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A methodology to generate power profiles of electric vehicle parking lots under different operational strategies

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HIGHLIGHTS

- Kernel density estimation is used to model the characteristics of the EV fleet.
- A method to derive representative electricity price series is proposed.
- Load duration curves can be closely approximated with few simulations.
- EV parking lot load profile significantly varies with the employed strategy.

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ABSTRACT

The electrification of the transportation sector through the introduction of electric vehicles (EV) has recently emerged as a remedy to environmental and economic concerns. For this reason, governments around the world have been offering subsidies and other benefits to drivers that replace their conventional vehicle with an EV in order to facilitate the commercialization of the latter. However, when compared to conventional vehicles, EVs present a key disadvantage that could hinder their widespread uptake: the time that is needed to charge an EV is in the range of hours. For this purpose, EV parking lots have been proposed in order to recharge vehicles at a higher rate. Recent studies indicate that vehicles remain parked for most of the day, implying that different operational strategies may be used in order to achieve operational or economic benefits from the perspective of the EV parking lot owner. The aim of this study is to derive representative load profiles of parking lots under different operational strategies. To perform so, the parameters of the EV fleet are modeled by estimating kernel distributions from available traffic data, while a time series transformation in combination with a clustering approach is used in order to obtain representative price patterns. The examined case studies demonstrate that by performing a reduced number of simulations regarding expected charging profiles of EV fleets, generalized results may be obtained using the proposed methodology.

1. Introduction

1.1. Motivation

Over the last few decades concerns such as the environmental degradation, the depletion and the price volatility of fossil fuels, as well as the willingness of governments to reduce their dependence on the import of foreign petroleum has stimulated the interest in the electrification of the transportation sector. More specifically, the transportation sector has been found to be responsible for more than a quarter of the total energy consumption and for one third of greenhouse gas emissions worldwide [1]. As a consequence, electric vehicles (EV) are being considered as a cleaner alternative to fossil fuel vehicles. Moreover, the large scale integration of EVs may contribute to the smoother integration of renewable energy sources (RES) generation in the power system [2], increasing the self-sufficiency of a country's electricity sector. However, RES production, which is significantly affected by meteorological and other factors, can be intermittent and volatile. The capability of EVs to act as sinks and sources of energy and therefore, their potential for increasing the RES hosting capacity of power systems has been extensively studied [3].

In order to take advantage of the projected benefits of the electrification of the transportation sector, several governments have offered a series of motives to promote the EV uptake: subsidies for the purchase of an EV, tax exemption, driving benefits such

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Nomenclature

Indices

e	index referring to electric vehicles
t	index referring to time periods (h)

Parameters

CR_e	charging rate of EV e (kW)
DR_e	discharging rate of EV e (kW)
E_e	energy EV e uses in commuting (kW h)
l	lower limit of truncation for the EV departure time (h)
m	mean of periods the EV departs after arrival (h)
N	large positive number (kW)
N^{EV}	number of EVs
SOE_e^{max}	maximum capacity of the battery of EV e (kW h)
$STATUS_{e,t}^{EV}$	binary parameter – 1 if EV e is available in period t
T	number of time periods
T_e^a	arrival time of EV e
T_e^d	departure time of EV e
$T_e^{C,E}$	exact time needed to fully charge EV e (h)
$T_e^{C,R}$	rounded number of periods EV e needs to fully charge
$Type_e$	type of EV e
u	upper limit of truncation for the EV departure time (h)
ΔT	duration of time interval (h)
λ_t	electricity price in period t (€/kW h)
σ	standard deviation of EV departure time (h)

Variables

ENS_e	energy not served to the e (kW h)
$P_{e,t}^{ch}$	charging power of EV e in period t (kW)
$P_{e,t}^{dis}$	discharge power of EV e in period t (kW)
$P_{e,t}^{dis,out}$	power from EV e that is injected back to the grid in period t (kW)
$P_{e,t}^{dis,u}$	power from EV e that is used within the parking lot in period t (kW)
P_t^{in}	power drawn from the grid in period t (kW)
P^{max}	maximum power requirement of the EV parking lot (kW)
P_t^{out}	power injected back to the grid in period t (kW)
$SOE_{e,t}$	state-of-energy of EV e in period t (kW)
$u_{e,t}^{EV}$	binary variable – 1 if EV e is charging in period t
u_t^{grid}	binary variable – 1 if the EV parking lot is drawing power from the grid in period t

as parking permits in dense urban areas (e.g., in Amsterdam) and permission to drive in bus and taxi lanes in order to save traveling time during rush hours (e.g., in Oslo). As a result, the market share of EVs has been increasing in the recent years [4].

Despite the attractive fringe benefits targeting at motivating drivers to replace their conventional vehicles with EVs, a factor that may hinder the widespread adoption of EVs is that their charging requires several hours [5], effectively limiting the usability of EVs even for relatively short distance traveling. Specifically, a recent study supports that for an average person, the aforementioned inconvenience (also known as drivers' range anxiety) may outweigh the environmental and fuel cost benefits of the EVs [6]. Nevertheless, several studies indicate that vehicles are used only 4–7% of the time during a day [7] and therefore, remain in idle state for long periods. Based on this fact, using EV parking lots as charging points [8] while drivers are in a non-residential/commercial area [9], at work [10–12] or at municipal parking lots [13], has been proposed in order to ease this drawback.

1.2. Relevant literature

From the perspective of the power system, the increasing penetration of EVs is controversial. On the one hand, an EV fleet provides a useful flexible resource for the system that, if suitably controlled, can be used in order to provide reserve services and contribute to load shaping [14]. In addition to this, new business opportunities and market players (e.g., aggregators, EV parking lot owners, etc.) emerge. On the other hand, failing to sufficiently engage EVs is likely to increase the loading of the system, jeopardize its reliability and necessitate transmission and distribution system reinforcements [15]. A significant amount of studies is motivated by this controversy and focuses on different aspects of the EV integration.

The provision of primary, secondary and tertiary reserves together with energy services by EVs is investigated in [16]. Also, in [17] the contribution of EVs to dynamic frequency response in the system of Great Britain is studied. Another important aspect that is discussed in the relevant literature is the potential of employing coordinated EV charging in order to accommodate increased amounts of variable renewable generation [18–20]. The market integration of EVs is also the subject of various studies. For instance, in [21] a two-stage stochastic programming based model for the participation of an EV aggregation in the day-ahead market is presented, while a general framework for the charging of EVs in a market environment is presented in [22]. Another category of studies focuses on the impacts of EVs on the transmission and distribution system. In [23] a thorough review of the impacts of bi-directional EV interaction with the grid under different charging strategies is provided. The consideration of EVs in transmission expansion planning is treated in [24]. The vehicle-to-grid (V2G) service and the network constraints are taken into account in [25], while in [26] the impact of EV penetration on Volt-VAR optimization is examined. Finally, a potential implication of EV charging load, i.e. the acceleration of the thermal aging of power transformers is studied in [27].

The majority of the studies concerns EVs that are available at different locations of the distribution system. Nevertheless, an EV parking lot constitutes a distributed resource of a significant size that can be optimally placed in a distribution system in order to enhance its operation by reducing active power losses, improve voltage profiles and increase reliability. Thus, it is essential that the EV fleet parameters are suitably modeled in order to be adapted to the available real data. In order to quantify the positive and negative aspects of integrating EV parking lots in the distribution system, its load profile should be accurately derived. For this purpose, several characteristic parameters of the EV fleet such as the number of available EVs in each period, their initial state-of-energy (SOE) and the technical specifications of each car must be known. Most of the relevant studies model the EV fleet in terms of rough assumptions [7,28–30], different parametric distributions [31,32], or are based on real EV traffic behavior; yet, the number of EVs considered in the latter category of studies is limited [33]. Moreover, in [34,35] spatial–temporal models for grid impact analysis of EVs are presented. However, in the first study parametric distributions are also used in order to specify the fleet parameters, while in the second study the EVs are assumed to be charged at a constant power; therefore, the proposed techniques are not suitable for the obtainment of representative load profiles for EV fleets available at a single location under different operational strategies. A more complete overview of the mobility parameters considered in different studies can be found in [8]. The aforementioned fleet modeling techniques present limitations in obtaining generalized traffic patterns suitable for EV parking lots. The EV power profiles that are specified are optimal from the point of view of the system operator. Nevertheless, an EV parking lot may be operated under different strategies by its owner in order to fulfill goals related to profit making. The present study focuses on deriving representative power profiles for an EV parking lot which are required to optimally locate it, as well as to investigate the effects of its operation on a wider scale.

