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Development of an Algorithm to Control and Optimize the Charging Process of a Group of Electric Vehicles

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Development of an algorithm to Control and Optimize the Charging Process of a Group of Electric Vehicles

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Abstract

The increasing penetration of electric vehicles (EV) usage will require a control system to manage their recharging process. This work proposes the development of a locally decentralized EVs' charging algorithm, which controls and optimizes the charging process of a group of EVs, based on a binary sequence. In this work the proposed method and the development of the charging algorithm are respectively explained. Then, by simulating various scenarios the performance of the algorithm is assessed. The algorithm controls the charging process in a coordinated way and it was designed to be implemented in a local distribution grid, allowing to accommodate all the EVs without needing to reinforce the grid infrastructure capacity. It considers users' preferences, such as their desire state of charge, while takes their electricity tariffs into account. The optimization objective was set for the consumers, to minimize the deviation of the actual charging cost from the minimum charging cost. The integration of different EVs' charging patterns and various types of electricity tariffs, leads to a realistic approach. It was concluded that, through the proposed method, charging a greater number of EVs is feasible without needing to invest in increasing the capacity of the grid infrastructure, while the charging cost for each and every user is kept close to the minimum one.

Keywords: *electric vehicles; coordinated charging; decentralized control; optimization; evolutionary algorithm*

Resumo

O aumento crescente da utilização de veículos elétricos (VE) vem exigir, num futuro próximo, o uso de um sistema de controlo para gerir o seu recarregamento. Este trabalho propõe o desenvolvimento de um algoritmo de carregamento de veículos eléctricos, localmente descentralizado, que controla e optimiza o processo de carregamento de um grupo de EVs, baseando-se para tal numa sequência binária. Neste trabalho são descritos o método proposto e o algoritmo desenvolvido. O desempenho do algoritmo é avaliado através da simulação de vários cenários. O algoritmo controla o processo de carregamento de uma forma coordenada, e foi desenvolvido para ser implementado numa rede de distribuição local, permitindo acomodar todos os VEs sem a necessidade de reforçar a infra-estrutura de rede elétrica. As preferências dos utilizadores, como por exemplo, o estado de carga (state of charge) desejado, são tidas em consideração pelo algoritmo, assim como as suas tarifas de eletricidade. Em relação à optimização, a função objectivo foi definida para os consumidores, de modo a minimizar o desvio entre o custo efetivo de carregamento e o custo mínimo de carregamento. A integração de vários padrões de carregamento de VEs e de vários tipos de tarifas de eletricidade, permitem uma abordagem realista. Concluiu-se que, através do método proposto, é viável o carregamento de um número maior de VEs, sem a necessidade de investir no aumento da capacidade da rede, ao mesmo tempo que o custo de carregamento individual de cada VE é mantido próximo do valor mínimo.

Palavras-chave: *veículos eléctricos; carregamento coordenado; controlo descentralizado; optimização; algoritmo evolutivo*

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1 Introduction

The deployment of Electric vehicles (EVs) as an alternative to internal combustion engines, which are also able to be recharged at home or workplace will pose new challenges to electric power systems, grid operators, electricity suppliers and even consumers. According to Eurostat (2011) 60% of the total electricity consumption in European Union is due to buildings sector, which has already made the electricity demand in this sector a crucial issue. On the other hand, EVs in the near future may manifest themselves as new end-use loads, significantly contributing to pushing upwards the electricity demand in this sector.

The impacts of the increasing penetration of EVs, firstly will be felt at the level of the local distribution in electric power grids. The lack of infrastructure capacity may hinder the increasing number of EVs from simultaneously being charged. Therefore, the electric power grids can be subjected to several changes caused by the simultaneous charging of EVs' batteries, such as: *i)* creating undesirable peak demands; *ii)* overloading the distribution grid; *iii)* increasing stress on grid infrastructure, and *iv)* increasing power losses (Monteiro et al., 2012; Gan et al., 2013; Clement-nyns et al., 2010).

These problems are more of a concern when a large number of EVs are simultaneously connected to the electric power grid. Dealing with these problems and responding to such demand is more feasible and reliable, if a smart management system is employed. Therefore, the increasing number of EVs may strongly benefit from a control system to manage their recharging process.

Several studies demonstrate that "smart" charging strategies can not only mitigate some of the aforementioned problems but also stabilize the grid and defer new infrastructure investments, for instance, by scheduling EVs' charging periods to fill the valleys in electric load profile (Gan et al., 2013). However, due to lack of the capacity of local power transformers it may become difficult to accommodate the increasing number of EVs. This study proposes the development of a charging algorithm, which is able to control and optimize the charging process of a group of plugged-in EVs;

i) in a locally coordinated way,
ii) considering supplying the power through a unique Distribution Power Transformer,
iii) following the approach of "peak shaving",
iv) while keeping the charging costs for all consumers close to the minimum.

Therefore charging a greater number of EVs will be feasible without needing to invest in increasing the capacity of the grid infrastructure. To accomplish this, the algorithm considers the users' preferences, such as their desired state of charge (SOC), while takes every user's tariff scheme into consideration (i.e. different price structures/values and contracted power). In this study the optimization objectives are set for the consumers, minimizing the deviation from the minimum possible cost of charge, while considering the available power (power transformer capacity) and the individual contracted power values as constraints. It is worth mentioning that through presented method, by rationally using the available

capacity of the grid, a greater number of EVs can be charged simultaneously. In other words, improving the electricity market by selling it more. The main goal of this work is to develop a flexible algorithm, which may be used in scenarios with different electric grid characteristics, constraints and consumers' load profiles. The consideration of different alternatives, such as various charging patterns and dissimilar electricity tariffs leads to a more realistic simulation.

Smart grids are the key-enablers of future low-carbon electricity systems. They facilitate demand-side efficiency and enable the increasing number of renewable and distributed generation shares, as well as EVs. Furthermore, smart grids allow for the development of the internal energy market and security of networks, while maintaining availability for non-renewable generation (European Commission, 2011).

The management of EVs' charging process should be an automated process. Accordingly these type of algorithms can have different optimization objectives, depending on the stakeholders. Several entities might be interested in such autonomous management:

Distribution grid operator is interested in managing the charging actions to incorporate the maximum number of EVs without massively reinforcing the grid (Sundstrom and Binding, 2010);

Retailer is interested in balancing electricity purchase and sale in order to increase its profit in the electricity trading context;

Consumers are interested in minimizing the cost of charging and increasing the reliability of supply.

This work is structured as follows: the literature review is presented in the next chapter. The proposed method is introduced in chapter **III**. The function of the algorithm is described in chapter **IV**. In order to assess the proposed algorithm, different scenarios are simulated and results are given in chapter **V**. Finally chapter **VI** discusses and concludes the work.

2   State-of-the-Art

In this chapter, firstly an overview about Demand Side Management is presented. Afterwards the history of EVs from their invention to present is shortly described. And the last part, Charging Algorithms, the literature review of various similar works is presented.

2.1   Demand Side Management

Traditionally, supply is adjusted in real time to match the demand. However, in order to lower the energy use, consumers are encouraged to modify their demand through a strategy known as Demand Side Management (DSM) (Torriti, 2012). Some objectives of DSM are peak shaving, load shifting, and valley filling (Gellings and Smith, 1989). Demand response programs are one of the tools to achieve the desirable demand pattern changes (Inage, 2010), either by price-based programs, allowing consumers to voluntarily adjust their load based on electricity prices, or by incentive based programs, offering consumers monetary bonus to reduce their loads (Faria and Vale, 2011). DSM techniques have a wide range of benefits which lead not only to direct energy and economic savings but also to indirect savings due to an increased efficiency of the electric power system (Strbac, 2008).

