

Assessment of Technical and Economic Impacts of EV User Behavior on EV Aggregator Smart Charging

Jean-Michel Clairand, Javier Rodríguez-García, and Carlos Álvarez-Bel

Abstract—The increase in global electricity consumption has made energy efficiency a priority for governments. Consequently, there has been a focus on the efficient integration of a massive penetration of electric vehicles (EVs) into energy markets. This study presents an assessment of various strategies for EV aggregators. In this analysis, the smart charging methodology proposed in a previous study is considered. The smart charging technique employs charging power rate modulation and considers user preferences. To adopt several strategies, this study simulates the effect of these actions in a case study of a distribution system from the city of Quito, Ecuador. Different actions are simulated, and the EV aggregator costs and technical conditions are evaluated.

Index Terms—Electric vehicle (EV), smart grid, aggregator, smart charging, charging power modulation, charging strategies.

I. INTRODUCTION

POWER systems will have important challenges in the future. These challenges include a growing population and the need for greater implementation of green energy. With this in mind, new policies have been implemented with a focus on the research and development of smart grids (SGs). An SG can be described as the interaction of different engineering techniques to perform a reliable, secure, and efficient grid that uses the maximum of renewable source generation. The new grid can store, communicate and make decisions [1].

SG functionalities involve the improvement in fault detection [2], the deployment of distributed energy resources [3], [4], energy efficiency in buildings [5], and the integration of techniques such as demand response and demand-side man-

agement [6]. SG research includes microgrids [7], control and communications, and sensing and measurement.

The electric vehicle (EV) is a new technology that could play a relevant role in the SG. EVs have a battery with a considerable amount of energy, which can provide capacity storage [8]. EV batteries could offer many benefits to the grid.

Nevertheless, a massive access of EVs can impact on the power grid. These issues generally occur if large numbers of EVs are charged at the same time from a distribution grid. Problems such as voltage deviations and voltage drops [9], distribution system losses [10], peak load increase [11], important investment costs [12] and transformer loss of life [13] may occur. Thus, the proper management of the vehicle fleet is required, and relevant data such as charging behavior have to be known [14], [15].

Several studies have examined the opportunities for EV charging management in SG. The techniques and objectives differ. In [16], the opportunities and challenges of vehicle-to-home were discussed. A strategy for peak shaving and valley filling of grid power, using vehicle-to-grid systems, was proposed in [17]. In [18], an efficient management methodology was presented for EV charging and discharging through multi-objective optimization, considering the minimization of the system operation costs and the level of the power demand curve. In [19], evolutionary game dynamics for the decentralized load management of plug-in EVs was proposed for providing ancillary services to the grid. Refenerce [20] studied the EV scheduling in the SG, using fireworks algorithms.

Other studies focused on the design and evaluation of smart chargers. In [21], a voltage-based controller for EV chargers was presented. In [22], a bidirectional smart charger was proposed for EV, which can control active and reactive power. This paper was complemented by [23], in which a three-stage algorithm was proposed for coordinating the operation of four-quadrant EV chargers and other volt/var control equipment in a distribution feeder. In [24], a model predictive control of an off-board charger based on a two-level four-leg inverter topology was studied considering photovoltaic integration.

For the better management of EV charging, an EV aggregator was proposed in [25], [26]. It is a new electric agent that manages a considerable amount of EV charging. It will

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J.-M. Clairand (corresponding author) is with the Facultad de Ingeniería y Ciencias Agropecuarias, Universidad de las Américas - Ecuador, 170122 Quito, Ecuador (e-mail: jean.clairand@udla.edu.ec).

J. Rodríguez-García and C. Álvarez-Bel are with the Institute for Energy Engineering, Universitat Politècnica de València, 46022 Valencia, Spain (e-mail: jarodgar@iie.upv.es; calvarez@die.upv.es).

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group a large amount of EVs in an area to function as a large generation or load. For this purpose, it needs a smart charging infrastructure, e. g., the smart chargers mentioned before. The principal objective of this new player is to perform the economic and technical management of EVs. Several studies proposed methodologies considering this new agent [27]-[30].

However, most of the prior research applied the methods such as shifting or schedules for EV charging management. These methods could be efficient for the grid; however, from the point of view of the users, they could feel uncertain about the end of charging or uncomfortable with the schedules proposed. Thus, the vehicle users could consider not adopting EVs or these programs [31], [32]. It is necessary to account for some uncertainties of EV charging behavior.

Thus, in [33], a smart charging methodology for an EV aggregator was proposed. It considers three different customer choice products (CCPs) depending on EV user preferences. The EV aggregator has to optimize costs through charging power modulation. Results show that with this methodology, the EV aggregator has essential benefits compared with uncoordinated charging while respecting technical grid conditions. The impact of some uncertainties from external conditions such as EV penetration levels, different residential loads that differ from each day and daily specific electricity price, was also evaluated.

Although the effectiveness of this methodology and others has been demonstrated, several input parameters are assumed and fixed considering local user preferences such as minimum required energy, time delay of the starting charging time, number of users from each CCP, and average charging power rates. Moreover, user behaviors differ depending on the country. Thus, the EV aggregator might adjust its conditions, modifying these input parameters. Therefore, a variation of these parameters could lead to important changes in the EV aggregator benefits or in the grid conditions. For these reasons, an evaluation of different parameter variations on the model has to be performed.

In [34], an evaluation of strategies for this methodology was studied. However, the analysis considered only a few scenarios for each parameter; thus, the results may not be meaningful. Hence, a broader study is needed to obtain proper results.

The aim of this paper is to perform an assessment of various strategies based on different input parameters that can be applied to this methodology. It presents several results of the various tests that are performed. These EV aggregator strategies can be applied in user CCPs, depending on the conditions of the grid and the user. The innovative contributions of the proposed study are highlighted as follows:

- 1) Several sensitivity analyses for each crucial parameter are performed with the EV smart charging technique to analyze the technical and economic implications.
- 2) The critical input variables in the optimization process associated with EV user behavior by using the EV aggregator smart charging technique are identified.
- 3) Stochastic analyses using Monte Carlo simulations are performed to evaluate the impact of different input param-

eters, in which uncertainties such as hour of charging and required energy are considered. These were implemented in a case study with real information.

The paper is organized as follows. Section II resumes the methodology mentioned. Section III is devoted to the parameters of the test evaluated. Section IV presents the results of the different tests. The conclusion of this study is provided in Section V.

