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Smart home charging of electric vehicles using a digital platform

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ABSTRACT

As the penetration of electric vehicles (EVs) grows, it is important to understand the implications of home charging technologies for grid operations and for the budget of users. We conduct an empirical study analyzing data on 438 EVs over a period of 3,687 consecutive hours, collected by an energy aggregator which operates a digital platform. We first develop an optimization model to compute an optimal schedule of charging for all EVs in the dataset at minimum cost. Then, we compare the realizations against this optimal solution, distinguishing householders who use a *smart charging* functionality of the digital platform from those who do not use it. Our findings indicate that the smart charging behaviour conduces to better results, and close to the optimal solution. The non-users tend to start charging as soon as they plug-in their EVs, often at peak consumption times. In contrast, the smart charging strategy usually shifts the charging schedules towards times where the consumption is cheaper and the grid is less congested, facilitating a higher load factor and lower power losses. These results highlight the positive role of energy aggregators and digital platforms in coordinating users to lower the cost and enhance efficiency of energy consumption.

1. Introduction

The penetration of battery electric vehicles (EVs) has grown considerably over the past decade. Even when the pandemic has hit the car industry hard, the electric car registrations increased by 41% in 2020, a remarkable growth in comparison to the 16% drop in sales of the global car sales [5]. As the penetration of EVs grows, it is important to understand the implications of different charging technologies on the energy grid operation and on the budget of users. The progress on smart charging technology and digital platforms provides great opportunities not only to better analyze the behaviour of energy consumers, but also to coordinate the efforts of different stakeholders towards a more efficient pattern of energy consumption. Moreover, in the context of Smart Energy Systems, EVs have been recognized as one of the sources of flexibility necessary for the integration of fluctuating renewable energy [22].

Although a lot of discussion has emerged about the insertion of EVs and the potential implications in energy systems, little empirical evidence has been provided, as most countries are yet in a preliminary stage. In fact, the total amount of plug-in electric cars represents just 1% of all passengers vehicles around the world [5]. An exceptional case is being experienced in Norway, the first country in the world where the sales of EVs became higher than the sales of other passenger car types. In 2020, the plug-in car segment market share of the total new car sales in Norway reached about 75%, in contrast to the 4.6% share worldwide. More than 90% of the Norwegian EV owners are able to charge their EVs at home, either through a regular socket or a dedicated home charging unit. The energy consumed by an EV has not only an effect on the individual bills that the car owners have to pay, but also on the efficient operation of the energy grid. Coping with high differences in consumption throughout a day is costly for the energy providers, as they have to accommodate their capacity to address demand in peak hours, while a large share of this capacity might stay idle during valley hours. Therefore, how the energy consumption from EVs might be shifted from high-peak to non-peak hours is an important question to address.

In collaboration with the Norwegian company Tibber, an energy aggregator and retailer which has created a fully digital energy platform, this paper conducts an empirical study analyzing anonymized data on home charging of EVs. The platform is implemented in practice and is currently being used by thousands of people in Norway, to a great extent motivated by the adoption of EVs. The platform has a *smart charging* fea-

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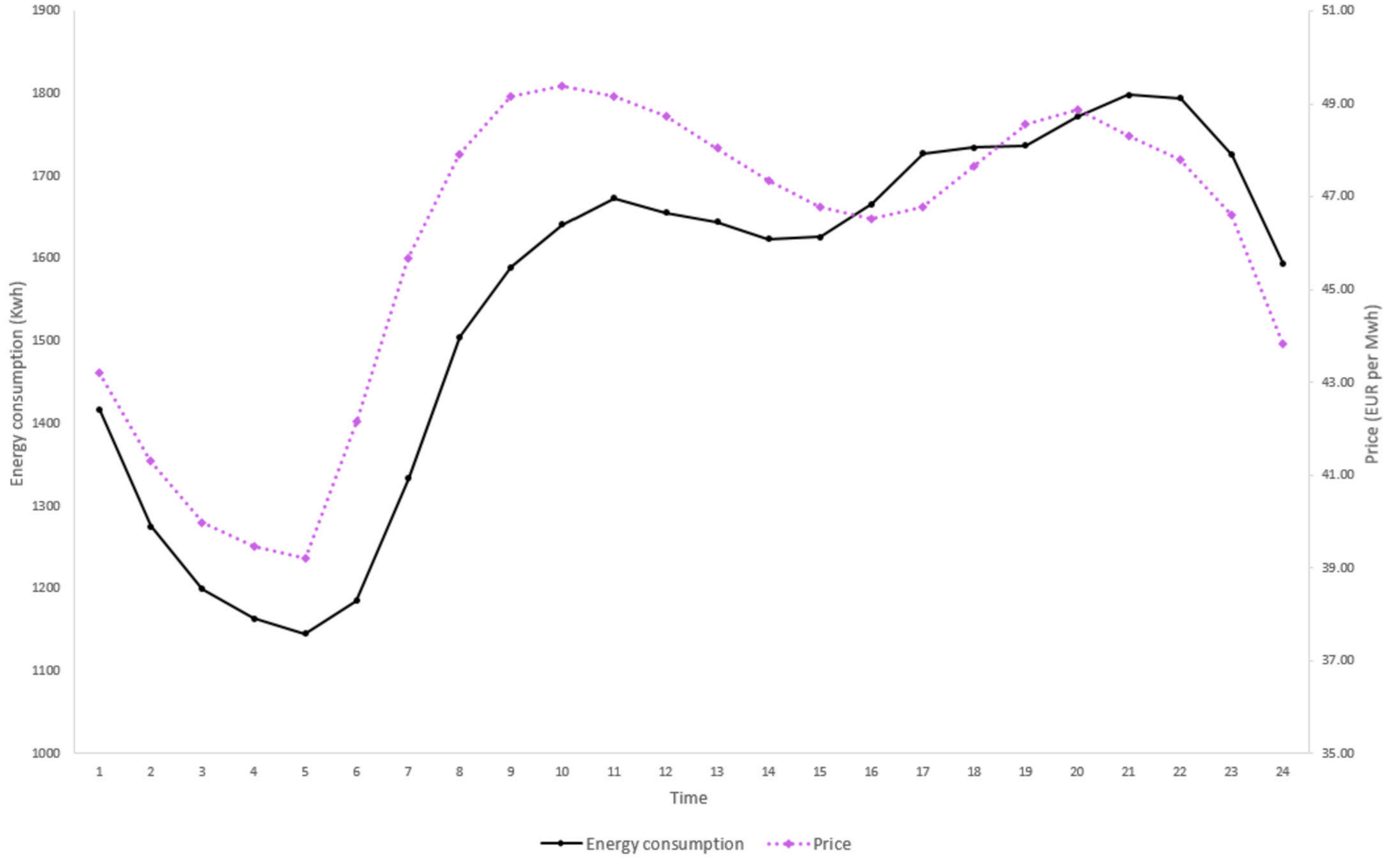

Fig. 1. Typical power consumption and prices over a day. The consumption data aggregates about 2000 households over a period of five months in 2018, served by three stations operated by a power company in Western Norway. The price data correspond to the average price per hour over the same period of five months, published by Nord Pool.

ture which allows EV owners to automate the charging schedule of their vehicles. In practice, this means that the platform looks for the times at which charging is cheaper, while considering the demand requests by the users and the time interval over which this demand must be fulfilled. Alternatively, the EV owners may choose to manually control the charging schedules of their vehicles. By comparing the two groups (those who do and those who do not use the smart charging feature), we are able to assess the impact of smart charging at home in terms of costs, load shifting, and grid efficiency. Our results reveal that the majority of the non-users of the smart charging feature start charging as soon as they plug-in their EVs. This often occurs at peak consumption times, negatively affecting the grid in terms of congestion and also the consumers' budget, since the energy consumption is more expensive at these peak times. In contrast, the smart charging strategy effectively shifts the charging schedules towards times where the consumption is cheaper and the grid is less congested. We illustrate the effect on the grid by incorporating into the analysis data from the distribution system operator and computing standard metrics on efficiency.

