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Decentralized EV charging and discharging scheduling algorithm based on Type-II fuzzy-logic controllers

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ABSTRACT

Electric vehicles suppose a new paradigm in mobility and a challenge for today electric grids because its number increases day by day. Therefore, it is of paramount importance to keep the electric grid stable to allow an efficient charging of electric vehicles, besides keeping the traditional energy services for every other electric devices in industry, cities and homes. To achieve that, the process of charging and discharging of electric vehicles should be taken under consideration to allow an efficient use of the available energy in the grid and batteries. As a consequence, new intelligent control systems have to be developed because uncontrolled charging of electric vehicles can not only cause grid instability, but at certain times of day can be a significant cost to the user. It is therefore important not only to make intelligent control, but also to take advantage of the charging/discharging capacity of electric vehicles and charging stations, so that not only the grid can be stabilized, but also the cost of electric vehicle charging can be significantly reduced. In the present work, we propose a type-II fuzzy cascade controller that will be run in every electric vehicle following a decentralized approach when it is plugged. In the first level of the controller the need and urgency of charging/discharging are evaluated based on grid voltage that the EV charging station measures. The electricity prices are also considered in this first phase. In the second level, the amount of charging/discharging energy is finally decided based on the battery state and the time remaining for departure specified by the user. The implemented type-II fuzzy controller presents an significant advantage compares to type-I systems because of its better suitability for systems where measures have high levels of uncertainty like those existing in the electric grid or batteries. The controller has been tested on a branch type distribution network, where load demand and energy cost vary dynamically over a three days simulation period. Finally, the results obtained have been compared with other fuzzy controllers proposed in other articles, where similar parameters are taken into account, showing the proposed system a better behavior that those controllers.

1. Introduction

At the present, governments are increasingly investing on Electric Vehicles (EVs) as a viable alternative for the replacement of combustion engine vehicles. Behind this action lies the fact that EVs do not produce pollutant gases such CO_2, CO, NO_x, SO_x, which are recognized as harmful for the environment and for the population's health as stated in [1]. However, integrating a relevant number of EVs into the grid presents some challenges to solve since it could induce a significant stress on the power systems. This fact was studied in [2], which reflects an expected increase of the EV penetration rate of 15.98% in the European Union in the year 2050, incurring in a raise of 90 TWh on the annual production of electricity on the period 2030–2050. As observed in [3], this could cause overloads in the transformers or relevant power losses. In the particular case of Portugal, it is estimated that a 10% penetration of EVs causes an important voltage drop [4]. The negative consequences on the grid are expected to be even more severe because of the simultaneity of the charging: consumers tend to have a fixed pattern when charging EVs, which usually occur when they return from work in a common period of time. This behavior increases the peak demand, which accentuates the stress problem on the electrical system.

In this current context towards a sustainable use of the energy resources, it is become critical the development of algorithms which could manage the energy assets efficiently, preventing overloads in the power system while avoiding unnecessary investment on the electrical infrastructure [5]. This requirement is also applicable to EVs so that advanced scheduling algorithms for EVs should benefit from the fact that their charging is flexible. This implies that the charging periods

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can be planned for a future if that is convenient for the grid or for the user, being not mandatory an immediate plug-and-charge strategy. For instance, the charging of the EVs could help to regulate the discontinuous power supplied by renewable energy sources by acting as energy reservoir, thus dampening possible shortages of energy. These control algorithms could be also extended for Vehicle-to-Grid (V2G) operations, in which the EVs participate in the grid services as energy suppliers. Thus, in the V2G context, the EV is envisioned to perform a dual role for the grid: (i) it can be charged as a load with energy flowing from the grid to the EV or (ii) it may discharged as a source, with an energy flow from the vehicle to the grid. As a source, the EV could help in ancillary services and participate in frequency regulation or economic dispatch, among others [6]. The dual role is expected to be operative for ordinary or emergency situations in a wide set of scenarios, including microgrids, minigrids or cities. This two-fold possibility of integrating the use of EV batteries in grid control should be conveniently exploited. The advanced dispatching algorithms must decide which type of operation should be performed (charging, discharging or none) at a specific time. It is needed smart control techniques which can be operated at different load levels and adapt their configuration depending on the necessities of the grid, EV, and different power generators.