II. SMART CHARGING CONSIDERING USER PREFERENCES

The methodology is presented in detail in [33]. The EV aggregator provides technical services to the distribution system operator (DSO) and transmission system operator (TSO) while managing EV charging. In exchange, the EV aggregator is paid by these services. The technical services consist of not exceeding the “maximum load profile”, which is provided by grid operators such as DSO and TSO. The maximum load profile represents the upper bound of demand in a specific area, which could result from different causes such as congestion problems in lines or transformers, energy balancing, or the availability of power from the grid. If this value is surpassed, the grid could suffer generation shortage, which could lead to stability problems and other problems such as network congestion or reduction in the useful life of assets due to overheating. This maximum load profile is defined as:

$$P_k^O = P_k^{cri} - P_k^{tot, res} \quad (1)$$

where P_k^O is the maximum load profile at step k ; P_k^{cri} is the critical power; and $P_k^{tot, res}$ is the total residential load at step k . In addition,

$$P_k^{cri} = 1.05 P_{max}^{res} \quad (2)$$

where P_{max}^{res} is the maximum residential load in the day ahead. In Fig. 1, the maximum load profile of the day for the case study is represented.

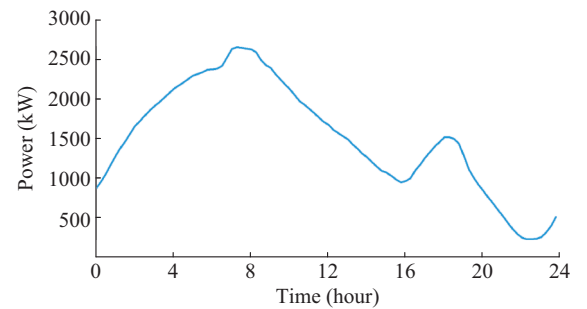


Fig. 1. Maximum load profile.

Critical power P_k^{cri} is assumed to be 5% higher than the maximum value of the residential load. This assumption is considered because the feeder has reactive energy compensation, and the limit of the transformer can be determined by this active power.

The EV aggregator has to manage EV slow-charging stations in parking lots or in households. It is assumed that the charging power rate of EVs could be modulated between 0 kW and 7.2 kW [35]. These different levels can be obtained

with a smart charging station that modulates the charging power rate. Note that bidirectional communication is required to send the charging states from the EVs and receive the charging orders from the EV aggregator. The objective of the EV aggregator is to minimize daily charging costs while respecting the technical constraints.

The analysis presented above and others could result in efficient grid performance; however, it is mostly based on EV load shifting or scheduling, which might discourage users from purchasing EVs. Thus, in the methodology, three CCPs are considered according to various user behaviors. When an EV user plugs in the EV, the charging price and duration from each CCP will be known by the user, permitting the selection of a schedule that is appropriate for his/her time flexibility. This could be performed by a smart charger. Each CCP will depend on an average charging power rate that will be established at the beginning of the charging. Three CCPs are defined: green, blue, and red. The green CCP is considered the most economical one, and the red one is considered the most expensive one. Green and blue CCPs allow the EV aggregator to modulate their charging power rate. The red CCP avoids charging power rate modulation and will serve users that are in a hurry. The red CCP allows users to charge their EV at the maximum power of slow charging, which is 7.2 kW. It could be considered that red CCP users do not have any participation in EV management; thus, they will have to pay the highest price, and some of the red CCP parameters will not be considered in the evaluation of EV aggregator strategies. Each CCP x for an EV i will determine the duration T_x^i , which will depend on the energy required for EV i E_{req}^i and the average power rate $P_{x,av}$, is defined as:

$$T_x^i = \frac{E_{req}^i}{P_{x,av}} \quad (3)$$

It is also considered that:

$$P_{x,av} T_x^i = E_{req}^i \quad (4)$$

The average charging power rates from green, blue, red CCPs are 1.5 kW, 2.5 kW, 7.2 kW, respectively. Each value is selected according to the traditional interval of slow charging, which corresponds to 0 kW to 7.2 kW.

Figure 2 illustrates the architecture of the smart charging technique by highlighting different CCPs.

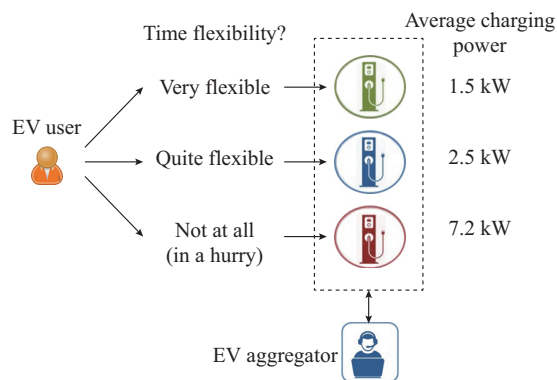


Fig. 2. Methodology system architecture.

As an example, considering the assumed average charging power rates mentioned above, different charging durations considering the different energies required from the users are summarized in Table I, where E_{req} is the energy required from the users; and T_G , T_B , T_R are the charging durations for green, blue, red CCPs, respectively.

TABLE I
CHARGING DURATION FROM EACH CCP DEPENDING ON ENERGY REQUIRED FOR ASSUMED AVERAGE CHARGING POWER RATES

E_{req} (kWh)	T_G (hour)	T_B (hour)	T_R (hour)
4	2.7	1.6	0.6
8	5.3	3.2	1.1
12	8.0	4.8	1.7
16	10.7	6.4	2.2
20	13.3	8.0	2.8
24	16.0	9.6	3.3

