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An optimal solution for charging management of electric vehicles fleets

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ABSTRACT

Electric vehicle (EV) is an advanced solution by car manufacturers to gradually replace the conventional vehicle and reduce our dependence on petroleum. Nevertheless, an EV need many hours for a full charge, and reducing charging time and energy consumption of EVs are among the major challenges for promoting this type of vehicles. Disturbed traffic conditions such as traffic jam, roads with sever slopes may affect seriously the energy consumption and then the performances of EVs. In this paper, scheduling and suitable assignment of EVs to charging stations (CSs) is approached as an optimization problem, formulated as linear programming problem. The assignment of EVs should satisfy certain constraints related to CSs status, the EV conditions, traffic conditions, etc. The proposed approach will be illustrated considering two operating modes of the system. The assignment of EVs to CSs under normal conditions (driving without using electrical accessories, roads without slops and traffic jam, etc.), and under disturbed conditions for the second mode. For this first scenario, the two main components of the system are supposed to be homogeneous (EVs have the same characteristics, and the same for CSs). For the second scenario, we focus on a charging system with heterogeneous components. As we will show, the suitable assignment of an EV is when the state of charge (SoC) of its battery remains at its highest possible level at the destination (assigned CS). Keeping the battery SoC at a high level allows to reduce consumed energy and required charging time, and consequently ensures a flexibility in the management of system charging.

1. Introduction

Performance of electric vehicles depends mainly on traction batteries and their characteristics. With the development of EVs, several traction battery technologies have emerged. These technologies include lead acid batteries [1], nickel and cadmium [2], lithium ion/polymer [3], lithium iron phosphate($LiFePO_4$) [3], sodium/nickel chloride(the so-called ZEBRA) [4], and zinc-air batteries [5]. The autonomy of a EV depends mainly on the battery capacity, type of traveled routes (route with/without slopes, urban areas), driving mode and usage of electrical accessories (lights, heating, air conditioning, wipers, etc.)

Charging stations provide power supply for EVs batteries. So, the deployment of complete infrastructures with sophistic equipment is unavoidable for promoting EVs [6]. EVs need often many hours for charging. This means that the time spent for charging in CSs is long and consequently provokes the long queues within these stations as well as unsupportable waiting times. This is one of the main problems that may slow the promotion of EVs. Reducing required charging times is the challenge of many researchers. One of the proposed solutions in the literature to remedy to this problem is to change discharged batteries by fully charged batteries. It would practically take few minutes to change a battery instead of re-fuelling an internal combustion engines. This operation can be done only in dedicated service stations [7,8].

For a driver of EV, finding not only most nearest CS but free and most relevant (with additional capabilities and points of interest) is one of the most important issues. This requires finding a path with a minimum distance to travel in order to reach a free and suitable CS. As traffic conditions change regularly and number of charging requests is unstable, suggesting adequate CSs for EVs is required in order to ensure an acceptable quality of service.

To remedy to this problem, we already proposed in our previous work an optimization approach based on mathematical programming allowing to assign EVs to CSs with minimum energy consumption and minimum waiting times. The aim is to reach this objective while satisfying many constraints related to EVs characteristics, charging infrastructures and traffic situation on the roads.

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The proposed approach gives a solution for optimal charging managing for a fleet of EVs in a system with homogeneous components (all EVs have the same characteristics and technologies, CSs provide the same charging power), and under normal conditions such as normal traffic on the roads, itineraries without severe slopes, without excessive use of electric accessories of the EV, etc. An extended study of this case is proposed in [9]. In fact, we proposed in this study the optimal charging management of a fleet of EVs in a system with homogeneous components functioning under disturbed conditions.

In the current paper, we extend our efforts in this field by proposing a new optimization approach for a charging system with heterogeneous components. Indeed, we consider a great number of EVs with various and different technologies and characteristics. Moreover, CSs have different characteristics. With these heterogeneous components, we will compare the performances of the system in both cases under normal and disturbed conditions as defined previously and we will report and analyze the obtained results. In this study we will introduce a major constraint related to the minimum SoC of the batteries. In fact, the assignment of EVs to charging stations will be done while ensuring that the SoC of each EV battery remains superior to a minimum threshold. For each battery technology, this threshold is defined by manufacturers. This threshold is noted SoC_{min} in the rest of the paper.

The reminder of this paper is organized as follows: Section 2 presents an overview of the related work. Assignment problem with more details about the charging system is addressed in Section 3. The formulation of the problem is introduced in Section 4. An illustrative example with analysis of obtained results for homogeneous system components are addressed in Section 5. A case study representing the system with heterogeneous components is given in Section 6. An illustrative example with analysis of obtained results are addressed in the same section. Finally, Section 7 concludes this work and gives some future research directions.

2. Related work

In the literature, the charging management of EVs has been largely addressed by many researchers. Particularly, several research works focused on optimization of charging and discharging strategies of EVs. We focus in this related work on some developed works about the management and optimal charging/discharging strategies of EVs.

In [10], the authors have presented a scheduling strategy based on moving window optimization scheme. This strategy shows a fast convergence characteristic and is more robust against the global optimization scheme. So, a reliable determination of optimum charging schedules with low costs has been done. As well as, moving window optimization scheme was suitable for online applications due to continuously information update pattern and a fixed forecasting horizon.

A framework for optimization charging/discharging of EVs given variations in electricity spot prices and driving patterns of vehicles is presented in [11]. The proposed optimization approach in this work shows that low prices provide an incentive to charge EVs at night time although day time charging occasionally occurs in spite of high prices. It shows also the incentive to discharge the EVs with favorable taxes while considering the difference between the night time and day time.

A supervised predictive energy management framework is presented in [12]. This framework aims to improve the fuel economy of a power-split plug-in hybrid electric vehicle (PHEV) by incorporating dynamic traffic feedback data. It is evaluated in three cases: without traffic information, with static traffic information, and with dynamic traffic information.

In [13], the authors have presented a scheduling optimization problem for charging/discharging EVs. The charging powers are used to minimize the total costs of all EVs performing charging and discharging during the day. The global optimal solution provides the global minimal total cost and it is impractical since it assumes that the arrivals of all EVs and the base loads during the day are known in advance. Moreover, a local scheduling optimization problem is formulated. It aims to minimize the total cost of EVs in the current ongoing EV set within the local group.

A decentralized algorithm to optimally schedule EV charging is proposed in [14]. The algorithm uses the elasticity of EV loads to fill the valleys in electric load profiles. The scheduling problem of EVs charging is formulated as an optimal control problem, whose objective is to impose a generalized notion of valley-filling, and study properties of optimal charging profiles.

In [15], the authors have proposed an online energy management to economize the cost of using energy and to minimize the capacity fade of a lithium-ion battery bank used for a photovoltaic-based system. Another solution for reducing required charging time concerns the increasing of energy power transferred to EV in appropriate charging stations by increasing charging voltage and current [16–18].

On the other hand, the approach of constant current/constant voltage (CC/CV) follows a charging algorithm applied to obtain fast charging [19–21]. In this approach, the entire charging process is divided into two modes. The first concerns constant current mode and the second is constant voltage mode. A fast charging station with an energy storage system (ultracapacitors) is proposed in [16]. The proposed solution in this work can decrease charging time duration and reduce the stress on the grid at the same time.