The contribution of our article is two-fold. First, we provide a pioneer piece of evidence on the economic impact of smart home charging on the cost of EV owners and its implications on the congestion of distribution grids. Second, our article demonstrates the positive role of energy aggregators and digital platforms in coordinating users to lower the cost and enhance the efficiency of energy consumption. Although both smart charging and the role of energy aggregators have been studied in previous literature, very little empirical evidence has been provided from real-world experiences and this is the most innovative point of our work.

The remainder of this article is organized as follows. Section 2 provides literature background on electricity markets, aggregators, and EV charging. Section 3 presents different scheduling strategies for EV charging and metrics to compare them. Section 4 computes numerical results and discusses the performance of smart and non-smart charging. We conclude the article with final remarks in Section 5.

2. Literature review

In this section, we provide some background on the role of aggregators in electricity markets and on the charging of EVs.

2.1. Electricity markets and aggregators

Electricity systems are currently facing significant changes as a result of the deployment of information and communication technologies and distributed energy resources [6]. Among these, a prominent trend is the growing popularity of electric vehicles, which have been identified as the most promising transport technology for the integration of renewable energy [21]. While the electrification of urban mobility is helping to reduce dependence on fossil fuels, it also puts pressures on power generators and grid to meet consumers' demand. As shown in Fig. 1, the typical pattern of energy consumption and the prices over a day may exhibit large variability between day and night times. Since the generators and grid must accommodate capacity to cope with the highest peak of consumption, some capacity will naturally sit idle during the low consumption hours. Large variability is undesirable, because starting up and shutting down power units imply costs (particularly high for conventional power generation, while lower for hydro power generation). In the end, all these costs are reflected in the tariffs paid by consumers, which in Norway are usually dictated by variable price contracts (equivalent to about 96% of the households, while only the remaining 4% have fixed price contracts). Often, the prices are more expensive at the times of high consumption and cheaper at the times of lower consumption, as illustrated by the similar shapes of the curves in Fig. 1. In addition, less variability in the consumption is helpful to secure a more reliable service and to conserve the lifespan of the grid components.

In trying to achieve a less variable pattern, the role of energy aggregators and digital platforms is receiving increasing attention [27]. An energy aggregator is an intermediary between consumers and producers of energy, which can increase or moderate the electricity consumption of a group of consumers according to the total electricity demand and supply available on the grid [20]. As the end-users may offer some flexibility on when exactly their consumption triggers, the energy aggregator may accommodate the schedule of consumption of the different consumers, so that a coordinated and more efficient consumption pattern realizes. Accordingly, it is indispensable to develop automate systems that make decisions on behalf of residential customers [35]. Although the concept has been present for years in the literature and some energy aggregators have actively appeared in markets from Europe and the USA, most related contributions in the literature remain at theoretical or conceptual level. An exception is Stede et al. [31], which conducts a survey on German aggregators and concludes that many of them create significant economic value in Germany, particularly in helping overcome the barriers to industrial demand response.

The latest European regulatory framework assigns aggregators a fundamental role in the clean energy transition [18], among others, because of its ability to coordinate distributed energy resources (DER). Likewise, in the USA, Shen et al. [29] assert that third-party DER aggregators have emerged to play a significant role as intermediaries, pooling resources across a large number of customers and coordinating these resources in a way that benefits the power grid, distribution utilities, and end-users. To achieve this, aggregators must facilitate information exchange between various power system actors, a problem which has been theoretically studied in previous literature (see e.g. Burger et al. [6]). In coordinating DER and orchestrating services and needs of the stakeholders, the role of digital platforms and infrastructures can be fundamental [8]. Yet, no empirical evidence has documented how consumers utilize the energy aggregator platforms to charge their electric vehicles and what is the value created by their utilization, and this is a gap that our article attempts to bridge.

2.2. Electric vehicles charging

Due to the increasing popularity of EVs and the considerable impact they are expected to have on power distribution grids, a number of questions about battery charging have received attention from the literature. One stream has focused on the formulation of optimization models to schedule the charging of EVs, comparing coordinated and non-coordinated strategies. Early contributions in this regard are Clement-Nyns et al. [7] and Nguyen et al. [24], which study the impact of EV charging on the load profile of the power distribution systems. A more recent review by Zheng et al. [37] summarizes a number of other EV scheduling methods and economic criteria used in subsequent literature.

Another stream of literature has focused on the charging behaviour of EV owners. Azadfar et al. [2] conducted a case study in Australia to analyze the charging patterns of EV drivers using a network of charging stations in the city of Perth. Although they acknowledge the importance of shifting the charging process from peak demand hours to hours when there is low demand on the grid, their findings only focus on travelled distances and charging frequency, rather than the specific times at which the charging events occur, and their study is limited to only 11 vehicles on a trial period. Sun et al. [33] and Sun et al. [34] examine the timing choice behaviour of EV users in Japan. The focus of these studies is the estimation of mixed logit models to understand the choices of the users in relation to factors such as pricing schemes and battery load status. In New Zealand, Su et al. [32] analyze different EV charging schedules, labeled as non-smart (schedules without optimizing) and smart (schedules optimizing as to minimize peak-valley difference) charging strategies. Their study, however, is based on data obtained from a Monte-Carlo simulation, projecting a future scenario of EV penetration towards 2030. Their findings indicate that coordinated EV charging works better than when the timing decision on charging is left to individuals, but they remark that the achievement of such coordination requires data communication between EV chargers and local servers. Helmus et al. [16] perform an empirical study to understand where and for how long EV owners charge their cars, among a network of public charging stations in Netherlands. They calibrate an agent based model to simulate the charging transactions of the individual users, which can support policy makers' decisions on charging infrastructure development. Hinson et al. [17] reports a pilot project in Texas studying load shifting strategies for the charging of EVs at 92 homes of Pecan Street. The findings indicate that there are promising opportunities for shifting charging to nighttime when electricity prices are lower. As a policy recommendation, they suggest to incentivize and deploy smart charging technologies. More recently, Lagomarsino et al. [19] conducted an experiment in the UK to investigate smart charging preferences and strategies. Their findings indicate that about 63% of the users are willing to install smart charging systems and also that they tend to overestimate energy requirements. The study concludes that user engagement in smart charging schemes may become crucial for the acceptance of the smart charging technology. Also recently, a survey by Ramsebner et al. [28] on smart charging infrastructure in multi apartment buildings in Austria, found that users are willing to provide information about their demand if an intelligent interface provides easy handling. In another recent study, Wu et al. [36] use the term smart charging from a utility owner perspective, referring to the strategy of delaying charging until the electricity generation cost is lower. In their setting, a utility firm owns and operates an EV charging station with parking spots with chargers available to customers. When customers arrive, the firm offers a menu of pairs of charging price and completion time. Then, each customer selects the pair that maximizes their utility, which decreases in the charging price, completion time, and sensitivity to delay. The numerical analysis uses some data from the largest wholesale electricity market in the US, but the data on customers and their arrival times is based on the assumption that each customer needs to charge the same amount (20 kWh) and that 500 customers arrive at the stations at some predefined times of the day. This setting differs considerably from ours, where the EV owners charge at home, their cost depends on the price of electricity at the time(s) they charge, and the charging needs and time availability for charging is given by real data and vary across customers.

