

Optimization of Night Electric Vehicle Fleet Charging at Regional Level

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Abstract

Electrification of the road transportation sector is one of the ways to reduce the green-house gases (GHGs) emissions worldwide, but an increasing number of electric vehicles (EVs), will impact on the power system, particularly on the residential distribution low-voltage grid. In order to reduce this impact during the peak periods, it is possible for these vehicles to get energy not only from the grid, but also from other EVs parked at the same time in the same place through a peer to peer (P2P) energy trading. In this paper a night charging method that optimizes the recharging process of an EV fleet at regional level depending on hourly energy price in a P2P energy trading system is presented. This algorithm determines how much energy should be recharged in the battery of each EV and the corresponding time slot to do it, avoiding the discontinuities in the charging process and considering the users' personal mobility constraints.

Keywords: *Electric Vehicles; Peer-to-Peer; Optimization*

1. Introduction

Climate change is becoming one of the primary concerns worldwide. GHGs emissions are growing faster than they did the last three previous decades and CO₂ concentration levels in the air are at the highest in 650,000 years. The global temperature has increased 0,94°C since 1880 and the global average sea level has risen 17.8 cm in the same period [1].

In order to reduce the world climate change impact, in December 2015 near 200 countries reached an agreement in Paris to sets out a global action plan to reduce GHGs emissions, avoiding exceeding an increment in global average temperature above 2°C compared to pre-industrial levels [2]. Road transportation is one of the main air pollutants producers [3-5] and, for this reason, the promotion of the electrification of the road transportation is an essential objective to decarbonize the sector, allowing to reduce the air pollution in crowded urban areas. But this deployment can negatively impact on the electric grid, particularly in the distribution network. The impact of charging EVs on the electric grid has been extensively studied in different works that have evaluated the increase of the net power losses, the voltage drops in power

distribution lines, the voltage unbalance of a three-phase distribution network due to unequal distribution of the single-phase chargers, the reduction of power quality due to the generation of harmonic pollution by the use of non-linear power electronics in the EV chargers and finally the overload of different distribution lines and power transformers, which reduces the life expectancy [6-10].

One solution to reduce the impact of the EV charging process on the power grid during business hours is to allow a P2P trading system among EVs parked in the same parking area during the same time slot. This original idea was proposed by the authors in [11] and this seminal study was further expanded later in [12]. In order to ensure security and privacy protection issues in this P2P trading system, some authors have proposed to use blockchain technology allowing to avoid the presence of a third trusted party [13]. In all these references [6-12] it was initially assumed that all vehicles were fully charged at the beginning of the day, just before the start of their daily trips. However, it was not specified how this night-charging should be carried out taking into account the variable hourly price of electricity. In this paper, a new algorithm for EV night charging optimization in this P2P energy trading system is proposed.

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2. Mobility model

This section describes the concept of the FEATHERS (*Forecasting Evolutionary Activity Travel of Households and their Environmental RepercussionS*) model, an activity-based model which is used to predict the mobility in the zone of study, Flanders (Belgium). This model was employed in [13] to predict electric power demand due to the charge of EVs under specific assumptions of EV market share and vehicle charging behavior.

Each agent of the synthetic population created by FEATHERS has its own daily agenda, which are mutually independent except for members of the same household to limit computational complexity. The daily agenda consists of a sequence of episodes, each of them containing exactly one trip followed by one activity.

The locations of the activities are traffic analysis zones (TAZ) with an average area of 5 km². Each activity has associated a type (home, work, leisure, social visit, etc.) and a start and end times. Each trip has associated a specific transportation mode (car, walk, bike, bus, train...).