In [22], the authors have proposed a genetic algorithm to achieve the best allocation of EVs' parking lots considering distribution reliability. The proposed approach is implemented and obtained results demonstrate that parking lots location is dramatically sensitive to total number of EVs and charging method. Moreover, these results prove that unscheduled allocation of parking lots may lead to an ineligible reliability of distribution system. In order to limit problems of unscheduled high penetration of EVs that may result in the distribution network detrimental effects, the same authors have proposed in [23] a probabilistic model for EVs charging which based on historical driving data and technical specifications of different EV classes. Through, the proposed model and obtained results, it is shown that increasing in charging rate and parking lot capacity leads to charging demand increment. These efforts have been continued by proposing in [24] an autoregressive integrated moving average method for charging demand of EV parking lots based on ARIMA model. In order to determine the expected charging load profiles, the proposed prediction model takes daily driving patterns and distance as an input. Moreover, a chance-constrained scheduling problem is formulated using the output of the forecaster approach. The authors have concluded that this approach might help achieving significant cost savings in power system operations.

Moreover, managing EVs charging in real time is one of the challenges in this domain. In [25], the authors propose a holistic methodology aiming to manage EV charging in quasi-real-time by considering the participation of aggregation in the markets and the grid technical restrictions. The final objective is double: minimizing of the deviation between the energy bought in the market and the energy consumed by EVs, and managing of the grid and solving operational problems that may appear by controlling EV charging. The proposed approach used a synthetic EV dataset created using a Markov chain algorithm to simulate the EV movement and their power needs.

Our research concerns the usage of the electric energy from the grid for EVs charging, but other sources of energy may be used for EVs as well as for other usages. The research work presented in [26] deals with the integration of renewable energy (especially wind energy) into the transport on one hand, and for the electricity system for habitual usage on the other hand. The objective is to maintain a balance between electricity supply and demand by improving the efficiency of the electric power system, reduce the CO_2 emissions, and reduce our dependence on petroleum by promoting EVs. In this work, V2G (for vehicle-to-grid) technology, referring to the capability to deliver power from EV to the grid, was adopted by the authors and provides potential solution to reach the fixed objectives aforementioned.

We end this brief related work by the work presented in [27] about the energy management for EVs. In this work, the energy management is addressed under another angle. The authors have proposed a multi-agent modeling technology for the EV integration. The finality of this work is to prevent grid congestion problems and voltage-band violations. To this end, a multi-agent simulation platform is developed in order to simulate the collaboration behavior between all involved agents in the network. EV is considered as an agent and it is used to demonstrate the proposed agent-based control system.

3. Problem positioning

The major issues that worry EV drivers are "when" and "where" they can charge their vehicles with suitable charging stations and minimum waiting times. We agree that a suitable CS is a station with free charging points, providing services without waiting time, located nearby other interest centers, reachable using itineraries without traffic jam, etc. It worth noting that the nearest CS is not necessarily the most suitable one. In order to position the addressed problem in this paper, we put the reader in the general framework of our approach. This framework is given by the flowchart of Fig. 1.

As shown in this flowchart, the system starts from the EV journey, if the battery SoC is enough to propel the vehicle, this last can continue its journey. Otherwise, if the battery SoC reaches a certain limit, driver gets a warning message regarding battery low. In this case, a charging request is sent (automatically or manually) to a collaborative platform [28]. Next step is managed by the platform while searching suitable charging CSs for all received charging requests according to stored information in its database or communicating directly with CSs. After finding free CSs, the platform invokes other services in order to assign adequately EVs to free CSs while taking into account their characteristics (battery SoC, GPS coordinates, needed power, provided power by each CS, etc.). Among these services, the collaborative platform invokes an optimization algorithm (red rectangle in the flowchart) in order to calculate an optimal assignment tacking into account the system characteristics but also provided information by other invoked services (traffic information service, roads status servicers, etc.). When the optimal assignment is found, EVs are warned while suggesting for each of them a CS corresponding to its criteria. After finishing charging process, used charging point will be free and the platform DB is updated. After that, each EV can continue its journey. In this paper, we focus on the calculus service (optimization algorithm) and show how to assign optimally EVs to CSs.

To this end, we represent the system by an optimization model using with linear programming for decision making and optimal assignment. The objective to reach is to assign each EV to a suitable CS while keeping the battery SoC of the EV at its highest possible level when reaching the CS location. By consuming a small amount of energy while reaching the suggested CS, the EV driver is more confident with a minimum risk to breakdown (without energy). Moreover, this may participate to reduce charging times and therefore the occupation time of CS. Such objective is subject to many constraints to be satisfied. Among them, resource constraints such as remaining energy in the EV battery, availability of free CS, provided power by charging points; location constraints such as the location of each EV, CS and the distance separating them, road traffic, nature of itineraries; temporal constraints such as required time to reach a CS, remaining time (proportional to the distance) to make with the remaining energy in the battery, required time for charging. We have also to take into account some technical constraints like non-response from the CS, disturbance in the communication/location means, etc. This last type of constraints will not be addressed in this paper. It will be the subject of next extension of this work.

In order to formulate the problem we need to define a set of parameters. Let us consider n EVs and m CSs (n and m are supposed to be non-negative integers with $n \gg m$ meaning that m is much smaller than n). We define the assignment matrix C as follows: the matrix element $c(i, j)$ represents the assignment coefficient of the EV_i to the CS S_j. The assignment matrix is further detailed in [29].

For $1 \leq i \leq n$ and $1 \leq j \leq m$, each coefficient $c(i, j)$ is expressed according to the system data. It worth noting that the coefficient $c(i, j)$ evolves over time while expressing the dynamic behavior of the system as we will show hereafter. So, the assignment coefficient becomes $c(i, j, t)$.

4. Problem formulation

4.1. Nomenclature and notations

The following parameters are used to express the linear program model of the problem.

n	total set of EVs ($EV_1, \ldots, EV_n$)
I	subset of EVs which need fast charging
K	subset of EVs which need slow charging
m	total set of charging stations ($S_1, \ldots, S_m$)
m_j	number of charging points within the CS S_j
R	subset of fast charging stations.
L	subset of slow charging stations
$c(i, j, t)$	assignment coefficient of EV_i to S_j at time t
$v(i, j, t)$	vehicle speed depending on the traffic conditions (km/h)
$v_f(i, j, t)$	reference speed on the road without traffic jam at time t (km/h)
$k_{jam}(i, j, t)$	traffic density on the road between the location of EV_i and S_j at time t
$q(i, j, t)$	vehicles flow on the road between the location of EV_i and S_j at time t (veh/h)
$d(i, j)$	distance between the location of EV_i and charging station S_j (km)
$SoC_0(i, t)$	initial state of charge of the EV_i battery at time t
$dis(i, t)$	distance to make with the remaining energy related to $SoC_0(i, t)$ of the battery of EV_i at time t (km)
$SoC_f(i, j, t+T)$	final state of charge of the EV_i battery at S_j at time $t+T(i, j, t)$
$SoC_{min}(i)$	minimum threshold of the EV_i battery
$T(i, j, t)$	required time to make the distance $d(i, j)$ (h)
$E_{cn}(i, j, t+T)$	energy consumption between the location of EV_i and the station S_j under normal conditions (kWh)
$E_{cp}(i, j, t+T)$	energy consumption between the location of EV_i and the station S_j under disrupted conditions (kWh)
$C_n(i)$	EV_i battery rated capacity (kWh)
$A(i)$	EV_i battery autonomy (km)
$x(i, j, t)$	binary variables