As referred in a review on consumer preferences by Hardman et al. [15], having access to charging at home is the most influential aspect in encouraging consumers to purchase EVs [4,26,30]. Empirical works have also shown that the most frequently used location for EV charging is home. For example, a survey conducted in Germany by Franke and Krems [13] found that about 83.7% of the charging events occur at home, while similar figures have been obtained in a survey conducted in California by Nicholas et al. [25]. In Norway, it has been estimated that about 80% of the total households have access to charging at home [11], either through domestic outdoor sockets or through the installation of home charging units so-called wall-boxes. In particular, among the population of EV owners in 2018, 93% of them could charge at home [10]. Also, people in Norway are increasingly investing in stable and faster charging wall-boxes with built in safety and smart connectivity features. As for 2022, the cost of a wall-box in Norway is about USD 675 and the installation cost is about the same. Although the adoption of home charging solutions is more limited in other countries, we foresee this trend experienced in Norway might start to replicate in other regions of the world. In fact, as the range of EVs has considerably increased in the last car models released to the markets, the *range* *anxiety* (i.e., the fear of fully depleting an EV battery in the middle of a trip, leaving the driver stranded, Neubauer and Wood [23]) is being perceived by drivers as less stressful than the risk of charge queues at charging stations [12]. Therefore, home charging is often a more preferred option than public charging stations.

As home charging of EVs becomes more popular, it is important to understand the impact of how digital technologies can support the charging decisions of the households. Although some early surveys found that people might be skeptical to smart charging due to lack of understanding or loss of control on how their vehicles are charged [3,1], experiences in practice start to show more acceptance. Yet, as asserted by Hardman et al. [15], evidence relating to smart charging is limited. Our aim in this article is to contribute in this direction, by an empirical comparison between users and non-users of smart charging along several performance criteria, using real data collected through an aggregator's platform.

3. Charging scheduling

García-Villalobos et al. [14] define smart charging of EVs as a demand side management strategy which allows customers and network operators to schedule charging profiles in order to get technical and economic benefits. It can be implemented by either centralized or decentralized control architectures. In the centralized architecture, the car owners allow the aggregator to have direct control on the schedule of charging of their EVs. In the decentralized case, the decision-making on when and how much to charge resides in each EV owner, rather than in the aggregator. Here, although each EV owner autonomously seeks to optimize the cost of charge, the aggregator might still have a role in the form of price or control signals that can be sent to the owners. We refer to the review by García-Villalobos et al. [14] for more technicalities on smart charging of EVs and to Crespo Del Granado et al. [9] for a broader smart grid perspective on the domestic use of electrical devices at home. In what follows, we perform an empirical study comparing users and non-users of a smart charging service provided by Tibber's digital platform. The platform has centralized and decentralized smart charging capabilities. We focus on the centralized case here, in which customers can plug their EVs and specify their charging needs over a time interval, and then let the platform define a schedule such that the cost of charging is minimized. For this, the customers can simply turn on the smart charging feature of the app, offering flexibility to the energy aggregator to define the charging schedule.

3.1. Data

Our dataset includes hourly data registers on 438 EVs over a period of 3,687 consecutive hours corresponding to five months spanning from May to September, 2018. When an EV appears in the dataset for a specific hour, it indicates that the vehicle was available for charging. Each data register indicates whether a vehicle was charging or not at a specific hour, the state-of-charge at the beginning of the hour, how much energy it charged if it was charging during that hour, and whether the smart charging functionality of the app was enabled or not. The latter feature is important, because it allows us to distinguish the two subsets of data in which we segment our analysis.

We also have data on the electricity prices per hour during the time horizon under study, which correspond to the Norwegian market. These prices are publicly available on the website of *Nord Pool*, a platform for power exchange managing the daily trade of energy in Norway and other countries of Europe. Although taxes and other aspects of the tariffs are not reflected in these wholesale prices, most of the Norwegian household customers have contracts where the electricity cost follows directly from these prices.

In addition, we have data from a power grid operator indicating the power consumption per hour recorded at three stations in Western Norway during five months in 2018. The data describes the aggregated power consumption of about 2000 households, depicting a load profile as shown in Fig. 1.

3.2. Charging scheduling solutions

In what follows, we describe four alternative charging scheduling solutions, which we will use later in our numerical analysis. The first solution comes from solving an optimization model. The second and third solutions correspond to the actual observations in the charging schedules realized by users and non-users of the smart charging feature. The fourth solution comes from a plug-and-start strategy, which is commonly found in previous literature [7,33]. Our aim is to compare these solutions to gain insights on how the charging schedules and costs differ between smart charging users and non-users.

Optimal scheduling solution. Retrospectively, as we know how the charging needs and prices realized throughout the time periods under analysis, we can formulate a mathematical programming model to find what would have been the optimal schedule of charging. We will then use the optimal solution to this model as a basis for comparison of the realizations observed empirically. The realizations in the dataset are segmented in smart charging and non-smart charging events, thus we can run the model in the different data instances defined by these different groups of events.

The model receives as main inputs the hourly prices of energy consumption and the initial and the desired final states-of-charge of each EV during a certain time horizon (in practice, the initial state-of-charge is read automatically by the communication protocol between the platform and the vehicle, while the desired final state-of-charge is manually inserted by the user). As output, the model prescribes the amount to be charged by each EV in each period of the time horizon. The goal of the model is to minimize the total charging cost, while ensuring the desired final states-of-charge are fulfilled and respecting other technical constraints. The mathematical formulation of the model is detailed below.

Sets

K: set of vehicles.

T: set of time periods.

U: set of tuples (k, i, f) such that vehicle k is available for charging during the time interval $[i, f]$, where $k \in K, i \in T, f \in T$.

Parameters

$s^{start}_{k,i}$: state-of-charge of vehicle k at the beginning of period i (defined for $k \in T, i \in T$ such that there exists a tuple (k, i, f) in U for some $f \in T$).

$s^{end}_{k,f}$: state-of-charge of vehicle k desired at the end of period f (defined for $k \in T, f \in T$ such that there exists a tuple (k, i, f) in U for some $i \in T$).

m_k: maximum charge per time period allowable for vehicle k.

p_t: price per kWh at time t.

c_t: maximum charging capacity utilization by the total fleet of vehicles during time period t.

Decision variables

$x_{k,t}$: power charged by car k during period t.

