Optimizing Resource Usage in an Unobtrusive Way Through Smart Aggregation: The Case of Electric Vehicle Charging in Amsterdam

Kees van Montfort, Halldora Thorsdottir, and René Bohnsack

1 Introduction

The United Nations has adopted the first international regulation (ENECE Regulation 100) and the European Union and Japan confirmed to adopt this UNECE Regulation for the technical standards of Electric vehicles (EVs). These regulations aim at the development of the technological innovations of EVs to make them safer and more environmentally sound.

EVs deliver a number of potential benefits (Eberle and Helmolt 2010; Skerlos and Winebrake 2010; Mak et al. 2013; Bohnsack et al. 2014; Bohnsack 2018). EVs have no tailpipe emissions and thus produce less pollution on the end-user side. Furthermore, the total emissions by EVs in the entire electricity supply chain are relatively low, because of the potential usage of cleaner and more efficient power generators like solar panels and wind turbines. Finally, EV operations are relatively insensitive to factors such as the depletion of fossil fuels and supply uncertainty of crude oil. In short, EVs are viewed as part of a more sustainable and cleaner future.

In the Netherlands during 2014 only 4620 full electric vehicles (FEVs) and 24,370 Plug-in Hybrid Electric Vehicles (PHEVs) were sold. During 2018, these numbers increased to 21,840 FEVs and 97,270 PHEVs, which represents a growth of 373% and 299% over a period of four years, respectively (Rijksdienst voor Ondernemend Nederland 2019). These EVs can be charged at more than 7500

K. van Montfort (✉)
Urban Technology, University of Applied Science Amsterdam, Amsterdam, The Netherlands

Nyenrode Business Universiteit, Breukelen, The Netherlands
e-mail: c.a.g.m.van.montfort@hva.nl

H. Thorsdottir
Urban Technology, University of Applied Science Amsterdam, Amsterdam, The Netherlands

R. Bohnsack
School of Business and Economics, Universidade Católica Portuguesa, Lisbon, Portugal

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public and more than 11,500 semipublic charging stations. These numbers will keep on rising in the upcoming few years. With the rise of the Internet of Things (IoT), i.e., the internetworking of physical devices, it is also possible to remotely control the charging of EVs. This has created the opportunity for a new business model, the charging aggregator, which remotely controls the charging of a “swarm” of distributed EV batteries in order to optimize supply and demand. Several companies, particularly utility companies, distribution system operators, or charging point providers have naturally spotted the opportunity to exploit this new business model. Increasingly, the electric grid exhibits large peaks and valleys depending on the time of day (Bancz-Chicharro et al. 2014). By timing the charging of EVs in a smart way, these peaks and valleys could be exploited, e.g., to smoothen the load curve, to reduce peaks or to balance grid imbalances. Despite the opportunity, at this moment, most charging infrastructure providers charge electric vehicles with maximum charging speed from the moment they are plugged into a charging point until the battery is fully charged or the EV is disconnected, i.e., the potential of the aggregator business model is not used. Next to technological challenges (i.e., having access to the charging unit in the car or charging point), this is due to the fact that requiring change in the consumer’s behavior could reduce the attractiveness of EV charging services. Also, due to the niche status of the technology, large-scale data to calculate the effectiveness of this business model is not available.

To address the latter problem, a robust optimization strategy is developed which calculates charging strategies for charging sessions to reduce electricity costs for aggregators in cities with electric mobility (Girotra and Netessine 2013). More specifically, we assume that aggregators can adjust the charging pattern of the session by postponing the charging, varying the charging speed, or introducing charging breaks to optimize their profit function. For this study, the calculations are based on the day-ahead Amsterdam Power Exchange (APX) electricity prices on a quarterly basis and the electricity requirements of individual EV users, which are based on more than 360,000 charging sessions at public charging points in Amsterdam during the year 2015. In the context of public charging spots, it should be noted that such infrastructure is a scarce good. Many charging spot providers and municipalities struggle with over occupancy or “hogging” of charging spots, where drivers leave their vehicle connected long after charging has been completed. Although this behavior has negative effects for EV charging throughput, it provides an opportunity for smart charging, as will be demonstrated.

Our optimization strategy minimizes the costs of charging an EV (for an aggregator and for EV drivers) without violating the charging preferences of EV drivers. This includes the electricity costs and a penalty on the occupancy of a charging point. The developed optimization model calculates for each specific EV charging session the cheapest charging pattern given the 15-min day-ahead APX prices and the charging requirements specified for the session (i.e., the connection time, the required charging load, and the required disconnection time of the specific EV user). The principle of the optimization strategy is as follows: high electricity prices will be linked to low electricity demand of EV users, and low electricity prices will be linked to high electricity demand of EV users (Espey 1998; Sioshansi 2012).

What is more, in alternative scenarios we additionally consider the effect of EV drivers changing their behavior to charge at different times. In the former, the user makes use of smart charging without changing current charging preferences. In the latter, the smart charging approach is combined with the changed timing of charging of different user groups, e.g., as a response to an incentive from an aggregator. Given the charging requirements of the EV users and the day-ahead APX electricity prices, the optimization strategy will charge the EVs with minimal electricity costs.