The variables of the program are expressed as follows:

$$x(i, j, t) = \begin{cases} 1 & \text{if } EV_i \text{ is assigned to } S_j \text{ at time } t \\ 0 & \text{otherwise} \end{cases}$$

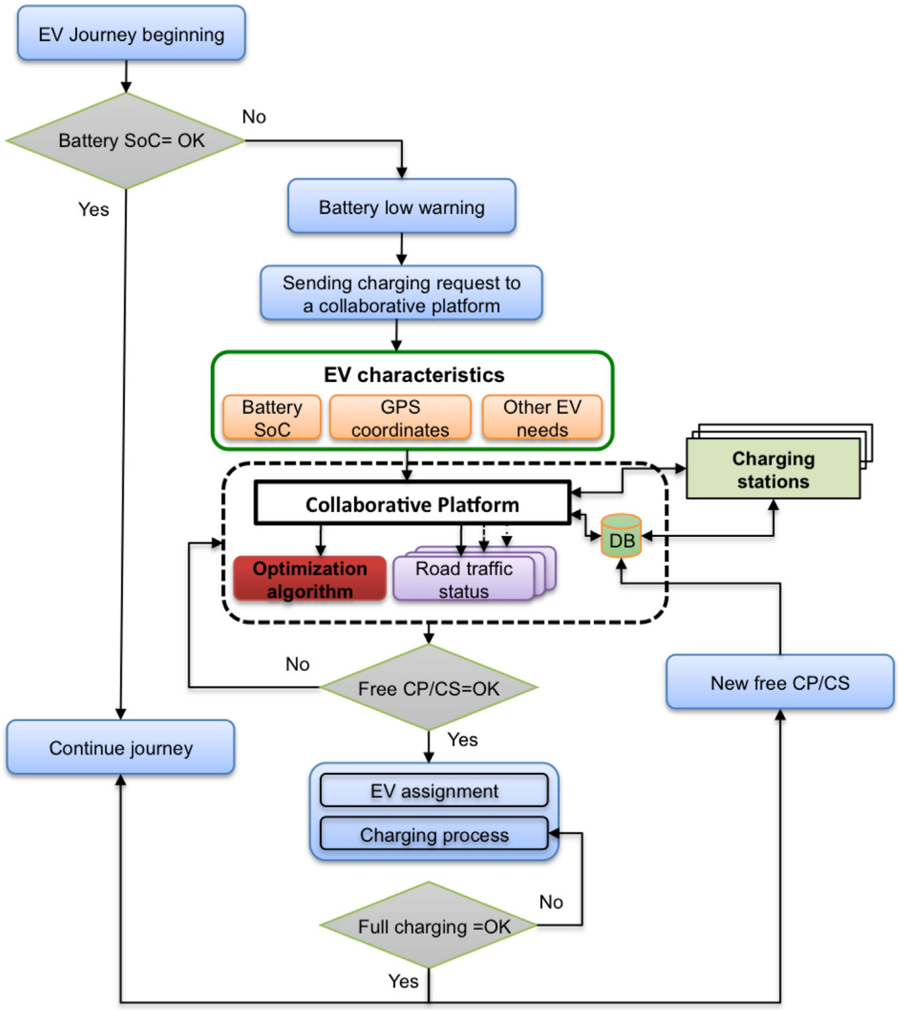

Fig. 1. General framework of the proposed approach.

4.2. Objective function

As mentioned above, our goal is to keep the final SoC (SoC_f) of the EV battery at its destination at the highest possible level. With this objective, we aim to:

(1) reduce as much as possible the EV needs in terms of energy (charging over long time).
(2) reduce the charging times.
(3) reduce the costs of charging (not addressed in this paper).
(4) avoid a long queues at charging stations.
(5) prevent the battery to reach its minimum threshold SoC_{min}.

An electric vehicle EV_i is adequately assigned to a charging station S_j when the associated coefficient $c(i, j, t)$ takes the maximum value. Considering the fixed objective of keeping the battery SoC_f at its highest possible level, the assignment coefficient $c(i, j, t)$ will be replaced in the assignment matrix by $SOC_f(i, j, t+T(i, j, t))$, which represents the final SoC of the battery of EV_i when it reaches the CS S_j at time $t+T(i, j, t)$, for $i = 1, 2, \ldots, n$; $j = 1, \ldots, m$; and at any time t. The parameter $SOC_f(i, j, t+T(i, j, t))$ depends on many system parameters related to EVs and CS characteristics, road characteristics and traffic influence such as: $SOC_0(i, t)$, $d(i, j)$, $q(i, j, t)$, $T(i, j, t)$, $k_{jam}(i, j, t)$, $v_f(i, j, t)$, $C_n(i)$, and $A(i)$. For the study requirements, certain of these parameters, and other system parameters, are quantified especially in the illustration section such as number of EVS, number CSs, traffic density, EV speed, various distances, SoC_{min}, etc. The quantification of other parameters is not required for the proposed studied and it is out of scope of this paper. Among these parameters, there is: road natures (such as itineraries with slopes), excessive usage of electrical accessories of the EV, etc. Further details and quantification of all parameters influencing the energy consumption are addressed in [30].

As detailed in [9,30], the new assignment coefficient can be expressed as:

$$SOC_f(i, j, t+T(i, j, t)) = SOC_0(i, t) - E_{cn}(i, j, t+T(i, j, t)) \cdot Y(i, j, t) \quad (1)$$

where

$$Y(i, j, t) = \int_{t+T(i,j,t)}^{t} v(i, j, s)\, ds \quad (2)$$

$$v(i, j, t) = v_f(i, j, t)\left(1 - \frac{q(i, j, t).T(i, j, t)}{d(i, j) \cdot k_{jam}(i, j, t)}\right) \quad (3)$$

$$T(i, j, t) = \frac{v_f(i, j, t) - \sqrt{\Delta}}{2 \cdot \frac{v_f(i,j,t).q(i,j,t)}{k_{jam}(i,j,t) \cdot d(i,j)}} \quad (4)$$

$$E_{cn}(i, j, t+T(i, j, t)) = \frac{C_n(i) \cdot d(i, j)}{A(i)} \quad (5)$$

Considering the expression of the battery SoC (Eq. (1)), the objective function of the linear program (LP) model representing the system is given by:

$$Z(t) = \sum_{i=1}^{n}\sum_{j=1}^{m} SOC_f(i, j, t + T(i, j, t))x(i, j, t). \quad (6)$$

In what follows, we try to maximize the objective function Z while considering two different behaviors of the charging system. First, all EVs have the same characteristics and the same for CSs (we talk about a charging system with homogeneous components). Second, the system components are with different characteristics (system with heterogeneous components). The constraints related to each case will be formulated as mathematical linear equations. As we aforementioned, we focus in this work on a charging system working under disturbed conditions. In other terms, the parameter $Y(i, j, t)$ of Eq. (2) impacts considerably the energy consumption and consequently the final SoC of the EV battery. This impact can be expressed by: $\forall i \in 1, \ldots, n$, $\forall j \in 1, \ldots, m$ and at any time t, $Y(i, j, t) \neq 1$. Furthermore, the expression of $Y(i, j, t)$ will be explicitly calculated later in this paper.