Nevertheless, DSM tends to disturb the natural diversity of loads, and without some form of coordination, it may create some undesirable effects. Such effects become worsen with the presence of EVs. The electric power grid, hereafter simply designated by grid, can be subjected to several changes caused by the simultaneous charging of EVs' batteries, which includes creating unwanted peak demands, overloading the distribution grid (possibly leading to a blackout), exceeding stress on the grid infrastructure (reducing their lifespan), increasing power losses (contributing to the degradation of the electrical power quality) (Monteiro et al., 2012; Gan et al., 2013; Clement-nyns et al., 2010; Commission, 2000). Regular use of DSM techniques requires the ability to control devices, rescheduling the operation or continuing it during the interruptions.

The concept of smart grid brings new opportunities to DSM, allowing changing EVs' charging loads. For example, it allows for the interruption of charging process for short periods of time, changing the parametrization of the charging power (voltage and/or current) and turning several ongoing charging off or postponing their operation time (Hammerstrom et al., 2007). The installation of smart meters allows electricity suppliers to create innovative pricing schemes. This lets consumers, who typically tend to consume less when electricity prices are high (The et al., 2006), manage their electricity consumption in line with price movements.

Over the last decade several pricing schemes have been proposed. The most notable are *i)* real-time (RT) pricing, *ii)* time-of-use (TOU), and *iii)* in critical peak (CP). RT pricing considers the day divided into contiguous blocks of hours. In this scheme, the price of electricity varies among different blocks, reaching its highest point around peak hours. TOU is similar to RT, but the day is divided into a relatively small number of blocks. In CP pricing, the price may vary hourly as it is tied to the real electricity market cost and is not known in advance, requiring price signals from the supplier to the smart meter (Newsham and Bowker,

2010). Implementing a RT scheme would require the installation of automated metering and a communication infrastructure, as well as regulatory changes. However, the potential savings from peak reduction covers the installation costs (Ilic et al., 2002). On the other hand, implementing a TOU scheme would not require a complex two-way communication system, simplifying information and communication technologies (ICT) and data management issues.

2.2 Electric Vehicles

In this section a brief review about the history of EVs is presented, to clearly determine where EVs took place in the past and why lots of attention have recently given to such vehicles as a transport system.

2.2.1 Early Years

The history of EVs began in the mid-19th century, although it is uncertain who invented the very first EV (Wikipedia, 2014). In 1828, *Ányos Jedlik*, created a small model car powered by a type of electric motor that was earlier invented by him. In 1835, professor *Sibrandus Stratingh* with his assistant *Christopher Becker* created a small-scale electric car, powered by non-rechargeable battery (University of Groningen, 2013).

In 1859, a French physicist, *Gaston Planté*, invented a lead-acid battery. That battery was the first generation of rechargeable batteries. Afterwards, in 1881, another French scientist, *Camille Alphonse Faure* significantly improved the design of the battery. His improvements greatly increased the capacity of such batteries. Since then, due to the invention of rechargeable batteries, which had made the EVs possible, they became more popular in markets and manufactures were persuaded to develop EV's technologies.
In the United States of America, the first electric car, capable of reaching a speed of 23 km/h, was built in 1890. By that point, Europeans had been using of electric tricycles, bicycles, and cars for almost 15 years. France and the United Kingdom were the first nations to support the widespread development of EV (Bellis, 2006). It is worth mentioning that at the beginning of the 20th century, 38 percent of American automobiles were powered by electricity, where 33,842 EV were registered in the United States at that moment. America became the country where EV had gained the most acceptance (Cromer and Foster, 2013).

By 1920, due to following reasons, EVs began to lose their position in markets:
i) at that point, countries had a better system of roads, bringing the need for vehicles with a greater range than that offered by electric cars;
ii) worldwide discoveries led to the wide availability of affordable gasoline, making internal combustion engine cars cheaper to operate over long distances (Wikipedia, 2014);
iii) The invention of the electric starter for starting a gasoline engine by *Charles Kettering* in 1912, gas-powered vehicles became ever easier to operate;
iv) by the use of muffler, which had been invented by *Hiram Percy Maxim* in 1897, the noise emitted by gas-powered vehicles became more bearable;
v) and finally, the mass production of combustion engine vehicles by *Henry Ford* with the

price about half of the electric one. Due to these reasons, EVs declined their popularity so that they had totally disappeared by 1935 (Bellis, 2006). The years following until the 1960s the development of EVs had shut down.

The energy crises of the 70s and 80s, the environmental impact of the petroleum-based transportation infrastructure, and the need to reduce the dependency on imported foreign crude oil (in Oil-importer countries), all together brought a renewed attention to the electric transportation infrastructure. Therefore, numerous experimenters began to work on EVs and their batteries technologies (Cromer and Foster, 2013).

2.2.2 90s to present

Since 1995 several legislation and regulatory actions in the United States and worldwide renewed the electric vehicle development efforts (Bellis, 2006). Moreover, the global economic recession in the late 2000s led to increased requests from automakers to abandon fuel-inefficient cars and instead focus on the development of hybrid and electric vehicles technologies. Therefore, various known manufacturers such as Honda, Toyota, Nissan and General Motors had started to develop related technology of such vehicles and improve their performance.

As a result *Toyota RAV4*, *General Motors EV1* and *Honda EV Plus* were the products of their efforts. At that point, EVs satisfied the driving requirements, however, in comparison with gasoline-powered vehicles they were still expensive. The mass production and improvements in the manufacturing process later reduced prices competitive to gasoline-powered vehicles (Bellis, 2006). Tesla Motors, the pioneer American plug-in EV manufacturer had released the *Tesla Roadster* in 2008. The *Roadster* was the first EV powered by a lithium-ion battery, highway-capable all-electric along with a remarkable mileage about 320 km per charge.

2.3 Charging Algorithms

The impact of a high penetration of EVs on the grid is currently an active area of research. In Clement-nyns et al. (2010), the power losses and voltage deviation are analysed for a local distribution grid by considering an uncoordinated charging process which starts randomly, either when EVs are plugged-in or after a fixed delay. The authors concluded that this charging process can lead to grid problems and therefore they proposed a coordinated charging to minimize the power losses and maximize the main grid load factor, by considering smart meters sending signals to each and every EV. They demonstrated that if a coordinated charging system is used, less grid reinforcement is required, the maximum load is lower, while the power losses are reduced, and the power quality is improved to a level similar to a case where EVs are excluded. However, the implementation of such charging mechanism can be costly for both the distribution system operator (DSO) and consumers.

Different approaches have been suggested to help dealing with these impacts, such as controlling and/or coordinating the EVs' charging process, or regulating the required power according to the grid capabilities and constraints (Monteiro et al., 2012). Several studies demonstrate that "smart" charging strategies can not only mitigate some of the aforemen-

tioned problems but also stabilize the grid and defer new infrastructure investments, for instance, by scheduling EVs' charging periods to fill the valleys in electric load profile (Gan et al., 2013).

Coordination strategies can be divided into centralized and decentralized strategies (Deh-Chang Wei and Nanming Chen, 1995). In centralized strategies, a central operator dictates precisely the rate and length of charging to each and every EV. Decisions can be made according to system-level consideration and/or vehicle-level preferences, as for instance the desired charging periods (intervals) or the final state of charge (SOC). Decentralized strategies are more flexible. For example, decisions can be made according to electricity prices (time of use or critical peak pricing) or every user may be able to determine its own charging pattern.