The expenses for green and blue CCPs are defined as:

$$C_{G,VAR} = \sum_{k=1}^D \pi_k P_k^G \Delta T \quad (5)$$

$$C_{B,VAR} = \sum_{k=1}^D \pi_k P_k^B \Delta T \quad (6)$$

where $C_{G,VAR}$ and $C_{B,VAR}$ are the EV aggregator expenses for the green CCP and the blue CCP, respectively; π_k is the specific cost at the step k ; P_k^G and P_k^B are the total power consumed by cars participating in green and blue CCPs at step k , respectively; and ΔT is the time between each step time. The daily cost for the EV aggregator C_{VAR} is defined as:

$$C_{VAR} = C_p + \sum_{k=1}^D \pi_k (P_k^G + P_k^B + P_k^R) \quad (7)$$

where C_p is the penalty cost if the EV aggregator surpasses the charging pattern; and P_k^R is the total power consumed by cars participating in a red CCP at step k . The total energy dispatched in a day to all EVs participating in a green CCP $E_{G,tot}$ is defined as:

$$E_{G,tot} = \sum_{k=1}^D P_k^G \Delta T \quad (8)$$

The total energy dispatched in a day to all EVs participating in blue CCP $E_{B,tot}$ is defined as:

$$E_{B,tot} = \sum_{k=1}^D P_k^B \Delta T \quad (9)$$

The total energy dispatched in a day to all EVs $E_{EV,tot}$ is defined as:

$$E_{EV,tot} = \sum_{k=1}^D (P_k^G + P_k^B + P_k^R) \Delta T \quad (10)$$

The EV aggregator cost per energy delivered to green CCP users $C_{G,eq}$ is defined as:

$$C_{G,eq} = \frac{C_{G,VAR}}{E_{G,tot}} \quad (11)$$

The EV aggregator cost per energy delivered to blue CCP users $C_{B,eq}$ is defined as:

$$C_{B,eq} = \frac{C_{B,VAR}}{E_{B,tot}} \quad (12)$$

The EV aggregator cost per energy delivered C_{eq} is defined as:

$$C_{eq} = \frac{C_{VAR}}{E_{EV,tot}} \quad (13)$$

A. Objective Function

The objective is to minimize the daily costs for the EV aggregator. The EV aggregator has to optimize the charging pattern of each EV of each CCP. The charging power of each EV will vary from 0 kW to 7.2 kW as explained before, depending on the grid and EV user conditions. Furthermore, the EV aggregator has to avoid, if possible, the penalty cost, which occurs via exceeding the maximum load profile, and fully charge the battery energy required by EV users. This problem can be tackled as a linear optimization. The problem is formulated as:

$$\min C_{VAR} = \min[C_p + \sum_{k=1}^D \pi_k (P_k^G + P_k^B + P_k^R)] \quad (14)$$

B. Constraints

The objective function is subject to these different constraints:

$$0 < P_k^i < \bar{P}^{ch} \quad \forall k \in T \quad (15)$$

$$E_{req}^i = \sum_{k=1}^D P_k^i \Delta T \quad \forall k \in U_i \quad (16)$$

$$0 < P_k^G + P_k^B + P_k^R < \bar{P}_k^{EV,O} \quad \forall k \in T \quad (17)$$

where P_k^i is the charging power of EV i at step k ; \bar{P}^{ch} is the maximum charging power rate for an EV; U_i is the set of samples of EV i that corresponds to the charging period; T is the set of time steps; and $\bar{P}_k^{EV,O}$ is the operator load constraint at step k .

Constraint (15) sets the limitation of the charging rate, complying with the charging capability of the charging devices. Constraint (16) indicates that all the energy that the EV user requires is supplied. Constraint (17) ensures that grid capability is respected.

The problem is solved by linear optimization, and the software MATLAB 2016 is used for the different simulations.

III. DESCRIPTION OF SENSIBILITY ANALYSIS

A. Determination of Variables to Be Evaluated

In a mathematical model, some input variables can determine one or many different output variables through a function f . In many cases, this variable could be very complex (e.g., non-linear). Thus, it is not easy to know the impact of the inputs on the output [36]. Sensitivity analysis is a method that studies how the uncertainties in the model inputs affect model response [37]. It describes the relative input in determining the output variability. The function considered for the model is non-linear, and it is determined by a mathematical code. Thus, there is interest in performing sensitivity

analysis. Moreover, it is difficult to know how realistically the behavior of EV user is modeled. Thus, the sensitivity analysis can provide insights into the influence of the user preferences on the EV load and charging costs. The users concern to have the EV charged when needed. Therefore, any parameter that may affect this fact is relevant. The variables that are influenced by these factors in the proposed smart charging technique are: minimum required energy, time delay of the starting charging time, and average charging power rates of green and blue CCPs. However, the proportions of green and blue CCP users influence the management capacity of the EV aggregator, which could change the charging specific cost. Thus, a sensitivity analysis is performed on these variables. As mentioned before, the variations in the variables from a red CCP are not studied, because it is the CCP that allows users to charge the EV at the maximum power. In each case, the EV load and the different costs are studied as represented in Fig. 3.

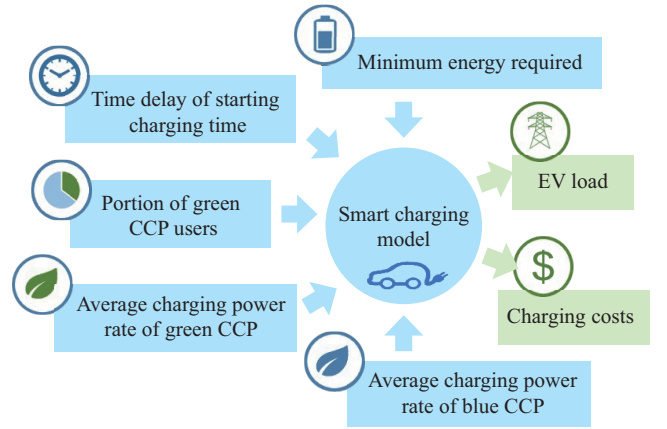


Fig. 3. Scheme of sensitivity analysis.

For each parameter under study, the EV load profile is simulated for each scenario to have a technical view of the crucial periods of the day. In addition, Monte Carlo simulations of the specific costs are performed to analyze, through a regression analysis, the impact of the variation of each parameter. The EV user behavior could change significantly (e.g., starting charging time, energy required from each user). Thus, the model presents some uncertainties, necessitating the execution of a significant number of simulations. Because of the complexity and computation time, 100 simulations of Monte Carlo are performed for each scenario. The regression of the specific cost is performed with the mean of each scenario and without considering anomalous values.

In Fig. 4, an example of a box and whisker plot for the case of the minimum required energy is represented. And it is possible to view the variation in the upper and lower values and means, depending on each scenario. This plot facilitates the removal of anomalous values and making the most precise regression curve with the mean values for each variation.

The range of different parameters is selected, considering some aspects of user behavior and the information provided in [38]-[40].