1.3. Contribution and organization of the study

The contribution of this paper with respect to other studies in the literature is twofold:

- Unlike most studies that utilize parametric distributions in order to model the characteristics of the EV fleet, this study demonstrates that non parametric distributions can accurately represent the key modeling factors. In addition to that, in order to derive representative load profiles for operational strategies that are based on electricity market prices, a suitable time series transformation and clustering technique that allows extrapolating results by performing a reduced number of simulations is proposed.
- Representative load profiles are derived for the EV parking lot under four different operational strategies considering both unidirectional and bi-directional power flow. In addition to that, a case in which the EVs connected at the parking lot follow different charging strategies is examined.

The remainder of this paper is organized as follows: in Section 2 the proposed modeling methodology of the EV fleet characteristics is presented. Then, in Section 3 the approach to derive representative price profiles is elaborated. The mathematical formulation of the different operational strategies is developed in Section 4. Subsequently, in Section 5 several numerical case studies are investigated and discussed. Finally, conclusions are drawn in Section 6.

2. Modeling of the EV fleet characteristics

An EV fleet is characterized by several parameters: (a) arrival time, (b) departure time, (c) SOE upon arrival, and, (d) fleet composition. The arrival and the departure times denote the time span that an EV is parked at the EV parking lot or is plugged-into its individual charger and therefore, signify the number of EVs that are available in a given period. The SOE of an EV at the moment it is plugged-in (initial SOE) and its battery capacity define the amount of energy that must be delivered to the EV battery by the time it departs. A typical assumption is that the owner ideally desires to have the EV battery fully charged by the time the EV departs (mileage anxiety). Currently, there are numerous EV models available on the market with different charging rates and battery sizes. The knowledge of these parameters is important in order to estimate the power that is drawn by the EV fleet in each period. Thus, it is essential to adequately specify the composition of the EV fleet.

In the literature several approaches to specify the characteristic parameters of an EV fleet can be found, as discussed in Section 1.2. The majority of these approaches assume that a parametric distribution can be fit to the data. However, the characteristics of different EV fleets may significantly vary and might not be properly described by a parametric distribution (e.g. due to multimodality). For this reason, in this study statistical data regarding commuting and the market share of different EV types are collected and kernel distributions are adapted to the data.

A kernel distribution produces a nonparametric probability density estimate in order to represent the probability distribution of the random variable based on the sample. The kernel distribution is defined by selecting a kernel density estimator, i.e. a smoothing function that affects the shape of the curve used to generate the distribution of the data, and a bandwidth that controls the smoothness of the density estimate. A kernel estimator is of the general form (1).

$$\widehat{f}_h(x) = \frac{1}{n \cdot h}\sum_{i=1}^{n} k\left(\frac{X_i - x}{n}\right) \tag{1}$$

where $X = \{X_1, \ldots, X_n\}$ is the examined sample, $k(\xi)$ is a kernel function and h is the bandwidth value. In this study, the normal kernel that is expressed by (2) is used [36].

$$k_\phi(\xi) = \frac{1}{\sqrt{2\pi}} e^{\left(-\frac{\xi^2}{2}\right)} \tag{2}$$

The value of the bandwidth h affects the density estimate. Although the optimal bandwidth can be theoretically specified, it is not practically used since it requires the knowledge of the unknown density function. Several techniques have been proposed in order to practically specify the bandwidth value [36]. However, since a normal reference kernel function is selected, rule (3) applies for the selection of the optimal bandwidth value.

$$h = 1.06 \cdot \sigma_s \cdot n^{-1/5} \tag{3}$$

The bandwidth that results from (3) is not robust against outlier data (fat tails). Instead, a more robust estimator can be achieved by using the interquartile range R (third quartile minus first quartile) as a measure of spread. In this case the bandwidth is calculated as in (4).

$$h = 1.06 \cdot \min\left(\sigma_s, \frac{R}{1.34}\right) \cdot n^{-1/5} \tag{4}$$

Algorithm 1 that is presented in Fig. 1 describes the proposed approach for modeling the EV fleet characteristics. First, statistical data regarding arrival times, the energy used in commuting (or an equivalent parameter, e.g. traveling distance, time of commuting, etc.) and the market share of the EVs are collected. Typically, such data are concisely presented in publicly available reports. Thus, pre-processing may be required in order to bring the raw data in an exploitable form. Subsequently, kernel distributions are estimated for the key parameters. Then, for a specified number of EVs the following procedure is repeated: the distribution of the arrival times is sampled and the result is rounded because it might be a fraction of a period. Since data regarding the departure time of the EVs are scarce, a normal distribution is assumed with mean $T_e^a + m$ and standard deviation σ, where m is the average time the EVs remain connected at the EV parking lot after arrival. The fitted distribution must be also truncated between a lower limit $T_e^a + m - l$, in order to avoid obtaining a departure period before the arrival period and an upper limit $T_e^a + m + u$. A sample is then obtained from the departure time distribution. Having obtained the arrival and departure times, the status of the EV (connected or not) can be defined. After that, a sample is obtained from the distribution that is fit to describe the energy that is used in commuting. The final step is to define the type of each EV. Based on the energy E_e that is used during commuting, a vehicle type is selected based both on the distribution of the EV types according to their market share and the requirement that the selected vehicle must be able to cover the corresponding traveling distance. More specifically, first, a sample is drawn by the non-parametric distribution that is fit to the EV market share data. Then, the battery

Algorithm 1

collect statistical data regarding arrival times, energy used in commuting, market share of EVs and create histograms
fit non-parametric distribution for arrival times $\mathcal{D}^a$
fit non-parametric distribution for energy used in commuting $\mathcal{D}^e$
fit non-parametric distribution for EV types D^{type}
define size of EV fleet N^{EV}
for $e = 1 \rightarrow N^{EV}$ **do:**
    sample $T_e^a \leftarrow round(\mathcal{D}^a)$
    fit normal distribution for departure time of EV e, $\mathcal{D}_e^d$ $\mathcal{N}(T_e^a + m, \sigma)$
    $truncate_{T_e^a+m-\ell}^{T_e^a+m+u}\{\mathcal{N}(T_e^a + m, \sigma)\}$
    sample $T_e^d \leftarrow round(\mathcal{D}_e^d)$
    for $t = 1 \rightarrow T$ **do:**
        if ($t \geq T_e^a$ *and* $t \leq T_e^d$) **do:**
            $STATUS_{e,t}^{EV} \leftarrow 1$
        else
            $STATUS_{e,t}^{EV} \leftarrow 0$
        end
    end
    sample $E_e \leftarrow \mathcal{D}^e$
    sample $Type_e \leftarrow round(D^{type})$ so that $SOE_e^{max} \geq E_e$ for $Type_e$
end

Fig. 1. Algorithm 1. Modeling of the EV fleet characteristics.

capacity of the selected EV is compared with E_e. If the vehicle cannot fulfill this energy requirement, this EV type is discarded and a new sample is drawn from the nonparametric distribution. This procedure is repeated until the selected vehicle type can satisfy the driver's demands. Naturally, selecting the EV type entails that the charging power and the battery size are rendered known since the selection is performed from a finite number of vehicle types.

3. Derivation of typical price signals

The power profiles of parking lots that exercise a strategy based on exploiting the temporal differences in market prices clearly depend on the price signal itself. As a matter of fact, electricity prices may significantly vary from day to day. For example, in Fig. 2 the historical day-ahead market prices for 2014 in the Pennsylvania Jersey Maryland Interconnection (PJM), Comed zone [37] are presented. It may be noticed that the magnitude of the prices in the first quarter of the year is relatively greater than of those in the rest of the year. In addition to that, prices may present other peculiarities such as negative values for a limited amount of periods throughout the year. In the case of Fig. 2 negative prices appear only in 6 h during the year.

Nevertheless, the daily price signals may present several common characteristics that allow deriving a few typical price signals. For instance, the relatively lower prices may occur early in the morning and the relatively higher prices in the afternoon. As a result, clustering techniques may be utilized in order to identify and group price patterns and therefore, to obtain generalized results by focusing only on the study of a few characteristic cases. K-means is a well-known exclusive clustering technique that has been applied to time series clustering on many occasions [38]. It is based on the simple principle of grouping the time series by minimizing a distance metric between each individual time series and the cluster's centroid. However, in the case of clustering the daily price signals that constitute an input for the optimization problems of an EV parking lot owner that seeks to minimize its energy procurement cost or to maximize its profit, two problems arise.