Ahn et al. (2011) presented a sub-optimal decentralized charging control algorithm for the EVs connected to a smart grid with the aim of reducing the power generation cost and the carbon dioxide emissions. Their controller is a function of a number of factors, including the estimated numbers of EVs and their plug-in and off times, the estimated SOC of their battery, and the predicted total power demand to charge all the batteries within a specific period of time. The method focuses on load shifting and valley filling: the charging process starts as soon as the valley period begins, when the base demand curve decreases. The charging process will be finished by the end of the valley period. In their approach, only one type of EV charging profile is considered, and user's preferences are completely out of concern. The authors concluded that the electricity generation cost can be reduced. However, the cost-effectiveness of the charging process from the users' point of view was not explained. Furthermore, due to the fact that batteries with higher input power can be charged faster, the developed algorithm probably does not fairly distribute the electricity among users, a key issue in these algorithms.

Ma et al. (2013) employed the concept of non-cooperative games in order to coordinate the decentralized charging of a number of independent plugged-in EVs. The authors assumed that the supply and base loads (non-plugged-in EVs' load) are perfectly predictable, and EVs are weakly coupled via a common electricity price which is determined by the average charging strategy of the plugged-in EVs population. The goal of the optimization was to minimize the total cost of charge. The authors only considered a fully charging criterion as users' preferences. They showed that, under certain mild conditions, the large population charging games will converge to a unique Nash Equilibrium which is optimal only for homogeneous populations. Due do this fact, the method may not be flexible and applicable to a heterogeneous population, where there are different types of EVs.

Several concepts have been proposed for charging management using price-based methods. Cao et al. (2012) proposed an optimized model for EV charging facilities (charger), responding to a TOU electricity price, for charging a group of EVs, considering SOC curves. The authors assumed that the starting time of charging obeys a daily Normal Distribution. They concluded that, from the user's point of view, the obtained charging pattern can bring a significant reduction in the charging cost for each and every EV. However, they did not explicitly present information about the communication process between the EVs' charger and the aggregated system operator in a case with not enough power responding to the

demand side. Moreover, they did not consider a scenario in which there is not enough available power to satisfy the requested SOC within low electricity rates moments, what decision would be taken to plan the charging process.

In another work (Sundstrom and Binding, 2010), a method with the focus on proposing a novel algorithm to perform the charging process of a large EV fleets is described. The algorithm is called grid-aware price-based algorithm, where the grid constraints (i.e. transformer capacity) were taken into consideration. It was assumed that there was a centralized EV aggregator that can act on the power market and use financial instruments to, for example, minimize the cost of charging the EVs. The electricity grid was simulated using a conventional load flow simulation and the grid model was based on the grid on the Danish island of Bornholm. The algorithm was applied to plan the charging of an EV fleet with 3500 commuter vehicles driving over the simulated grid. The authors assumed that EVs could be charged at workplace and also at home. It was shown that through the proposed algorithm the overloading in the grid was significantly reduced (due to grid constraints). However, from the users' point of view they did not demonstrate, results about the total charging cost, whether the charging cost for each and every user were reduced or not, or if the overall charging cost was decreased or not. Only one type of EV with unclear battery capacity was used and also only one type of electricity tariff was considered for all the users.

Mareels et al. (2014) proposed a method to manage the EVs charging process. Charging decisions are made individually for every household, without any access to full network state. The decision is taken in real time, using both instantaneous and historical local voltage measurements to estimate the present network load. The main goal was to maximally use of the grid capacity at any time, while ensuring about the fairness of charging for all the users (fairly demand responds for all the users).

As earlier mentioned there are two approaches in terms of charging problems from the demand side. One is to manage the EVs' charging process in a centralized way, where an aggregator communicates with every EV and dictates a suitable charging profile for every vehicle based on global information (Richardson et al., 2012). The other, which also Mareels et al. employed in their work, is the decentralized approach, in which every EV charger can calculate its own charging profile in a distributed manner. The centralized approach requires all agents to participate in decision making process and this requires a large communication and computational cost where the network size is also large. The second approach is less-complex and less costly, but also less effective if limited information is used in the procedure.

Mareels et al. (2014) assumed that each EV's charger has a digital controller installed able to read local voltages, battery SOC and performs calculations to give charging instructions. The authors presented three different scenarios: *i)* the aggregator with no control over the grid; *ii)* an implementation of their algorithm where an aggregator has perfect knowledge about how much spare capacity the grid has and how many EVs are plugged-in; *iii)* and implementation of their algorithm where only local information are available for every EV. By simulating an actual distribution network they had shown that, for the third scenario, even

with a high penetration rate of EV, the algorithm successfully mitigates the peak demand and fairly satisfies the users' requested SOC without breaking any grid constraint. Even though, as they also mentioned, the performance was not as efficient as a centralized solution. They did not explicitly present information about the EV's battery capacity and it was not clear whether they had used only one type of EV or more. Furthermore, they only assumed the power transformer capacity as a constraint and they did not talk about the charging cost. However, their main goal was to maximally use the grid capacity at any time, slightly different from this project.

In another work (Ahmad and Othman, 2014) an optimal charging strategy for plugged-in hybrid EV using Evolutionary Algorithm is presented. The paper describes three methods to charge the plugged-in hybrid EVs: price-based charging, load-based charging and SOC-based charging. Evolutionary programming (EP) is used to optimize the charging rate and SOC, thus minimizing the charging cost. The charging cost is calculated based on real time electricity price (i.e. the day ahead information).
Only one type of EV is considered while no constraints is taken into account. The authors assumed a scenario in which it is possible to change the battery charging input power while it is undercharge. They did not mention what would be the effect of changing the charging rate on the battery performance or on its lifespan. They had shown for load-based and price-based charging methods, when the base load or electricity price is high the given charging rate is low and vice-versa. They showed 20 different possibilities of daily charging rate (different charging profiles).
However, they did not explicitly present what is the minimum cost and how much is the charging cost in scenario in which the proposed algorithm is not employed. Moreover, according to the available information, the charging duration that can be done in dump-charging scenario is 7 hours, whereas through their proposed method it takes about 12 hours that is too long from users' point of view.

Table 2.1 briefly describes the reviewed works of this chapter.

Table 2.1: Summary of the reviewed works: Clemente-nyns et al., 2010 (a); Ahn et al., 2011 (b); Ma et al., 2013 (c); Sundstrom and Binding, 2010 (d); Mareels et al., 2014, (e); Ahmad and Othman, 2014, (f)

Ref.	Method	Goal	Constraints	Results	Disadvantages
a)	Coordinated charging, centralized, considering smart meters, charging at home	Minimizing the power losses and maximizing the main grid load factor	Not mentioned	Less grid reinforcement was required, the maximum load and the power losses were decreased and the power quality was improved	High cost of implementation, electricity tariff was not considered in corresponding the charging's cost
b)	Decentralized charging control, considering a smart grid, load shifting, valley filling	Reducing the power generation cost and carbon dioxide emissions	Was considered	It was shown that the electricity generation cost can be reduced	The electricity was not fairly distributed among all the users, the users' preferences were not taken into consideration
c)	Coordinated charging, decentralized, EVs are weakly coupled via the electricity price signals, non-cooperative game based	Minimizing the total charging cost	Was considered	The charging cost was decreased for the case homogeneous population	The method may not be applicable to a heterogeneous population (various type of EV), different electricity structures were not considered, one type of EV was assumed, it is not flexible to use in different scenarios
d)	Coordinated charging via a centralized EV aggregator, charging at home and workplace	Performing the charging process of a large EV fleets, reducing the charging cost	Power Transformer Capacity	Reducing the overloading in the grid	Only one type of EV was considered, it is not clear if the charging cost was reduced or not, and one type of electricity tariff was considered for all the users
e)	An aggregator was assumed, decentralized, instant decision is taken for every user separately, less demand of communication	Maximally using the grid capacity at any time, to satisfy the users' request	The Power Transformer Capacity	Preventing overloading in the grid	It was not mentioned if the charging cost was reduced or not, it is not flexible to use in different scenarios and one type of EV was considered
f)	Coordinated decentralized charging, regulating the power of the charger, evolutionary programming	Reducing the charging cost	The available power at every moment of the charging process	At pick moments and high electricity rates the charging rate was low, the cost of charge was reduced	Long duration of the charging process (12 hours), it was not shown how much the charging cost was reduced, only one type of electricity structure and EV were considered

3 Methodology

As earlier mentioned, the goal of this work was to develop a locally centralized algorithm which is able to control and optimize the charging process of a group of independent EVs. For each and every user, the electricity price scheme and their requested SOC are taken into consideration. This process is subject to two constraints: *i)* the available power at level of the distribution grid (the local power transformer capacity); and *ii)* the contracted power of every consumer which depends on the supplier's services. In this chapter the mathematical model and the fundamental principles of the work are described.