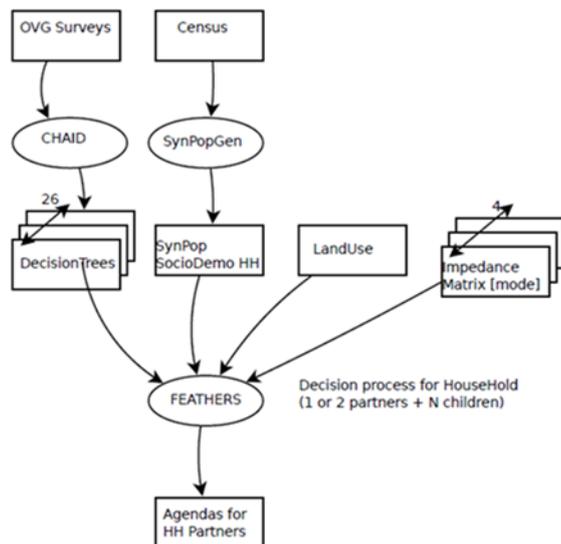


Fig. 1. Data flows for the FEATHERS activity-based model. Ovals represent processes, rectangles represent data sets.

FEATHERS predict the outcome of the decisions taken by each agent while building their daily agenda through a process of planning –which activities the agent does during the day– and scheduling –when are the activities done during the given day-. The agenda for each individual is generated by a series of decisions, determined by a stochastic process making use of decision trees. These trees are trained by means of survey data and involve considerations, among others, of land use in each TAZ, census data, performance of the transportation network and survey data.

The predictions from FEATHERS were validated by aggregating traffic flows between TAZ for each hour of the day. The resulting link flows were compared to time dependent hourly flows from traffic counts.

Not every agent is fit to adopt an EV. To simplify, only those agents that perform a daily consumption lower than 20 kWh which corresponds to almost 112 km having considered an average consumption of 0,18 kWh/km, (an average consumption value according to [14]). This means that, from a total of 1 142 000 agents using a private vehicle for its daily

agenda, around 950 000 of them can make use of an EV to accomplish their agenda under those conditions.

Fig 2 shows the number of first departures (red line) and last arrivals (blue line) of the considered agents. First departure describes the first moment in which an agent starts to drive its EV during his/her daily trips, and the last departure determines the moment in which the agent finishes its last trip using his/her EV.

The first departures take place very early in the mornings, between 04:15 and 04:30, with a total of 5 agents. The number of the first departures is only significant after 05:00, when more than 27 000 agents start their trips between 05:00 and 06:00 compared to the about 200 agents that departure in the precedent hour. The highest number of departures takes place between 07:45 and 08:00, when almost 940 000 agents do their first departure. There are some agents that do their first departure in the last time slot (23:45:24:00), but the number of first departures after 20:00 is very reduced, with only around 17 000 agents.

The last arrival of the agents is more distributed. A few agents arrive after 00:00 (around 9 000) and also a few early in the day, between 05:00 and 08:00 (about 4 900). Later, this number increases to values above 3 000 agents every 15 minutes, with a local maximum of 13 000 agents before 12:00, reaching its maximum value between 17:15 and 17:30, with almost 32 000 agents. There are three other peaks of last arrivals, with close number of agents involved: 18:00-18:15, 22:15-22:30 and 23:15-23:30.