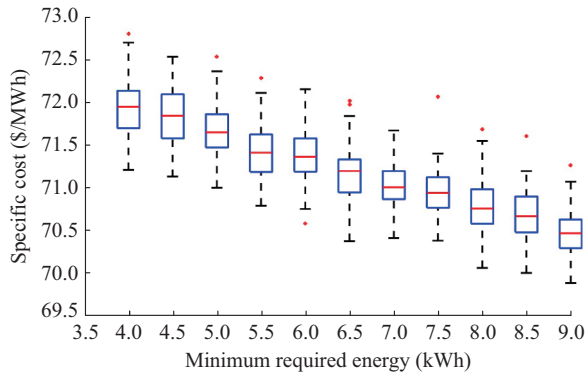


Fig. 4. Box diagram of specific cost from each case.

B. Reference Scenario

The simulations are performed for a selected zone of Quito. This case study is selected because the Ecuadorean government plans to introduce EVs in the country [41], and Quito is the capital of the country. Furthermore, in Quito, traffic issues such as pollution and noise, are a problem [42], [43]. In previous studies, this zone is assumed to contain 1000 vehicles [38]. The assumed EV penetration level is 50%, representing 500 EVs. Electricity is distributed by Empresa Eléctrica Quito (EEQ), and the distribution feeder of this zone is selected.

To perform a proper comparison among the different tests, a reference scenario is proposed, in which the proportions of green, blue, and red CCPs are assumed to be 60%, 30%, and 10%, respectively.

In Ecuador, there is no electricity wholesale market. Thus, a method was proposed in [38] to calculate the electricity prices π_k based on the real costs of the Ecuadorian power system (generation, transmission, and distribution). For the reference scenario, the date June 9, 2014 is considered because the electricity price curve is relatively flat in that period, representing a critical day for the model. The electricity prices have to be delivered to the EV aggregator to perform the methodology optimization. In Fig. 5, the day-ahead electricity price curve applied to different scenarios is represented [33].

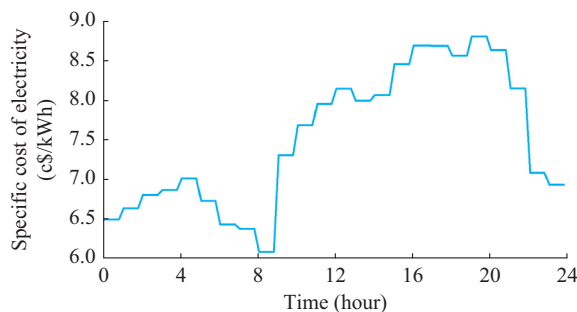


Fig. 5. Proposed electricity price on June 9, 2014.

For the EV user behavior, some considerations are adopted regarding the starting charging time and daily energy needed to charge the EV through the information of Ecuadorian data.

C. Evaluated Variables

1) Minimum Required Energy per Charging

The minimum required energy per charging is the minimum amount of energy that the EV aggregator requests from each user to charge the EV battery. The objective is to quantify how the EV aggregator specific costs per kWh decrease. In the reference scenario, the minimum energy for each user needed is established to be 4 kWh. However, if EV users charge their EV at this minimum energy, the duration of charging T_x^i will be short. The methodology could not achieve proper performance within such a short time, especially if the electricity price variation is not significant. In this way, a sensitivity analysis is performed considering a variation of 0.5 kWh for the minimum energy required. For the sensitivity analysis, the lower bound for the minimum required energy is 4 kWh. The upper bound is established as 9 kWh, which is envisaged to be the highest value that users can feel confident without a problem with the battery the next day.

2) Time Delay of Starting Charging Time

Owing to the high prices of electricity between 4 p.m. and 9 p.m. and the fact that people generally will not disconnect their EVs during night time, the EV aggregator can benefit from reduced charging costs if a delay in the starting charging time exists. The sensitivity analysis starts with no delay and continues with an increment of 30 min until 5 hours reach. The value of 5 hours is selected because it is considered an extreme delay for which users can wait.

3) Proportion of Green CCP Users

The objective is to quantify which impact causes a variation in the green CCP users in relation to the total users. In the reference scenario, the proportion of the green CCP users is established to be 60%. For the sensitivity analysis, the proportion of green CCP users is adjusted from 0% to 100%, in increments of 10%, to determine the range of proportion of green CCP users. For this analysis, it is assumed that the percentage of blue CCP users is double that of the red CCP users.

4) Average Charging Power Rate of Green and Blue CCPs

The implications of average charging power rate of the green CCP and blue CCP are investigated. In the reference scenario, it is considered that the average power consumption of an EV participating in a green CCP is 1.5 kW and, for the blue CCP, 2.5 kW.

For the sensitivity analysis, the selected lower and upper bounds of the average charging power rate of the green CCP are 0.5 kW and 3.0 kW, which represent one third of and double the value of the reference parameter (1.5 kW), respectively. Note that the objective is to analyze the effects of the variations of this parameter, because if the average charging power rate for the green CCP is near 3 kW, the blue CCP has to be higher.

For the sensitivity analysis, the selected lower and upper bounds of the average charging power rate of the blue CCP are 1.25 kW and 5.0 kW, which are half and double the value of the reference parameter (2.5 kW), respectively. As in the case of the green CCP, if the charging power rate of the blue CCP is too low, the green one has to be lower still. The

criterion for choosing these values is that they correspond to the time limits for the EV users to charge their EV and interact with the grid.

In this case, only the load demand from each CCP is studied, because the number of vehicles considered is not too large, such that a variation in the power consumption from the CCP of other EV users can exist owing to the operator constraint. However, the costs of the corresponding CCP and the total costs are evaluated.

IV. SENSITIVITY ANALYSIS RESULTS FOR CASE STUDY

A. Variation in Minimum Required Energy

In Fig. 6, analysis curves of the variation in the minimum required energy are presented. It is observed that the total energy dispatched to the EV, $E_{EV, tot}$, grows with an increase in the minimum required energy. With the rise of the minimum required energy, the EV load grows considerably during hours 0 to 3 and hours 8 to 9. In these hours, electricity is at its cheapest price. The EV load stays stable in hours 16-23 when the electricity is the most expensive. This means that despite the growth of the minimum required energy, the EV aggregator does not dispatch power to the EV at time periods when the electricity is expensive and takes advantage of a larger duration T_x^i to charge the EVs in time periods when electricity is cheaper. Note that during hours 4 to 6, the EV load remains at a minimum level in all cases, because these hours are one of the last of the evening, and as such the electricity price is quite high compared to the other hours in the evening.