The first is the scaling problem when utilizing the raw electricity prices as an input to the clustering algorithm and can be better illustrated by a simple example. In a given day the value 50 $/MW h may stand for the minimum price, while the same value may represent the maximum price of another day. It is possible that the k-means method clusters together time series of electricity prices that would induce different power profiles since the optimal decisions under price-based strategies depend on the relative magnitudes of the electricity prices during the day, rather than the magnitude of the prices itself. To demonstrate this issue, Fig. 3 presents two time series clustered together using the k-means algorithm. It may be seen that these two time series have been grouped together because they present very similar price magnitudes in the first 8 periods. However, the peak price that occurs in the 8th period for the one time series is an intermediate price for the other and evidently, the optimal power allocation would be significantly different for these two price signals.

In order to exploit the knowledge on the nature of the EV parking lot optimization problems and derive a more meaningful clustering, a transformation of the electricity prices time series is

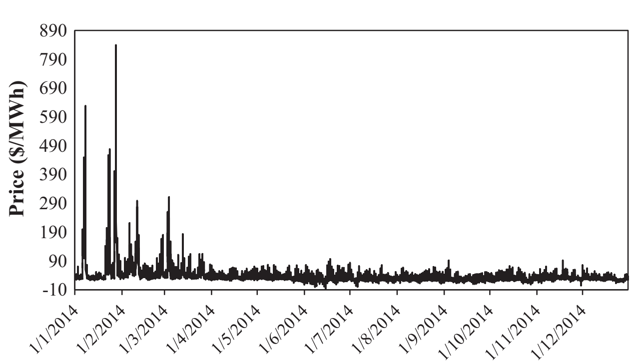


Fig. 2. Day-ahead market prices for PJM/Comed area in 2014.

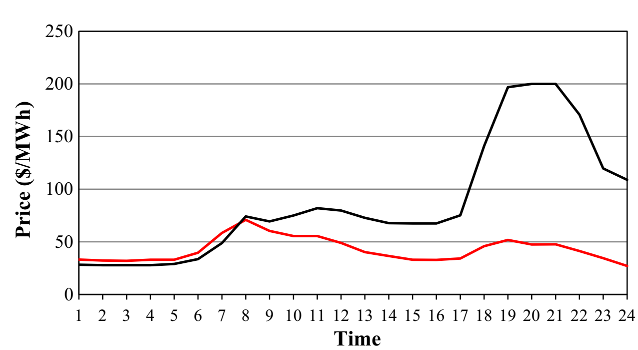


Fig. 3. Example of k-means clustering. Two time series clustered together.

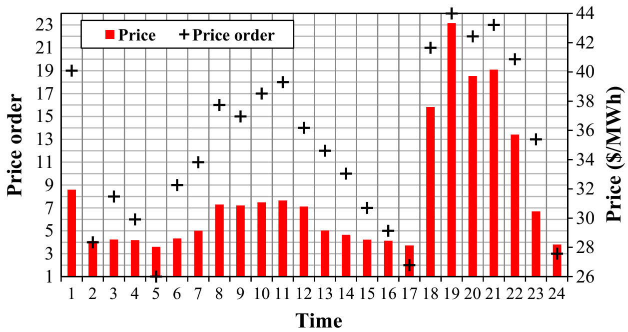


Fig. 4. Example of proposed time series transformation.

proposed. More specifically, each daily time series is transformed by applying the ordinal ranking transformation. As a result, the time series with hourly resolution are transformed from quantitative to categorical data with unique integer values in the set $\{1,\ldots,24\}$. To illustrate the transformation Fig. 4 is provided as an example. The proposed transformation has the following properties:

- Each element $\lambda_t \in \Re$ of the 1×24 day-ahead electricity market prices vector is uniquely mapped to a discrete finite set of distinct ordinal numbers, i.e. $rank(\lambda_t, \forall t \in [1,24]) : \Re \overset{\exists=1}{\mapsto} x_t \in \{1,2,\ldots,24\},\ \forall t \in [1,24]$.
- It is strictly monotonically increasing, i.e., $\lambda_t < \lambda_{t'} \iff rank(\lambda_t) < rank(\lambda_{t'}),\ \forall t,t' \in [1,24]$.
- Because of the previous property, it follows that the property of transitivity holds too, i.e., if $x_t < x_{t'}$ and $x_{t'} < x_{t''}$, then $x_t < x_{t''}$.

The ordinal ranking transformation eliminates the magnitude of the differences between the electricity prices in different periods. As a result, the actual operating cost or profit for the EV parking lot owner cannot be retrieved. However, from the perspective of the system operator, that is adopted in this paper, it is only important to quantify the magnitude of the power that is demanded or injected back to the grid by the EV parking lot, expecting a rational behavior of cost minimization (or profit maximization) from its owner. Thus, it is essential to guarantee that the optimization problems which consider the real and transformed price signals, respectively, yield the same optimal values for the decision variables (i.e., power, state-of-energy, etc.) for the strategies considered in this study:

- The EV parking lot owner buys the required energy so that its daily operating cost is minimized (see Section 4.3). Intuitively, this means that minimizing the objective function entails assigning relatively higher values to the penalized decision variables, i.e. power that is drawn from the grid, during time periods with relatively lower prices (on a descending price order basis) to the extent that the constraints of the optimization problem are not violated.
- The EV parking lot owner buys the required energy so that its daily cost is minimized and injects energy back to the grid so that the daily benefit from selling that energy is maximized; yet, in each given period the EV parking lot will be found in either of these two states (see Section 4.4). This implies that, as long as the constraints of the optimization problem permit it, the EV parking lot will draw more power from the grid in periods with relatively lower prices (on a descending price order basis), and would inject more energy back to the grid in periods with relatively higher prices (on an ascending price order basis).

The properties of the ordinal ranking transformation guarantee that the relative order of the prices is preserved. Thus, the original and the transformed optimization problems return exactly the same optimal values for the decision variables in both cases. In this paper, the optimization problems are formulated as linear or mixed-integer linear programming problems. Thus, the Karush–Kuhn–Tucker (KKT) conditions are both necessary and sufficient (for mixed-integer linear problems all the possible combinations of values for the binary variables must be considered) and can be applied in order to demonstrate that the optimization problems which use the actual and the transformed electricity prices yield the same optimal values for the decision variables. For the sake of simplicity and without loss of generality, let us consider the minimum cost unidirectional charging optimization problem for a single EV which is plugged-in at the EV parking lot during periods $\tau \in T' \subseteq [1,24]$. The objective function of problem (5) states that the overall cost of buying power from the grid must be minimized. The first constraint enforces that the EV must be fully charged within the considered horizon given its initial SOE E, while the second and the third constraints bound the charging power P_t between zero and the maximum charging power CR of the EV, respectively. Note that μ, ν_τ and ξ_τ are the KKT multipliers associated with each set of constraints. The last constraint forces the charging power to be zero if for the periods that the EV is not plugged-in. Note that the constraints involving the SOE of the EV can be disregarded since the only variable that is penalized in the objective function is P_t.

$$\begin{aligned}
&\min \sum_t \lambda_t \cdot P_t \cdot \Delta T\\
&s.t.\\
&\sum_\tau P_\tau \cdot \Delta T = SOE^{max} - E : \mu\\
&P_\tau \geqslant 0, \quad \forall \tau : \nu_\tau\\
&CR - P_\tau \geqslant 0, \quad \forall \tau : \xi_\tau\\
&P_t = 0, \quad \forall t \notin T'
\end{aligned} \tag{5}$$

The Lagrangian function of problem (5) is described by (6).

$$\begin{aligned}
\Lambda = &\sum_t \lambda_t \cdot P_t \cdot \Delta T - \mu \cdot \left(\sum_\tau P_\tau \cdot \Delta T - SOE^{max} + E\right)\\
&- \sum_\tau \nu_\tau \cdot P_\tau - \sum_\tau \xi_\tau \cdot (CR - P_\tau)
\end{aligned} \tag{6}$$

The KKT conditions are represented by (7)–(9) for periods $\tau \in T' \subseteq [1,24]$, which express stationarity, complementary slackness and dual feasibility, respectively.

$$\lambda_\tau - \mu - \nu_\tau + \xi_\tau = 0, \quad \forall \tau \tag{7}$$

$$\begin{aligned}
&\mu \cdot \left(\sum_\tau P^*_\tau \cdot \Delta T - SOE^{max} + E\right) = 0\\
&\nu_\tau \cdot P^*_\tau = 0, \quad \forall \tau\\
&\xi_t \cdot (CR - P^*_\tau) = 0, \quad \forall \tau
\end{aligned} \tag{8}$$

$$\begin{aligned}
&\mu \geqslant 0\\
&\nu_\tau \geqslant 0, \quad \forall \tau\\
&\xi_\tau \geqslant 0, \quad \forall \tau
\end{aligned} \tag{9}$$

Let us consider the following general solution instance:

- $\mu > 0$ so that the first constraint of problem (5) is satisfied as an equality.
- $\exists \tau_1 \in T'$ for which the optimal values of the decision variables P_{τ_1} are at their upper bounds. Thus, $\nu_{\tau_1} = 0$ and $\xi_{\tau_1} > 0,\ \forall \tau_1 \in T'$ due to the second and third conditions in (8).