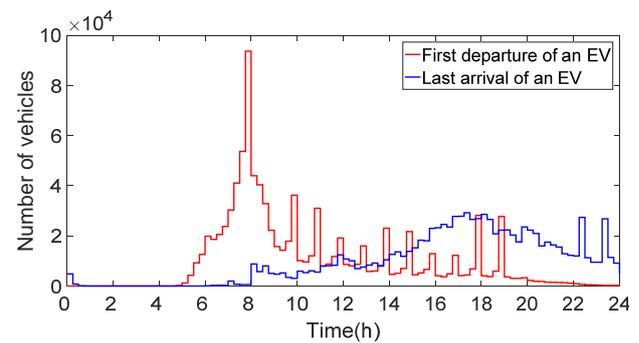


Fig. 2. Drivers' first departure and last arrival

3. Charging optimization process

3.1. Problem description

Like smartphone users, all drivers involved in the P2P energy trading system proposed in [11-12], will charge their vehicles during the night period between the first and the second day in order to start their daily trips at 100% capacity. There are some assumptions to be considered: Firstly, it is assumed that the variable hourly grid electricity price for their home-charging period, denoted by $PEX_{supply}(t)$, is known in advance (on a day-ahead basis) for all drivers. It is also assumed that the daily schedules for all agents are known and these schedules are equal for both consecutive days. From this mobility information, it is possible to determine, for each vehicle v , the home arrival time, $t_a(v)$, the home departure time, $t_d(v)$ and the total demanded energy to carry out all daily trips using an EV. In our case, it is considered that each EV will arrive with a certain initial State of Charge, denoted by $SOC(t_a(v)) = SOC_{ini}$, and it will reach its maximum value, SOC_{max} , at the departure time, $t_d(v)$. In order to compare the charging schedules of

different vehicles and reduce the amount of variables used, T_a is defined as the first time period in which a vehicle ends the schedule of day 1, whereas T_d is defined as the last time period in which a vehicle begins the schedule for day 2. The time is

discretized into time slots of 15 minutes ($\Delta t=4$ time slots per hour) which are used as index for the optimization process. The indexes, constants and variables considered for this problem are defined in Table 1.

Table 1. Charging problem model: indexes, variables and parameters.

Description	Symbol	Value	Unit	Type
Vehicle	v	$[1, V]$	-	Index
Time slot	t	$[T_a, T_d]$	-	Index
Energy hourly price	$PEX_{supply}(t)$	$[PEX_c]$	€/kWh	Parameter
Battery capacity	C	20	kWh	Parameter
State of charge	$soc(t, v)$		%	Variable
Number of time period t per hour	Δt	4	-	Parameter
Energy extracted from the grid	$i(t, v)$		kWh	Variable
Charge rate	CR	0.176	-	Parameter
Charge efficiency rate	γ_{eff}	0.95	-	Parameter
Self-discharge factor	Φ_{decay}	1.6E-5		Parameter
Minimum allowed SOC	SOC_{min}	5	%	Parameter
Maximum allowed SOC	SOC_{max}	100	%	Parameter
Initial SOC vector	$SOC(t_a(v))$	SOC_{ini}	%	Parameter?
Conn./Discon. Matrix	$BCT(t, v)$	$\{0, 1\}$	-	Parameter

The parameter CR represents the charging power as a function of the EV battery capacity, C . In this case, this charging power will be $CR \cdot C = (0.176) \cdot (20) = 3.52$ kW.

The optimization problem is defined through the equations (1)-(5) for each vehicle v . It is similar to the one presented by the authors previously for optimal charging of the EV fleet while their drivers are fulfilling its daily activities. Initially, a battery self-discharge coefficient, Φ_{decay} , has also been included to generalize the problem.

$$\min \left[\sum_t PEX_{supply}(t) i(t, v) / \gamma_{eff} \right] \tag{1}$$

Subject to the following restrictions:

$$soc(t_a(v), v) = SOC_{ini} \quad ; \quad soc(t_d(v), v) = SOC_{max} \tag{2}$$

$$SOC_{min} \leq soc(t, v) \leq SOC_{max} \tag{3}$$

$$i(t, v) \leq \gamma_{eff} \cdot C \cdot CR \cdot BCT(t, v) \cdot \Delta t \tag{4}$$

$$soc(t, v) = (1 - \Phi_{decay}) \cdot soc(t-1, v) + i(t, v) / C \tag{5}$$

$$soc(t, v), i(t, v) \geq 0 \tag{6}$$

The objective of the cost function defined in (1) is to minimize the cost of charging the battery during the night period. Equation (2) constrains the SoC of the vehicle v between the initial SoC, SOC_{ini} , and the final SoC, SOC_{max} . Constraint (3) sets the limits for the battery SoC in each time slot and constraint (4) represents the battery effective charging limit. Equation (5) describes the SoC time evolution due to charging process, which only takes place when the EV is available to charge according to the connection/disconnection matrix $BCT(t, v)$ - which is equal to 1 between $t_a(v)$ and $t_d(v)$, nil otherwise- in (4). Efficiency is considered for battery charging at (1), increasing the charging cost, and (4), and reducing the