5. Charging system with homogeneous components

5.1. Constraints definition

For this first case, we consider the following constraints.

- Each CS is characterized by a finite number of charging points with the same charging power.
- All EVs have the same characteristics (the same mark and the same model), but not the same needs in terms of energy.
- Each EV_i should be assigned to only one CS, the suitable one.
- Each CS can serve simultaneously a finite number of EV_i (equals to the number of its charging points).
- The decision variables are binary (we either make an assignment of an EV_i to a charging station S_j or not).

5.2. Constraints formulation

The constraints that must be satisfied during the optimization process are:

- Assignment of each EV_i:
  Each vehicle EV_i ($\forall 1 \le i \le n$) should be assigned to only one charging station at the time t.

$$\sum_{j=1}^{m} x(i, j, t) = 1 \quad (7)$$

- Remaining autonomy in the EV battery:
  The distance to make with the remaining energy in the battery of EV_i should be lower than the distance separating the EV_i location and suggested CS S_j.

$$dis(i, t) \le d(i, j) \quad (8)$$

- Charging station capacity:
  The capacity m_j of each CS S_j ($\forall 1 \le j \le m$) should not be exceeded at any time t.

$$\sum_{i=1}^{n} x(i, j, t) \le m_j \quad (9)$$

5.3. Optimization method

Frontline systems' optimizers solve linear programming (LP) problems using many methods such as Primal and Dual Simplex Method, Active Set Method, Interior Point or Newton-Barrier Method. The addressed optimization problem in this work is solved using the standard Microsoft Excel Solver. This solver uses a basic implementation of the primal Simplex method to solve LP problems. We note that this version is limited to 200 decision variables. The premium solver of LP problems uses an improved primal Simplex method with two-sided bounds on the variables. This improved version may handle up to 1000 decision variables. Furthermore, the premium solver platform uses an extended LP version of this Simplex solver and may handle problems of up to 2000 decision variables. In order to save time and memory, the large-scale LP solver for the premium solver platform uses a state-of-the-art implementation of the primal and dual Simplex method. We find very useful, to underline some advanced algorithms for solving LP problems. Among these algorithms: branch and bound, branch and cut, branch and price, cutting-plan method, column generation. Many researches and applications are developed in the literature about these algorithms and methods. The studied problem in this paper can also be solved by one of these algorithms. Details about these methods and further algorithms are given in [31].

5.4. Illustrative example

5.4.1. Numerical values of system data

The examples presented in this paper to illustrate the proposed approach allow a sensitivity analysis. This enables to analyze the system by studying the impact of the variability of system inputs (operating modes) on the obtained results (system outputs or assignment results). All studied examples and scenarios illustrate the interpretation of the proposed sensitivity analysis.

The following numerical values are quantified to illustrate this first case of the system.

- $n = 6$: number of used EVs;
- $m = 4$: number of used CSs;
- EVs locations as well as distances $d(i, j, t)$ are supposed to be known;
- $SOC_0(i, t)$ of each vehicle EV_i is supposed to be known;
- EVs flows $q(i, j, t)$ in each road are supposed to be known;
- The time is started from $t = t_0$ (for calculation reasons, we suppose that $t_0 \neq 0$). For $t \neq t_0$, the system status may be evolved over time, and then the values of the assignment coefficient $c(i, j, t)$ change too;
- Number of charging points within charging stations are respectively: $m_1 = 1$, $m_2 = m_3 = m_4 = 2$.
- $k_{jam}(i, j, t) = 200$ [veh/km];
- $v_f(i, j, t) = 60$ [km/h];

Table 1 illustrates the numerical values of $SOC_0(i, t)$, $q(i, j, t)$ and distance $d(i, j, t)$ between each EV and all considered stations. Similarly, we consider that EVs are the same mark (Heuliez) and the same model (MIA Electric) with the autonomy $A(i) = 80$ [km] and the rated capacity of the battery $C_n(i) = 8$ [kWh].

5.4.2. Obtained results: discussions and analysis

In our previous work [29], we have studied the assignment problem under normal conditions where the impact of traffic conditions is neglected. The $SOC_f(i, j, t + T(i, j, t))$ of each EV battery can be expressed according to Eq. (1) (in this case, the parameter $Y(i, j, t)$ is supposed to equal to 1). Consumed energy by EV_i for reaching the charging station S_j can be obtained by Eq. (5). In [9], we have studied the assignment problem under disturbed conditions. In this

Table 1
Problem data: SOC_0, $d(i, j, t)$ and $q(i, j, t)$.

Parameters of $(EV_i)/S_j$		S_1	S_2	S_3	S_4
EV_1:SOC_0 = 70	$d(1, j, t)$ [km] $q(1, j, t)$ [veh/h]	2 1300	5 600	10 2000	7 1000
EV_2:SOC_0 = 75	$d(2, j, t)$ [km] $q(2, j, t)$ [veh/h]	10 1200	4 2000	7 1700	6 1800
EV_3:SOC_0 = 65	$d(3, j, t)$ [km] $q(3, j, t)$ [veh/h]	10 1350	5 1200	3 1500	7 2400
EV_4:SOC_0 = 60	$d(4, j, t)$ [km] $q(4, j, t)$ [veh/h]	10 1000	7 900	9 800	4 2100
EV_5:SOC_0 = 66	$d(5, j, t)$ [km] $q(5, j, t)$ [veh/h]	2 1550	5 1200	3 1000	9 2000
EV_6:SOC_0 = 53	$d(6, j, t)$ [km] $q(6, j, t)$ [veh/h]	4 1400	2 1900	10 950	6.5 1800

Table 2
Energy consumption by EVs under normal and disturbed conditions.