Objective function

$$\min z = \sum_{k \in K} \sum_{t \in T} p_t \cdot x_{k,t} \tag{1}$$

Constraints

$$s^{start}_{k,i} + \sum_{t \in \{i,\dots,f\}} x_{k,t} = s^{end}_{k,f} \quad \forall (k, i, f) \in U \tag{2}$$

$$x_{k,t} \le m_k \quad \forall k \in K, t \in T \tag{3}$$

$$\sum_{k \in K} x_{k,t} \le c_t \quad \forall t \in T \tag{4}$$

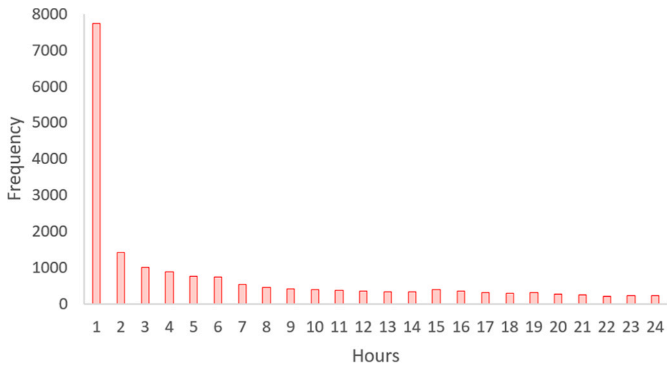

Fig. 2. Frequency of the quantity of hours elapsed from plug-in time until charging starts in the data registers where smart charging is not enabled.

$$x_{k,t} \geq 0 \quad \forall k \in K, t \in T \tag{5}$$

Objective function (1) minimizes the total charging cost. Given a relevant tuple (k,i,f) in set U and an initial state-of-charge $s^{start}_{k,f}$, constraints (2) assure that the state-of-charge of vehicle k reaches the desired level $s^{end}_{k,f}$ at the end of the time interval spanning from i to f. Constraints (3) state the maximum charging power per period for each vehicle. Constraints (4) state the maximum charging capacity available for each time period, which in practice in our study is unlimited (in general, however, it may be important to limit the capacity per hour if the fleet of EVs grows substantially and it becomes undesirable that all the EVs charge at the same time.) Constraints (5) state the non-negativity of the variables.

The model above can be implemented in any mathematical programming language or other general-purpose programming language, and solved using commercial solvers such as CPLEX or Gurobi. In the computational implementation of the model, the tuples (k,i,f) are defined by the appearance of vehicle k in the dataset during the interval of consecutive hours $[i,f]$. In retrospective, the optimal objective value of the model provides us with a cost that serves as basis for the economic assessment of the observed consumption and other charging strategies.

Smart charging solution. The optimization model above resembles, to a great extent, what the smart charging platform prescribes. In practice, however, the electricity prices for a given day are known only at 12:42 hr of the previous day. This means that the prices are available approximately 12 to 36 hours before real-time. Thus, Tibber faces some uncertainty when performing the charging schedules, if the EV owners' requests span beyond this time window. Also, the nominal maximum charge per time period for a given car m_k does not always coincide with the actual power charged, due to random variations in the energy transmission and charging speed. In addition, while the model allows multiple ON and OFF sequences over a time interval at which the car is available for charging, at the time of this study the platform could only prescribe a single starting time and a single ending time of charging, so that the loading occurs continuously within the interval defined by these times. Also, in our model the time periods are full hours, while in practice the times at which customers connect their vehicles might include fraction of hours in the earliest and latest time of an interval.

Non-smart charging and the *plug-and-start* solution. The data registers where the smart charging feature is disabled correspond to users who decide on their own when to charge their cars. Although their behaviour may vary from one to another consumer, a characteristic feature is that the majority of the non-smart charging events start as soon as the EVs are plugged-in. This behaviour, is illustrated in the plot of Fig. 2. The plot shows the frequency of the starting hour of charging with respect to plug-in time, revealing that in the great majority of the non-smart events, the charging starts immediately within the hour the vehicle has been plugged to the grid. Recall that the energy prices per hour are publicly available to everyone one day ahead, so in principle all EV owners could optimize their charging schedules. Defining what drives the choice of each individual to deviate from a less costly solution is outside the scope of our study, as we rather focus on exploring the consequences of the observed behaviour. This motivates us to study the *plug-and-start* charging strategy. Under this strategy, for each tuple (k,i,f), vehicle k starts charging in the initial hour i at rate m_k and keeps doing so until reaching the desired state-of-charge needed by the end of the hour f.

3.3. Performance measures

In addition to the overall cost function (1), other performance measures are important to analyze at user and operator levels. For this purpose, we introduce some new definitions below.

Price of energy. For the car owners, an important metric is how much is the cost paid for charging their vehicles. Given the consumption $x_{k,t}$ for each car k on each time period t, we can compute an average price per energy consumption as follows:

$$\bar{P}_k = \frac{\sum_{t\in T} p_t \cdot x_{k,t}}{\sum_{t\in T} x_{k,t}} \tag{6}$$

Naturally, a solution that achieves a lower average price $\bar{P}_k$ is more convenient for the owner of vehicle k.

Consumption share per hour. Let $H = \{1, 2, \ldots, 24\}$ be a set representing the 24 hours of the day. Here, the element 1 corresponds to the hour spanning from midnight until 1AM, the element 2 to the hour between 1AM and 2AM, and so on. Since the time horizon defined by T may include several days, we also define set T_h as the set of time periods in T that corresponds to the hour h (thus, $T = \cup_{h\in H} T_h$). Then, the total energy consumption of car k during the hour h throughout the time horizon can be expressed by $\sum_{t\in T_h} x_{k,t}$. The percentage share that this amount represents over the total consumption of car k is equal to $E_{h,k} = (\sum_{t\in T_h} x_{k,t} / \sum_{t\in T} x_{k,t}) \times 100\%$. Taking the average of this share across all cars renders what we call the consumption share per hour, denoted by $\bar{E}_h$ and computed as follows:

$$\bar{E}_h = \frac{\sum_{k\in K} \left(\frac{\sum_{t\in T_h} x_{k,t}}{\sum_{t\in T} x_{k,t}} \right)}{|K|} \times 100\% \tag{7}$$

The values of $\bar{E}_h$ help us study the distribution in time of the share of energy consumption per car. If for a given h the value E_h is large (in an extreme case, close to 100%), it would indicate that on average across all vehicles, a large share of the energy consumption occurs at time h.

The favourite hour for charging. For each car k, we might identify the favourite hours for charging by looking at the different values of $E_{h,k}$ throughout the 24 hours of the day. We define the binary parameter $f_{h,k}$ as equal to 1 if the percentage share over the total consumption of k is maximum at time h, that is, $h = \text{argmax}_{\hat{h}\in H} E_{\hat{h},k}$. Then, we can calculate the percentage frequency in which every hour h appears as the most popular hour for charging across all cars as follows:

$$\bar{F}_h = \frac{\sum_{k\in K} f_{h,k}}{|K|} \times 100\% \tag{8}$$

A large value of $\bar{F}_h$ indicates that a large percentage of vehicles has time h as the most frequent time for charging among the 24 hours of a day.

Fleet share charging per hour. The number of cars whose consumption is greater than zero on a given time period t is equal to $N_t = \sum_{k\in K:\, x_{k,t}>0} 1$.

Then, we define the average fleet share charging per hour $\bar{N}_h$ as follows:

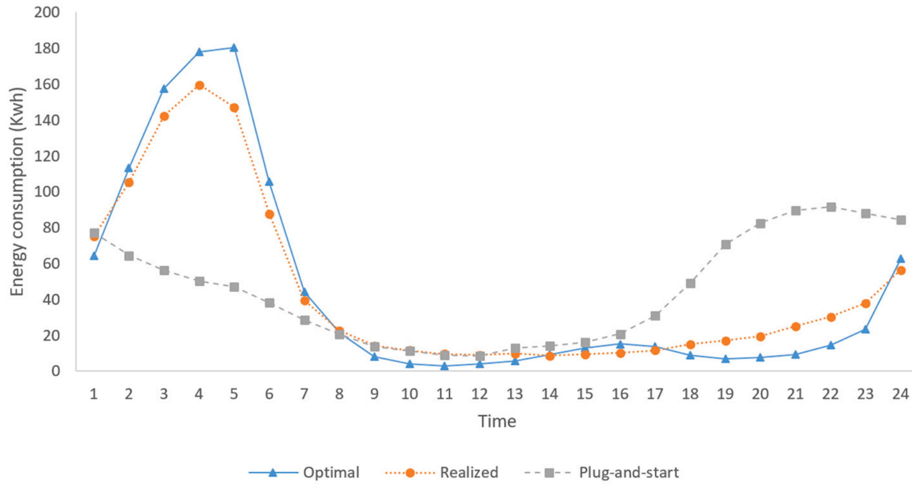

Fig. 3. Aggregated power consumption under optimal, realized, and plug-and-start strategy using the data on smart charging users.

$$\bar{N}_h = \frac{\sum_{t \in T_h} N_t}{|T_h|} \tag{9}$$

A large value of $\bar{N}_h$ indicates that a large percentage of vehicles charges at time h.