We empirically evaluate the effects of deploying such an optimization for two key stakeholders, the aggregator and individual EV drivers. For the aggregator, the current total energy demand is compared to the modified, optimized one, as well as the resulting cost reduction is calculated. In addition, it is demonstrated which sessions are most suitable for optimizing. As a result, the suggested charging patterns reduce the electricity costs of EV charging substantially. Based on the model, an average reduction of electricity costs between 20% and 30% can be achieved, depending on the day of the week. We also show that changing EV owner's charging preferences such as starting earlier or later can benefit certain groups of EV drivers substantially and reduce electricity charging costs up to 35%. Moreover, we contribute in building a model that is based on actual charging sessions; we account for occupancy of charging points; and the model is straight forward to implement in practice. Most importantly, the developed optimization strategy does not violate the preferences of the EV users, which is critical for social acceptance.

In what follows we first provide background information on the definitions and principles of smart electricity grids, decentral and central EV charging approaches, and optimal smart EV charging approaches. Then an optimization model is formulated to reduce the charging costs of electrical vehicles. Next, the optimization model is tested based on 360,000 charging sessions at public charging points in Amsterdam during the year 2015. The empirical study will quantify two separate effects on EV charging: the cost reductions of EV charging due to the developed optimization model and the cost reductions due to the changes of the EV user charging behavior. Importantly, due to the relatively unique dataset, our empirical study provides a realistic assessment of the savings potentially resulting from optimized public charging, both in the case of an aggregator and for an individual EV driver. Finally, the implications of our findings are discussed.

2 Background and Relevant Literature

The term smart grid is used to describe a next-generation electrical power system that is typified by the increased use of communications and information technology in the generation, delivery, and consumption of electrical energy (Amin and Wollenberg 2015; Valogianni 2016; see Table 1). The smart grid is also different from the traditional grid due to the large-scale integration of renewable sources and the potential double role of electricity consumers also being producers. These

Table 1 Relevant literature related to definitions and principles of smart electricity grids, decentral and central EV charging approaches, and optimal smart EV charging approaches

Subject	Articles
Definitions and principles of smart electricity grids	Gottwalt et al. (2011), Verzijlbergh et al. (2012), De Creamer et al. (2014, 2015), Amin and Wollenberg (2015), Valogianni (2016), Helms et al. (2016)
Decentral and central EV charging approaches	Molderink et al. (2010), Mohsenian-Rad et al. (2010), Anderson et al. (2011), Xu and Wong (2011), Gottwalt et al. (2011), Vandael et al. (2013), Dias et al. (2011)
Optimal smart EV charging approaches	Espey (1998), Brons et al. (2008), Ahn et al. (2011), Hidrue et al. (2011), Wu et al. (2012), Sioshansi (2012), Hahn et al. (2013), Vandael et al. (2013, 2015), Valogianni (2016)

so-called "prosumers" for instance produce electricity using solar panels or store electricity in electric vehicle batteries. To orchestrate this on a larger scale to effectively exploit the combined flexibility of the users, an aggregator can be the agent (Helms et al. 2016). An aggregator is a demand side service provider, usually in a utility market such as the electricity market. Aggregators are relevant market newcomers in Europe with growing integration of smart systems (which enable quick contact with consumers, smart charging profiles) and add electricity generation from fluctuating renewable resources. Furthermore, aggregators can bundle energy from different retailers to provide independent offerings to consumers.

In the case of electric vehicles, an aggregator could optimize the electricity demand curves of the charging EV users to reduce the electricity costs of EV charging (Gottwalt et al. 2011; Verzijlbergh et al. 2012; De Creamer et al. 2014, 2015). Coordination mechanisms to lower the costs of EV charging can be decentralized (bottom-up) or centralized (top-down) (Vandael et al. 2013; Dias et al. 2011). Decentralized approaches (Molderink et al. 2010; Mohsenian-Rad et al. 2010) require no formal coordinating entity and assume that each individual electricity customer communicates with the electricity grid via pricing signals. These signals have the ultimate goal of incentivizing consumers to charge the car when demand is low (low price period) and provide counter-incentives for charging when there is a peak in the electricity demand (high price period). Bottom-up approaches assume that the customers have the freedom to schedule their power consumption based on their own individual preferences. Centralized mechanisms (Anderson et al. 2011; Xu and Wong 2011) assume an external coordinator, who is usually the grid operator. This grid operator is responsible for maintaining the stability and reliability on the grid and usually prevents non-urgent electricity consumption during periods when electricity demand is peaking.

Depending on the market, the above-mentioned approaches have advantages and disadvantages (Gottwalt et al. 2011; Vandael et al. 2013). Bottom-up approaches have the benefit that customers' individual comfort is not violated and the EV users have the freedom to schedule their EV charging based on their individual preferences. However, the main disadvantage is that since the same price signals are provided to all customer agents, the EV charging schedules could coincide.

Assuming that all EV users are cost minimizers, they tend to shift power demand to the cheaper time instants, creating new peaks. The benefits of the top-down coordination mechanisms are that they easily satisfy the constraints imposed by the smart grid operator. However, there are significant shortcomings in this approach. The most important challenge is that often the smart grid operator must intervene and may as a result violate the EV driver's comfort (for instance, by delaying charging or switching off charging points).

Wu et al. (2012) propose an operating framework for aggregators of plug-in EVs. First, a minimum-cost load scheduling algorithm is designed, which determines the purchase of energy in the day-ahead market based on the forecasted electricity prices and forecasted EV power demands. Second, a dynamic dispatch algorithm is developed, used for distributing the purchased energy to EVs on the operating day. In this algorithm, electricity prices and EV charging behavior are considered deterministic. The results of the empirical study of Wu et al. (2012) show that the dispatched load perfectly matches the purchased energy. However, the assumption of deterministic (i.e., known beforehand) charging behavior is likely not realistic and a disadvantage of their approach.

