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Algorithm development for night charging electric vehicles optimization in big data applications

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Abstract

In this paper a night charging method that optimizes the recharging process of electric vehicles (EVs) depending on hourly energy price in a peer to peer (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

According to World Health Organization (WHO)[1], 90% of people living in cities do not breathe safe air. Road transportation is one of the main air pollutants producers[2-4] and, for this reason, the promotion of the electrification of the road transportation is a critical objective for local, regional and national administrations. A massive deployment of EVs can help to reduce the greenhouse gases (GHG) emissions and meet the international air

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pollution standards in crowed towns but also, this deployment can negatively impact on the electric grid, particularly in the distribution network. This impact has been extensively studied in different works that have evaluated the increase of the line power losses, the voltage drops in power distribution lines, the voltage unbalance of a three-phase distribution network due to unequal distribution of the singe-phase chargers, the generation of harmonics due to the non-linear characteristics of the power electronics in the EV chargers and finally the overload of different distribution lines and power transformers[5-10].

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[11] in Reference 11 and this seminal study was further expanded later[12]. In all these references [5-12] 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.

2. Charging optimization process

2.1. Problem description

All drivers involved in the P2P energy trading system will charge their vehicles during the night period between day 1 and day 2. It is assumed that the variable hourly grid electricity price for their home-charging period, denoted by $PEX_{supply}(t)$, is available for all drivers on a day-ahead basis.It is also assumed that the daily schedules for both days are known and equals. 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 vehicle arrives with a certain initial State of Charge, denoted by $SOC(t_a(v)) = SOC_{ini}$, and it has to 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 (Δt=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	
Vehicle	v	[1,V]	-	Index
Time slot	t	$[T_a, T_d]$	-	Index
Energy hourly price	$PEX_{supply}(t)$	$[PEX_t]$	€/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	$SOC(t_a(v))$	SOC_{ini}	%	Parameter?
Conn./Discon. Vector	$BCT(t,v)$	{0,1}	-	Parameter

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

The optimization problem is defined in equations (1)-(5) for each vehicle *v*. It is a similar to the one presented by the authors previously[6] 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.

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

Subject to the following restrictions:

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

$$\text{SOC}_{min} \le soc(t,v) \le \text{SOC}_{max} \tag{3}$$

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

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

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

The objective function (1) is to minimize the cost of charging the battery during the night period. Constraint (2) defines the initial SoC of vehicle *v* and that its final SoC is equal to the maximum *SoC_max*. Constraint (3) sets the limits for the battery state of charge in each time slot and constraint (4) represents the battery effective charging limit. Equation (5) describes the SOC time evolution due to charging (considered lineal), which only takes place when the vehicle is available to charge according to BCT*(t,v)*- 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 vehicle. Finally, variables are defined as positive to guarantee that energy input is always positive.

2.2. 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 previous to 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:

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

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. 1 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[12]. The effective energy charged per 15-min time slot is 3.3 kWh/4=0.83 kWh.
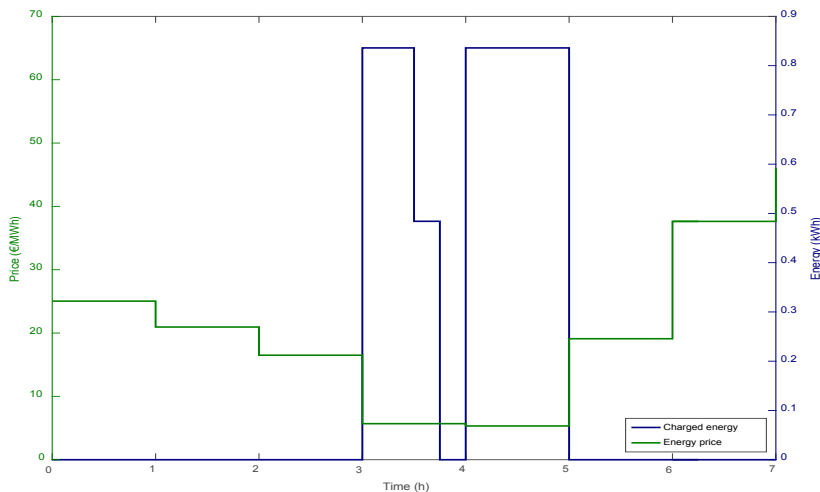

Figure 1. Initial energy assignment for night charging

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

$$\frac{5.5\,\text{kWh}}{0.83\,\text{kWh}} = 6.6265 \tag{8}$$

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.