How to make an optimized planning of the EV charging and/or discharging is a current research topic [7–10]. There are multiple approaches for this, which can be classified according to the criteria on which they are based or on the methodology that they follow. Considering the criteria, they could attend to the grid requirements or users' satisfaction, mainly. As for the integration in the grid, the algorithms could help in frequency and voltage regulation as well as in complying with the limits of active and reactive power. As an illustrative example of this approach, [11] reviews how the EVs can be integrated into the grid as virtual power plants. With this methodology, the EV can give grid-support by means of active power support [12], regulate voltage using reactive power support [13], provide power factor regulation [14], and work as a harmonic filtering [15]. Concerning the user's satisfaction, the algorithms usually take into account satisfying the charge requirements at the lowest cost. In this sense, the work in [16] describes two online algorithms.

Scheduling algorithms can also be divided into three categories according to the methodology they follow: centralized, distributed and decentralized. In the centralized algorithms, all information is saved and managed by a central controller. Next, the central unit uses a single control system that decides the best charge/discharge strategy considering factors like power grid capacity, grid frequency, energy price, EV energy storage needs, EV capacity, etc. There also exist distributed control systems, in which each element in the grid can decide how to act, with reduced interaction with other controllers working at other EVs. They can also use additional information about the grid information that can be extracted locally. The decentralized algorithms avoid the interaction with other peers, so the decision is purely local. In the decentralized algorithms, local information or estimations pay special relevance as they are the main parameters that can be used as input for the controllers. Although centralized algorithms could get the optimum configuration of the EV controllers, they require considerable data and communication costs, which make the solution not scalable. In addition, having an only element for the decision of a set of fleets is a relevant vulnerability. The work in [17] identifies significant cyberattacks in EV charging stations. One of the vulnerable points is the central server where the centralized control works. In [18], the impact that these cyber-attacks have on the electrical grid are studied and tested. This is overcome in distributed and decentralized solutions, leading to more robust and scalable techniques if the estimated data are precise.

Taking into account the high amount of uncertainty in the decisions that should be covered by the decentralized algorithms in the presented charging problem, fuzzy rule-based systems (FRBS) arise to a feasible solution. Moreover, FRBS have the advantage of a more flexible and adaptable performance in a wide range of scenarios. These systems are based on type-I or type-II Fuzzy logic. Fuzzy logic has demonstrated its suitability in those situations in which uncertain information is handled, with possible errors or incomplete data. In the context of power systems, some studies about voltage regulation have been done into the conventional grid employing a fuzzy controller, as in [19]. There are also FRBS for Photovoltaic systems, [20,21], for the control of the plug-in supercapacitor modules into hybrid energy storage systems [22] to improve thermal-electrical management of the battery, to shape energy policy in cities [23] or for wind energy installations [24], among others. As can be observed, fuzzy controllers can process and analyze many different kinds of inputs to provide a correct response based on the system situation. In particular, type-II fuzzy logic has revealed itself as specially suitable in those scenarios where the inputs are not precise. This advantage is convenient for V2G/G2V systems to consider both grid and user-related parameters.

Table 1 summarizes some relevant proposals for EV scheduling based on fuzzy logic. The related work focus on type-I fuzzy logic system but type-II fuzzy logic could report important advantages in this context. Some inputs (e.g. V, ΔV and Δf as the grid voltage, voltage variation and frequency variation) of the proposed algorithms are derived from physical measurements, which may be prone to errors due to the tolerance of the equipment. Actually, the tolerance of the new grid meter complies with the UNE-EN IEC 61557-12:2022/A1:2022 standard [25]. The value specified in the standard is 1.5% plus other % depending external conditions. The extra value varies between 0.5 and 6.0%. Other parameters may be also affected by inexactness, specially those computed from estimations. This is the case of the time remaining to departure (TRD).

Considering the previous control algorithms, we propose a novel controller with three relevant advantages. First, it is based on type-II fuzzy logic to cope with the inputs' inherent inaccuracy. The second advantage relies on the fact that it is based on a cascade design to reduce the complexity of the system. In turn, this type of design improves the control performance. Finally, the controller is implemented and runs in each EV independently of others when it is plugged. In this way, we provide a controller feasible for local implementations with a decentralized EV dispatching strategy.