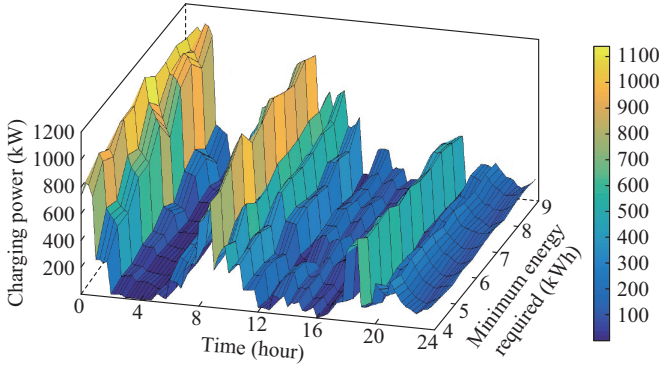


Fig. 6. EV load considering different strategies for minimum required energy.

The minimum required energy is denoted as \underline{E}_i^{req} . In Table II, the mean values of scenario results are presented. As expected, an increase in the minimum required energy leads to an increase in the total costs and total energy dispatched to EV. However, the EV aggregator cost per energy delivered decreases from 71.93 \$/MWh ($\underline{E}_i^{req} = 4$ kWh) to 70.47 \$/MWh ($\underline{E}_i^{req} = 9$ kWh), which represents a decrease of 2.03%.

In Fig. 7, the regression curve with the mean points of each scenario is shown. The next regression function is obtained:

$$C_{eq}(\underline{E}_i^{req}) = -0.288 \underline{E}_i^{req} + 73.08 \quad (18)$$

TABLE II
SUMMARY OF MEAN VALUES CORRESPONDING TO DIFFERENT STRATEGIES FOR MINIMUM REQUIRED ENERGY

\underline{E}_i^{req} (kWh)	C_{VAR} (\$)	$E_{EV, tot}$ (kWh)	C_{eq} (\$/MWh)
4.0	371.1	5158.8	71.93
4.5	387.7	5397.4	71.83
5.0	406.5	5671.6	71.67
5.5	422.4	5914.7	71.42
6.0	440.5	6174.0	71.35
6.5	455.8	6404.8	71.16
7.0	473.0	6660.3	71.02
7.5	490.8	6920.4	70.93
8.0	507.9	7175.8	70.78
8.5	524.2	7415.8	70.68
9.0	540.0	7663.0	70.47

In conclusion, an increase in minimum required energy decreases the cost per energy delivered. Nevertheless, note that the variation between the upper and lower values is not very significant.

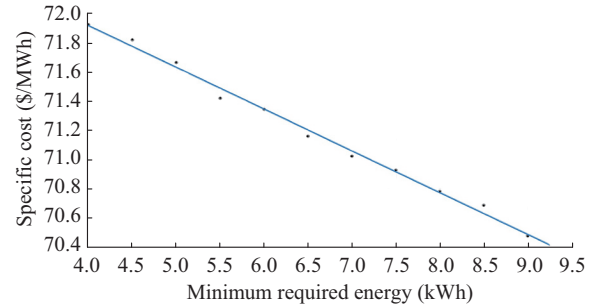


Fig. 7. Regression curve and mean points for minimum required energy.

B. Time Delay of Starting Charging Time

Figure 8 depicts the EV charging power in a day depending on the time delay of the charging starting time scenarios. Peak values are observed during hours 18 to 19 for scenarios with a small time delay. These peaks are not more evident in scenarios with a significant time delay.

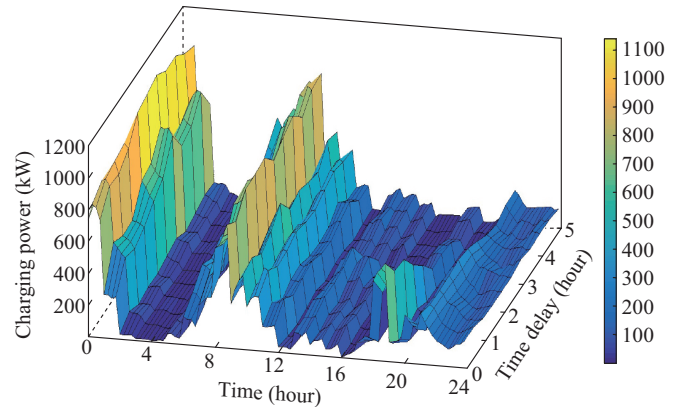


Fig. 8. EV load considering different strategies for time delay of charging starting time scenarios.

EV users plug in their EV sometime before hour 18 and hour 19, which has the cheapest electricity costs during hours 16 to 21. Thus, the EV aggregator tries to charge more during this hour. With a delay in the starting charging time at night, the EV aggregator can benefit from cheaper electricity prices later at night, and also in the first few hours of the morning. This is why the peaks of these hours grow with increase in time delay. Nevertheless, after a delay of 3.5 hours, these peaks do not grow any more.

The time delay of starting charging time is denoted as T_d . Table III presents the mean costs and energy dispatched for each scenario. The EV aggregator cost per energy delivered decreased from 71.93 \$/MWh ($T_d = 0$ hour) to 68.33 \$/MWh ($T_d = 5$ hours), which represents a decrease of 5%.

TABLE III
SUMMARY OF MEAN VALUES CORRESPONDING TO DIFFERENT STRATEGIES OF TIME DELAY

T_d (hour)	C_{VAR} (\$)	$E_{EV,tot}$ (kWh)	C_{eq} (\$/MWh)
0	371.1	5158.8	71.93
0.5	370.2	5181.4	71.46
1.0	366.8	5161.3	71.08
1.5	364.1	5157.6	70.60
2.0	362.4	5163.4	70.18
2.5	360.2	5166.1	69.73
3.0	359.2	5176.9	69.40
3.5	355.8	5152.1	69.05
4.0	354.8	5156.3	68.81
4.5	353.1	5155.9	68.49
5.0	353.3	5170.7	68.33

Figure 9 represents the regression curve with the mean points of each scenario. The next regression function is obtained as:

$$C_{eq}(T_d) = 0.55T_d^2 - T_d + 71.95 \quad (19)$$

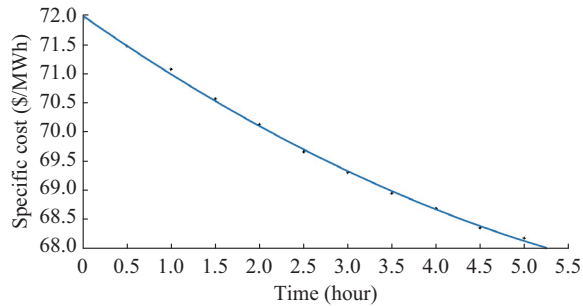


Fig. 9. Regression curve and mean points for time delay.