amount of energy that can be effectively charged into the battery. Finally, variables are defined as positive to guarantee that energy input is always positive, meaning that EV are always charging during this period (vehicle to grid applications are not considered in this work).

3.2. Conventional optimization charging algorithm

Due to the presence of the self-discharge coefficient, the previous algorithm guarantees a unique solution for each vehicle. If the solution of this algorithm requires charging less than 4 time slots per hour and, due to the inclusion of the self-discharge parameter, it will be more advantageous to firstly charge the time slots closest to the end of this particular hour. In this case, the amount of lost energy due to the self-discharge process will be minimized, further reducing the total charging cost. Additionally, a minimum charge in the time slot immediately before the vehicle departure is required for a full charge of the battery.

Nevertheless, when compared with the total amount of charged energy during night charging, the energy due to self-discharge process is almost negligible and the self-discharge coefficient can be suppressed from equation (5). Thus, restrictions (2), (3) and (5) can be merged into:

$$SOC_{max} - soc(t_a(v)) = \sum_t i(t, v) / C \tag{7}$$

Reducing the amount of restrictions (and, thus, the amount of variables considered) the amount of time required to calculate the solution for the problem is also decreased. This is particularly important when extending this methodology to a great number of vehicles. In the particular situation cited in this article, more than a million of EVs have to be analysed by the P2P energy trading system.

Under this assumption, the algorithm works properly, minimizing the total cost of the recharged energy defined in (1), but it does not provide a single solution, generating an

interesting problem. In this particular case, it is observed that there can be discontinuities in the charging process depending on the total energy demanded.

For example, in Fig. 3 the result of the optimization process applied to a particular EV which requires 5.5 kWh charging during the night period to fulfill all its daily trips is shown. It is assumed an effective charging rate of 3.3 kWh per hour, slightly lower than the corresponding to a standard type-2 charging point of 230V-16A with a charging efficiency rate of 0.95. The effective energy charged per 15-min time slot is 3.3 kWh/4=0.83 kWh.

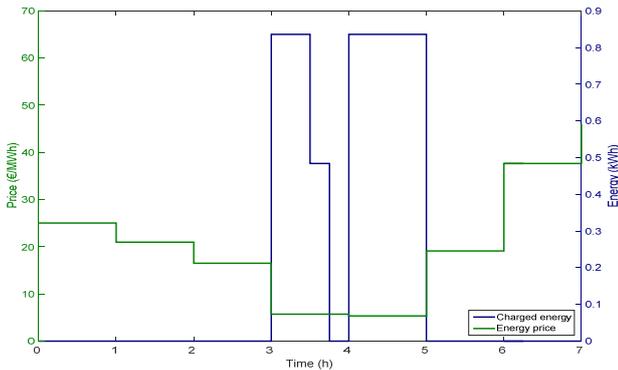


Fig. 3. Initial energy assignment for night charging

The total amount of time slots required by this EV will be:

$$\frac{5.5\text{kWh}}{0.83\text{kWh}} = 6.6265 \quad (8)$$

This vehicle will require 6 complete time slots of 15 minutes at a maximum power of (0.83 kWh/timeslot) and one extra time slot of 15 minutes charging at a lower power (0.52 kWh/timeslot). The minimum price is reached between 4:00 to 5:00, corresponding to the first 4 time slots. Then, the optimization algorithm selects two additional time slots at maximum power during the next cheaper hour, from 3:00 to 3:30, and the last time slot selected by the algorithm is from 3:30 to 3:45 (at 0.52 kWh/timeslot). It is observed that this vehicle will start the charging process at 3:00 until 3:45, then it will stop until 4:00 and it will start again from 4:00 to 5:00.