Load factor. For every hour h in H, we may compute the average load l_h over all the days under study by adding up the loads observed at hour h and dividing the so obtained sum by the number of days. Here, the loads refer not only to all EVs but also to all other electricity consumption activities served by the grid operator. Let L_{avg} be the average load over all hours h in H, i.e., $L_{avg} = \sum_{h \in H} l_h/24$. Let L_{peak} be the maximum load over these hours, i.e., $L_{peak} = \max_{h \in H} l_h$. Then, we compute the load factor LF as the ratio between the average and peakload, that is:

$$LF = \frac{L_{avg}}{L_{peak}} \tag{10}$$

The highest possible value of LF is equal to one. Usually, however, the peakload defining the capacity of a system is higher than the average load, thus the load factor is an indicator of the variability in the capacity utilization of the grid. A low LF indicates that the capacity sits idle for long time periods and that there is possibly large variability in the consumption throughout a day. By reducing the variability, the distribution system operator (DSO) can also obtain higher reliability and longer lifespan of the grid components.

Power losses. Due to component resistance and the physical length of the transmission lines, there are unavoidable differences between the energy fed into the grid and the actual energy supplied to end-users. These differences are referred to as power losses (PL). A commonly used formula to approximate the technical network losses is given by

$$PL = RI^2, \tag{11}$$

where R is a resistance factor and I is current. In turn, the current can be calculated as $I = P/V$, where P is the power consumption and V is the voltage. Lower power losses are more convenient for the DSO, as the regulation in Norway requires the DSO to cover the economic consequences of these losses. Given its quadratic form, the losses throughout an interval of time can be reduced by shifting the load away from time periods with high consumption and by shaving the peaks of the load-curve.

4. Results

We organize our results in three subsections, discussing the behaviour of the different solutions in regards to cost of charging, time of charging, and grid efficiency.

Table 1
Total cost (in EUR) paid by EV owners, including smart charging, non-smart charging, and all charging events.

	Smart charging	Non-smart charging	All
Optimal	6,435	8,773	15,192
Realized	6,626	9,553	16,179
Plug-and-start	7,144	9,587	16,718

4.1. Cost of charging

Fig. 3 shows the average power consumption per time of the day, using the smart charging dataset. Note the curve corresponding to the realized solution in this case is very close to the curve drawn by the optimal solution of the scheduling model. These solutions tend to prioritize charging during the night, when the prices are lower. In contrast, the plug-and-start strategy is much more distant. In particular, the plug-and-start solution tends to charge more in the afternoon/evenings, when people come home from work. The economic performance of these solutions is shown in the first column of results in Table 1. The total cost perceived by the users of smart charging is about 3.0% more expensive than the optimal cost computed by the model, while the plug-and-start solution in the smart charging dataset is 11.0% more expensive.

Fig. 4 shows the average power consumption per time of the day, using the non-smart charging dataset. The trend of these realizations shows that the behaviour of the non-smart users is close to the plug-and-start policy and that they do not generally optimize the charging themselves. Again, the differences with respect to the optimal solution are more noticeable at evenings and nights. The plug-and-start solution and the non-smart realizations charge considerably more than the optimal solution during the evenings and considerably less during the night. This indicates that the non-users of the smart charging feature perceive a considerable higher cost in comparison to the optimal solution, and their consumption adds up to the peakload hours rather than helping to peak shaving. From the cost results in the second column of Table 1, it follows that the total cost perceived by the non-smart charging realizations and the plug-and-start solution are 8.9% and 9.3% more expensive than the optimal cost computed by the model, respectively.

The average price paid by car owners who use the smart charging feature is considerably lower than the average price paid by those who do not use it. This is clearly illustrated in Fig. 5, where the boxplot on the left represents the average prices perceived by car owners in the smart-users dataset and the boxplot on the right represents the average prices perceived by car owners in the non-smart-users dataset, com-

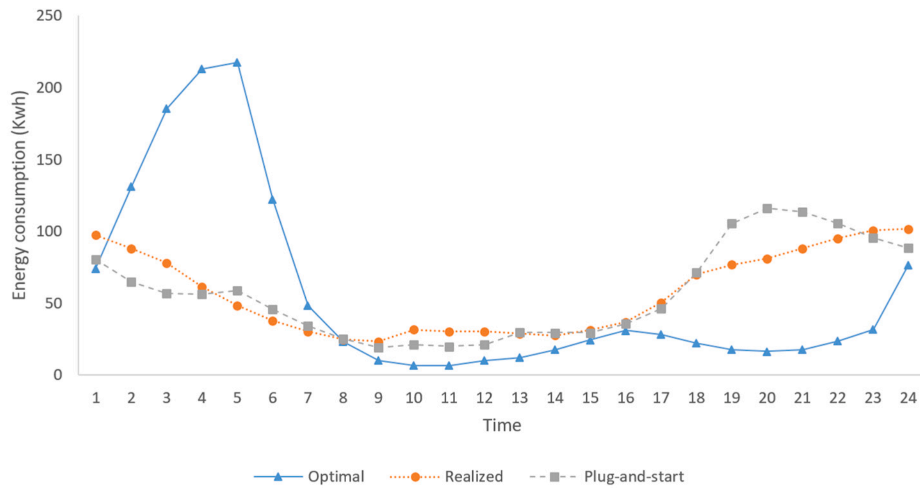

Fig. 4. Aggregated power consumption under optimal, realized, and plug-and-start strategy using the data on non-smart charging users.

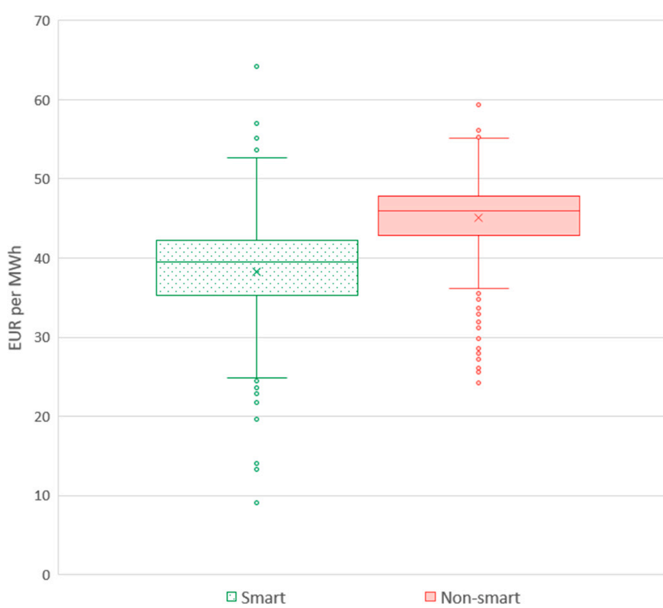

Fig. 5. Average price per MWh paid by car owners.

puted according to formula (6). On average, the price paid by the smart users is 38.2 EUR/MWh, while the price paid by the non-smart users is 18.1% higher, that is, 45.1 EUR/MWh. Also, the great majority of the smart users pay less than the non-smart users. As a referential price, the average paid across all users is 42.2 EUR/MWh. About 75.1% of the smart-user population pay less than this price, while only 19.3% of the non-smart users pay less than this price. The median of the prices paid by the smart-users is 39.5 EUR/MWh. Almost 90.0% of the non-smart users perceived a higher average price than that. In contrast, almost 93.0% of the smart-users perceived a cheaper price than the median of the prices paid by the non-smart users, which was 45.9 EUR/MWh.