Theoretically, in an uncoordinated charging system, the probability of all the EVs being charged at the same time may be higher, in comparison to a coordinated system. Indeed, due to taking advantage of electricity price during off-peak periods, consumers plug-in their EVs at the same time where there is no controller to adjust them. However, due to grid constraints (i.e. the distribution power transformer available capacity) it is not possible to simultaneously charge all the EVs at the maximum power rate. Therefore, this section introduces a framework to simultaneously charge a group of EVs in a coordinated system.

In such coordinated system, an aggregator controls the charging process, taking into consideration the periods of lowest electricity price of every consumer while avoiding to overload the transformer capacity. As a consequence, a higher number of EVs can be charged during the periods in which electricity rate is low. Therefore, the optimization objectives in this work are set for consumers, minimizing the deviation from the minimum possible charging cost of all the members in a coordinated charging system. Moreover, indirectly, for the Distribution Grid Operator, maximizing the number of EVs being charged simultaneously. In the following paragraphs assumptions and the foundation of the method are presented.

Nowadays, most of the embedded batteries in EVs are advanced Lithium-ion, Lead-Acid or Nickel-Metal hydride. Fortunately, EVs are controllable loads and therefore their charging process can be interrupted without any memory effects on some types of them (Clement-nyns et al., 2010). This flexibility makes it possible to manipulate EV's charging process. In this study two different types of EVs, with different demand characteristics are considered. This involves different battery capacities and EV's mileages (the consumed energy to drive one kilometre). For simplicity, it is considered that Lead-Acid batteries have also no memory effects caused by interrupting the charging process. Figure 3.1 illustrates the charging profile of these two EVs: Nissan is equipped with Lithium-ion battery (29 kWh capacity) and GM1 with Lead-Acid (27 kWh capacity) (Madrid et al., 1999; Mendoza and Argueta, 2000).

For both, it is remarkable that the charging rates steep rise in power demand in the beginning of the process and a sharp decline for Nissan at the end. The charging profile of these two EVs, from empty state to fully charged, were obtained by fitting curves to experimental data, available in the literature (Madrid et al., 1999; Mendoza and Argueta, 2000).

The total charging length of every EV is split into time-slots of one minute, t, (e.g., if a fully charging process takes 5 hours, the number of intervals of charge are 300, ($t = 300$)). For instance, the charging function for an EV equipped with a Lithium-ion battery (Nissan)
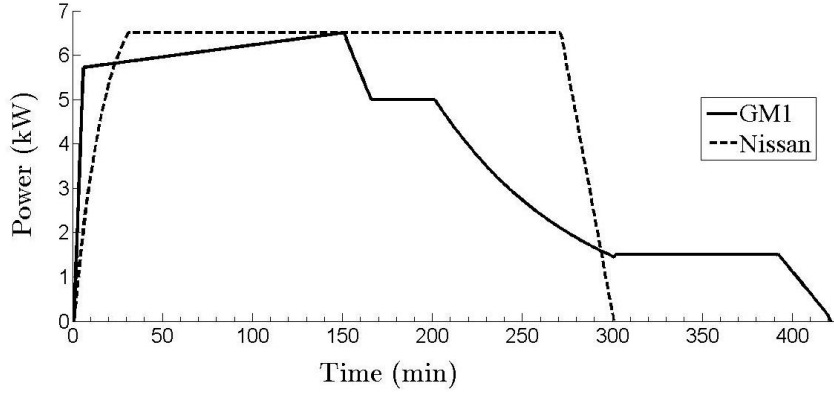
Figure 3.1: The charging profile for two different EVs, starting from empty state to fully charged

is written according to equation (1).

$$
P_i(t) = \begin{cases}
-7.80 \times e^{0.06t} & 0 < t \le 30 \\
6.60 & 30 < t \le 270 \\
-0.22 \times t + 66.26 & 270 < t < 300
\end{cases} \tag{1}
$$

Through equation (1) the demanding power to charge the embedded battery in Nissan, $P_i(t)$, is known at every moment, t, for each and every user i. Equation (2) also demonstrates the demanding power to charge the GM1's battery, $P_i(t)$, for every minute of its charging process from empty state to fully charged.

$$
P_i(t) = \begin{cases}
1.140 \times t + 0.013 & 0 < t \le 5 \\
0.005 \times t + 5.700 & 5 < t \le 150 \\
-0.098 \times t + 21.2 & 150 < t \le 165 \\
5 & 165 < t \le 200 \\
60.270 \times e^{-0.012 \times t} & 200 < t \le 300 \\
1.5 & 300 < t \le 390 \\
-0.049 \times t + 20.990 & 390 < t < 420
\end{cases} \tag{2}
$$

The general charging period is considered to be from 18:00 to 0'9:00 of the next day (15 hours). This period is also split in one minute intervals, j, meaning when the charging process is started at 18:00, $j = 1$, and when the process is finished at 8:59, $j = 900$. For every user, i, at interval, j, according to their charging patterns a constant input power, $P_i(t)$, or zero will be assigned. To accomplish this, a decision variable, $\lambda_{(i,j)}$, is defined, indicating whether the charger must be connected (assigned with the value 1) or disconnected (assigned with the value 0).

The total charging time of an EV depends on its initial SOC. The relation between the batteries' cycle charging time (t) and the planning time (j) is as follows:
t_s is the period of the time corresponding to the initial SOC of the battery, meaning that for an EV at the beginning of its charging process $t = t_s$. When the battery is charging, t increases and its charging's time can be computed as $t = t_s + \sum_{k=1}^{j} \lambda_{(i,k)}$.

To generate the charging plan (i.e a matrix containing 0's and 1's) for all the members

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(EVs), the decisions are taken according to the following aspects:

- The **Total Available Power**, the available power at interval j, TAP_j;

- The **user's Available Power**, at the moment j, regarding it's contracted power, $AP_{i,j}$;

- The users' **Electricity Cost rates**, $EC_{i,j}$;

- The **requested Power at the moment** j from the EV_i according to its battery charging's profile, $P_i(t)$.