Vandael et al. (2013) present an approach for demand side management of EVs. Their approach consists of three steps: aggregation, optimization, and control. In the aggregation step, individual EV charging constraints are aggregated. In the optimization step, the aggregated constraints are used for computation of a collective charging plan, which minimizes costs for electricity supply. In the real-time control step, this charging plan is used to create an incentive signal for all individual EVs, determined by a market-based priority scheme. The most significant difference between this approach and centralized approaches is that the central part of this approach calculates a collective charging plan for each EV and does not calculate an individual charging plan for each EV. Next, this collective charging plan is translated to individual EV power set points through a market-based priority scheme. One limitation of this approach is the discrepancy between the derived individual charging plans and the charging requirements of the individual EV users. An individual EV user wants to connect his/her car at a specific time point, wants to charge a specific electricity load, and wants to finish the charging session on a specific moment (Hidrue et al. 2011; Sioshansi 2012). Often the approach of Vandael et al. (2013) does not meet these EV user requirements.

Vandael et al. (2015) address the problem of defining a day-ahead operational plan by the aggregator for charging a fleet of EVs. The decisions made by the aggregator are divided in two phases. In the first decision phase, the aggregator predicts the energy required for charging its EVs for the next day, and purchases this amount in the day-ahead market. During the second decision phase, the aggregator communicates with the EV users to control their charging, based on the amount of energy purchased in the day-ahead market during the first decision phase. EV charging is controlled during operation by a heuristic scheme, and the resulting charging behavior of the EV fleet is learned by using batch mode reinforcement learning. Based on this learned behavior, a cost-effective day-ahead consumption plan can be defined.

A shortcoming of the above-mentioned approach is the fact that it is not clear whether the individual EV users are willing to charge according to the constructed charging plans. In case the constructed charging plans (for instance, charging in the night) differ much from the initial charging plans (for instance, charging in the morning) of the individual EV users, not many individual EV users will change their initial charging plans. It is not clear to what extent the individual charging plans meet these individual EV user requirements. In fact, the approaches of Vandael et al. (2013, 2015) have the potential to achieve balance on the grid but most of the times they do not satisfy individual comfort and require direct control, which might not be easy to implement in practice.

Last, Valogianni (2016) proposes an EV charging coordination mechanism that combines benefits both from the decentralized and centralized approaches. The mechanism is capable of reducing peak demand, satisfying individual preferences as well as broadcasting the same price function to all customers in the market. However, the mechanism assumes that the day-ahead electricity price per hour (in Euro/kWh) depends linearly on the total charged electricity (in kWh) by the EV users of the aggregator's charging points during this hour. Maybe the EV users of the charging points of a specific aggregator could slightly influence the hourly electricity prices of the next day (depending on the amount of the charged electricity by the EV users), but these prices do likely not depend linearly on the expected total electricity charging load of the specific aggregator (Espey 1998; Brons et al. 2008).

Ahn et al. (2011) and Hahn et al. (2013) developed an algorithm for calculating load shift potentials defined as the range of all charging curves meeting the customer's required amount of electricity. They found that the charge curve reaches minimal costs and charges the minimal amount of required electricity (varying the charging speed continuously over the time). Based on these (theoretical) calculations, it turned out that the EV load shifting potential of EVs is significant.

As an extension of these papers, an optimization model is developed to reduce the electricity costs of EV charging in two scenarios, i.e., with and without requiring the user to change their charging preferences. Next, the consequences of the implementation of our model are calculated based on 360,000 charging sessions at public charging points in Amsterdam during the year 2015.

3 The Modelling of an EV User Charging Strategy

The day-ahead APX electricity prices (of quarters of an hour) vary over the day. An optimization model will be developed to obtain EV user charging strategies that reduce the aggregator's electricity costs (given the day-ahead APX electricity prices and the EV users' electricity demand). The entity in the model is an EV user. The principle of the model is as follows. The day-ahead electricity APX-prices (on a 15 min level) and the EV user electricity demand are known. These data will be used to calculate the optimal day-ahead demand curve of the individual EV user with minimal electricity costs: the optimal user charging strategy. To do so, we minimize

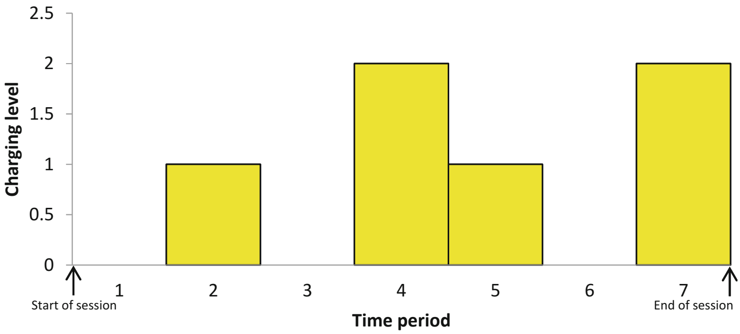

Fig. 1 An optimal charging strategy of an individual EV user

the differences between the cheapest electricity demand pattern and the optimal electricity demand pattern, i.e., user charging strategy. By doing this, the optimal electricity demand pattern depends on the APX-prices on a 15 min level, as well as the EV user electricity demand requirements. The result of the optimization model is an optimal electricity demand curve corresponding to the preferences of an individual user, i.e., user charging strategy, which will usually differ from the current (not optimized) demand curve (see Fig. 1).