4.2. Time of charging

On a given dataset (smart or non-smart), for each car we can compute how much of its total consumption occurred at each hour of the day. Then, we can add up the total consumption at each hour during all the days in the time horizon under study, and calculate how much this represents over the total consumption of this car, according to formula (7). For each of the datasets, the average across all cars of such consumption share per hour is shown in Fig. 6. For all hours spanning from midnight until 9AM, the share loaded by smart users is larger than the share loaded by the non-smart users. About two thirds of the energy consumption per car occurs at those times for smart users. In particular, their highest share of consumption occurs in the hour from 3AM to 4AM, accounting for about 13.6% of the total consumption of the smart users' cars. From 9AM until midnight, the share loaded by non-smart users is larger than the share loaded by smart users. In particular, about 52.5% of the consumption of the non-smart users' cars occurs from 4PM until midnight.

The most popular hour to charge per car owner is the most frequently observed hour at which such car is charging throughout the time horizon. Then, we can calculate the frequency in which each hour of the day is the most popular across all car owners, according to formula (8). Fig. 7 shows the outcome obtained for both smart and non-smart groups of users. It can be seen that the most popular times to charge a car among smart users spans from 3 to 5 AM, which includes about 71.8% of the preferences. In particular, 4AM is the most frequently observed loading hour for 33.8% of these users. The preferences among non-smart users are more spread, with about 64.5% of the preferences ranging from 6PM to 1AM. In particular, the hour spanning from midnight until 1AM is the most frequently observed favourite hour for the non-smart group.

A similar fact is reflected in Fig. 8, which shows the share of the fleet connected on average at each time of the day, computed according to formula (9). Between 10.9% and 15.6% of the total number of smart users on average are loading in the interval 2-6AM, while less than 8.7% of them in all the other hours of the day. In the non-smart group, the most demanded hours range from 9PM-1AM, when between 8.3% and 9.3% of the fleet on average is loading.

4.3. Grid efficiency

To illustrate the peak shaving effect, Fig. 9 shows the results obtained by adding up the whole EV fleet consumption into the overall consumption presented earlier in Fig. 1. Clearly, the curve using the optimal solution shows less variability along the daily consumption pattern. The consumption using the plug-and-start solution, in contrast, exhibits a larger difference between the minimum and maximum load consumption, reached at 5AM and 9PM, respectively. The realized solution in this case contains both smart and non-smart charging users, which conduces to a curve that at the peak periods lies approximately between the optimal and plug-and-start curves.

Table 2 summarizes results on the load factor and power losses, following formulae (10) and (11), respectively. Note again how in the smart charging events, the realized load factor gets very close to the

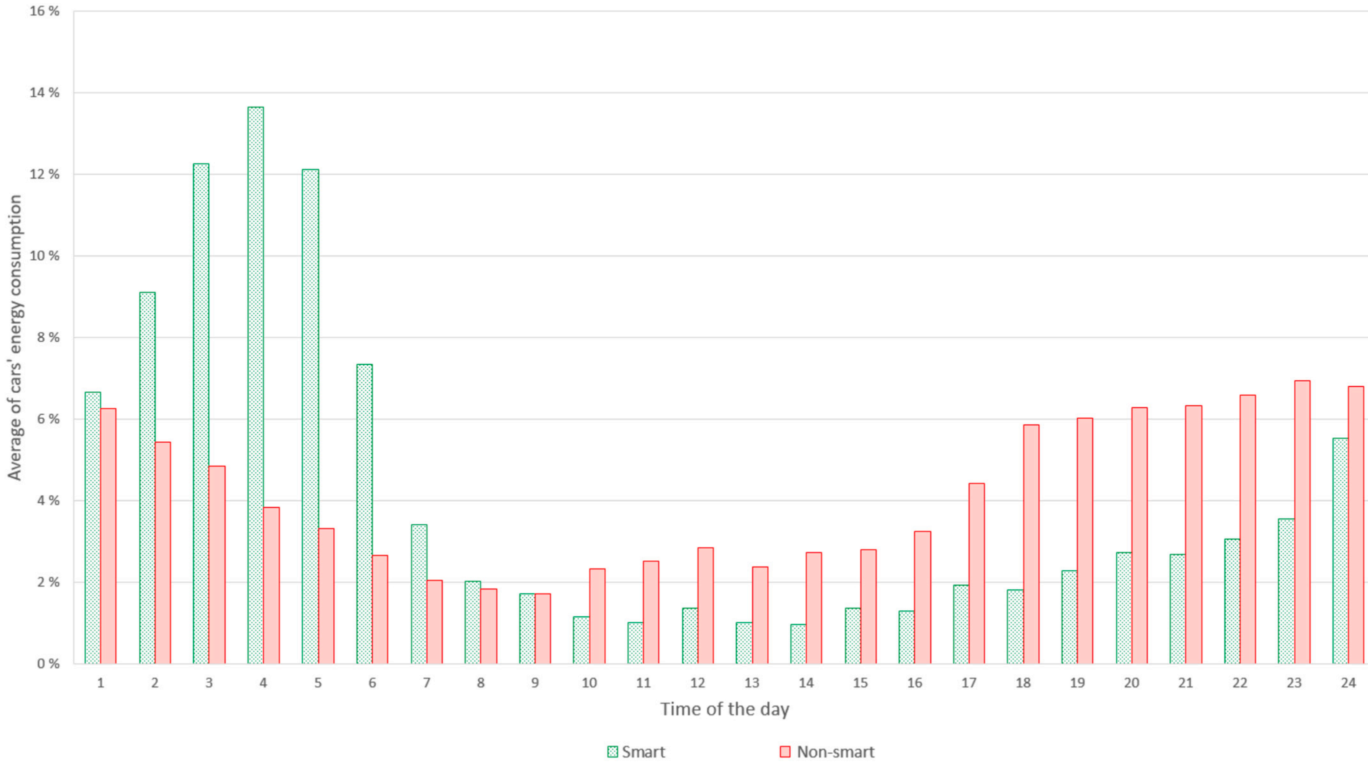

Fig. 6. Average over all cars of the percentage of each car's total consumption charged per hour.