In following, equations from (3) to (6) translate the described method into its mathematical form. Equation (3) shows the total available power for every instant j of the charging process:

$$TAP_j = PTC - \sum_{i=1}^{n} BL_j \tag{3}$$

The total available power, TAP_j, at every moment j equals the power transformer capacity, PTC, minus the summation of all the base loads, $\sum_{i=1}^{n} BL_j$, at the moment j. In addition, through equation (4) the available power of user i regarding its contracted power, CP_i, is known for every moment j:

$$AP_{i,j} = CP_i - BL_{i,j} \tag{4}$$

Moreover, as earlier mentioned the decision variable, $\lambda_{i,j}$, for user i at the moment j, can be either 1 or 0. Equation (5) shows the amount of input power of charge, $P_{i,j}$, for user i at the moment j. It can be a positive number, $P_{i,t}$, or zero.

$$P_{i,j} = \lambda_{i,j} \times P_{i,t} \tag{5}$$

According to the aforementioned statements, the pattern of the charging process for each and every EV will be separately generated, meaning that for each EV will be assigned a vector of charging plan consisting of time slots j, containing the binary sequence of 0's and 1's, $\lambda_{i,j}$. These binary sequences show at the moment j, what decision was taken, then what is the input power of charger of the EV_i, $P_{i,j}$.
In short, the algorithm for every EV spreads the binary sequence out in such a way that the load's intervals of all the EVs are adjusted to fill the valleys of their base load profiles. It must be mentioned that the scheduling will be updated each time an EV is added to or subtracted from the group.

Two different electricity pricing schemes are considered for each user: real time pricing with three different prices (blocks of hours) and Time of Use scheme varying hourly. These schemes are one of the most significant factors affecting the results of the study. In figure 3.2 two different tariffs are illustrated from 06:00 pm to 09:00 am. It is assumed that the households' base load are perfectly predictable and the algorithm will be implemented in low voltage distribution grids with different characteristics. Different values of contracted power, as individual constraint, are considered for every household.

In terms of optimization, as highlighted earlier, the objectives are set to minimize the deviation of the actual charging cost from the minimum charging cost (MinCost), for all n
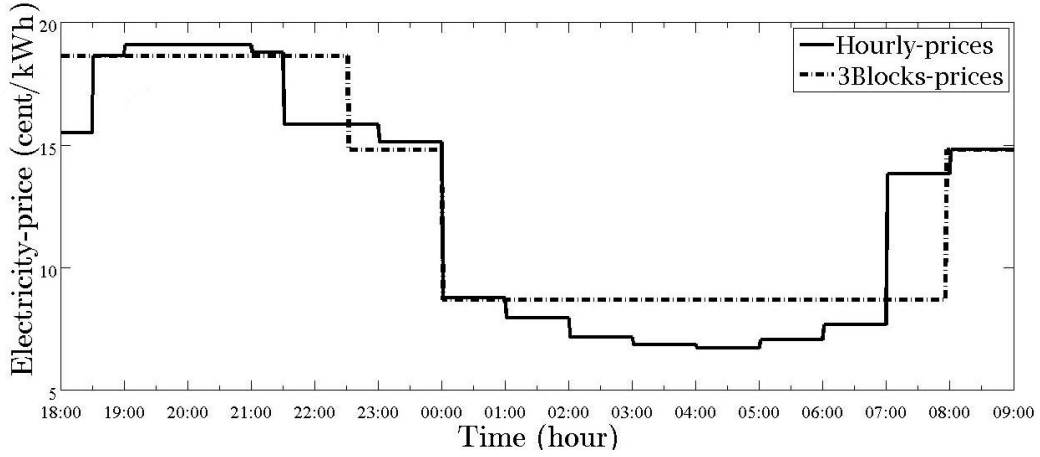
Figure 3.2: Two different Electricity rates cost, from 18:00 to 09:00 of the next day(15 hours)

users, as well as to minimize the maximum individual cost deviation, according to equation (6):

$$min\bigg[\alpha\bigg(\sum_{i=1}^{n}\bigg[\sum_{j=1}^{900}EC_{i,j}\times P_{i,j}\times\Delta t\bigg]-MinCost\bigg)+\beta\bigg(max_{\forall i}\bigg(\bigg(\sum_{j=1}^{900}EC_{i,j}\times P_{i,j}\times\Delta t\bigg)-cost(i)\bigg)\bigg)\bigg)\bigg]$$
(6)

Where Δt is equal to $\frac{1}{60}hour$ (one minute), $EC_{i,j}$ is the electricity rate of user i at the moment j regarding its tariff scheme, and $cost(i)$ is the minimum possible cost of charge for the user i. In addition, α and β are weighting factors, allowing to compare the two different objective functions. Moreover, they allow users to change the level of importance of each one of two objective functions, depending on the decision maker's goal.

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4   Charging Algorithm Design

In this chapter the implemented algorithm is briefly presented. Due to the combinatorial nature of the problem and the size of the search space, an Evolutionary Algorithm (EA) is implemented to resolve the optimization problem. Figure 4.1 represents the flowchart of the algorithm. The process is started by generating a population with a certain size (parents) and in every iteration the algorithm searches among the search space to find the best possible solution. Below the different parts of the algorithm are briefly described.
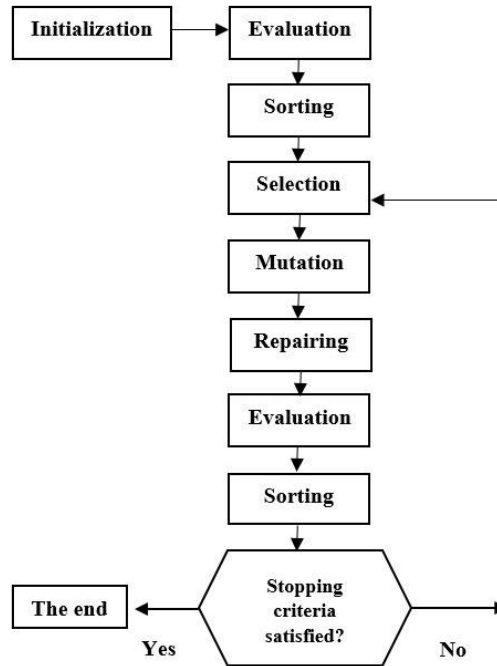

Figure 4.1: Flowchart of the algorithm

a) **Evaluation and Sorting:** the initial population is generated randomly, containing 0's and 1's. Like other EAs, the algorithm is characterized by competition among individuals, so that some of them are selected based on their fitness for contributing to the next generation. The fitness represents the quality of each element in the population and thus the selection of offspring which are going to contribute to the next generation is also done according to it. In this problem the fitness addresses both the total and individual charging costs.

b) **Selection and Mutation:** a mutation operator is used as a way to discover new solutions. In order to improve the efficacy of the algorithm and to avoid random walk through the search space, the mutation operator works with available information about the environment, such as the users' electricity tariffs. The dynamic behaviour of this operator, allows the algorithm to search in regions of the search space in which more interesting solutions can be found. As the alphabet used in the construction of the chromosomes is a binary one, two kinds of mutation are considered:

$m\_0 \longrightarrow 1$: value "1" indicates that the EV is being charged (mutation from 0 to 1)

$m\_1 \longrightarrow 0$: value "0" means that the EV's charger is off (mutation from 1 to 0).

c) **Repairing:** after creating the new generation, the genetic material of individuals will be repaired according to the considered constraints. In this work, as earlier mentioned,

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due to limited power transformer capacity, the aggregated load at every time slot j, must be equal or less than the transformer capacity. The constraints are applied in such a way that when at a given time j there is not enough available power, the algorithm chooses one or more users to shut its/their charging process off until the total load becomes equal or less than the transformer capacity.

Since all the users could fairly benefit from charging their EVs at times when the electricity rates are low, the decision to turn the EVs' charging operation off is taken according to the difference between users' requested SOC and the instant SOC. In this way, the operations with a lower difference will be chosen to be turned off. Therefore, by turning off some chargers at some moments, the EVs' charging profiles will be affected by this change. To overcome this undesirable effect, another action, called repairing phase, is considered. The algorithm tries to find EVs, which are not fully charged and identifies, among the total available profile, moments in which both, the electricity rate is low and there is enough available capacity to respond to the requested power by the EVs' charger at that moments. This operation may also change the EVs' charging profiles. Therefore all charging profiles will be arranged at the end of this phase. After applying the constraints, individuals will be evaluated and sorted according to their fitness. This process continues until the optimum answer is achieved.

d) **Stopping condition:** two stop conditions are defined. The process of searching among the search space will stop either when the optimum answer is reached or the maximum number of iterations has been completed.