Figure 1 shows a specific optimal charging strategy of an individual EV user with postponed charging, on–off charging, and two levels of charging speed. In our approach, the number of levels of charging speed can be raised (Schäuble et al. 2017). Charging in the current situation could be visualized by a simple horizontal straight line that starts at "start of session" (i.e., only one level of charging speed). The optimal charging strategies will depend on, among others, differences between weekdays and weekends, seasonal effects, day-ahead APX electricity prices (on a 15 min level), and user-specific requirements (i.e., required connection starting time point, required charging load, required disconnection time point).

As mentioned above, the entity in the optimization model is an EV user. In our model, the EV user can:

1. Use an on–off charging strategy (to postpone the continuation of the charging).
2. Use different charging speed levels (for instance, full speed level and half-speed level).
3. Choose the desired amount of electricity (kWh) to charge or a desired state of charge (SOC).
4. Combine the above strategies.

These assumptions regarding the possible user charging strategies will be included in the optimization model by adding model restrictions. The restrictions will shape the form of the optimal demand curve. With these user charging strategies, it is nearly impossible to get a complete alignment with the input electricity price curve, because perfect alignment requires continuous adjustment of the speed levels, which would render the optimization (in its current form) computationally intractable.

In fact, the electricity costs of a charging session can be reduced by applying the optimization model to get optimal charging strategies (corresponding to the EV user-specific requirements) and by changing the EV user charging behavior. Changes in the EV user behavior can be modelled, among others, by changing the connection starting time point, the disconnection time point, and the required load of a charging session of a specific EV user.

Observe that intuitively, the result of the optimization calculations could be that it is most profitable to start all charging sessions at, say, 2 am. This seems suboptimal for user engagement and might in addition result in a substantial shift of the usage peak, instead of its reduction. To alleviate the former concern while allowing the EV user to connect at his preferred times, the optimized charging session should be remotely controlled by using appropriate software. For the latter concern, it should be noted that shifting EV energy demand from current peak hours, even if it forms a new peak, is still an improvement in the context of the overall electricity grid.

Therefore, our algorithm calculates the optimal charging strategy of an individual EV user given his/her own preferences of a charging session (i.e., the required connection starting time point, required load, and required disconnection time point of the charging session), followed by addressing which sessions are most suitable for optimization. Next, the financial consequences of the behavioral changes (for instance, postponing the connection starting time point) will be calculated. Finally, based on the provided financial information the EV user can choose his/her preferred connection starting time point.

4 The Optimization Model

A Linear Programming model with discrete decision variables will be formulated to calculate the cheapest day-ahead charging strategy of a specific EV user charging session. To do this, we need values of the following user characteristics of a specific EV charging session as input of the optimization model: required connection time of charging session; required disconnection time of charging session: DT; different charging speed levels available, for instance: level Speed1 and level Speed1 + Speed2; state of charging: SOC; required total charging load: LOAD; total capacity of EV battery: CAP. The calculated cheapest charging strategy of a specific charging session includes the possibilities of postponed charging, on–off charging, and different levels of charging speed.

The following model parameters are needed as input of the optimization model:

- APX electricity prices for tomorrow every quarter of an hour i: P_i (i = 1, 2,. . ., 96)
- Penalty Occupancy Period in quarter of an hour i: POP_i (i = 1, 2,. . ., 96)
- Penalty Overflow 80% Threshold Battery: POTB.

The above model parameters will be expressed in terms of Euros. The penalties are proposed as an instrument that the exploiter of the charging infrastructure can use to nudge the charging behavior in a desired direction. For instance, $POP_1, \ldots, POP_{96}$ are induced to discourage undesirable charging strategies, i.e., these penalties will discourage periods of occupying without loading. POTB should discourage the lengthy occupancy period needed to charge the last 20%, since due to the physical properties of most EV batteries, charging the last piece of the battery goes slower than the first 80% (Yong et al. 2015).

4.1 Decision Variables

The following decision variables are used in the optimization model: $Y_{1i} = 0$ if not loading in time period i with Speed1 and $Y_{1i} = 1$ if loading in time period i with Speed1. Similarly, $Y_{2i} = 0$ if not loading in time period i with Speed1 + Speed2 and $Y_{2i} = 1$ if loading in time period i with Speed1 + Speed2. Here, $i = 1$ corresponds to the first quarter of an hour during the charging session and $i = 1, 2, \ldots,$ DT, where DT is at most 96. The linear programming model searches for an optimal charging strategy within a maximum of 24 h (i.e., 96 quarters of an hour from the starting time of a charging session) by determining for which i's Y_{1i} and Y_{2i} are equal to 1.

4.2 Objective Function

For notation convenience, we introduce the variable "total electricity charged" (TEC), defined as

$$\text{TEC} := \Sigma\left(\text{Speed1} * Y_{1i} + \text{Speed2} * Y_{2i}\right). \tag{1}$$

The costs of the EV charging session of one specific EV user will be minimized as follows:

Minimize

$$\begin{aligned} &\Sigma\left(\text{P}_i * \text{Speed1} * Y_{1i}\right) + \Sigma\left(\text{P}_i * \text{Speed2} * Y_{2i}\right) + \Sigma\left(\text{POP}_i * (1 - Y_{1i})\right) \\ &\quad + \text{POTB} * [\text{TEC} - 0.8 * \text{CAP}], \end{aligned} \tag{2}$$

where the summations are from $i = 1$ up to $i =$ DT.