- $\exists \tau_2 \in T'$ for which the optimal values of the decision variables P_{τ_2} are at their lower bounds. Thus, $v_{\tau_2} > 0$ and $\xi_{\tau_2} = 0,\ \forall \tau_2 \in T'$ due to the second and third conditions in (8).
- $\exists \tau_3 \in T'$ for which the optimal values of the decision variables P_{τ_3} are strictly between their lower and upper bounds. Thus, $v_{t_3} = 0$ and $\xi_{\tau_3} = 0,\ \forall \tau_3 \in T'$ due to the second and third conditions in (8).

Then, using conditions (7) and (9), relations (10) may be deduced.

$$\begin{aligned} &\lambda_{\tau_1} < \mu, \quad \forall \tau_1 \in T' \\ &\lambda_{\tau_2} > \mu, \quad \forall \tau_2 \in T' \\ &\lambda_{\tau_3} = \mu, \quad \forall \tau_3 \in T' \end{aligned} \tag{10}$$

It follows that at the optimal solution $\lambda_{\tau_1} < \lambda_{\tau_3} < \lambda_{\tau_2},\ \forall \tau_1, \tau_2, \tau_3 \in T'$. By definition the ordinal ranking transformation preserves this relationship. Thus, the optimization problems using the actual and modified price time series yield the same optimal values for the decision variables. The same approach can be straightforwardly applied for multiple EVs and strategies that allow for bi-directional power flow. In this case, the different combinations for the state of the EV (charging, discharging, idle) should be considered and similar price order relations can be derived at optimality.

Comparing the load duration curves obtained from solving the optimization problems using the original and modified price time series for each individual day, the only discrepancy that may be noticed stems from the fact that the price of electricity may be the same in several periods (in practice in a few consecutive periods), in which case multiple solutions may exist for the optimization problem, i.e. allocating the same amount of power to either of these periods would result in the same cost. In this case, commercial solvers usually return only one of these solutions (e.g., the one that is discovered first). Due to the fact that the proposed transformation appoints one distinct ordinal number per period, the solution that will be returned by the solver may not correspond to the one (out of the multiple optimal solutions) that is returned when using the original price data. The rule that is applied to rank prices of equal value is that the price which occurs in an earlier period will be assigned with a lower ordinal number. This allows to consistently identify which of the multiple optimal solutions is returned.

The second problem with using k-means is that when applying it to categorical data, the centroid (mean value) does not lie within the initial data set. As a result, the k-medoids clustering method which has a similar working principle with the k-means method is used instead, employing the partitioning around medoids (PAM) algorithm [39]. Fig. 5 portrays two time series that have been clustered together using the k-medoids algorithm and their transformation based on the proposed approach. Despite the fact that the magnitudes of the two price series are not similar as it can be seen in Fig. 5a, their relative orders match closely and as a result, as illustrated in Fig. 5b, they should belong in the same cluster since they would induce similar power profiles.

4. Electric vehicle parking lot operational strategies

4.1. Strategy 1: instant EV charging

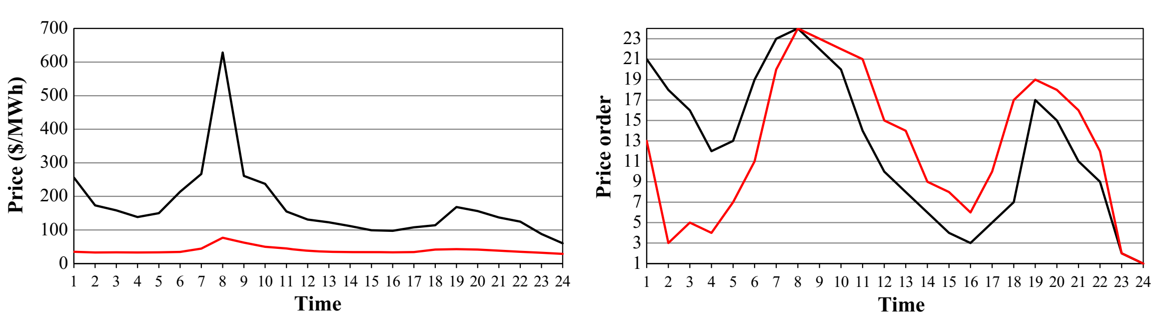
In the first strategy it is considered that the EVs start charging at their full charging rate as soon as they arrive at the parking lot. In order to derive the corresponding load profile, Algorithm 2 that is displayed in Fig. 6 is used. First, the exact time that is needed (real number) is calculated by dividing the energy that has been consumed during the commuting by the charging rate of each vehicle. Also, an integer number that corresponds to the ceiling of the exact time required to fully charge the vehicle is calculated since the optimization time intervals constitute a discrete set. Subsequently, in order to calculate the charging power profile of each individual EV, the time at which the EV is connected to the parking lot is identified. Then, for the next $T_e^{C,R} - 1$ periods the charging power corresponds to the maximum charging rate of the vehicle, while in the last charging period, the power is set to a fraction of the maximum charging power. Evidently, the EV parking lot power profile is the sum of the individual EV power profiles.

4.2. Strategy 2: minimization of the charging peak power

The strategy that has been described in Section 4.1 may lead to significant power peaks, especially in the case in which a large number of EVs arrive simultaneously. As a result, the system operator may request that the EV parking lot operates in such a way that the maximum power that is drawn from the grid is as minimal as possible. Otherwise, penalties may apply. The strategy that is investigated in this section aims at minimizing the peak power of the EV parking lot during the day. The objective function is represented by (11).

$$\text{minimize } P^{max} \tag{11}$$

The optimization problem is subject to constraints (12)–(19). More specifically, (12) states that the charging load of the EV parking lot in each optimization period should be less than or equal to the peak power of the day. Constraint (13) states that as long as it is connected to the EV parking lot, the charging power of each EV is limited by its maximum charging rate, while it is set to zero when the EV is not connected as enforced by (14). The update of SOE of each EV is expressed by (15), while the SOE is initialized by (16). Constraint (17) limits the SOE of an EV to be positive and less than or equal to the rated capacity of it battery. Similarly to (14), Eq. (18) forces the value of SOE to zero when the vehicle is not connected in the parking lot. Finally, (19) states that the EVs should



(a) original price series (b) transformed time series

Fig. 5. Example of k-medoids clustering. Two time series clustered together.