5 Simulation, Results & Analysis

To asses the described method and the performance of the algorithm, in this chapter different scenarios are described and then compared. It is assumed that the households' base load are perfectly predictable. Moreover, as earlier mentioned, different electricity tariff schemes (i.e. different price structures/values and contracted power) for each user is considered. Due to the maximum chargers output (6.5 kW), it is considered that for houses equipped with the EV's charger, 8.05 kW or 9.20 kW are the contracted power. These values have been chosen since: *i)* it had been considered that the method can be employed in other regions and countries, with various base load profiles and policies; *ii)* and to have a harder case from the algorithm's point of view, regarding the individual constraint. In following, different scenarios are described and an analysis for each one is presented. All simulations have been done using the MATLAB software through the Windows 7 Professional, Service Pack 1, installed in a computer with the following specifications: 32 GB installed memory (RAM) and Intell(R) core(TM) i7 - 3.20 GHz as processor.

Scenario 1: A neighbourhood with 120 houses is considered. It is assumed that 40 households, each one, drive an EV (Nissan or GM1). It is considered that these 120 houses are fed via a unique power transformer with the maximum capacity of 250 kW. It is assumed that all the EVs' batteries are completely empty and 100% of SOC requested. Figure 5.1 illustrates the base load of 120 houses along with 40 EVs' charging profiles in case there is no controller. It was assumed that users tried to take advantage of low electricity rates' time
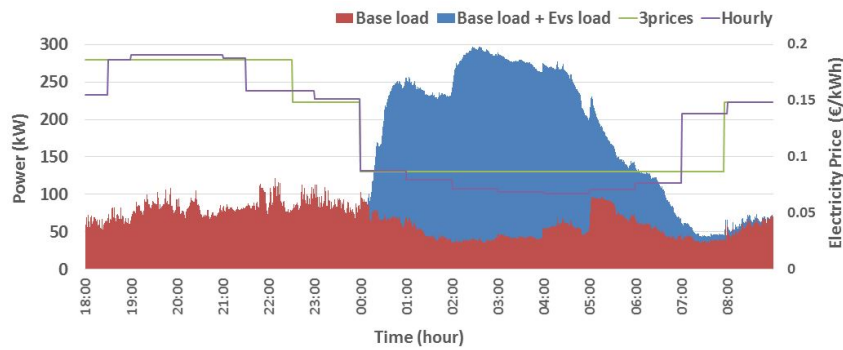
and charged their EVs at these moments.

Figure 5.1: Integrated load profile (120 houses + 40 EVs), not applying the algorithm, *Scenario1*

According to figure 5.1, the EVs' charging profile took place at moments where the electricity rates are low (regarding users' electricity tariffs) however, a higher transformer capacity is necessary to respond to the demand, maximum load = 295 kW (overloading transformer capacity). In this scenario the total charging cost is about 92 €.
In the second situation, all the parameters are kept constant, but the algorithm is employed to accommodate the EVs' charging loads. Figure 5.2 illustrates the result of the implementation.
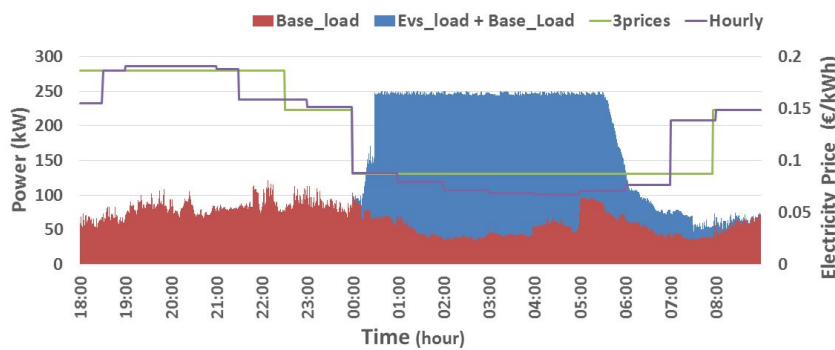

Figure 5.2: Integrated load profile (120 houses + 40 EVs), *Scenario1*

According to figure 5.2, the EVs' charging loads took place at moments where: ***i)*** the electricity rates are low (regarding users' electricity tariffs); ***ii)*** there are available capacity in terms of power transformer capacity; and ***iii)*** where there are also enough available power regarding the every user's contracted power and their base load. In this case the total charging cost is calculated 93€, while the integrated load never exceed the power transformer capacity. 5 iterations have been done to obtain the best solution, where it took 748 seconds corresponding the computational time.

Figure 5.3 shows the individual load profile of *user23*, without applying the algorithm. As it is shown, around 01:00 am, the total load can exceed the contracted power.

Figure 5.4 illustrates the load profile of *user23* when the algorithm is employed to ac-
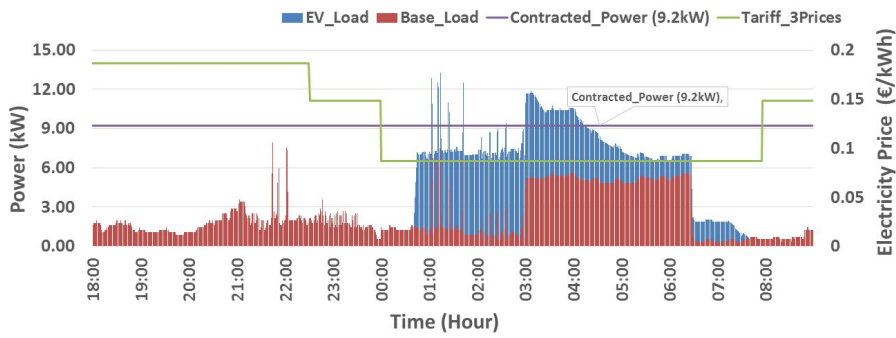
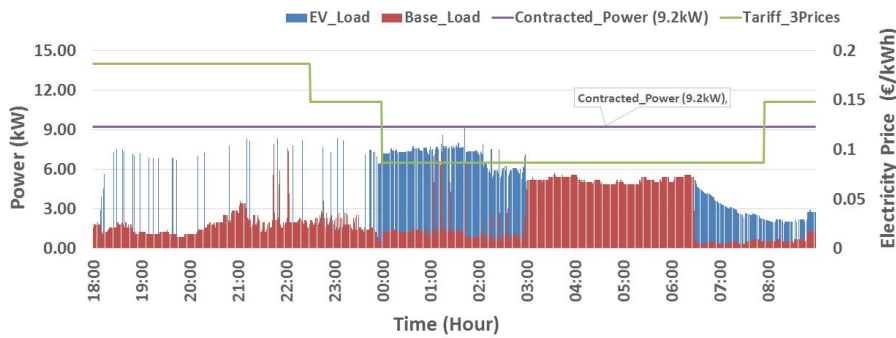Figure 5.3: Integrated load profile of *user23*, not applying the algorithm
.

Figure 5.4: Integrated load profile of *user23*
.

commodate the EVs' charging load. The algorithm generated the charging plan, avoiding to exceed the individual constraint (i.e contracted power). The charging process took place at moments when the electricity rates is low and there is enough available power to charge the battery regarding its demand.