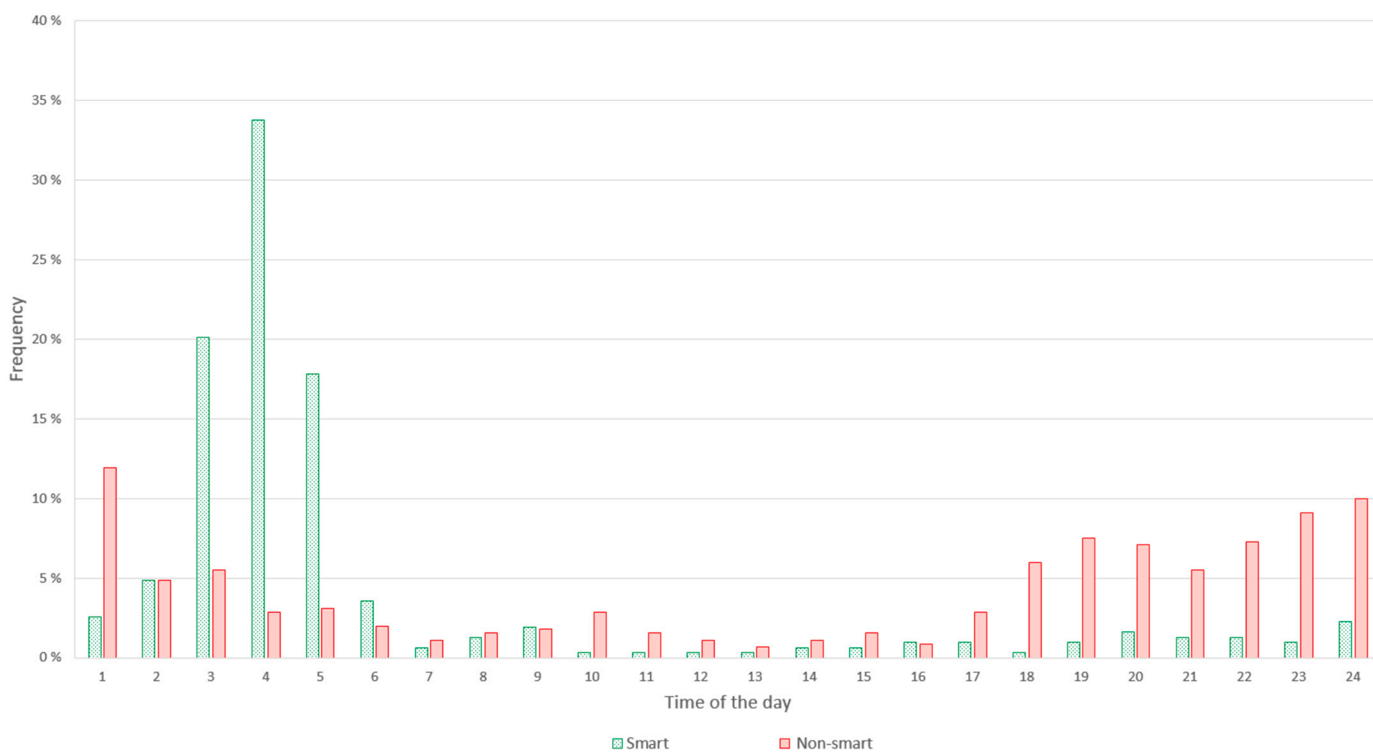

Fig. 7. Frequency of the favourite hour to charge.

load factor observed in the optimal scheduling solution, differing by only 0.7%, while the power losses differ by only 1 kWh. In contrast, in the non-smart charging events, the absolute difference between the realized load factor and the load factor of the optimal scheduling solution is 3.4%. Also, the power losses in the non-smart charging events become closer to the power losses of the plug-and-start solution than to the power losses of the optimal scheduling solution. We remark that this optimum refers to the solution obtained by a cost minimization objective and not by a peak shaving objective.

To sum up, the discussion of results above shows that the smart charging at home strategy facilitated by the aggregator's digital platform:

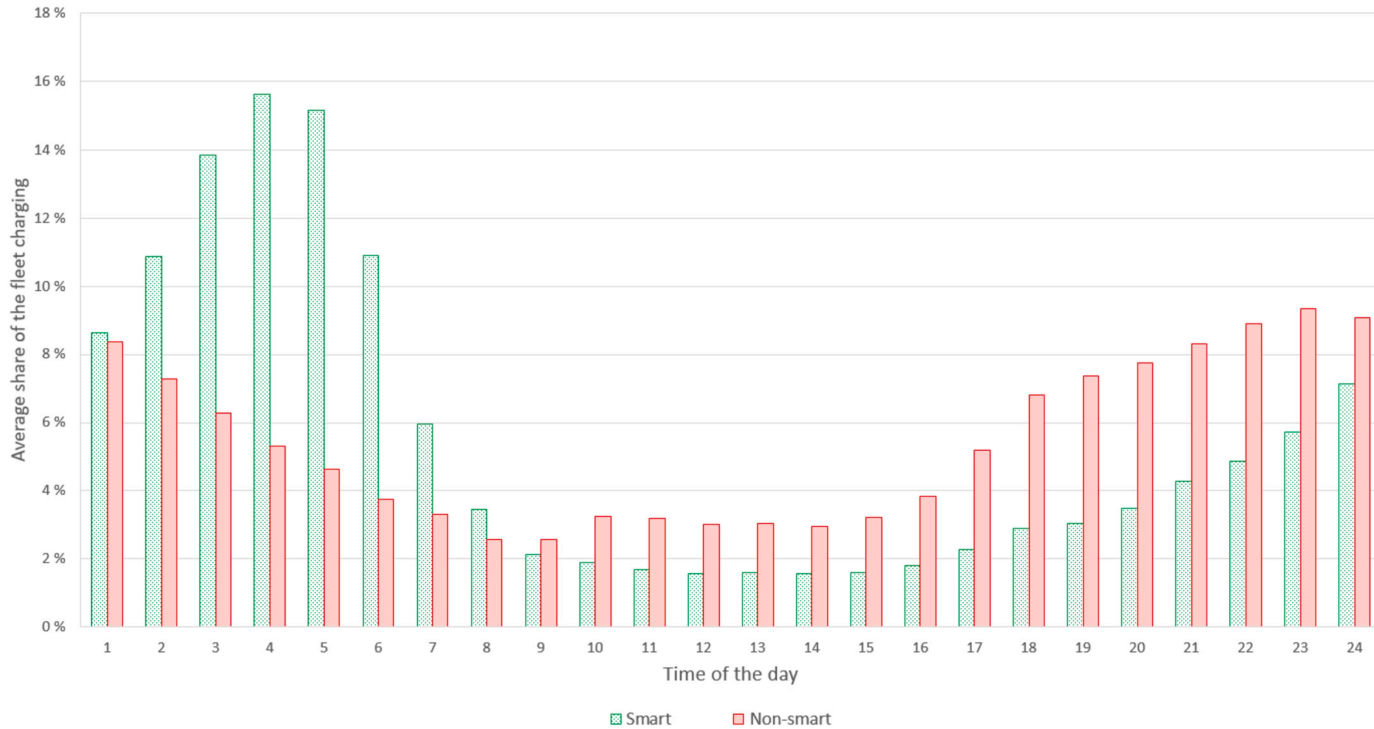

Fig. 8. Share of the smart and non-smart fleet charging on average per each time of the day.