Parameters of EV_i		S_1	S_2	S_3	S_4
EV_1	$E_{cn}(1, j, t+T(1, j, t))$ $E_{cp}(1, j, t+T(1, j, t))$	0.2 1.05515	0.5 0.9861	1 1.3397	0.7 1.2939
EV_2	$E_{cn}(2, j, t+T(2, j, t))$ $E_{cp}(2, j, t+T(2, j, t))$	1 3.873	0.4 3.2574	0.7 1.77124	0.6 2.6105
EV_3	$E_{cn}(3, j, t+T(3, j, t))$ $E_{cp}(3, j, t+T(3, j, t))$	1 2.99	0.5 0.7223	0.3 1.6588	0.7 5.7727
EV_4	$E_{cn}(4, j, t+T(4, j, t))$ $E_{cp}(4, j, t+T(4, j, t))$	1 5	0.7 1.6877	0.9 4.5348	0.4 3.5936
EV_5	$E_{cn}(5, j, t+T(5, j, t)))$ $E_{cp}(5, j, t+T(5, j, t))$	0.2 1.3927	0.5 0.7223	0.3 0.7061	0.9 2.2263
EV_6	$E_{cn}(6, j, t+T(6, j, t))$ $E_{cp}(6, j, t+T(6, j, t))$	0.4 1.5117	0.2 1.9177	1 5.2737	0.65 2.4665

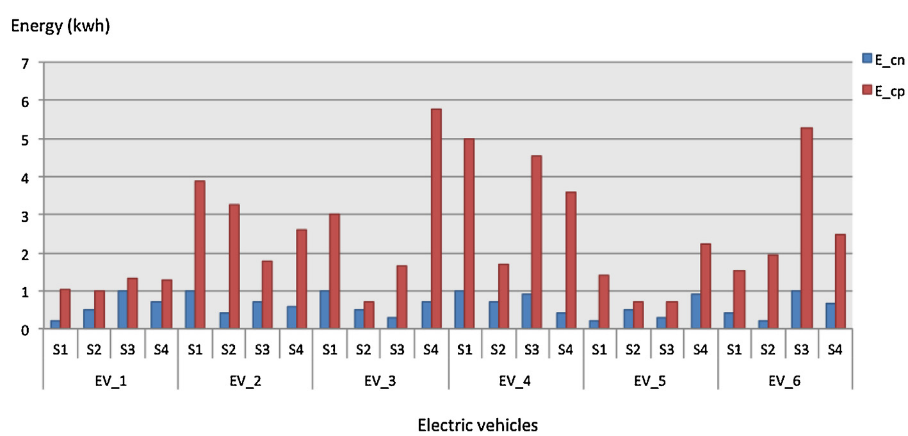

Fig. 2. Energy consumption by EV_i for reaching each CS S_j under both normal and disturbed conditions.

case, we have taken into consideration the impact of road traffic on energy consumption of EVs. $SOC_f(i, j, t+T(i, j, t))$ of each battery can be expressed according to Eq. (1) and the parameter $Y(i, j, t)$ (2). A comparative study between energy consumption by EVs in these two cases is addressed and obtained results are reported in Table 2. A graphical representation of these results is illustrated by Fig. 2.

Fig. 2 shows a comparison between the energy consumption of each EV when reaching the charging stations S_j under normal and disturbed conditions. On the x-axis, we make a link between each EV_i with the four CSs by presenting an estimation of the required energy to reach each of them. These amounts of energy are given in the y-axis for both cases normal and disturbed conditions.

As illustrated by this figure, we remark that the energy consumption of each EV EV_i to reach charging station S_j under disturbed conditions E_{cp} is higher than the energy consumption in normal conditions E_{cn}. This means that the final SOC of EV_i at S_j under disturbed conditions (SOC_{fp}) is less than the final SOC of EV_i under normal conditions (SOC_{fn}). The obtained value of SOC_f of each EV in both cases using Eq. (1) are given in Table 3.

5.4.3. Optimal assignment

We obtain the optimal solution (maximum values of SOC_f) of the linear program representing the suitable assignment of EVs to charging stations under normal conditions (see Table 4).

Table 3
Obtained SOC_f for all vehicles under normal and disturbed conditions.

Parameters of EV_i/S_j		S_1	S_2	S_3	S_4
EV_1	$SOC_{fn}(1, j, t+T(1, j, t))$	69.8	69.5	69	69.3
	$SOC_{fp}(1, j, t+T(1, j, t))$	68.9448	69.014	68.66	68.706
EV_2	$SOC_{fn}(2, j, t+T(2, j, t))$	74	74.6	74.3	74.4
	$SOC_{fp}(2, j, t+T(2, j, t))$	71.127	71.743	73.2288	72.389
EV_3	$SOC_{fn}(3, j, t+T(3, j, t))$	64	64.5	64.7	64.3
	$SOC_{fp}(3, j, t+T(3, j, t))$	62	64.278	63.341	59.227
EV_4	$SOC_{fn}(4, j, t+T(4, j, t))$	59	59.3	59.1	59.4
	$SOC_{fp}(4, j, t+T(4, j, t))$	55	58.312	55.4652	56.406
EV_5	$SOC_{fn}(5, j, t+T(5, j, t))$	65.8	65.5	65.7	65.1
	$SOC_{fp}(5, j, t+T(5, j, t))$	64.607	65.278	65.294	63.774
EV_6	$SOC_{fn}(6, j, t+T(6, j, t))$	52.6	52.8	52	52.35
	$SOC_{fp}(6, j, t+T(6, j, t))$	51.488	51.082	47.7263	50.534

Table 4
Optimal values of assignment coefficients under normal conditions.

EV_i/S_j	S_1	S_2	S_3	S_4
EV_1	**69.8**	69.5	69	69.3
EV_2	74	**74.6**	74.3	74.4
EV_3	64	64.5	**64.7**	64.3
EV_4	59	59.3	59.1	**59.4**
EV_5	65.8	65.5	**65.7**	65.1
EV_6	52.6	**52.8**	52	52.35
n_j	1	2	2	2

Table 5
Optimal values of assignment coefficients under disturbed conditions.

EV_i/S_j	S_1	S_2	S_3	S_4
EV_1	68.95	69.01	68.66	**68.71**
EV_2	71.13	71.74	**73.229**	72.39
EV_3	62.01	**64.28**	63.34	59.23
EV_4	55	**58.31**	55.47	56.41
EV_5	64.61	65.28	**65.29**	63.77
EV_6	**51.49**	51.08	47.73	50.53

Table 4 shows the best assignment of EVs to charging stations under normal conditions (values with bold). We can see from this table the best assignment of each EV. Thus, S_1 with only one charging point, is more suitable for EV_1, and S_2, with two charging points, is more suitable for EV_2 and EV_6, etc.

In the same way, we obtain the optimal solution assigning EVs adequately to charging stations under disturbed conditions. This solution is illustrated in Table 5. Fig. 3 presents the optimal assignment of EVs to CSs under both normal and disturbed conditions. This figure enables to make a comparison be tween both cases.

The values of SOC_f corresponding to the suitable assignments in the two studied cases are given in Table 6. This table presents a comparative study between the optimal assignment of EVs to charging stations under normal and disturbed conditions. From this table, we remark that the assignment of EVs to charging stations is not the same for the two cases and it depends on the system state. As well as, this table shows that all problem constraints are satisfied in the two studied cases:

- The overall goal of the assignment is reached.
- The number of EVs allowed in each charging station is not exceeded.
- Each assignment of EVs is carried out with the maximum value of $SOC_f(i, j, t+T(i, j, t))$, that is to say, with a minimum of consumed energy. This minimizes the occupation time of charging stations by EVs.
- All EVs are assigned and each one is assigned to a single charging station.
- Assignment programs for both cases (normal and disturbed conditions) are not the same.

These results are illustrated graphically by Fig. 3. This figure enables also to show a comparison between both cases.