Scenario 2: In this scenario a neighbourhood with 120 houses is considered. This time it is assumed that 50 households are EVs' users (Nissan or GM1). It is considered that these houses are fed via a unique power transformer with the maximum capacity of 250 kW, the EVs' batteries are completely empty and 100% of SOC were requested. Figure 5.5 illustrates the base load of 120 houses plus 50 EVs' charging profiles when the control algorithm is not applied.
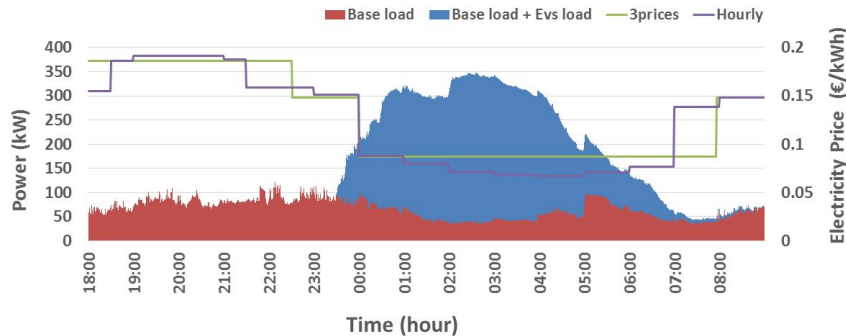

Figure 5.5: Integrated load profile (120 houses + 50 EVs), not applying the algorithm, *Scenario2*

According to figure 5.5, the EVs' charging profile took place at moments where electricity rates are low (regarding users' electricity tariffs), but a higher transformer capacity is necessary, since the maximum load is 350 kW (overloading transformer capacity). In this scenario the total charging cost is calculated about 117 €.

In the second situation, all the parameters are kept constant, but the algorithm is employed to accommodate the EVs' charging loads. Figure 5.6 illustrates the result of the implementation the algorithm in this scenario.
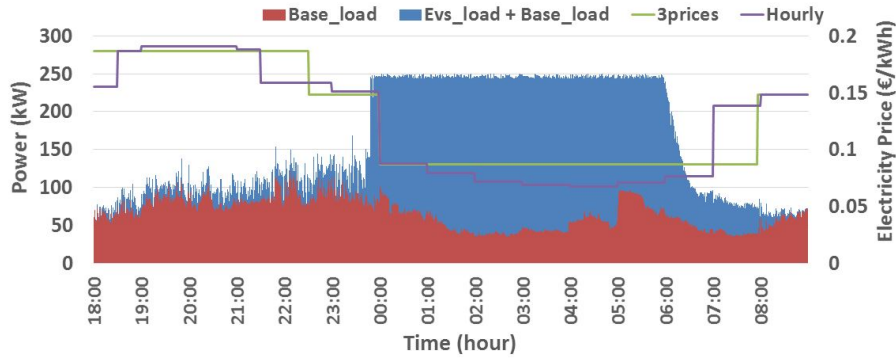

Figure 5.6: Integrated load profile (120 houses + 50 EVs), *Scenario2*

According to figure 5.6, the EVs' charging loads took place at moments where: ***i)*** the electricity rates are low (regarding users' electricity tariffs); and ***ii)*** there is available capacity in terms of power transformer capacity. In this case the total charging cost is calculated 128 €. The integrated load never exceed the power transformer capacity.

Scenario 3: It is assumed that 60 households are EVs' users (Nissan or GM1). The power transformer capacity is 250 kW. All the batteries are completely empty and 100% of SOC are requested. Figure 5.7 illustrates the base load of 120 houses plus 60 EVs' charging profiles for the case without the implementation of the algorithm.
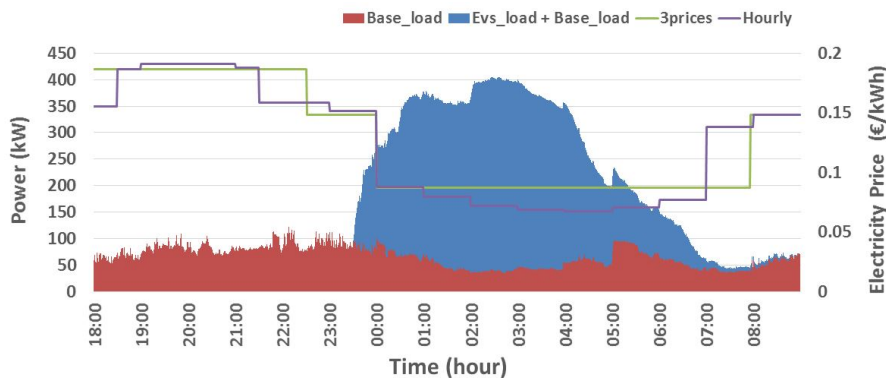

Figure 5.7: Integrated load profile (120 houses + 60 EVs), not applying the algorithm, *Scenario3*

According to figure 5.7, the EVs' charging profile took place at moments where the electricity rates are low (regarding users' electricity tariffs), but a higher transformer capacity

is necessary, since the maximum load is 405 kW (overloading transformer capacity). In this scenario the total charging cost is about 143€.

Regarding the second situation, in which the algorithm is employed to accommodate the EVs' charging loads, figure 5.8 illustrates the result of the implementation.
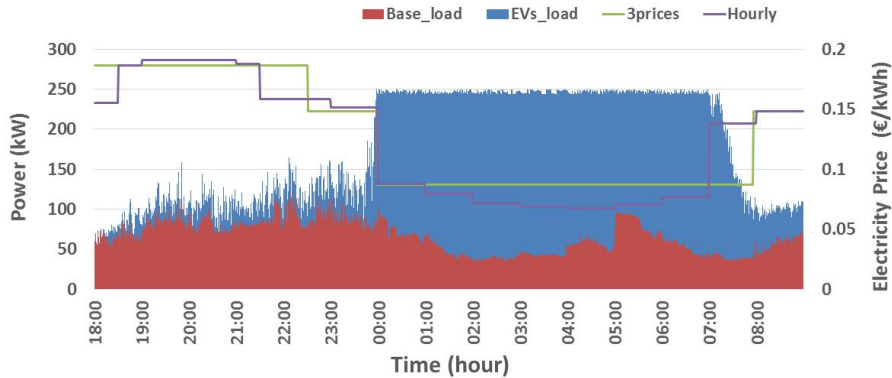

Figure 5.8: Integrated load profile (120 houses + 60 EVs), *Scenario3*

According to figure 5.8, the EVs' charging loads took place at moments: **i)** when the electricity rates are low (regarding users' electricity tariffs); **ii)** and where there are available capacity in terms of power transformer capacity. In this case the total charging cost is calculated 155 € and the integrated load never exceeded the power transformer capacity. The results for this scenario were obtained after 10 iterations and the total computational time was 5536 seconds. It is worth mentioning that around 90% of this time was taken by the repairing part of the algorithm. As earlier was highlighted, in chapter 4, one way to deal with none feasible solutions, in EAs, is repairing them.

It has been shown that, in the cases where there are no controller, the peak load increases with the number of EVs to be charged. Moreover, it can be concluded that by increasing the number of EVs to the grid the computational time also increase. For the considered scenarios, table 5.1 compares the total charging cost for the cases where the algorithm was and was not employed to plan the charging process of the EVs.