Algorithm 2

for $e = 1 \rightarrow N^{EV}$ **do:**
 compute the exact time required to fully charge the vehicle $T_e^{C,E} \leftarrow \frac{E_e}{CR_e}$
 compute the ceiling of the time required the vehicle to charge $T_e^{C,R} \leftarrow ceiling(T_e^{C,E})$
 for $t = 1 \rightarrow T$ **do:**
  if $(STATUS_{e,t}^{EV} - STATUS_{e,(t-1)}^{EV} = 1)$ **do:**
   for $t' = t \rightarrow t + T_e^{C,R} - 1$ **do:**
    if $t' < t + T_e^{C,R} - 1$ **do:**
     $P_{e,t'}^{ch} \leftarrow CR_e$
    end
    if $t' = t + T_e^{C,R} - 1$ do:
     $P_{e,t'}^{ch} \leftarrow CR_e \cdot (T_e^{C,R} - T_e^{C,E})/\Delta T$
    end
   end
  end
 end
end

Fig. 6. Algorithm 2. Power profile of individual EV for instant charging.

be fully charged by the time they depart. This constraint can be trivially modified in order to impose other charging requirements (e.g., achieve a minimum mileage). It should be noted that the positive variable ENS_e is used in order to express the amount of energy that was not possible to be provided to the vehicle, i.e. because of being connected for a limited time. Note also that it should be penalized by an artificial weighting factor in the objective function in order to limit its magnitude to a level that is sufficient to guarantee feasibility of the optimization problem.

$$\sum_e P_{e,t}^{ch} \leqslant P^{max}, \quad \forall t \tag{12}$$

$$P_{e,t}^{ch} \leqslant CR_e, \quad \forall e,t, \quad \text{if } STATUS_{e,t}^{EV} = 1 \tag{13}$$

$$P_{e,t}^{ch} = 0, \quad \forall e,t, \quad \text{if } STATUS_{e,t}^{EV} = 0 \tag{14}$$

$$SOE_{e,t} = SOE_{e,(t-1)} + P_{e,t}^{ch} \cdot \Delta T, \quad \forall e,t, \quad \text{if } STATUS_{e,t}^{EV} = 1 \quad \text{and} \quad STATUS_{e,(t-1)}^{EV} = 1 \tag{15}$$

$$SOE_{e,t} = SOE_e^{max} - E_e, \quad \forall e,t, \quad \text{if } STATUS_{e,t}^{EV} = 1 \quad \text{and} \quad STATUS_{e,(t-1)}^{EV} = 0 \tag{16}$$

$$0 \leqslant SOE_{e,t} \leqslant SOE_e^{max}, \quad \forall e,t, \quad \text{if } STATUS_{e,t}^{EV} = 1 \tag{17}$$

$$SOE_{e,t} = 0, \quad \forall e,t, \quad \text{if } STATUS_{e,t}^{EV} = 0 \tag{18}$$

$$SOE_{e,t} = SOE_e^{max} - ENS_e, \quad \forall e,t, \quad \text{if } STATUS_{e,t}^{EV} = 1 \quad \text{and} \quad STATUS_{e,(t+1)}^{EV} = 0 \tag{19}$$

The optimization problem described in this section is a linear programming problem, large instances of which can be efficiently solved.

4.3. Strategy 3: minimization of the daily operational charging cost (unidirectional power flow)

The owner of the EV parking lot is responsible for charging the EVs by the time the drivers decide to depart, either it is for-profit or non-profit (e.g., municipal facility). In either case, it may be advisable that the EVs be charged in such as way that the charging costs are minimized. This would yield a higher profit in case the EV owners are charged tariffs decided by the EV parking lot owner or would reduce the social cost of operating the EV parking lot. The objective function is expressed by (20).

$$\text{minimize} \sum_t \lambda_t \sum_e P_{e,t}^{ch} \cdot \Delta T \tag{20}$$

The optimization problem involves constraints (13)–(19) and is also a linear programming problem.

4.4. Strategy 4: minimization of the daily operational charging cost (bi-directional power flow)

The EV parking lot can be exploited in order to generate profit by exercising time arbitrage through the V2G option. It is assumed that the EV parking lot is exposed to the electricity market prices. The objective function is represented by (21).

$$\text{minimize} \sum_t \lambda_t \cdot \left(P_t^{in} - P_t^{out}\right) \cdot \Delta T \tag{21}$$

In each time period energy must be either bought or sold by the EV parking lot. The disjunctive constraints (22) and (23) are introduced in order enforce this requirement. N is a sufficiently large positive scalar.

$$P_t^{in} \leqslant N \cdot u_t^{grid}, \quad \forall t \tag{22}$$

$$P_t^{out} \leqslant N \cdot \left(1 - u_t^{grid}\right), \quad \forall t \tag{23}$$

In order to consider the bi-directional power flow, constraints (24) and (25) are introduced. More specifically, the binary variable $u_{e,t}^{EV}$ is involved in (24) and (25) in order to enforce that charging and discharging of EVs do not occur simultaneously. Furthermore, constraint (15) is modified as in (26) in order to take into account the effect of the discharging on SOE. The energy that is discharged from the EVs may be used in order to charge other EVs or it can be injected back to the grid. This is expressed by (27). The energy balance of the EV parking lot is represented by (28). In each period, the total charging load of the EV parking lot may be covered either by energy that is bought from the market, or from energy available from other EVs that are discharging. Finally, (29) states that the energy that is sold back to the grid is the total energy that is discharged from the EVs and is not used within the EV parking lot.

$$P_{e,t}^{ch} \leqslant CR_e \cdot u_{e,t}^{EV}, \quad \forall e,t, \quad \text{if } STATUS_{e,t}^{EV} = 1 \tag{24}$$

$$P_{e,t}^{dis} \leqslant DR_e \cdot \left(1 - u_{e,t}^{EV}\right), \quad \forall e,t, \quad \text{if } STATUS_{e,t}^{EV} = 1 \tag{25}$$

$$SOE_{e,t} = SOE_{e,(t-1)} + \left(P_{e,t}^{ch} - P_{e,t}^{dis}\right) \cdot \Delta T, \quad \forall e,t, \quad \text{if } STATUS_{e,t}^{EV} = 1 \quad \text{and} \quad STATUS_{e,(t-1)}^{EV} = 1 \tag{26}$$

$$P_{e,t}^{dis} = P_{e,t}^{dis,u} + P_{e,t}^{dis,out}, \quad \forall e,t \tag{27}$$

$$\sum_e P_{e,t}^{ch} = P_t^{in} + \sum_e P_{e,t}^{dis,u}, \quad \forall t \tag{28}$$

$$P_t^{out} = \sum_e P_{e,t}^{dis,out}, \quad \forall t \tag{29}$$

Apart from constraints (22)–(29), (16)–(19) should be also considered in the optimization problem, while (14) should be also enforced for the discharge power of the EVs. It should be noted that the introduction of the binary variables u_t^{grid} and $u_{e,t}^{EV}$ turns the linear programming problem into a mixed integer linear programming problem.

5. Numerical application

The proposed methodology was implemented in MATLAB [40], while the optimization problems have been solved in GAMS using the CPLEX solver [41]. All simulations were performed using a modern laptop computer (2.4 GHz, 4 GB RAM, Windows 64 bit). To demonstrate the applicability of the proposed approach a series of case studies are presented and discussed in this section.

5.1. Input data

In order to specify the composition of the EV fleet characteristics, recent data from the US are used [42]. In Figs. 7 and 8 the histograms of the EV arrival times and the kW h used during commuting are presented respectively. It is to be noted that in [42] the travel time from house to work is provided. In order to estimate the energy that is used during commuting the following calculation is performed: first, based on an average speed of 70 mph, the distance that the driver has to cover is first estimated. Then, assuming that the consumption of the vehicle is 0.271 kW h/mile [43], the charging needs of the EVs once they arrive at the EV parking lot are obtained. The relevant cumulative distribution functions (CDF) of the original data and the estimated kernel distribution functions are displayed in Figs. 9 and 10. It may be noticed that by fitting kernel distributions the sample data are closely approximated.

The departure time is assumed to follow a normal distribution with mean 8 h after the arrival time of the EV and a standard deviation of 1 h.

The next step is to specify the fleet composition. Several EVs with a considerable market share in the US are considered. Their technical characteristics [43] and the corresponding market share based on recent data [44], are presented in Table 1. In this table the number of vehicles of each of the 7 EV types considered is also displayed. Furthermore, it is interesting to notice that EVs with relatively higher nominal mileage present a significant market share due to the so-called drivers' range anxiety. Although different EV manufacturers claim specific mileages for their models, the conditions under which these ranges are achieved are not clearly defined. For this reason, as mentioned before, an estimated consumption of 0.271 kW h/mile at 70 mph is considered to be representative [43]. Note that from Table 1 an average consumption of 0.285 kW h/mile can be calculated. Nevertheless, this table is restricted only to a few EV models.

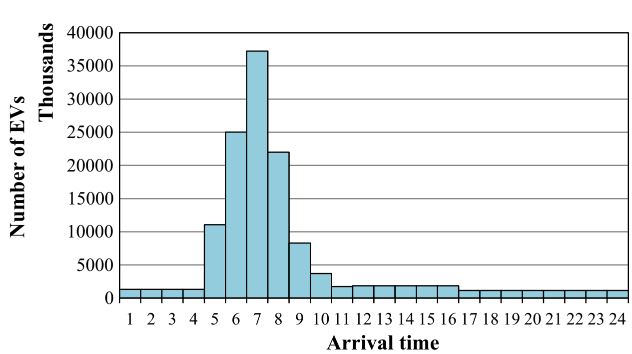


Fig. 7. Histogram of arrival time of EVs.