4. Proposed sequential optimization algorithm without charging discontinuity

To further reduce the amount of time required to solve this problem, a sequential algorithm is developed in this section. This algorithm calculates an optimal solution of the charging problem. It includes the sorting of the time periods in which the vehicle charges, which is required once the self-discharge has been neglected to reduce possible non-mandatory interruptions in the charging process.

The algorithm works as it is highlighted in Fig. 4, in clockwise, for each vehicle:

1. The first step is to divide the time slots considered in the particular problem to charge the vehicles according to its arrival and departure time. For a vehicle arriving at 00:00 and leaving at 07:00, 28 time slots have to be considered, numbering from 1 to 28.

2. The time slots are sorted according to their energy price. This sorting would be [17-20, 13-16, 9-12, 21-24, 5-8, 1-4, 25-28].

3. Assign the maximum energy that can be charged to each time slot according to the previous sorting. If the demand were 5.5 kWh, 0.83 kWh would be assigned for time slots [17-20, 13-14] and the remaining energy for time slot 15.

4. Time slots are reordered and it is checked if there is a discontinuity in the charging process. This only occurs for the last requested hour, when the number of required time slots are lower than 4. Previous hours present time slots with equal energy assigned, so there is no need to reorder them. The reordering is only necessary if there is no charging in the previous time hour and there is a charging event in the following hour. If this is the case (like the one considered here), a new assignation for the last period is necessary (next step); otherwise, the algorithm finishes in the current step.

5. For the new assignation, the time slots are reordered conversely: the energy assigned for the first time slot is reassigned to the last one, the second time slot to the penultimate, and so on. As a result, the maximum energy would be assigned to time slots [15-20], whereas the remaining energy would be assigned to time slot 14; in the end, energy assigned to time slot 13 would be zero.

Assuming that the vehicle always charges at maximum power, the amount energy charged in the last time slot implies that the vehicle does not charge during the full length of the time slot, but during a part of it.

Note that, for step 4, if the vehicle charges at the previous and the following hour of the last slot assignment two possibilities can be admitted: to do not reorder (as in the algorithm) or to do it. The advantage of no reordering is to decrease the algorithm execution time, whereas reordering gives a more closed solution to the linear programming problem in which the self-discharge factor has been added.

5. Results for individual vehicles

In this section, four different charging cases are examined to show the algorithm behaviour. The main data of these cases are presented in Table 2. They are defined by the amount of energy to be charged in the vehicles, their arrival and departure times and the charging power. Note that this charging power refers to the grid side, implying that the effective power in the battery side is somewhat lower due to charging efficiency. As shown in section 3, each hour has been divided in 4 time slots.

Table 2. Night charging examples

Case	A	B	C	D
Energy (kWh)	3	20	20	20
Arrival time	23:00	23:00	20:00	23:00
Departure time	08:00	08:00	05:00	08:00
Charging power (kW)	3,52	3,52	3,52	10,00

Case A represents the base case. In it, the vehicle can be fully charged during a period in which the price remains constant. Charging takes place during the lowest price period (04:00-05:00) and it is not necessary to perform the reordering of the last 4 time slots (step 5 in the algorithm).

Case B shows a full charge with the same characteristics of case A: the vehicle is parked between 23:00 and 08:00 and the charging power is 3,52 kW, which requires a total of 6 hours (24 time slots). Due to the difference in the prices between the time periods, the charging takes place from 00:00 to 06:00. Since the price during the first period, from 00:00 to 01:00, is the lowest one, it is necessary to reassign the energy charged in the first four time slots.