6. Charging system with heterogeneous components

In this section, we study the assignment problem in the case of charging system with heterogeneous components. This means that EVs have different characteristics and technologies. Likewise, CSs have different charging modes (fast and slow). With these new elements of the system, our objective is to keep the battery SoC

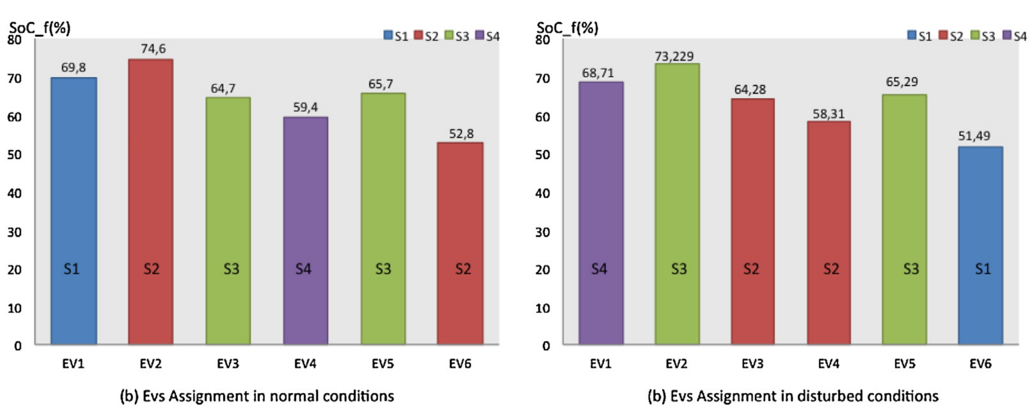

Fig. 3. Optimal values of SOC_f of EVs at charging stations under normal and disturbed conditions.

Table 6
Suitable assignment of EVs in the two studied cases.

Charging station		S_1	S_2		S_3		S_4
Nbr of authorized EV		1	2		2		2
Nbe of assigned EV		1	2		2		1
Normal conditions	Assigned EVs and optimal value of SOC_f	EV_1 69.8	EV_2 74.6	EV_6 52.8	EV_3 64.7	EV_5 65.7	EV_4 59.4
Disturbed conditions	Assigned EVs and optimal value of SOC_f	EV_6 51.49	EV_3 64.28	EV_4 58.31	EV_2 73.23	EV_5 65.29	EV_1 68.71

at its destination (charging station) at the highest possible level, so we can apply in this study the same model of Eq. (6) that we will complete considering the new charging system. To this end, we introduce a new constraint allowing to maintain the power level of EVs batteries at the arrival to CSs upper than the minimum threshold defined by manufacturers.

6.1. Assumptions

Besides the constraints already mentioned in the homogeneous system, we assume what follows in order to model the system under this new configuration:

- There are a great number of EVs asking for service charging.
- EVs have different characteristics and technologies (different marks and models). This means that certain EVs ask for a slow charging, and others asks for a fast charging.
- CSs provide two types of charging: fast and slow.

6.2. Program constraints

The constraints that should be satisfied are:

(1) EVs requirements:
a – A given EV_i which needs fast charging should be assigned to only one fast charging station at time t.

$$\sum_{j=1}^{R} x(i,j,t) = 1 \tag{10}$$

with i ∈ I (I: the set of vehicles which need fast charging).
b – A given EV_k which needs slow charging should be assigned to only one slow charging station at time t.

$$\sum_{j=R+1}^{L} x(k,j,t) = 1 \tag{11}$$

with k ∈ K (K: the set of vehicles which need slow charging).

(2) Charging station capacity:
A given charging station S_j may receive until n_j EVs at a given time t. This constraint is flexible and the number of assigned EVs to a given charging station S_j may change according to its status. n_j EVs under charging should not be exceeded at the same time.

$$\sum_{i=1}^{n} x(i,j,t) \le n_j \tag{12}$$

(3) Battery state of charge:
Final state of charge (SOC_f) of each EV battery must not exceed the minimum threshold (SOC_{min}) as defined by the manufacturer.

$$SOC_f(i,j,t+T(i,j,t)) \ge SOC_{\min}(i) \tag{13}$$

for $i \in I \cup K$, j ∈ $R \cup L$.

Table 7
Mark, model and charging requirement of EVs.

EV	*EV* mark	*EV* model	Charging mode
EV_3, EV_6, EV_9 EV_{12}, EV_{15}, EV_{18}	Heuliez	MIA ELECTRIC	Slow charging
EV_2, EV_{10}, EV_{16}	Citron	Citron C-ZERO	Fast charging
EV_1, EV_{17}	Renault	TIWIZY	Slow charging
EV_4, EV_{11}, EV_{14}	Peugeot	Peugeot ion	Fast charging
EV_5, EV_7 EV_8, EV_{13}	Peugeot	Peugeot Partner Electric Venturi	Slow charging

6.3. Illustrative example

6.3.1. System parameters

In order to illustrate the proposed solution for this heterogeneous system, we consider the following numerical example.

(1) $n = 18$ electric vehicles;
(2) $m = 7$ charging stations;
(3) $R = 4$ fast charging stations (50 kW DC) ($S_1, \ldots, S_4$);
(4) $L = 3$ slow charging stations (230 V single-16A) (3 kW)($S_5, \ldots, S_7$);
(5) EVs locations as well as distances $d(i, j, t)$ are supposed to be known;
(6) EVs flows $q(i, j, t)$ in each road are supposed to be known;
(7) Initial state of charge of each vehicle EV_i ($SOC_0(i, t)$) is given;
(8) Optimal assignment is calculated for $t = t_0$ (the assignment time is known). For $t \ge t_0$, the system status may be changed, and then the values of the assignment coefficient $c(i, j, t)$ change too;
(9) The number of active charging points within CSs are: $n_1 = 1$, $n_2 = n_3 = n_4 = 2$, $n_5 = 4$, $n_6 = 3$, $n_7 = 5$;
(10) $k_{jam}(i, j, t) = 200$ [veh/km];
(11) $v_f(i, j, t) = 60$ [km/h].

Table 7 illustrates these marks and models of EVs with charging requirement of each mark. Other technical characteristics of used EVs are presented in Table 8.

Considering these various models of EVs and charging stations, the goal is twofold. First, assign each EV model to suitable charging station. Second, perform this assignment while keeping the battery state of charge of EVs (SOC_f) at its destination at its highest possible level. Finally, the minimum threshold SOC_{min} of each battery as defined by the manufacturer (Table 8) should not be exceeded.

Problem data $d(i, j, t)$, $q(i, j, t)$, and $SOC_0(i, t_0)$ are given in Table 9.

Table 8
Characteristics of EVs.

EV model	C_n (kWh)	A (km)	EV battery	SOC_{min}
MIA ELECTRIC	8	80	$LiFePO_4$	30
Citron C-ZERO	16,3	130	Li-ion	20
TIWIZY	7	100	Li-ion	20
Peugeot ion	16.3	130	Li-ion	20
Peugeot Partner Electric Venturi	23.5	120	ZEBRA	0

Table 9
Problem data.