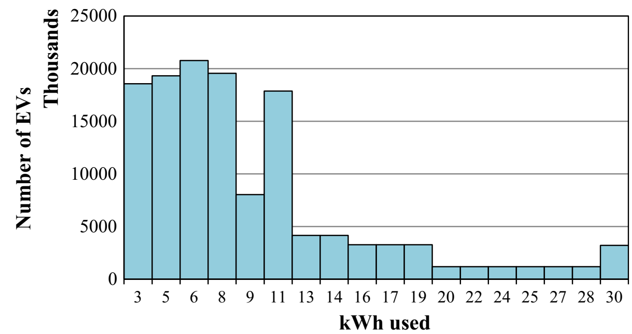


Fig. 8. Histogram of kW h used by EVs.

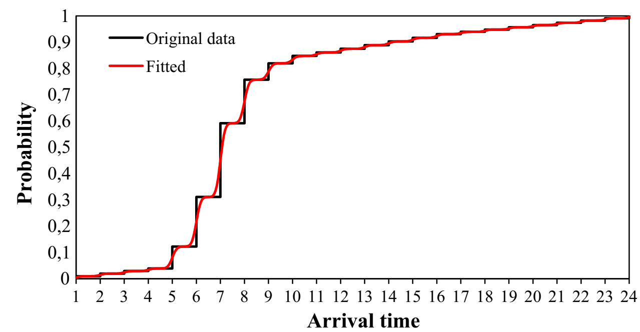


Fig. 9. CDF of the original data and the kernel distribution for EV arrival time.

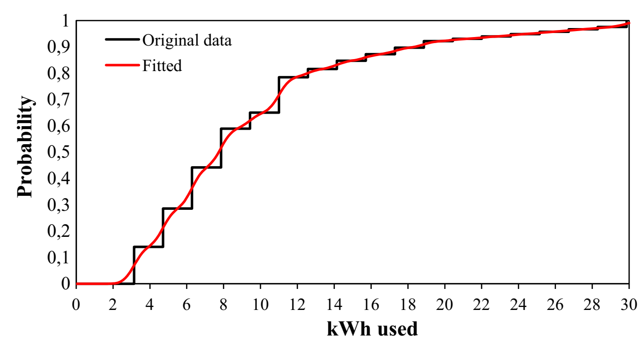


Fig. 10. CDF of the original data and the kernel distribution for energy consumed in commuting.

Furthermore, the pricing data depicted in Fig. 2 are considered. Since the available statistical data refer to working days, weekends are filtered out and the analysis focuses only on weekdays. It is to be noted that the data filtering in this case is not imposed by the significant changes in the electricity market prices, the magnitudes of which may significantly differ between weekdays and weekends, but by the unavailability of relevant data in order to estimate the charging load of the EV parking lot in weekends, instead.

By applying the methodology that was presented in Section 3 on the filtered data set (261 time series out of 365), the three electricity price profiles that are presented in Fig. 11 are be derived. In order to define the number of representative price signals, a parametric analysis was performed considering a range between 2 and 10 for the number clusters and the silhouette value was observed. The number of time series that fall into each of the resulting clusters is 112, 67 and 82, respectively.

Table 1
Technical characteristics and market share of the considered EV types.

Car	Battery size (kW h)	Charger (kW)	Range (miles)	#vehicles 2014–October 2015	#vehicles in fleet
Mitsubishi i-MiEV	16	3.3	62	257	0
Chevrolet Spark EV	19	3.3	82	3167	9
BMW i3	22	6.6	81	13,142	20
Ford Focus Electric	23	6.6	76	2997	12
Nissan LEAF	24	6.6	84	37,191	51
Mercedes B-Class Electric	28	10	85	1866	14
Tesla Model S	85	10	265	36,659	94

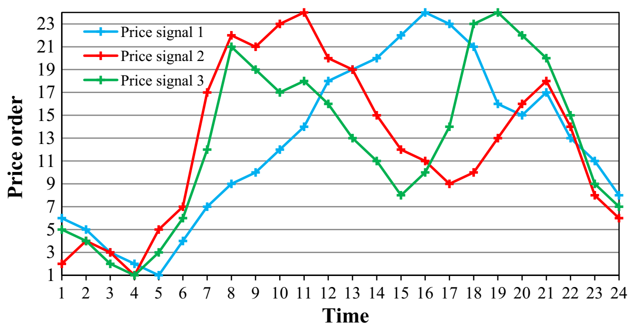


Fig. 11. Representative price signals.

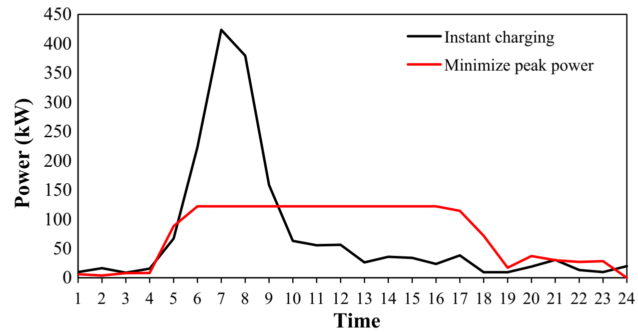


Fig. 13. Power profile of EV parking lot under strategies 1 and 2.

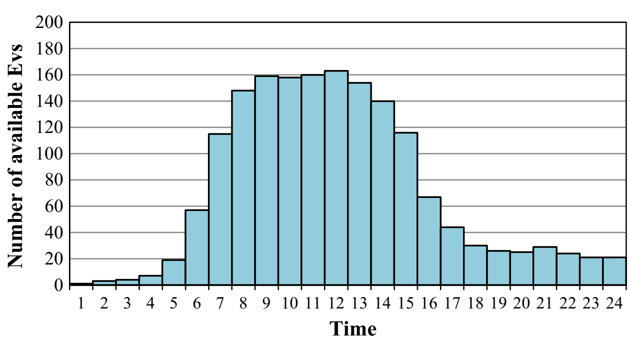


Fig. 12. Number of available EVs.

5.2. Case studies

An EV parking lot with a capacity of 200 EVs is considered. The number of EVs that are available in each period is depicted in Fig. 12.

In Fig. 13 the EV parking lot charging power profile for strategies 1 and 2 is depicted. It may be noticed that when the EVs charge in an uncontrolled way, i.e. at their maximum charging rate as soon as they are parked in the lot, a peak of approximately 420 kW occurs in period 7, the period in which the majority of the EVs arrive at the EV parking lot. Relatively high power is noticed up to period 9 since between periods 7 and 9 around 50% of the EVs are expected to arrive. Notice that the average power is approximately 73 kW. In order to avoid the significant power peaks that could lead to voltage drops, increase in active power losses and congestion, a minimization of the maximum power that is drawn by the EV parking lot may be required. As it can be seen, it is possible to control the charging of the EVs so that the peak power is reduced to 120 kW by maintaining the average power to 74 kW.

The next strategy that is examined is the EV parking lot unidirectional charging by exploiting the market prices in order to minimize the total cost of the energy that is bought. The power profile of the EV parking lot under this strategy depends on the day-ahead market prices. As a result, power may significantly vary from day to day, as it was previously discussed. In this study, the day-ahead market prices are represented by three characteristic price patterns. The relevant results are presented in Fig. 14. In all three cases, it may be noticed that significant power peaks occur during the least costly periods. In Fig. 14a the relatively lowest prices occur between periods 1–9. It is noticed that the highest peaks occur between periods 7 and 9 since the majority of the EVs arrive in this interval. Also, a second valley in the electricity prices is noticed between periods 22 and 24 and as a result, an increasing trend is noticed for the charging load. It should be noted that during the periods in which the electricity prices are relatively high, the load of the parking load is zero. The results in Fig. 14b and c can be also explained in a similar fashion. In Fig. 14b since the prices are relatively higher in periods in which a significant number of EVs is available, reduced charging load may be noticed. As a result, most charging load occurs between periods 14 and 17. Finally, in Fig. 14c it may be noticed that a significant power peak of 700 kW appears in period 15 which corresponds to a local minimum in the electricity price signal and is approximately 1.75 times greater than the maximum charging power in the other two cases.