In Case C, the parking time is moved in the period from 21:00 to 05:00, earlier than cases A and B. The user cannot profit from the grid price between 05:00 and 06:00 and the EV has to be recharged between 21:00 and 24:00. Due to the lowest price

at the beginning of this period, the charging process starts at 21:00, gets interrupted at 22:00 and then it restarts again at 00:00, finishing at 05:00. No reassign is necessary for this case. Finally, case D shows a case where the vehicle has a higher charging power, 10 kW, almost triple than the charging power from the previous cases. This reduces the time required to fully charge the vehicle to two hours and seven minutes, a period that, with the previous charging power, would only have allowed to charge the battery up to 8.3 kWh. This case requires the reassignment of the last charging period, moving it from period 02:00-02:15 to 02:45-03:00.

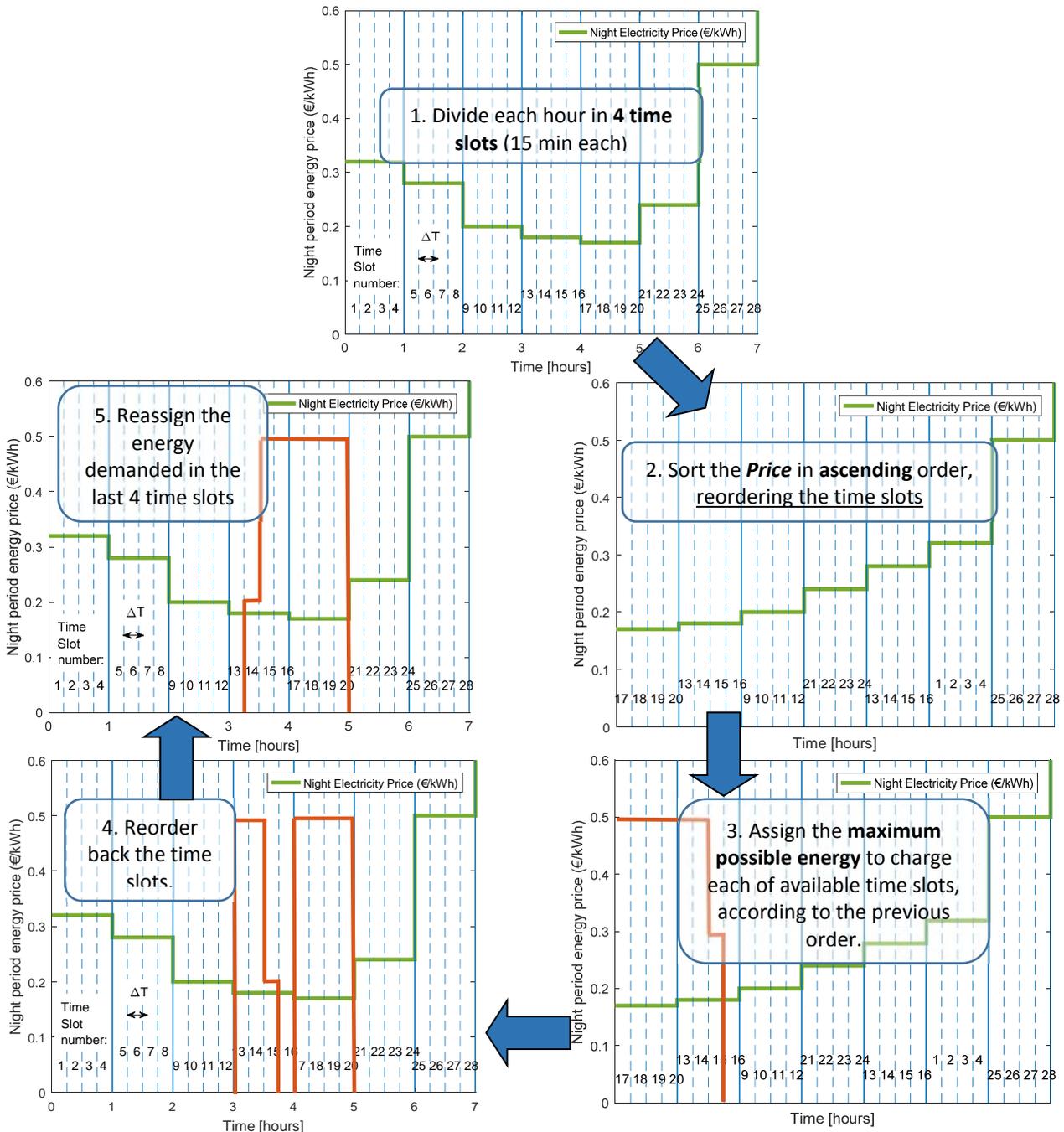


Fig. 4. Proposed optimization algorithm sequence

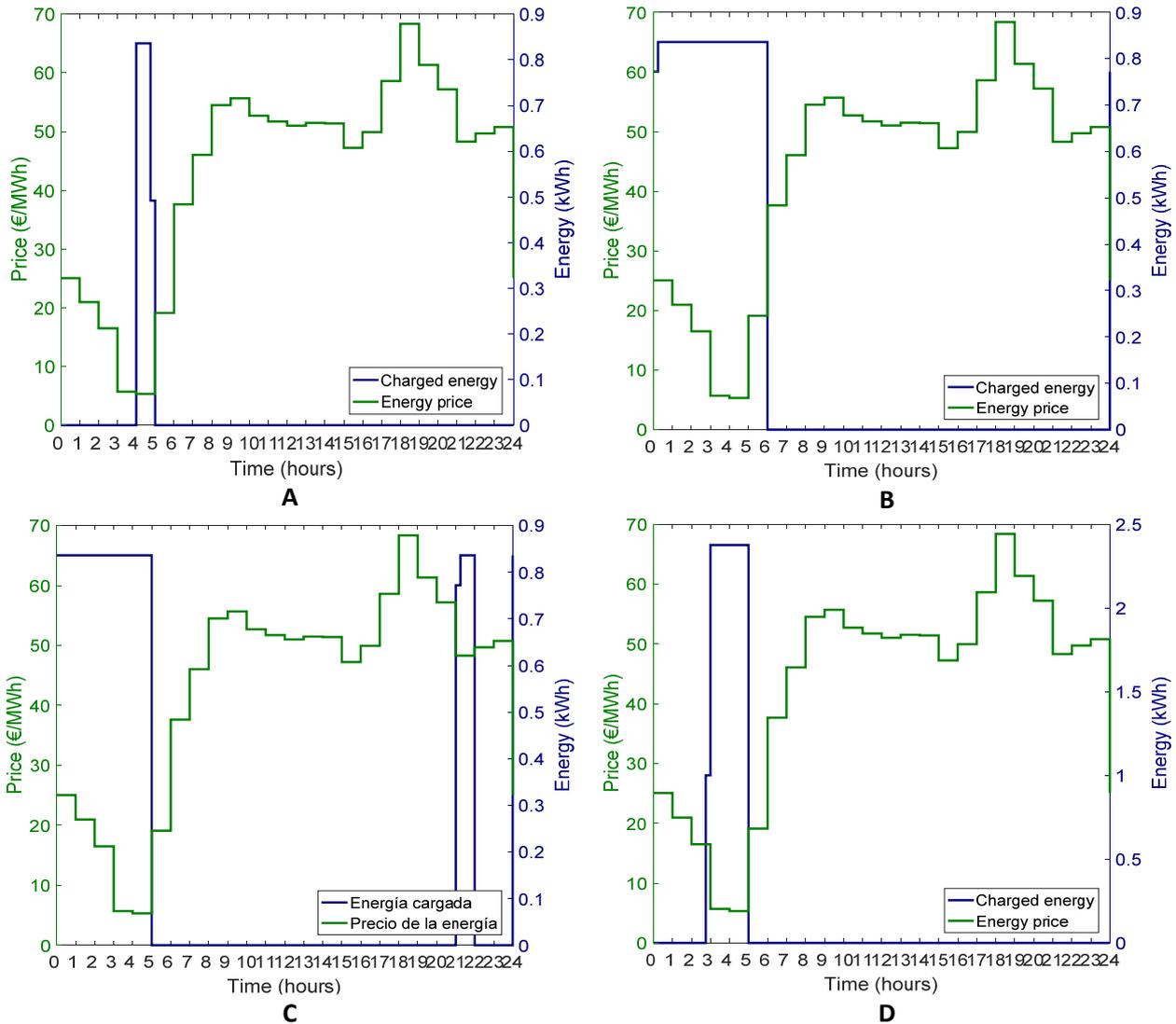


Fig. 5. Results of charging algorithm for cases A, B, C and D

6. Application to a regional fleet

In this section, the night charging algorithm described in section 4 is employed to study the impact of the electrification of the regional vehicle fleet from section 2. The result can be seen in Fig. 6.