Data EV_i/S_j		S_1	S_2	S_3	S_4	S_5	S_6	S_7
EV_1:$SOC_0=25$	$d(1, j, t_0)$	2	5	10	7	3	4	1
	$q(1, j, t_0)$	1300	600	800	1800	1400	1500	800
EV_2:$SOC_0=27$	$d(2, j, t_0)$	10	4	7	6	2	6.7	8
	$q(2, j, t_0)$	1200	2000	1700	1800	900	1900	2550
EV_3:$SOC_0=40$	$d(3, j, t_0)$	10	5	3	7	6	8	12
	$q(3, j, t_0)$	1350	1200	1500	2400	2300	2500	1500
EV_4:$SOC_0=33$	$d(4, j, t_0)$	10	7	9	4	2.4	3.2	8
	$q(4, j, t_0)$	1000	900	800	2100	600	1200	720
EV_5:$SOC_0=20$	$d(5, j, t_0)$	2	5	3	9	2.4	7	11
	$q(5, j, t_0)$	1550	1200	1000	2000	450	900	2350
EV_6:$SOC_0=34$	$d(6, j, t_0)$	4	2	10	6.5	1	12	3
	$q(6, j, t_0)$	1400	1900	950	1800	300	1500	800
EV_7:$SOC_0=50$	$d(7, j, t_0)$	1	2	3	5	8	14	11
	$q(7, j, t_0)$	1500	1200	1100	1300	1250	800	700
EV_8:$SOC_0=34$	$d(8, j, t_0)$	5.5	2.3	8.7	6.5	10	15	12
	$q(8, j, t_0)$	1400	1000	1050	1800	1340	1455	700
EV_9:$SOC_0=55$	$d(9, j, t_0)$	3	2.4	3.8	7	9	5.5	12
	$q(9, j, t_0)$	1100	1000	1400	2000	800	500	700
EV_{10}:$SOC_0=24$	$d(10, j, t_0)$	7	8	9	13	5	4	3
	$q(10, j, t_0)$	1000	1200	2200	1800	1300	1200	800
EV_{11}:$SOC_0=30$	$d(11, j, t_0)$	9	4.4	6.8	8	7.5	2	14
	$q(11, j, t_0)$	2100	1000	800	2000	950	450	1100
EV_{12}:$SOC_0=39$	$d(12, j, t_0)$	7.6	5	1	6.4	14	12	10
	$q(12, j, t_0)$	1000	1200	2200	1800	1700	1430	1600
EV_{13}:$SOC_0=28$	$d(13, j, t_0)$	4	5	7	6.1	3	9	10
	$q(13, j, t_0)$	900	1200	800	2000	700	1000	1200
EV_{14}:$SOC_0=22$	$d(14, j, t_0)$	6	5.7	10	8	2	3	1
	$q(14, j, t_0)$	1400	900	2300	1800	400	500	200
EV_{15}:$SOC_0=40$	$d(15, j, t_0)$	4	11	7	6.1	5	2	9.7
	$q(15, j, t_0)$	900	1200	800	2000	1920	600	950
EV_{16}:$SOC_0=30$	$d(16, j, t_0)$	3	1.7	11	4	10	8.4	7.2
	$q(16, j, t_0)$	1300	1100	2500	1500	400	750	480
EV_{17}:$SOC_0=23$	$d(17, j, t_0)$	2.3	8	5	9	7	13	1
	$q(17, j, t_0)$	400	1200	800	2000	1400	800	200
EV_{18}:$SOC_0=39$	$d(18, j, t_0)$	13	17	11	15	7	5	3
	$q(18, j, t_0)$	900	1500	700	1200	1750	800	400

6.3.2. *Energy consumption*

We evaluate the energy consumption $E_{cp}(i, j, t+T(i, j, t))$ of all vehicles EV_i (for $i=1, \ldots, 18$) between their locations at time $t=t_0$ and all charging stations S_j (for $j=1, \ldots, 7$). These results are given in Table 10. Based on the problem data of Table 9, Table 10 gives a matrix of energy consumption E_{cp} for each couple (EV_i, S_j). From this matrix, and using Eq. (1), we calculate the values of SOC_f for each EV when reaching each CS. In Table 11, we report a summary of these values for all EV and all CSs.

6.3.3. *Optimal assignment*

After determining the assignment matrix, the optimal solution of Eq. (6) is presented, using Microsoft Excel solver, in Table 11. The values of suitable assignments are given in this table with bold.

Fig. 4 illustrates the suitable assignment of each EV. This figure shows an estimation of SOC_f for each EV when reaching the suggested CS.

We can also compare the optimal values of $SOC_f(i, j, t+T(i, j, t))$ with the values of SOC_{min} for all vehicles in order to check the satisfaction of the last constraint of the linear program. Fig. 5 illustrates obtained results.

Fig. 5 shows that the optimal value of SOC_f never exceeds the value of SOC_{min} for each vehicle. We recall that the EVs of model Peugeot Partner Electric Venturi (EV_5, EV_7, EV_8, EV_{13}) have Zebra batteries which can be fully discharged without damage (i.e. $SOC_{min}=0$).

Tables 12 and 13 summarize the assignment of EVs to fast and slow charging stations. These results show that all problem constraints are satisfied:

(1) The overall goal of the assignment of all electric vehicles is reached.
(2) The number of EVs allowed in each charging station is not exceeded.
(3) Each assignment is performed with the maximum value of $SOC_f(i, j, t+T(i, j, t))$, meaning with the consumption of a minimum energy. This minimizes the occupation time of charging stations by EVs.
(4) SOC_{min} is never exceeded for each EV.
(5) EVs with models Citron C-Zero and Peugeot ion are assigned adequately to the fast charging stations.
(6) EVs with models TIWIZY, MIA ELECTRIC and Peugeot Partner Electric Venturi are assigned adequately to the slow charging stations.

Table 10
Matrix of energy consumption E_{cp} for each couple (EV_i,S_j).

EV_i/S_j	S_1	S_2	S_3	S_4	S_5	S_6	S_7
EV_1	0.738	0.69	4.254	1.586	1.02	1.244	0.228
EV_2	4.856	4.084	2.22	3.273	0.704	3.621	8.64
EV_3	2.99	0.722	1.658	5.772	5.077	6.457	5.0911
EV_4	6.269	2.116	5.685	4.505	0.21	1.347	4.441
EV_5	2.727	1.414	1.382	4.359	0.05	3.305	6.526
EV_6	1.511	1.917	5.273	2.466	0.052	5.091	0.358
EV_7	1.508	1.815	1.735	2.021	2.269	28.053	16.442
EV_8	2.329	1.391	5.713	4.83	5.973	22.80	20.36
EV_9	0.886	0.716	1.518	3.319	4.534	1.656	10.398
EV_{10}	1.622	1.751	4.596	5.602	1.294	1.257	0.448
EV_{11}	3.671	0.487	2.347	3.618	2.496	0.075	15.22
EV_{12}	1.883	0.722	1.334	2.499	7.267	5.598	1.435
EV_{13}	0.565	1.414	4.059	6.883	0.371	6.96	7.584
EV_{14}	1.221	0.752	4.721	2.132	0.008	0.17	0.001
EV_{15}	0.288	5.430	2.072	3.514	3.187	0.222	4.81
EV_{16}	1.581	0.922	6.125	2.228	10.165	4.931	4.38
EV_{17}	0.043	0.977	0.309	1.558	0.267	8.366	0.0006
EV_{18}	11.281	16.441	8.395	13.785	2.016	0.441	0.294

Table 11
Optimal assignment of EVs to charging stations.

