simpler interface with a restricted set of options, enables users to not only make decisions faster but also to make better decisions.

## 6. 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 are a growing number of publications, proposing different approaches to 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 the help of dynamic pricing. A drawback of many of the proposed approaches to distributed scheduling via dynamic pricing is that they require non-trivial optimizations on the user side. Some of the approaches require even multiple iterations of optimization. Hence, an additional logic is required on the user side in order to realize these approaches. For charging at home, distributed control via dynamic price signals can be a next step beyond time-of-use tariffs. For public charging and charging at work, distributed control might be of less interest, since here the control can be usually realized in a centralized (or hierarchical) way.

The flexibility in the battery utilization is another flexibility, which can be addressed by dynamic pricing schemes. Animating users to allow the use of their EV batteries for the provisioning of V2G services can be very beneficial for grid operators as well as for charging station operators or aggregators. This especially applies for charging at home, where EVs are usually plugged in longer than at public charging stations, which makes the reliable provisioning of grid services easier. However, an issue is that it is generally hard to determine or to estimate how much the battery is damaged with a certain dis-/charging pattern. This makes it hard for the user to decide whether the provisioning of battery capacity for V2G services is profitable or not.

The flexibility in the charging location can be exploited via dynamic pricing in order to balance the number of users or the electrical load over multiple charging sites. This especially applies for public charging, where in contrast to home charging, users potentially have a wide choice of charging locations. Operators or aggregators of multiple charging sites might be interested in regulating the customer demand over their different sites. However, grid operators might be even more interested in balancing charging loads over multiple areas, for example, to avoid transformer overloads. Influencing where users charge their EVs can be also useful for applications like traffic regulation.

Further flexibilities, which can be addressed by dynamic pricing schemes are the flexibilities in the amount of charged energy and in the charging duration. In the literature, price-profile-based as well as session-based pricing schemes can be found, which address these flexibilities. Session-based pricing schemes, where users get price offers for the complete charging session, have the advantage that they require only little planning effort from the users. It can be expected that users generally have a certain flexibility in the amount of energy. However, especially for public charging, the users' flexibility in the charging duration can be assumed to be very limited. In this case, a high incentive might be required to encourage users to change their departure times. However, even if it is not possible to get users to change their departure times, it may be worthwhile to encourage them to indicate their true departure times. The EVs are often plugged in longer than required for the charging [101]. A dynamic pricing scheme can help to unlock this flexibility. In the author's opinion, the flexibilities in the energy amount and in the charging duration are the most promising ones for increasing the profit of operators of public

charging stations. However, distribution system operators can take advantage of these flexibilities as well and the corresponding pricing approaches can be also applied for home charging.

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. There is only little work on evaluating such approaches in a more practical setting based on forecasts of charging demands. 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 user studies—especially of studies based on real-world data. Although existing studies to charging behavior can gain certain insights, it is not fully clear, how EV drivers would respond to dynamic prices. For example, how much discount does a user expect for charging 10 kWh less or for allowing 15 min 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 for monitoring and metering, for data storage and processing and for the communication between stakeholders like EV drivers, charging providers and distribution system operators, is required. Cloud-based EV charging management systems as proposed by Mierau et al. [111] and Saqib et al. [112] can represent a scalable solution. Data privacy is playing an increasingly important role. Techniques like secure multi-party computation [113,114] can help to protect the data of EV drivers. Another topic of current research is the application of blockchain technology for the billing of EV charging [115,116]. Furthermore, the development of adequate user interfaces might be crucial for the user acceptance.

Besides technical issues and the uncertainty of how users react to dynamic pricing, the adoption of dynamic pricing for EV charging might be hindered by legal issues. For example, in several U.S. states, billing per energy unit is not allowed for public EV charging [117], which makes a number of the described dynamic pricing approaches impracticable. The elimination of legal barriers and the introduction of adequate policies could promote the application of dynamic pricing techniques for EV charging [9,118].

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