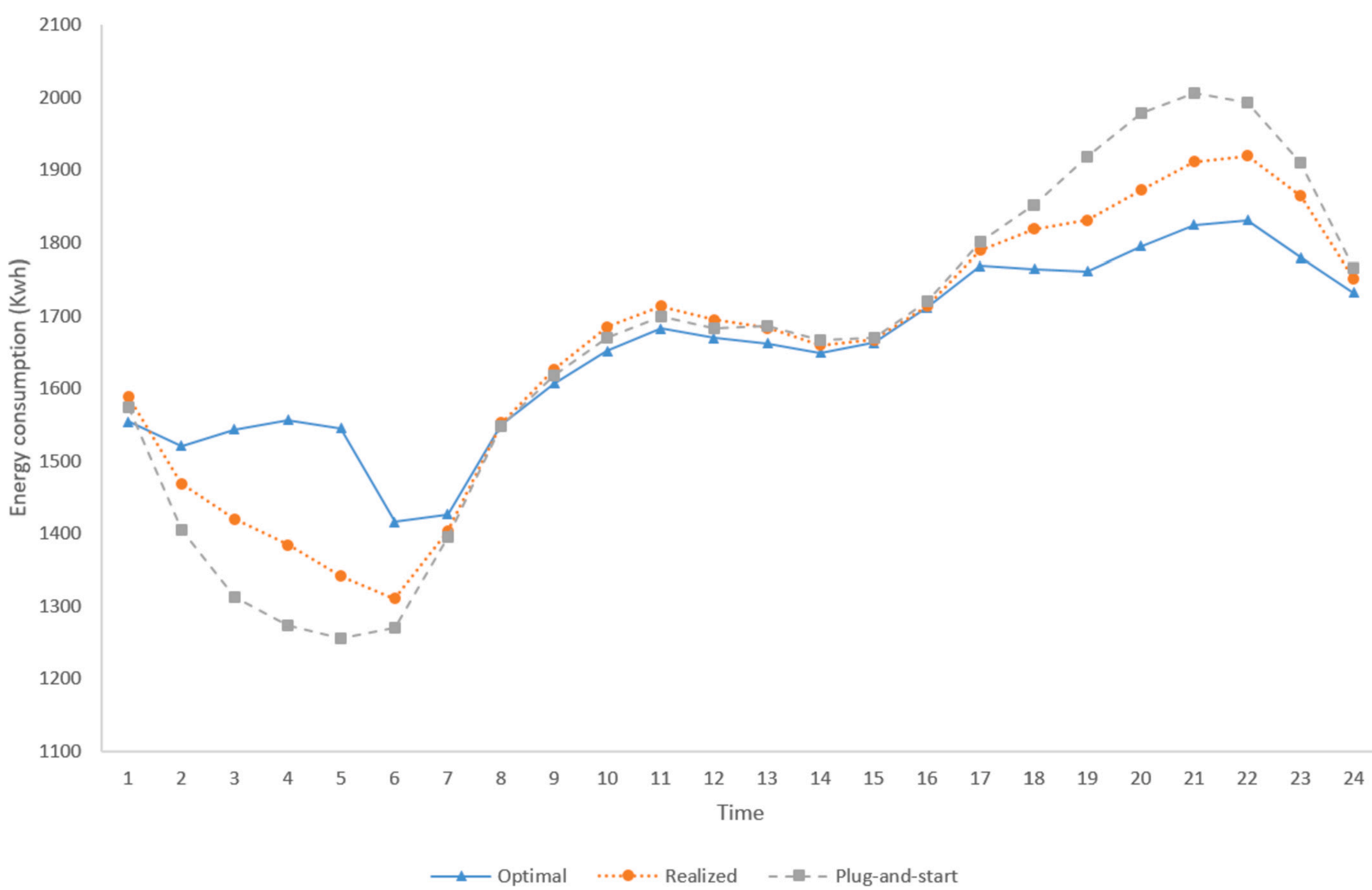

Fig. 9. Illustrating peak shaving: Total power consumption (including EV charging and all other households' needs) under optimal, realized, and plug-and-start schedules using the whole dataset.

Table 2
Load factor and power loss, including smart charging, non-smart charging, and all charging events.

	Load factor (%)	Power loss (kWh)
Smart charging events		
Optimal	88.2%	510
Realized	87.5%	511
Plug-and-start	84.5%	515
Non-smart charging events		
Optimal	88.5%	518
Realized	85.1%	522
Plug-and-start	84.1%	523
All charging events		
Optimal	90.2%	545
Realized	86.1%	548
Plug-and-start	82.4%	553

- is more economically convenient for the EV owners;
- conduces to a smoother energy consumption pattern from society, by shifting the EV charging load from peak-hours to hours which experience lower consumption;
- is more convenient to the grid operators.

5. Concluding remarks

Our paper has shown that a digital platform aggregating and automating the scheduling of the energy consumption needs of its users effectively helps achieve lower costs and higher efficiency. Our empirical work analyzed data on users and non-users of smart technology systems to schedule the charging of their electric vehicles. The results show that the cost perceived by the smart technology users is very close to the optimal solution of a scheduling model. In contrast, those EV holders who do not use smart charging perceive considerably more cost than such optimal solution and than the smart charging users. This occurs because the digital platform schedules the charging of EVs at hours when the energy is cheaper (usually during the night), while the non-users tend to start charging as soon as they arrive home, which coincides with higher peak consumption periods and higher prices. In addition to being more cost efficient for users, smart charging by digital platforms proves to also render more efficiency to the grid operation. This is reflected in a lower variation of the energy consumption over a day, since postponing the charging to the later hours helps shaving consumption from peak to valley hours. The more efficient grid operation thanks to smart charging is also reflected in less power losses. We have illustrated these effects by computing standard metrics in energy grid operation. With the penetration of electric vehicles increasing and the option to charge at home becoming a popular choice, our study suggests that smart charging platforms can play a fundamental role to prevent congestion in the power grid. Currently, Tibber has more than 400,000 vehicles paired to its platform and it has expanded from Norway to other countries, such as Sweden, Denmark, and the Netherlands.

As our work contributes a pioneer piece of empirical research about the use of smart technologies for home charging of EVs, plenty of opportunities for future research arise. First, while it is undeniable that coordinating the energy consumption of users increases economic and social welfare, it is challenging to split the benefits among the different stakeholders. On one hand, smart technology users perceive a cost reduction. In turn, the grid operator also benefits from having to operate a less congested grid and being able to more efficiently deploy capacities to operate the grid. Since this beneficial situation is prompted by the aggregator who runs the digital platform and performs the optimization of charging schedules, we may naturally think that the operator and the users should pay back a fraction to the aggregator by the value it creates. What is the best split of the benefits among the players, however, remains as an interesting question. Moreover, in cases where the grid is suddenly overloaded, the aggregator may act as a channel for automatically reducing consumption and relieving the operation of the grid, which also involves economic and operational consequences that the players must address. Another aspect that can be incorporated into the analysis is the interaction between day-ahead, intra-day and real-time purchases of energy by the aggregator. The ability to sell back energy to the system and to buy from it within a day adds an uncertain component to the problem, which may be addressed by stochastic methods. Moreover, the EV owners potentially also have the ability to sell back energy from their batteries to the system, but this ability is not implemented in our case yet. Also, while our study is conducted in Norway with data from 2018, performing similar studies with level of prices from more recent time periods and in other geographical areas remains of interest. From a sharing economy perspective, the wall-boxes installed at private houses may well foster new business models which would complement the infrastructure of charging stations spread around cities. Finally, while we focused on charging EVs, smart features for energy consumption are also available for other needs, such as heating. It is doubtless that digital platforms may play a fundamental role to enable these capabilities and foster their use by consumers.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: As a potential conflict of interest, please notice that the third and fourth authors are employed at the company which collected the data of this study. This was carried out in the context of a collaborative research project between academia and industry supported by public funds (see acknowledgment paragraph below). We all authors declare not having incurred in any action that would have inappropriately influenced the work reported in this paper.

Data availability

The data that has been used is confidential.

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