The first two terms correspond to the costs of electricity (based on the APX electricity prices). The third term corresponds to a penalty on a time period when connected without charging (i.e., occupancy costs). The value of this penalty, which is not charged to the user, could depend on i: occupancy without charging is less important during the night than during the day. Finally, the fourth term indicates a penalty on charging the battery more than 80% of the total capacity of the battery (i.e., slow charging costs). This is a different kind of cost to reflect the physics of batteries, i.e., slower charging when SOC is above 80%, but it is not a cost in euros to the user.

4.3 Restrictions

The optimization model uses the following restrictions:

$$Y_{1i} = 0 \text{ or } 1 \qquad \text{if } i = 1, \ldots, \mathrm{DT} \tag{3}$$

$$Y_{2i} = 0 \text{ or } 1 \qquad \text{if } i = 1, \ldots, \mathrm{DT} \tag{4}$$

$$\mathrm{TEC} \geq \mathrm{LOAD} \tag{5}$$

$$Y_{1i} = 0 \text{ and } Y_{2i} = 0 \qquad \text{if } i > \mathrm{DT} \tag{6}$$

$$Y_{1i} \geq Y_{2i} \qquad \text{if } i = 1, \ldots, \mathrm{DT} \tag{7}$$

$$Y_{2i} + (\mathrm{SOC} + \mathrm{TEC})/(0.8 * \mathrm{CAP}) \leq 2 \qquad \text{if } i = 1, \ldots, \mathrm{DT} \tag{8}$$

Restriction (5) guarantees that the total charged electricity is more than or equal to the required electricity load. Restriction (6) guarantees that after the required disconnection time point charging is not possible anymore. Restriction (7) guarantees that charging speed level "Speed1 + Speed2" is only possible if both Y_{1i} and Y_{2i} are equal to 1. Restriction (8) guarantees that high charging speed level "Speed1 + Speed2" is not possible if the charged electricity load is more than 80% of the capacity of the users EV, since charging the last 20% of the battery goes slower than the first 80%.

The model is a mixed integer linear programming model with "2 $*$ DT" 0–1 decision variables and "2 $*$ DT + 1" restrictions. For instance, if the connection duration is 6 h, then there are 48 0–1 decision variables and 49 restrictions.

As a result of the optimization algorithm values of the decision variables: Y_{11}, $Y_{12}, \ldots, Y_{1\,(96)}$, and Y_{21}, $Y_{22}, \ldots, Y_{2\,(96)}$ are obtained. Furthermore, we get values of the costs of electricity (related to the day-ahead APX prices); the costs related to the penalty on a time period when connected without charging (i.e., occupancy costs); and the costs related to a penalty on charging the battery more than 80% of the total capacity of the battery (i.e., slow charging costs).

5 Empirical Results

In this section, the empirical analysis of the effectiveness of the optimization algorithm will be described by comparing its output with data of real charging sessions. For the empirical analysis, data are used from the public charging stations of the city of Amsterdam (i.e., the CHIEF database of the University of Applied Sciences Amsterdam; references Van Montfort et al. 2016). During the year 2015, more than 363,000 sessions were logged of 17,626 unique user charge cards. Among others, for each charging session the following variables were registered: id-number of charging station, address of charging station, id-number of EV-user, the time of connecting and disconnecting, duration of charging (which is not the same as duration of connection), and energy (kWh) charged. By using the above-mentioned information, the capacities of the rechargeable EV batteries and the charging speed levels have been estimated (Wolbertus et al. 2016).

Observe that although three of the input parameters required for the optimization model are available through this database, namely the time of connecting and disconnecting, as well as kWh charged, the other three are not: charging speed, state of charge, and battery capacity. Whereas we chose to estimate each session's charging speed in a manner described below, we will not carry out empirical analysis using the part of the model that requires information about the state of charge and battery capacity, i.e., the penalty of passing the threshold of 80% of the battery.

The effect of the optimization algorithm developed in Sect. 4 is tested by comparing the costs it induces with the costs resulting from straightforward charging. To solve the linear program of the optimization algorithm, the lpSolve package was used with the R programming language. The optimization algorithm determines in which quarters of an hour an EV should or should not be charged, and with which speed. In this way, it results in a *smart charging profile* given the requirements of the specific EV user.

The input parameters for the algorithm are the connecting and disconnecting time of an individual charging session, as well as a *minimum required load*. These input parameters are obtained from a total of 363.093 real charging sessions that were carried out at the public charging infrastructure in Amsterdam in 2015. Whereas the connecting and disconnecting times are self-explanatory, the input referred to as *minimum required load* corresponds to the kWh that were charged in a given session.

The charging speed is estimated from the database based on the charging time and the kWh charged, both of which are measured and available in the database. The average charging speed is computed as: average speed = charged kWh/charging time. For the sake of enabling flexibility, the optimization algorithm uses two speed levels. The higher one equals the average speed, as defined above, the lower one is half of that. This allows the smart charging profile to make use of "second best" price slots, if needed. In theory, the model can be extended by including more than two speed levels (Schäuble et al. 2017). In practice, the values for the speed levels can be adjusted to what is suitable.