A delay in the charging starting time leads to a decrease in the day-ahead EV aggregator costs per energy delivered because of the cheaper electricity costs later in the evening. Note that the effect is more important between $T_d = 0$ hour and $T_d = 3$ hours (variation of 3.51%) than that between $T_d = 3$ hours and $T_d = 5$ hours (variation of 1.54%). This is caused by the fact the methodology is not applicable to a delay larger than 3 hours, because the EV aggregator cannot find cheaper electricity prices in night time.

C. Variation in Share of Green CCP

The results of the variation in the proportion of the green CCP users are shown in Fig. 10, showing that an increase in the share of EV users adopting green CCP leads to an increase in the load when the electricity is more economical (hours 0 to 3 and hours 7 to 9), and a decrease in the load when the electricity is more expensive (hours 16 to 22). The duration of the green CCP is longer than that of blue or red CCP, which allows the EV aggregator to benefit from better electricity prices later in the evening. However, the time is not sufficient for the majority of EVs to charge in the cheapest period of the day.

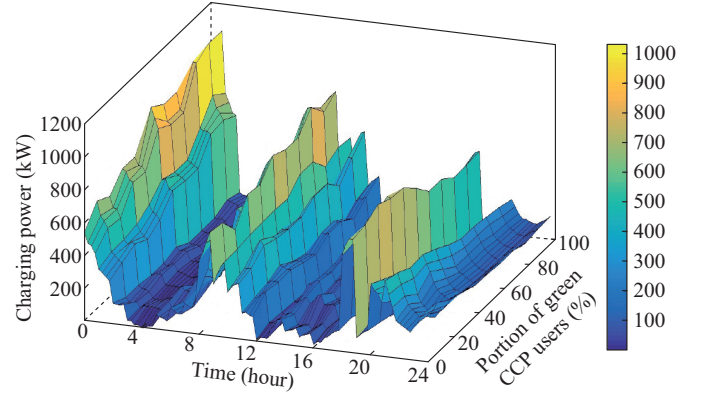


Fig. 10. EV load considering different strategies for variation in share of green CCP.

The proportions of EV users participating in green, blue, and red CCPs are denoted as ϵ_G , ϵ_B , and ϵ_R , respectively. In Table IV, the mean values of scenario results are presented. The EV aggregator cost per energy delivered decreased from 74.94 \$/MWh ($\epsilon_G = 0\%$) to 70.02 \$/MWh ($\epsilon_G = 100\%$), which represents a decrease of 7.03%. The number of EVs participating in green, blue, and red CCPs are denoted as N^G , N^B , and N^R , respectively. In Fig. 11, the regression curve with the mean points of each scenario is depicted. The next regression function is obtained as:

$$C_{eq}(\epsilon_G) = -0.05\epsilon_G + 74.9 \quad (20)$$

TABLE IV
SUMMARY OF MEAN VALUES CORRESPONDING TO DIFFERENT STRATEGIES FOR VARIATION IN SHARE OF GREEN CCP

ϵ_G (%)	ϵ_B (%)	ϵ_R (%)	N^G	N^B	N^R	C_{VAR} (\$)	$E_{EV,tot}$ (kWh)	C_{eq} (\$/MWh)
0	75.0	25.0	0	375	125	384.5	5161.7	74.94
10	67.5	22.5	50	337	113	383.3	5178.3	74.45
20	60.0	20.0	100	300	100	379.5	5163.5	73.94
30	52.5	17.5	150	262	88	378.4	5180.6	73.46
40	45.0	15.0	200	225	75	374.9	5167.8	72.97
50	37.5	12.5	250	187	63	372.4	5169.1	72.47
60	30.0	10.0	300	150	50	371.1	5158.8	71.93
70	22.5	7.5	350	112	38	368.1	5181.0	71.46
80	15.0	5.0	400	75	25	364.9	5170.3	70.99
90	7.5	2.5	450	3	13	361.9	5169.2	70.43
100	0	0	500	0	0	359.3	5162.0	70.02

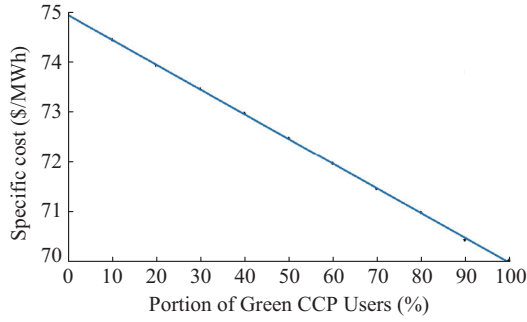


Fig. 11. Regression curve and mean points for proportion of green CCP users.

An increase in the share of green CCP users leads to a decrease in C_{VAR} .

D. Variation in Average Charging Power Rate of Green CCP

The simulations of the variation in the average charging power rate of the green CCP are shown in Fig. 12.

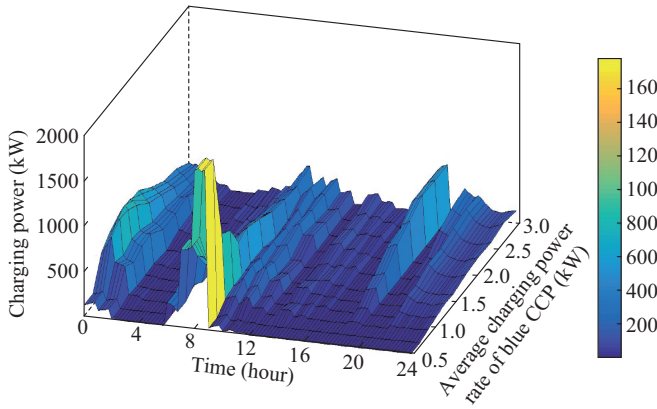


Fig. 12. EV load considering different strategies for variation in average charging power rate of green CCP.