	S_1	S_2	S_3	S_4	S_5	S_6	S_7
EV_1	24.2614	24.31	20.746	23.413	23.98	23.756	**24.771**
EV_2	22.144	22.915	**24.78**	23.73	26.3	23.38	18.36
EV_3	37.01	39.2777	38.3421	34.2273	34.922	33.5426	**34.909**
EV_4	26.73	**30.88**	27.314	28.5	32.789	31.652	28.56
EV_5	17.2726	18.5855	18.617	15.64	**19.95**	16.695	13.474
EV_6	32.5	32.1	28.726	31.5335	33.947	28.908	**33.642**
EV_7	48.492	48.185	48.2641	47.979	**47.731**	21.947	33.558
EV_8	31.6708	32.6086	28.2865	29.1697	**28.0265**	11.1991	13.635
EV_9	54.1135	54.284	53.482	51.681	50.465	**53.344**	44.601
EV_{10}	**22.3776**	22.2486	19.4038	18.3974	22.7059	22.7421	23.551
EV_{11}	26.33	29.513	**27.652**	26.381	27.5	29.925	14.779
EV_{12}	37.1161	38.278	37.665	36.5	31.7327	33.401	**37.565**
EV_{13}	27.434	26.5855	23.94	21.1165	**27.628**	21.04	20.415
EV_{14}	20.778	**21.247**	17.278	19.8677	21.991	21.829	21.999
EV_{15}	39.711	34.57	37.93	36.485	36.812	**39.778**	35.19
EV_{16}	28.418	29.077	23.874	**27.771**	19.8347	25.0684	25.62
EV_{17}	22.956	22.022	22.691	21.442	22.733	14.634	**23**
EV_{18}	27.7188	22.5583	30.604	25.2142	36.9832	**38.558**	38.705
n_j	1	2	2	2	4	3	5
		Fast charging				Slow charging	

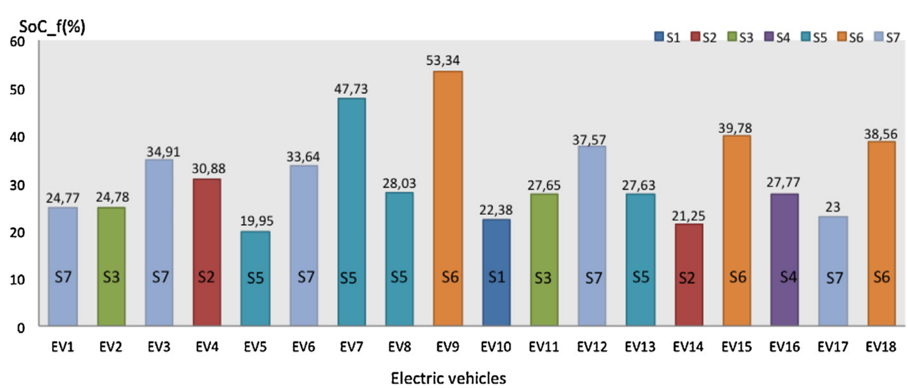

Fig. 4. Suggested CS for each EV and optimal value of its SOC_f.

Table 12
Suitable assignment for fast charging.

	Fast charging					
S_j	S1	S2		S3		S4
Nbre of authorized EV	1	2		2		2
Nbre of assigned EV	1	2		2		1
Assigned EV	EV_{10}	EV_4	EV_{14}	EV_2	VE_{11}	EV_{16}
SOC_f	22.37	30.88	21.25	24.78	27.65	27.77
SOC_{min}	20	20	20	20	20	20

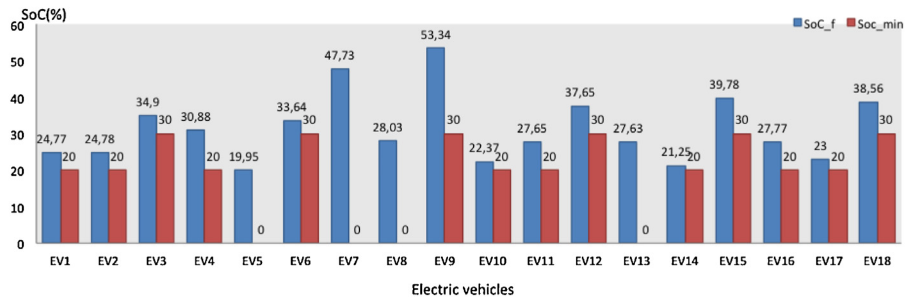

Fig. 5. A comparative study between optimal values of SOC_f and SOC_{min} for each vehicle EV_i.

Table 13
Suitable assignment for slow charging.

	Slow charging											
S_j	S5				S6			S7				
Nbre of authorized EV	4				3			5				
Nbre of Assigned EV	4				3			5				
Assigned EV	EV_5	EV_7	EV_8	EV_{13}	EV_9	EV_{15}	EV_{18}	EV_1	EV_3	EV_6	EV_{12}	EV_{17}
SOC_f	19.95	47.73	28.03	27.63	53.34	39.78	38.56	24.77	34.9	33.64	37.65	23
SOC_{min}	0	0	0	0	30	30	30	20	30	30	30	20

7. Conclusion

In this paper, we have addressed an optimization study and assignment management of a set of electric vehicles to charging stations. To do so, the problem is modeled by a linear program with a fixed objective to reach subject to a set of constraints. The proposed assignment takes into account the energy consumption of EV to reach a CS. An EV is suitably assigned when it consumes a minimum account of energy and the final SoC of its battery remains at a highest possible level when arriving the CS. The assignment problem is studied in two cases: charging system with homogeneous components and with heterogeneous components. For the homogeneous system, we give the optimal (or suitable) assignment in two cases: system working under normal and disturbed conditions. In disturbed conditions, we take into account the effect of road traffic, excessive use of electrical accessories of the vehicle, status of traveled itineraries. Under normal conditions the effect of these parameters on the energy consumption is neglected. A comparative study subject to the energy consumption for the two cases is carried out. By analyzing the obtained results, we remark that the energy consumption by EVs under normal conditions is less than the energy consumption under disturbed conditions. Consequently, the final SoC of EVs at charging stations under normal conditions is higher than the final SoC of EVs in disturbed conditions. Regarding heterogeneous system, we have presented the optimal assignment of EVs to CSs only in disturbed conditions. The proposed models allow to obtain optimal and suitable assignments while satisfying all problem constraints. Numerical examples are worked out to illustrate the proposed approach and the obtained results are reported and analyzed. These results show the effectiveness of the proposed approach.

As prospects of this study, we can consider to assign EVs to charging stations, not for charging, but also for discharging some unused energy into the grid. We talk about vehicle-to-grid energy flows or V2G flows. In this case, we will consider the batteries for energy storage. The stored energy into the EV batteries could then be reused in the CSs (grid) when the energy demand is upper than supply. Moreover, we will take into account the amount of energy to be unloaded by each vehicle. The main objective to be achieved being to ensure an energy stability in the grid when an imbalance occurs while keeping the normal operation of EVs. Finally, an economic analysis is more significant and may have an added value to this study. This is suitable in the future while performing real experimental tests.

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