The aim of the penalties introduced in the theoretical model is to show the opportunities of our model. However, in this empirical study our optimization model is applied without penalties, because we want to make a "fair" comparison between the electricity costs based on our optimization model and the realized electricity costs based on straightforward charging (i.e., full speed charging starts at the moment the EV is connected). Our optimization algorithm chooses the cheapest quarters and breaks when the price is deemed too high, with the condition that a *minimum required load* should be reached before the user disconnects. The optimization algorithm then chooses which charging speed to apply to which quarters. Therefore, the total electricity charged (TEC) in an optimized session satisfies the form.

$$\text{TEC} = \Sigma\, \text{Speed1} * \text{Qslow} + \Sigma\, (\text{Speed1} + \text{Speed2}) * \text{Qfast}, \tag{9}$$

where Q_slow refers to the quarters that were chosen for slow charging, and Q_fast the quarters chosen for fast charging. As a result of this form, TEC $> =$ *minimum required load* from the real session, that is, additional load may have been charged,

$$\text{Extra load} = \text{TEC} - \textit{minimum required load}. \tag{10}$$

If this extra load is non-zero, it must be accounted for in a comparison between the real session and the calculated optimal session. In order to compare the difference in costs, we create a so-called appended session on the basis of the original session, where the additional kWh are appended to the end of the real session. Note that the extra load is bounded, because the hypothetical potential extra load never takes more than 15 additional minutes to be charged. To summarize, this enables us to compare the costs for the same amount of electricity consumed within the same connection time period with only a minor adjustment to the real parameters.

The optimization model is run by using the historical data of all charging sessions (i.e., starting time points, disconnection time points, and charging loads) in Amsterdam for one year, 2015. This **first analysis** *quantifies the effect of the optimal charging algorithm compared to the realized straightforward charging method*: first, we calculate the electricity costs of all charging sessions during the year 2015 by using the realized current straightforward charging strategies (i.e., only one speed level, no breaks); next, we calculate the electricity costs of all charging sessions during the year 2015 by using the optimal charging strategies, which were calculated by applying our optimization model. The electricity costs are in both cases based on the quarterly APX prices for the year 2015.

The empirical results are evaluated for two stakeholders, the charging aggregator and the EV drivers. For the charging aggregator it is interesting to know (1) the total change in distribution of energy over the day and (2) the potential financial benefit as a consequence of modified charging patterns. Figure 2 illustrates the change in electricity demand when individual charging sessions have been optimized for price. The most prominent change is a major shift from the most expensive part of the day, between 5 pm and 8 pm, to the cheapest part of the day, between 2 am and

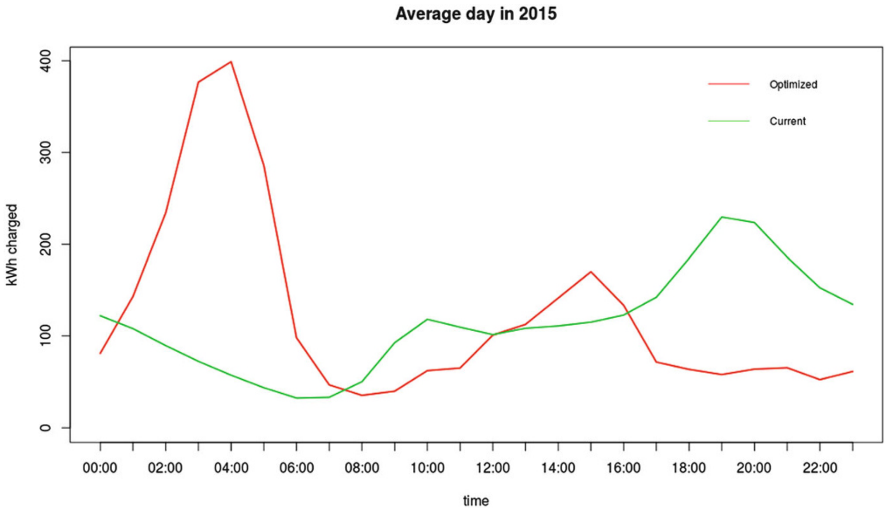

Fig. 2 Change in energy demand as a result of modified charging patterns

5 am. The total energy costs of all optimized charging sessions in the year of 2015 is 132,672.16 € instead of 166,643.27 €. This amounts to a 20.39% cost reduction for the same amount of energy, based on APX prices.

Table 2 describes the effects of the optimization model for the individual EV drivers on different days of the week. In the third column, we observe that the average electricity cost reduction per charging session is between 21.91% (Thursday) and 26.67% (Monday), where the only change in user behavior is enabling smart charging and the charging session requirements of the EV users do not change. With the problem of over occupancy of charging spots in mind, we report the average number of non-charging hours until completion of charging, which includes potential delay before starting a charging session as well as possible breaks therein. On average, the optimization algorithm thus chooses to complete charging almost 5 h later than in the current situation. After the charging has finished, many EVs stay connected without using the charging facilities, on average during 3 h. The difference between weekdays is negligible in all columns, also the difference between midweek days and weekends.