A peak between hour 7 and hour 9 with small values of $P_{G,av}$, another between hour 0 and hour 2 for medium values of $P_{G,av}$, and another at hour 18 to hour 19 for higher values of $P_{G,av}$ are recorded. This is due to the fact that the EV load is significant in the cheapest hours, corresponding to the duration in which the EV aggregator has to charge the EVs. A smaller $P_{G,av}$ indicates that the EV aggregator benefits from a larger period to charge the EVs. If the period is larger, the EV aggregator could benefit from better prices. For example, in the first scenario, there is a peak between hour 7 and hour 9 because the period to charge is long, and in these hours, the electricity is at the cheapest price. Thus, the EVs could be charged at the maximum power. However, if $P_{G,av}$ increases, the period for charging decreases, and the EV aggregator could not benefit any more in charging the EVs at hour 7 to hour 9 but rather has to charge the EVs at the maximum power during other cheaper periods. These new cheapest periods become hour 0 to hour 2 for medium values of $P_{G,av}$ and hour 18 to hour 19 for higher values of $P_{G,av}$.

Table V shows the means of the results for the variation

in the average charging power rate of the green CCP. The EV aggregator cost per energy delivered of the green CCP increased from 62.68 \$/MWh ($P_{G,av} = 0.5$ kW) to 75.18 \$/MWh ($P_{G,av} = 3.0$ kW), which represents an increase of 19.94%. The total EV aggregator cost per energy delivered increased from 68.11 \$/MWh ($P_{G,av} = 0.5$ kW) to 75.10 \$/MWh ($P_{G,av} = 3.0$ kW), which represents an increase of 10.26%.

TABLE V
SUMMARY OF MEAN VALUES CORRESPONDING TO DIFFERENT STRATEGIES FOR VARIATION IN AVERAGE CHARGING POWER RATE OF GREEN CCP

$P_{G,av}$ (kW)	C^G (\$)	C_{VAR} (\$)	$E_{G,tot}$ (kWh)	$E_{EV,tot}$ (kWh)	$C_{G,eq}$ (\$/MWh)	C_{eq} (\$/MWh)
0.5	194.6	356.2	3105.2	5229.1	62.68	68.11
0.7	199.3	358.7	3108.6	5206.5	64.13	68.89
0.9	203.4	362.3	3096.6	5195.8	65.68	69.74
1.1	207.9	364.6	3094.7	5168.2	67.18	70.55
1.3	212.0	367.9	3097.7	5162.8	68.45	71.26
1.5	215.6	371.1	3096.1	5158.8	69.64	71.93
1.8	220.2	375.7	3098.6	5164.9	71.08	72.75
2.1	224.7	379.6	3099.3	5159.7	72.50	73.57
2.4	228.0	382.4	3097.7	5154.2	73.60	74.20
2.7	230.5	385.3	3094.7	5158.1	74.48	74.69
3.0	232.4	386.5	3091.1	5146.8	75.18	75.10

In Fig. 13, the regression curve with the mean points of each scenario is represented. The next regression function is obtained as:

$$C_{eq}(P_{G,av}) = -0.687P_{G,av}^2 + 5.27P_{G,av} + 65.63 \quad (21)$$

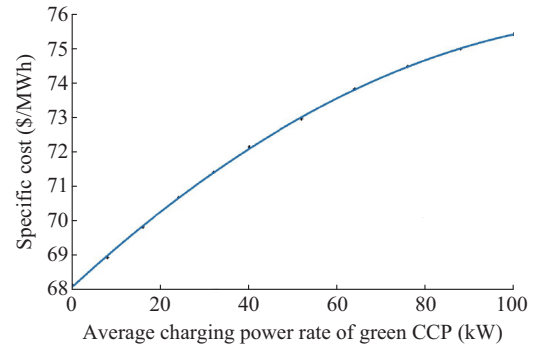


Fig. 13. Regression curve and mean points for average charging power rate of green CCP.

The increase in the average charging power for green CCP leads to an increase in the EV aggregator costs. Note that this variation is important.

E. Variation in Average Charging Power Rate of Blue CCP

The results are graphically illustrated in Fig. 14. A peak between hour 7 and hour 9 is recorded with small values of $P_{B,av}$. It is a similar finding in the case of the variation in the average charging power rate of the green CCP. However, with the increase of $P_{B,av}$, it is noted that the load become quite random during the entire day. The load also decreases

during the cheapest periods. The management of EV load loses its significance because of the limited charging duration. In addition, several user tests could not be performed during the simulation optimizations. This can be explained by the fact that the maximum constraint imposed by the operator limits the charging load. This means that the EV aggregator will have to pay the penalty cost C_p .

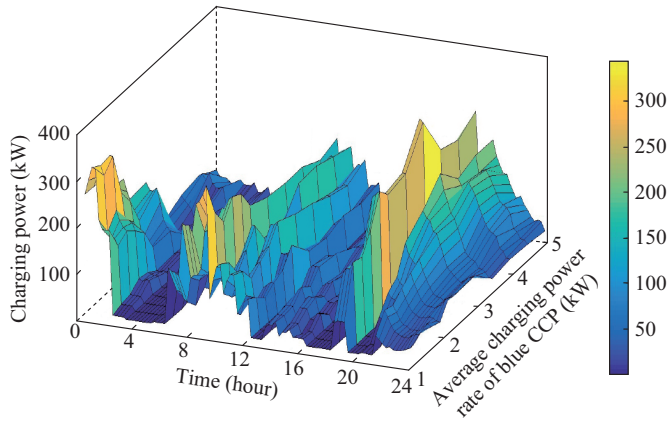


Fig. 14. EV load considering different strategies for variation in average charging power rate of blue CCP.

In Table VI, the means of EV aggregator expenses are presented for each scenario. The EV aggregator cost per energy delivered of the blue CCP increased from 67.76 \$/MWh ($P_{B,av} = 1.25$ kW) to 77.37 \$/MWh ($P_{G,av} = 5.0$ kW), which represents an increase of 14.18%. The total EV aggregator cost per energy delivered increased from 74.66 \$/MWh ($P_{G,av} = 1.25$ kW) to 77.20 \$/MWh ($P_{B,av} = 5.0$ kW), which represents an increase of 3.40%.