3. 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.
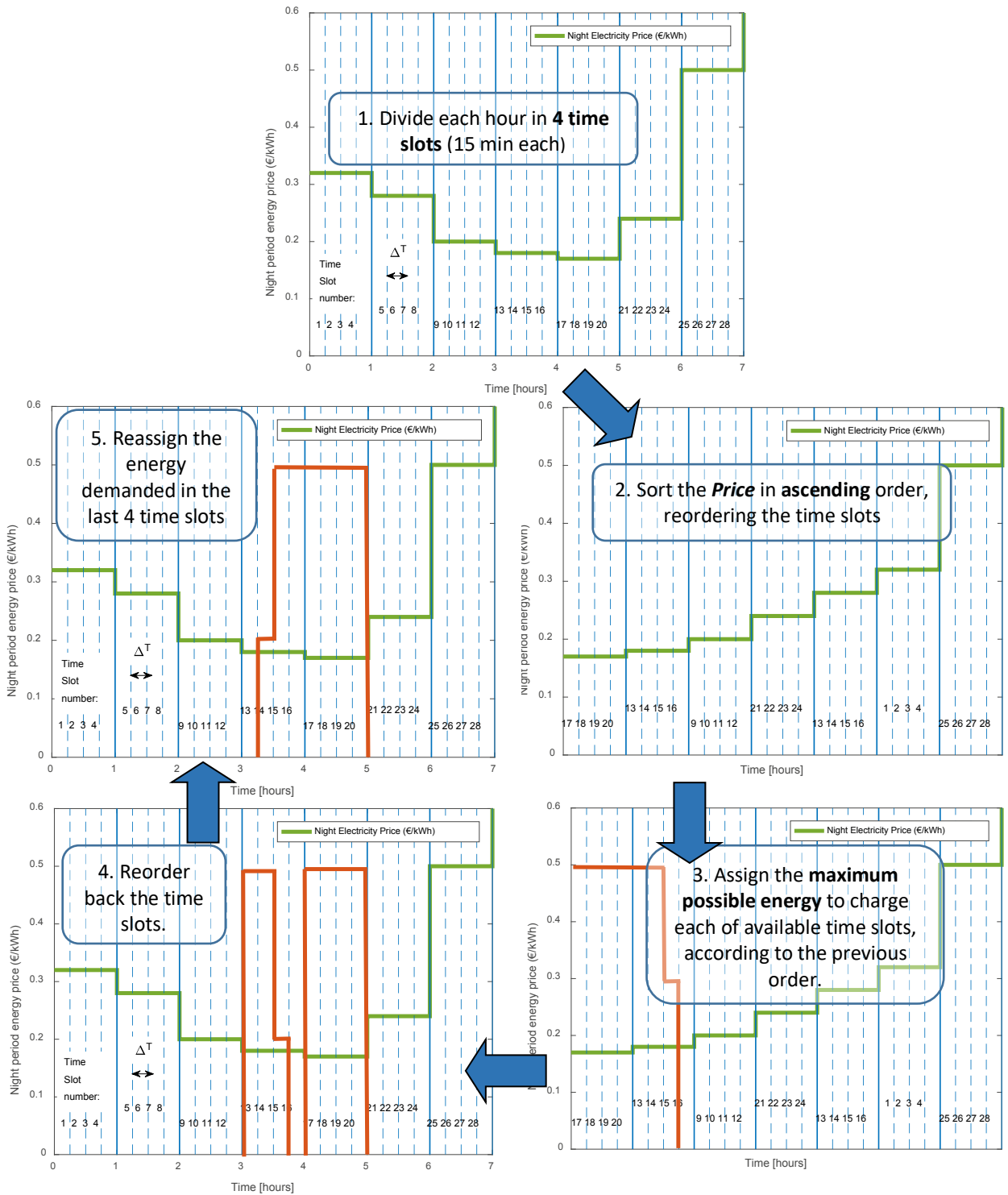
Figure 2. Proposed optimization algorithm sequence

The algorithm works as follows for each vehicle (see Fig.2):

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 demanded energy were 5.5 kWh, the assignation would be 0.83 kWh 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.