Table 5.1: Comparison of the different scenarios

Scenario	The Number of EVs	Peak Load (kW)	Total Cost of Charge (€)	$\bar{x}$	σ
Scenario 1, no controller	40	295	92	–	–
Scenario 1, method employed	40	250	93	0.020	0.019
Scenario 2, no controller	50	350	117	–	–
Scenario 2, method employed	50	250	128	0.24	0.11
Scenario 3, no controller	60	405	143	–	–
Scenario 3, method employed	60	250	156	0.24	0.13

Table 5.1 shows in scenario 1, when the method was employed, the peak load is 250 kW. Moreover, by adding EVs into the network, in scenarios 2 and 3, the peak load never exceeded the power transformer capacity (250 kW), while the users' desire SOC were satisfied. In the

cases where the method were employed, due to the constraints (i.e power transformer and contracted power), all the vehicles could not be satisfied within periods when the electricity rates is lowest. Due to this fact, their charging process had to be started earlier and taken into moments when the electricity rates are high (regarding the users electricity tariff schemes). In these cases the total charging costs are slightly higher than those, in which there were no controller. For example in scenario 3 the total charging costs are 156 € and 143 € respectively for the cases with and without controller. Moreover, $\bar{x}$ shows the average of the extra costs of all the users and σ is the standard deviation. Since the value of the standard deviation is not high, it can be concluded that most of the users pay a reasonable enough extra cost.

The algorithm adjusts the EVs' charging plan in a fairly way, meaning that for each and every user, the deviation of the actual charging cost from the minimum charging cost are close to each other, not significantly varying. However, it also depends on the total requested SOC. This deviation (the extra cost) must be paid by the users, who live in such neighbourhood with the described grid capacity. If such management not to be employed, it might be happened that, all the EVs can not be charged (blackout), or may some users pay the minimum cost and the others pay a much higher extra cost. Regarding the total available power at moments when the electricity rates are low, the algorithm tries to distribute the available energy in such a way that all the users equally benefit from low electricity rates. For the EVs which were not satisfied at these moments, their charging plan take place into periods, when the electricity rates are higher. Therefore their charging cost become higher than a case that there is no constraints. Figure 5.9 demonstrates the minimum charging cost plus the extra cost, for 25 users. These users were randomly chosen from scenario 3, in the case where the algorithm was employed to plan 60 EVs' charging process.
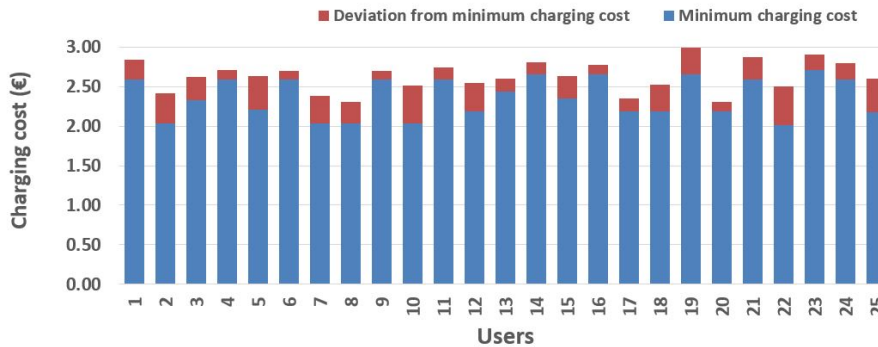

Figure 5.9: Deviation of the actual charging cost from the minimum charging cost

From figure 5.9, it is possible to conclude that the charging cost for all the users are slightly higher when the algorithm is employed. If the extra cost of each user is compared to the average deviation (i.e. the sum of the extra costs divided by the number of the users) small deferences are observed. Figure 5.10 illustrates these differences, for the users referred in figure 5.9.

Regarding the total actual cost (156 €) and the minimum charging cost (143 €), in this case, for every user, the value of the average deviation was calculated 0.24 €. For every
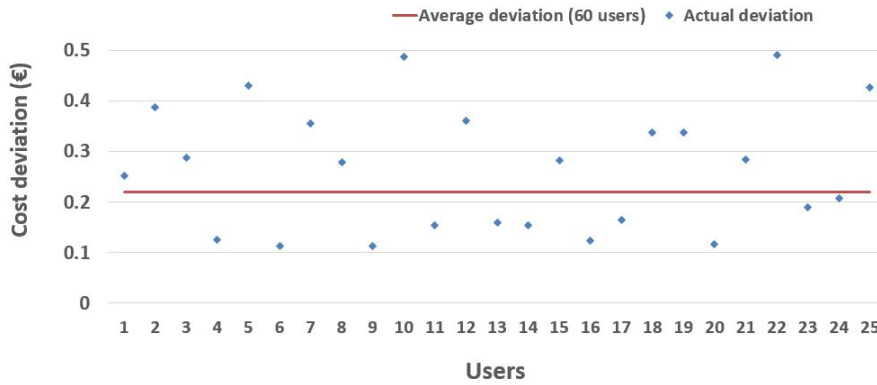
Figure 5.10: Comparison of the actual deviations with the average of extra cost deviations

user, the deviation of the actual charging cost from the minimum cost (obtained when the algorithm was not employed, exceeding the power transformer capacity) varies, depending on: **i)** the total requested energy by the users, regarding the available grid capacity **ii)** users' base load profiles; **iii)** the individually requested SOC and **iv)** the time of charge.

6 Conclusion and Future Work

An electric vehicle's battery capacity is measured in kilowatt-hours, the same unit that an electric meter records to determine the monthly electric bill. Charging comes down to two familiar resources: time and money. The duration of charging an EV depends on its battery size and chargers' power. The cost of charging depends on where and when the EV is charged. Basically, owners should recharge their EVs when the electricity rates is the lowest. This can usually be during night, when the vehicle is least likely to be needed. This work presented a method to accommodate the recharging process of a group of EVs in a local neighbourhood, with the aim to help the users to take full advantage of off-peak rates, while preventing the power transformer overloading.

It was shown that the algorithm is able to be implemented in different scenarios in which there are different electricity tariffs and constraints. Moreover, it is compatible with various batteries' charging profiles and it can also support different load profiles, as for example from different regions with various consumption patterns. Due to the optimization objective, every user pays a reasonable cost of charge, close to the minimum cost. It is worth mentioning that if some users pay more than that, it is due to the fact that there was not enough individual available power for that user, to response the EV's demand at moments when, electricity rate is low, as can be seen in figure 5.4 (contracted power constraint). The minimum cost of charge is achievable in scenarios in which there are no constraints on grid and all the EVs can take full advantage from low electricity price periods.

In addition, through the proposed method, charging a greater number of EVs is feasible (maximizing the number of EVs being charged) without needing to invest in increasing the capacity of the grid infrastructure, while the charging costs for each and every user is kept close to the minimum. The algorithm can be employed to plan the charging process of

group of independent EVs, weakly coupled through electricity price signals. In this way, due to less demand for communication infrastructures, the implementation of the proposed method will potentially be cost-effective. Moreover, various entities may be interested in such management. For instance, the distribution grid operator is interested in managing the charging process to incorporate the maximum number of EVs without massively reinforcing the grid. The retailer is interested in balancing electricity purchase and sale in order to increase its profit in the electricity trading context, whereas the consumers are interested in minimizing the cost of charge of their EVs and increasing the reliability of supply.

Future work arising from this topic, is related to the integration of other aspects in the algorithm, besides to the ones considered, which reproduce as realistic as possible the lifestyle of EVs' users. In this context, one important aspect should be included in future developments of the algorithm, is adding the next EV's usage time as an additional preference of the users (defining the charging termination time separately for every user). Another crucial aspect for the future developments is the consideration of EVs' users who refuse to participate in the integrated charging control. These type of users would not have any charging plan and would be seen as additional uncontrollable loads connected to the grid. Finally, for safety and comfort reasons, it should be established a minimum emergency level of SOC. In this way, all the EVs would be charged at least up to the minimum SOC level, for instance, by considering a priority criterion. Moreover, integrating other controllable loads into the algorithm, allows increasing the number of EVs being charged simultaneously, or may decrease the extra cost of charge.

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