TABLE VI

SUMMARY OF MEAN VALUES CORRESPONDING TO DIFFERENT STRATEGIES FOR VARIATION OF AVERAGE CHARGING POWER RATE OF BLUE CCP

$P_{B,av}$ (kW)	C_B (\$)	C_{VAR} (\$)	$E_{B,tot}$ (kWh)	$E_{EV,tot}$ (kWh)	$C_{B,eq}$ (\$/MWh)	C_{eq} (\$/MWh)
1.25	105.2	393.8	1552.6	5275.2	67.76	74.66
1.50	107.3	394.0	1549.3	5249.8	69.24	75.05
1.75	109.4	394.5	1552.9	5233.9	70.44	75.37
2.00	110.4	393.8	1542.4	5201.6	71.56	75.71
2.25	111.9	393.8	1543.0	5186.6	72.50	75.93
2.50	113.8	395.7	1551.5	5192.6	73.34	76.21
3.00	115.3	395.9	1546.1	5175.3	74.59	76.49
3.50	116.8	396.2	1545.3	5164.2	75.56	76.73
4.00	117.8	396.9	1541.6	5155.6	76.41	76.98
4.50	119.1	397.6	1548.3	5158.9	76.90	77.08
5.00	119.3	397.3	1542.5	5146.7	77.37	77.20

In Fig. 15, it is represented by the regression curve with the mean points of each scenario. The next regression function is obtained as:

$$C_{eq}(P_{B,av}) = -0.19P_{B,av}^2 + 0.18P_{B,av} + 72.75 \quad (22)$$

The increase in the average charging power for the blue CCP leads to an increase in the EV aggregator costs. Note

that this variation is not very significant.

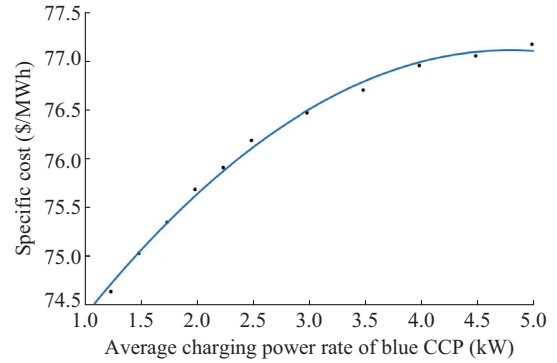


Fig. 15. Regression curve and mean points for proportion of green CCP users.

F. Discussion

The massive introduction of EVs will introduce significant demands in power systems. Without smart charging techniques, EV charging can lead to grid complications. The behavior of users will impose additional technical and cost constraints. EV aggregators can properly manage the uncertainties of this new load.

This work studies the impact of different input parameters applied to a smart charging technique. These parameters can significantly differ depending on user behavior. According to the results, the most critical expense variations are identified in the average charging power rate for green CCP, for which a difference of 10.26% is depicted for the total EV aggregator costs between the studied lower and upper bound. The variation in proportion of the green CCP depicted a difference of 7.03%, and the time delay presents a difference of 5% between the lower and upper bound.

Other variations such as the minimum required energy to charge an EV do not present significant variations in terms of cost, in which the variations between the lower and upper bound reach only a difference of 2.03% in terms of total EV aggregator costs. For the variation in the average charging power rate of the blue CCP, a difference of 3.40% is depicted for the total EV aggregator costs between the lower and upper bounds.

The EV aggregator could incentivize users to charge EVs during more extended periods to earn more benefits. However, even with the proper incentives, if EV users feel that the charging time does not match with their time flexibility, they could feel discouraged to adopt the smart charging technique. Thus, the values of these input parameters are key challenges for EV aggregators. The reaction of EV users to the incentives, in real case studies, should be studied first, to select the appropriate values. Therefore, fixing the value according to EV user preferences could result in an incentive to adopt this charging technique.

V. CONCLUSION

This work discusses the technical and economic impacts of EV user behavior on a smart charging technique, which considers three CCPs. Sensitivity analyses of different vari-

ables, based on Monte Carlo simulations, are performed to assess the impact of each one on the EV aggregator costs and the distribution system load. The studied variables are: minimum required energy, time delay of the starting charging time, proportion of green CCP users, and average charging power rate for green and blue CCPs. A regression analysis is also performed for each variable to correlate the relationship between the analyzed variables and the specific costs. Some simulation curves present a linear relation between the EV specific cost and the studied variables, while others show a quadratic relation.

The obtained results demonstrate that some variables have more influence than others on EV aggregator costs and the flexibility of the demand associated with the EV charging. The variation in the minimum required energy has not presented significant changes in EV aggregator expenses, which means that the aggregator has to establish this variable according to EV user preferences. The variation in the proportion of green CCP users has also more significant expenses such as variation in the time delay of the starting charging time but until 3 hours of delay, when the variations become insignificant. However, the most significant expenses variations have been observed in the variation of average charging power rate for green CCP.

In future studies, long-term EV planning with the smart charging technique could be examined, considering all the uncertainties due to these crucial variables.

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Jean-Michel Clairand received the M.Sc. degree from the Ecole Nationale Supérieure de l'Electronique et Ses Applications (ENSEA), Cergy-Pontoise, France, in 2014, and the Ph.D. degree in Industrial Production Engineering from Universitat Politècnica de València, València, Spain in 2018. He worked in Empresa Eléctrica Quito in 2014. He was an international visiting graduate student at the Department of Electrical and Computer Engineering at the University of Waterloo, Canada, from 2017 to 2018. He has been lecturer in Universidad de las Américas, Quito, Ecuador, from 2014 to 2017, and assistant professor since 2018. He is also Visiting Researcher at Università degli Studi di Bari Aldo Moro in 2019. His research interests include electric vehicles, smart grid optimization, and microgrids.

Javier Rodríguez-García received the M.Sc. degree in electrical engineering from the Universitat Politècnica de València, Spain in 2004, where he is currently pursuing the Ph.D. degree in industrial production engineering. After working in the private sector a couple of years, he has been with the Institute for Energy Engineering ever since. In this period, he has been involved in several international (USA, Europe, and South America) and national research projects and consulting works with public and private funding such as EU-DEEP (Europe), DRIP (Europe), DROP (USA) and Smart Grids in Ecuador Project (South America), among others. His interest areas are basically in the fields of demand response, smart grids, EV charging management, energy markets, energy efficiency and management.

Carlos Álvarez-Bel received the M.Sc. and Ph.D. degrees in Electrical Engineering in 1976 and 1979 from the Universitat Politècnica de València, Spain, where he is professor since 1989. His professional activity has been performed in the electric energy systems field in the framework of utilities, research centers and universities. He has been involved in many projects and consulting work with utilities both in Spain and abroad (USA, Europe), in the fields of load modelling, standard markets, microgrids, etc.