Around 41% of the charging sessions save less than 10% by optimizing charging. The remaining 59% sessions thus manage to cut more than 10% of costs by optimization, the distribution of their cost reduction can be seen in the left panel of Fig. 3. The length of the connection time is an important parameter of each session; a longer connection time provides more opportunities to optimize. This can be seen in the right panel of Fig. 3, which illustrates the sessions that manage to cut at least 10% of the costs in the context of all charging sessions. In fact, when only considering sessions with connection time of 4 h or longer, the average saving is 26.07%. In the case of 8 h or longer, the average costs reduction is 31.87%. Those cases amount for approximately half of all the charging sessions, implying that substantial savings can

Table 2 Effects of optimization model over the year 2015

	Average *costs* with *straightforward charging* per charging session (€)	Average *costs* with *optimal charging algorithm* per charging session (€)	Average cost reduction per charging session (%)	Average number of *non-charging* hours until completion of charging session with optimization model (h:mm)	Average *charging duration* with optimization model (h:mm)	Average *fraction* of charging duration with *speed 1* (%)	Average *time* connected *after charging is finished* with optimization model (h:mm)
Monday	0.44	0.32	26.67	4:41	1:24	38.39	3:55
Tuesday	0.50	0.38	24.36	4:54	1:23	38.57	3:07
Wednesday	0.48	0.37	23.08	4:42	1:22	38.36	3:00
Thursday	0.47	0.37	21.91	4:32	1:22	38.56	3:02
Friday	0.50	0.39	22.13	4:35	1:23	39.62	3:02
Saturday	0.48	0.37	22.55	4:54	1:21	38.97	3:17
Sunday	0.45	0.34	25.79	5:09	1:21	38.50	3:27
Average	0.47	0.36	23.73	4:47	1:22	38.71	3:16

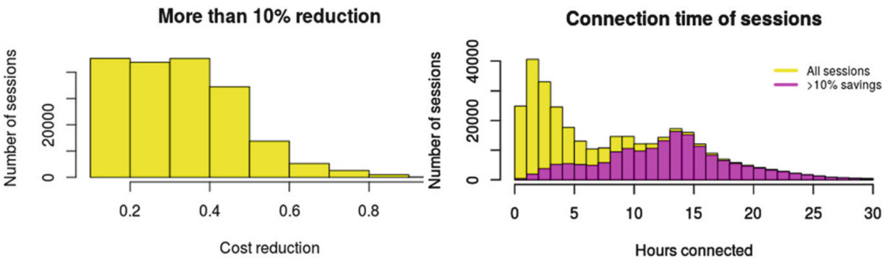

Fig. 3 (Left) Distribution of cost reduction of session with more than 10% cost reduction. (Right) Connection time of charging sessions

be reached by the optimization algorithm. Moreover, since the total savings amount to around 30,000 euros, it turns out that 88% of the overall cost reduction for the aggregator comes from optimizing these long sessions.

The **second analysis** *quantifies the effect of the changes in the user behavior* (combined with the application of the optimization model) for three different user groups. This is to evaluate if costs can be reduced even further by active participation of users, i.e., when users are willing to change their connection time according to an incentive from an aggregator. To do this analysis, we first identify three groups of EV users who typically start charging their EV in the morning (between 6.00 am and 12.00 am), the afternoon (between 12.00 am and 6.00 pm) or the evening/night (between 6.00 pm and 6.00 am). A user must have charged in a given time slot at least 50 times in the year 2015 to belong to the corresponding user group. From the original 360,000 sessions, this filtering process leaves 30,484 sessions of regular morning users (307 individual users, 47,492 sessions of regular afternoon users (637 individual users) and 78,258 sessions of regular evening users (912 individual users).

For each separate EV user group, a typical session is constructed with average charged energy and duration, and the median starting time. The median starting times of the three user groups are 8.00 am, 3.00 pm, and 7.00 pm, which are more representative for the typical users than the average starting times, particularly for the evening and night chargers. Next, for each user group, the charging costs are calculated resulting from applying average prices per quarter to our optimization model *and* by moving the starting time of the charging sessions with 1, 2,. . ., 12 h earlier or 1, 2,. . ., 12 h later. The results of these analyses are presented in Fig. 4.

Figure 4 shows for each EV user group (i.e., morning chargers, afternoon chargers, and evening/night chargers) the consequences of a behavioral change: moving the starting time of the charging sessions (i.e., the time at which to connect). In fact, the consequences are calculated in case the EV users have agreed to connect at a different time point. Note that the amount of electricity charged differs per user group, which is reflected in the different maximum and minimum costs. The electricity costs per charging sessions of the afternoon chargers (red line) reduce dramatically in case they start charging later. The minimum costs are achieved by starting between 5 and 12 h later (between 8 pm and 3 am). However, due to the

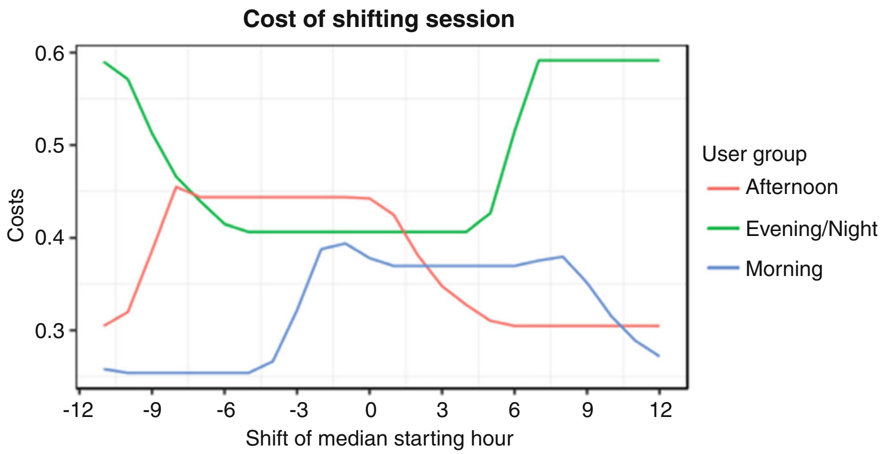

Fig. 4 Costs of shifting an average morning, afternoon, or evening session. The center represents each user group's median starting point; 8 am for morning chargers, 3 pm for afternoon chargers, and 7 pm for evening/night chargers