Green line shows the electricity price, which varies every hour. The blue line refers to the maximum amount of energy that would be charged by the EVs if all of them were fully depleted by the end of the day: that is, 20 kWh if the EV has enough time to fully charge the vehicle between its last arrival and its first departure or, on rare occasions, the amount of energy that can be charged at home effectively. Finally, the red line represents the amount of energy that is strictly charged during the night.

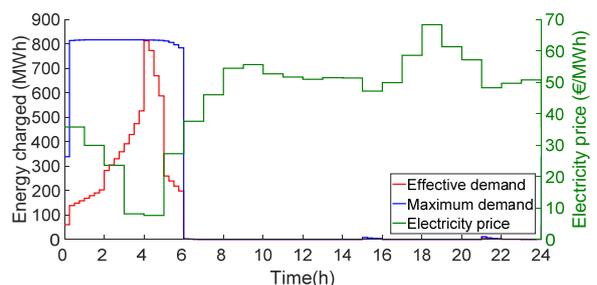


Fig. 6. Drivers' first departure and last arrival

It can be seen that the energy demand almost reaches the maximum value only during one specific time slot, the one between 04:00 and 04:15. This implies that there is a small number of vehicles that require less energy than the amount that can be charged in a quarter of hour, 0.855 kWh.

The power demand decreases in the next slot, but is not far from the maximum demand (95% of it). It decreases to around forth fifths of the maximum demand in the following slot (4:30-4:45) and less than three quarters in the subsequent slot. This implies that, during the hour with the lowest price –thus the highest demand– (4:00-5:00), the demand of the EVs is 87% of the maximum possible demand.

The demand decreases slowly slot by slot until the first time slot, from 00:00 to 00:15. Since the EVs require around 5 hours and 45 minutes to finish their charging process, only those that perform their first departure before 6:00, will charge during this time slot.

Finally, it is worthy to notice that some vehicle may benefit from low prices during the so-called day-time (earlier than 21:00). In this case, between 15:00-16:00 there is a small demand of almost 8 MWh, 38% of the maximum possible demand during that time.

6. Conclusion

In this paper, the impact of the electrification of the fleet of EV in the Flanders region (Belgium) has been studied. For this analysis, an algorithm that optimizes the night charging process of EVs previously presented by the authors has been employed.

The algorithm determines when and how much energy should charge each of the fleet's vehicles according to their parking time at home, the energy consumed along the day and the electricity price during the night.

For the analyzed scenario, the peak demand is reached only during a small fragment of time, corresponding to almost all vehicles charging between 04:00 and 04:15. During the hour with maximum demand, between 04:00 and 05:00, the average demand represents 87% of the maximum demand of the plug-in vehicles. The demand descends time slot after time slot following the electricity price during the night. Some vehicle owners benefit from low electricity price during some day-hours, but the amount of energy they demand is negligible compared to the night demand.

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