4. Results

In this section, four different charging cases to show the algorithm behaviour are examined. 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 betweem 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 reasignation of the last charging period, moving it from period 02:00-02:15 to 02:45-03:00.
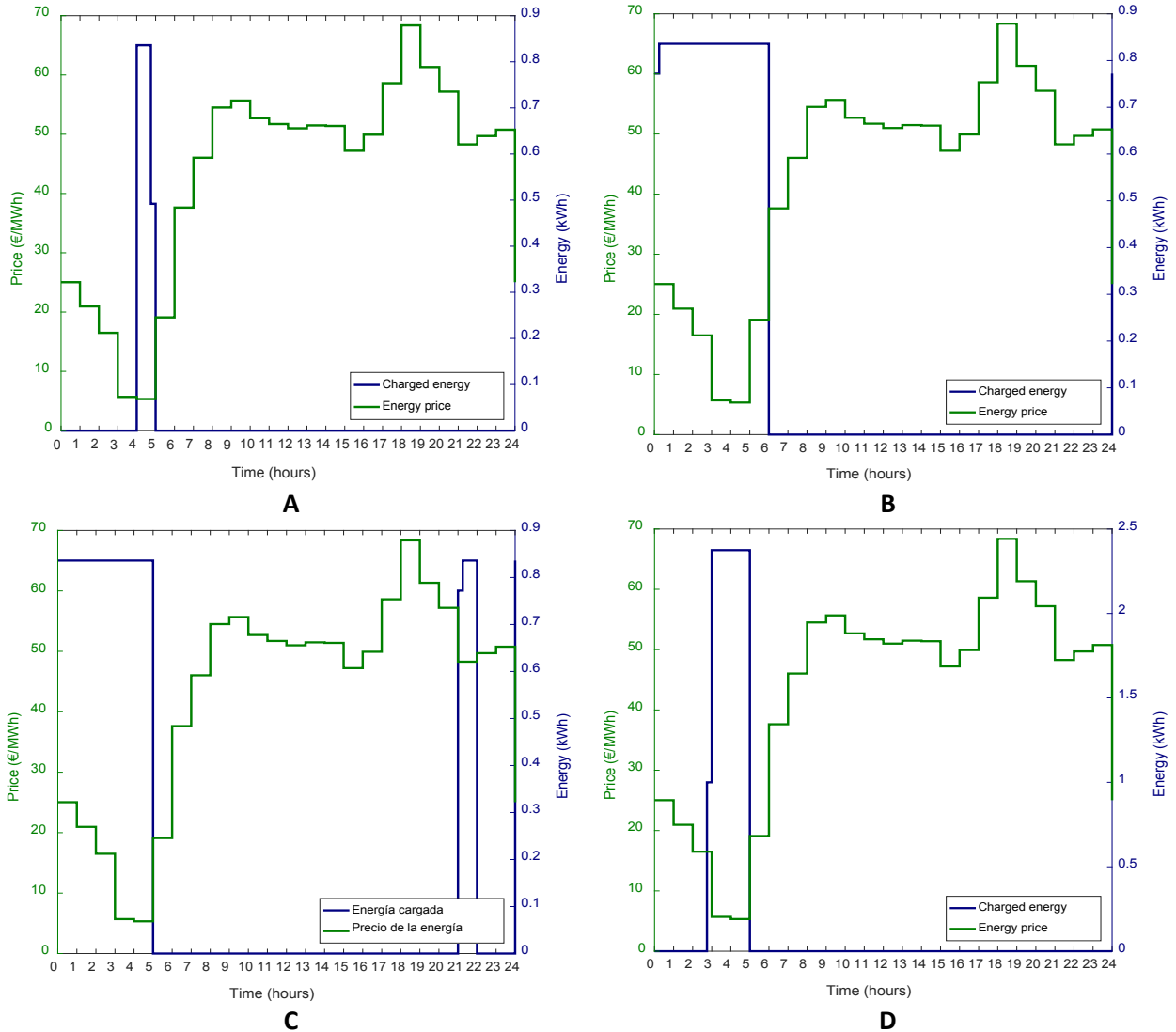

Figure 3. Results of charging algorithm for cases A, B, C and D.

5. Conclusions and future work

In this paper a night charging algorithm that optimizes the recharging process of EVs in big data application has been presented. This algorithm determines when and how much energy should be recharged in the battery of each EV during the night period, taking into account the variable electricity price and the mobility constraints. The algorithm provides the same result of a linear programming solution in which the self-discharge factor is assumed as negligible plus a reordering operation to avoid charging discontinuities.

This algorithm has been tested under four different scenarios, presented in the results section, and its final version has been applied to a more than one million EVs of a synthetic population in Flanders (Belgium), providing much lower execution times than the previously applied traditional optimization methods.

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