deployment of the optimized charging strategy, the evening/night chargers do not need to change the starting time point of their charging session, this will not reduce their average electricity costs of charging. Finally, it will be profitable for the morning chargers to connect some hours earlier. This behavioral change of the typical EV morning charger can reduce the electricity charging costs with up to 35%.

In the comparison of the straightforward charging pattern and our optimal charging pattern, the penalties of the occupancy and the slow charging are left behind for reasons listed above. The occupancy penalty stimulates a user to make the charging session as short as possible, whereas the slow charging penalty stimulates the user to stop the charging after 80% of the battery capacity is filled. Of course, the occupancy penalty reduces the cost benefit of our approach, because it demotivates the algorithm to postpone the charging to cheaper quarters.

6 Discussion, Conclusions, and Implications

In this chapter, an optimization model was developed that applies unobtrusive charging strategies (i.e., postponing, on–off charging, and two charging speed levels) for an electric vehicle charging aggregator. Our results show that applying such a model can significantly reduce energy costs for EV users. The analysis shows that the calculated charging patterns of a charging session will reduce the electricity costs on average about 25%. This is a significant saving and could benefit users and aggregators with regard to cost savings but also in terms of sustainability since this model uses resources more efficiently. Next, we empirically showed the consequences of a simple behavioral change: namely an EV user starts charging earlier or starts charging later. We found that especially for EV users who want to start their EV charging session in the morning or afternoon, it can be very profitable to start charging earlier or to postpone the charging session and result in between 20% and 30% additional electricity cost reduction. When new starting times are adapted in tandem with an optimized smart charging profile, they require only minor changes in user behavior. Encouraging changes in the charging behavior may thus be feasible even when smart charging is enabled.

Based on these findings, new business models for electric vehicles can be developed (Bohnsack and Pinkse 2017) and general guidelines may be offered to the EV users for optimal starting times of charging sessions (Gan et al. 2013; Wang et al. 2015). More concretely, we suggest that in order to communicate with the user and to provide the financial benefits of the optimization model an aggregator could develop an app. On the screen of the app, an EV user could fill in the preferred starting time point, the preferred disconnection time point, and the required electricity load of the intended charging session. By using this information, the app could present a curve like the curves in Fig. 4, based on which the EV user could decide whether it is attractive for him to change the initial starting time point, disconnection time point, or charged load of the forthcoming charging session.

The developed optimization model could be implemented by the aggregator in a multiperiod setting. It is not a one-shot decision, but rather a step-by-step rollout process. For each individual charging point, the operating software to control the charging speed level of a charging session has to be adapted. The operating software has to calculate the optimal charging pattern of a charging session given the starting time point, disconnection time point, and electricity load of the charging session, which was filled in on the app.

This chapter is the first attempt to study the emerging issues around aggregator business models for electric vehicles, providing a realistic empirical assessment of the financial benefits. This opens up significant research opportunities for operations researchers in this industry. Among the possible extensions of this work that we suggest would be the study of competition between aggregator business models, the application to other flexibility sources such as houses with smart meters or stationary battery storage, but also the influence of user-specific incentives and complementary market design decisions. With regard to business model competition, it would be worthwhile to study the effects of the competition of two or more aggregators on the cost reduction potential. The assumption would be that the competition reduces the cost savings. This would require an extension of the model. Thus, future research should study how this model could be applied in different settings such as the upcoming stationary battery market or smart devices at home. Last, this research could be enriched by studying the effect of complementary market design mechanisms. In the case of EV charging, the aggregator model could include some penalties to influence the calculated charging patterns of the charging sessions for the system as a whole, for instance via occupancy penalties or slow charging penalties. The occupancy penalty is a penalty on a time period when the EV is connected without charging, which can be imposed to discourage long occupancy of charging spots. The slow charging penalty indicates a penalty on charging the battery more than 80% of the total capacity of the battery, since the charging speed of the battery decreases radically when state of charging is more than 80%. By choosing appropriate values of the penalties, the aggregator can influence the occupancy and the slow charging of an EV charging session. These market design decisions can decrease costs even more and need to be studied further. Certainly, these can be different kinds of costs and are not necessarily costs in Euros to the user.

One additional advantage of EVs is that the batteries of the EV's can also be used for dispatch during peak demand for peak shaving. The infrastructure may have to be changed to allow for two-way up- and de-charging. But this particular type of flexibility could lead the EV owner to reduce costs further by selling during peak quarters and contribute to system flexibility.

This chapter and the suggested avenues for future research are clearly relevant in the age of the Internet of Things and artificial intelligence. We believe that understanding the optimized orchestration of user behavior and use of resources will open up great opportunities for a more sustainable future.

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