In order to generalize the obtained results, the power profiles for a longer term period should be obtained. As a result, it is estimated that 112 days present the price profile of Fig. 14a, 67 days the power profile of Fig. 14b and finally, 82 days the power profile of Fig. 14c. The approximation of the load duration curve, as well as the actual load duration curve that is obtained from simulations using the actual price signals are compared in Fig. 15. The mean absolute error (*MAE*) is 6.55 kW and a result, the approximation may be considered accurate.

Another strategy that is examined considers the possibility of establishing bi-directional power flow between the EV parking lot and the grid. The energy that is discharged from the EVs may be used in order to charge other EVs that are parked in the lot that are departing in periods in which the prices are relatively high, or it may be injected back to the grid in order to generate revenue for

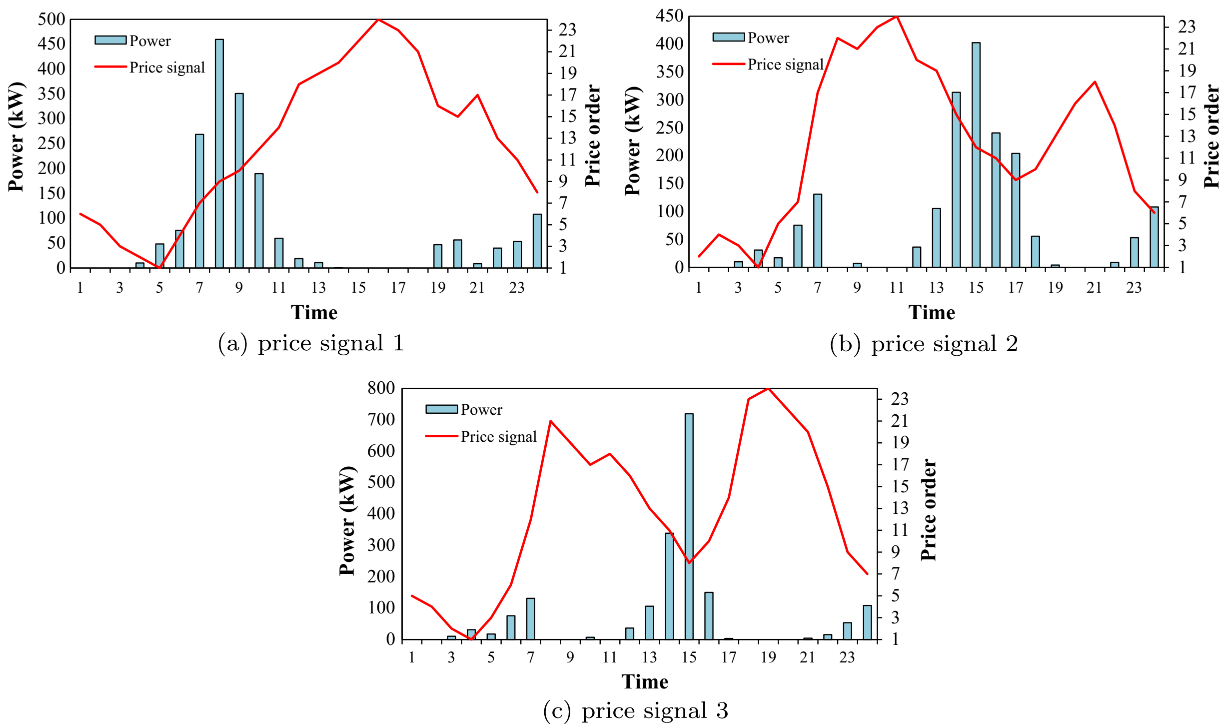


Fig. 14. Power profile of EV parking lot under strategy 3.

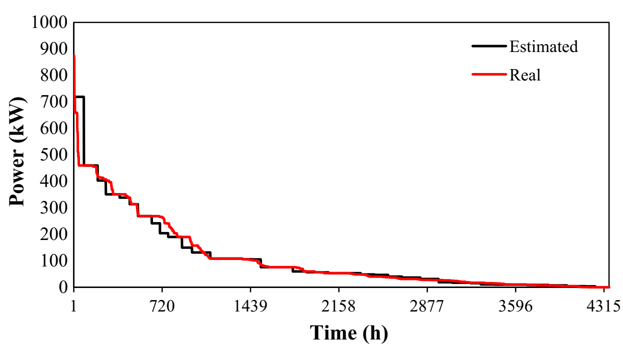


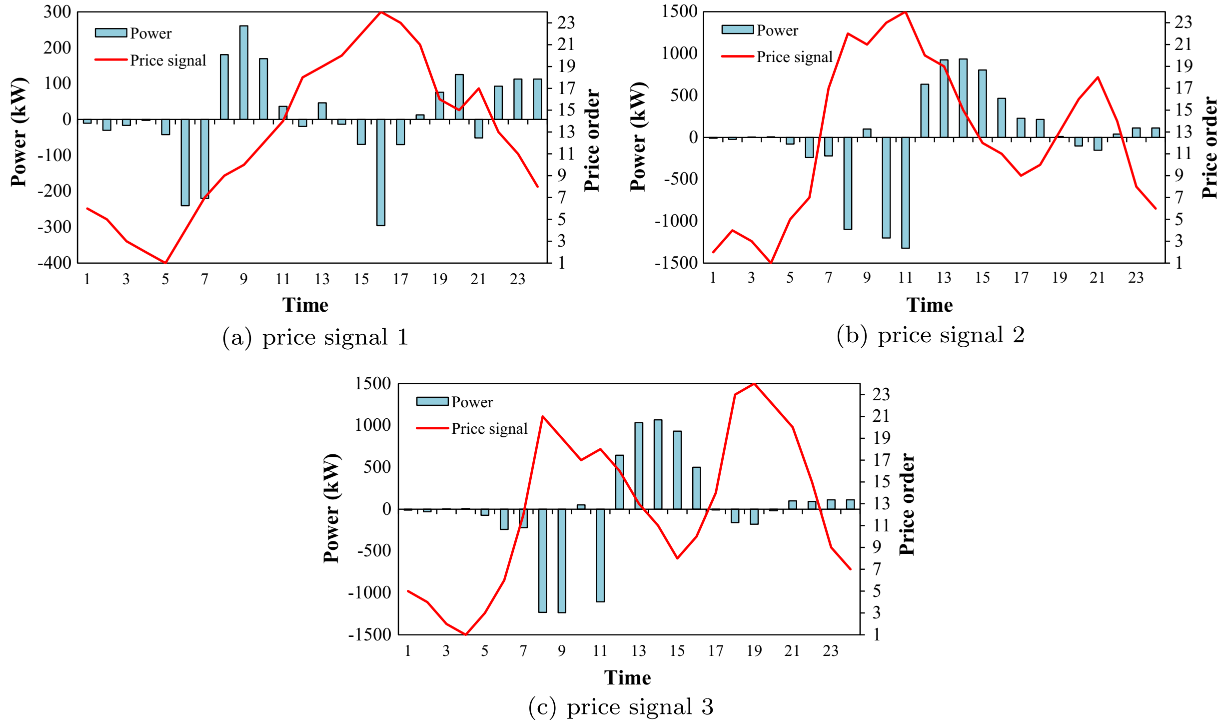
Fig. 15. Weekday load duration curve for EV parking lot under strategy 3.

the parking lot owner. The load profiles for the three representative price signals are presented in Fig. 16a–c. It can be noticed that energy is bought from the grid in periods presenting relatively low electricity price periods, while energy is injected back to the grid in periods of relatively high price periods. Moreover, the power profiles present significant peaks in both directions, reaching up to 1068 kW and −1235 kW, while in all the three cases the maximum power that is injected to the grid is greater than the maximum power that is drawn from the grid. Delving further into the analysis of the representative power profiles, several additional remarks can be made. In Fig. 16a two consecutive charging–discharging cycles may be noticed during periods 11–14. The prices of these periods are ranked as 14, 18, 19, and 20 respectively. The EV parking lot buys energy during periods 11 and 13 and sells it in periods 12 and 14. Also, a higher amount of power is sold during period 12 in comparison with the power sold in period 14 due to the fact that in period 12 three more EVs arrive. The amount of power that is bought in period 11 is less than in period 13, due to the fact that more EVs are departing in period 14. In addition to that, in Fig. 16c intensive discharging, followed by a slight charging and a second intensive discharging round are noticed during periods 9–11. A comparable amount of EVs is available in all the three periods which are associated with the prices ranked as 19, 17 and 18 respectively. The discharge power in period 9 is higher than in period 11 because of the relatively higher price in period 9. Since a relatively lower price occurs in period 10, the EV parking lot absorbs power. The charging power is relatively low due to the fact that the relative differences in the prices are not significant.

Similarly to the case of strategy 3, the load duration curve of the EV parking lot under strategy 4 is presented in Fig. 17 in comparison with the actual load duration curve that is produced utilizing the raw price time series. In this case, the *MAE* is 28.35 kW which implies a reasonable accuracy for this case as well. In addition to that, the approximated load duration curve is positive in 3154 periods, while in the actual load duration curve it is positive in 3168 periods.

It is to be noted that the energy that is bought from the grid in strategies 1–3 is equal to 1805 kW h. Nevertheless, in strategy 4, the total energy that is bought from the grid varies depending on the shape of the electricity price profile. The charging needs that are covered by the grid in the cases of Fig. 16a–c are 1227 kW h, 4598 kW h and 4659 kW h, respectively. The last fact implies that due to arbitrage, the energy that is required in order to satisfy the charging needs of the EVs increases because of intensive discharging and induces significant power peaks.

In all the four case studies that were previously presented, it is considered that all the EVs that are connected at the parking lot adopt the same charging strategy. However, in practice it is possible that different drivers select their preferred charging strategy and therefore, it is of interest to investigate how the previous results are altered when considering mixed charging strategies. The mathematical formulation that was presented in Section 4.4 can be employed in this case as well. To perform so, the discharge power of the EVs that allow for controlled charging is set to zero, while for the EVs that request instant charging, the charging power



(a) price signal 1

(b) price signal 2

(c) price signal 3

Fig. 16. Power profile of EV parking lot under strategy 4.

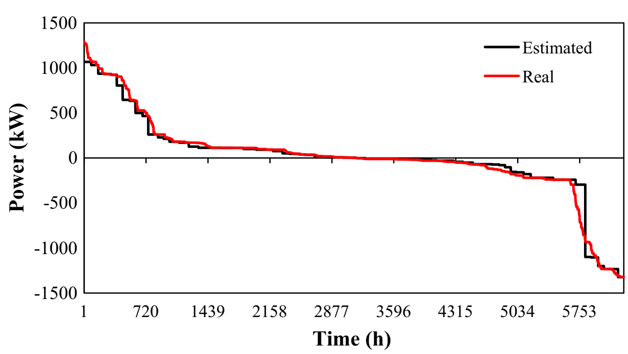


Fig. 17. Weekday load duration curve for EV parking lot under strategy 4.

Table 2
Number of EVs adopting different charging strategies.

Adopted EV strategy	Cases		
	A	B	C
EV that allows bi-directional flow	108	51	8
Controlled uni-directional charging	84	93	84
Instant charging	8	56	108

is set to the profile calculated using the methodology of Section 4.1.

Three different cases are examined. In each of them one of the three charging strategies is dominant. The number of EVs that are charged under each strategy is presented in Table 2. Note that the strategy followed by each EV is randomly selected. The estimated and actual load duration curves for these cases are portrayed in Fig. 18a–c. It is evident that the proposed price transformation is also valid under mixed charging strategies. As expected the extrapolation is more accurate as the dependence of the EV parking lot power profile on prices decreases. As a matter of fact, the *MAE* for cases A, B and C is 18.32 kW, 9.33 kW and 4.35 kW, respectively. Moreover, it can be noticed that in all the three cases, both the number of periods in which energy is injected from the EV parking lot back to the grid and the magnitude of charging/discharging are reduced with respect to the results obtained from Strategy 4. As a result, strategy 4 may be deemed to provide a bound for both directions of power flow.

6. Conclusions

In this paper, a methodology to derive power profiles for EV parking lots was developed. First, the characteristics of the EV fleet such as arrival time, the energy consumed during displacements, as well as its composition are modeled using non parametric probability distributions. Moreover, a transformation is applied to the historical price time series in order to resolve data scaling problems and a clustering approach based on k-medoids is employed in order to extract representative price signals from historical pricing data. Finally, the mathematical formulation for four different parking lot operational strategies, as well as a mix of different EV charging strategies, considering both unidirectional and bi-directional power flow, are presented.

Based on the examined case studies, the following conclusions may be drawn:

- The utilization of non parametric kernel density estimation can approximate sufficiently the empirical distributions that are derived based on the available data.
- Depending on the characteristics of the EV fleet, the uncoordinated charging of the EVs may not be the most dismal case in terms of peak power. In fact, price arbitrage may lead to increased energy flows due to extensive discharging of the EVs in order to raise revenue, which in turn causes significant consumption peaks, as the vehicles need to be recharged before their departure.

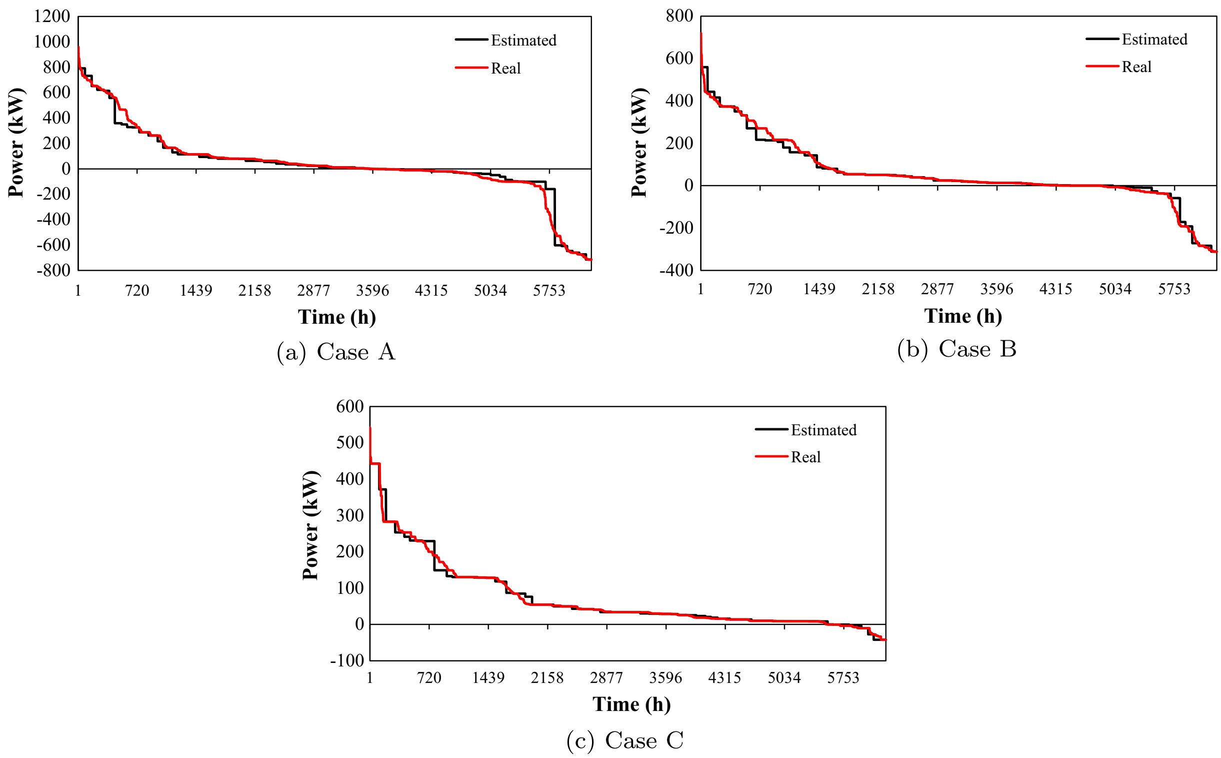


Fig. 18. Weekday load duration curve for EV parking lot under mixed EV charging strategies.

- Deriving representative price signals in order to investigate the power profiles for strategies that depend on electricity market prices with the proposed methodology, allows for load duration curves to be deduced with reasonable accuracy by performing a small number of simulations.
- When mixed strategies are considered, the accuracy of the extrapolated load duration curve is improved due to the reduced dependence of the power profile on electricity prices. Also, it is revealed that the case in which all the EVs are allowed to both charge and discharge is characterized by the highest peaks in both directions of power flow.

The proposed methodology can be applied to optimally placing EV parking lots in the distribution system as well as for evaluating the operational strategies from the EV parking lot owners' point of view. These topics will be the subject of future studies.

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