The main contributions of our work are described as follows. The first one is the proposed type-II fuzzy controller that manages the process of charging/discharging the battery in each EV independently. It is a decentralized approach based on internal and external parameters. Specifically, the parameters considered are the battery state of charge, the grid voltage and the time of departure estimated by the driver. The scheme of the controller is illustrated in Fig. 1 . This control maximizes the benefit for the customers and the electric grid balance.

The second contribution is the use of a type-II fuzzy control to deal with the uncertainties of the measurements and estimations in our design. Thus, they are conveniently managed with the type-II fuzzy control, in which we have modeled the conventional errors due to the tolerance of voltage sensors and the imprecise estimations of the users' behavior. The consideration of uncertainties is not modeled in the previous controllers described in the related work. In addition, we propose a controller system designed with two subsystems following a cascade approach. In this way, the fuzzy rules are reduced significantly, which could turn into simpler and more robust implementations. Finally, the performance of the proposed controllers have been evaluated and compared with other relevant decentralized techniques. For this task, some data related to the specific application in the Spanish scenario were considered.

A fuzzy system is used in the present approach because these systems are very often applied in those situations in which there is no exact mathematical function that relates the inputs to the outputs. Consequently, we have designed a fuzzy controller to overcome the uncertainty related to the convenience of EV charging/discharging.

Table 1
Summary of decentralized fuzzy controls in the literature.

Reference	Charging	Discharging	Fuzzy type	Grid-related inputs	User's preferences inputs
[26]	✓	✗	I	SoC, Cost	–
[27]	✓	✗	I	SoC, V	–
[28]	✗	✓	I	SoC, Δf	–
[29]	✓	✗	I	Cost	Required SoC
[30]	✓	✗	II	Cost, SoC, Renewable generation	–
[31]	✓	✓	I	ΔV, TOU, SoC	Required SoC, TRD
[32]	✓	✓	I	ΔV, SoC	Required SoC, TRD
Proposal	✓	✓	II	V, Cost, SoC	TRD

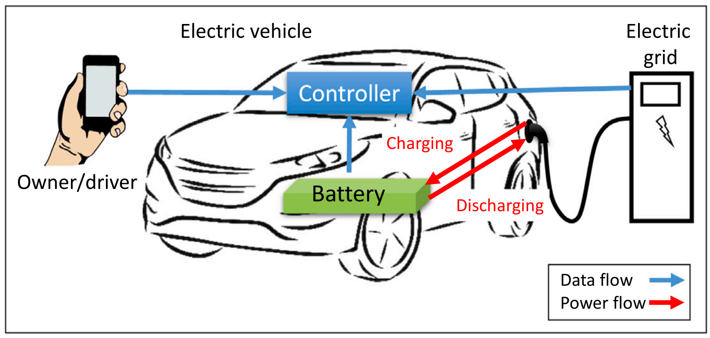


Fig. 1. Proposed type-II fuzzy controller for an electric vehicle.

Thus, in our proposal, the input fuzzy variables can vary over time between their minimum and maximum values for many reasons: the use of sensors that give an approximate voltage and with a high tolerance in the measurement, the difficulty of determining an exact behavior of each driver, etc. Then, input variables that have exact values are converted into qualitative variables through fuzzy sets. The inputs are related to each other through the rules and output functions designed in this approach, to obtain a crisp value. This output is the one used to know whether the vehicle is charged or discharged and the amount of power involved in the process.

The remainder of the paper is structured as follows. Section 2 describes the main features of other dispatching algorithms based on fuzzy logic. Section 3 explains the control design proposed for G2V/V2G operations based on type-I and type-II fuzzy logic. In a simulation scenario, Section 4 evaluates the designs proposed and compares their performance with other relevant fuzzy-logic based scheduling algorithms. Finally, Section 5 draws the main conclusions.

2. Related work

Fuzzy controllers are used in a wide variety of applications as was previously commented. In the context of power systems, fuzzy controllers are used for centralized or decentralized control algorithms in G2V/V2G systems. Different input parameters are used in these algorithms to regulate common grid variables in which the adequate operation of the power system depends on. Centralized algorithms require a common controller that collects the data from the EVs and the grid to generate the corresponding commands for the power flows. The works in [33–35] or [30] are representative centralized FRBS. The work in [36] presents a hierarchical structure in which EV local fuzzy controllers communicate with an Energy Management System (EMS). The local controllers are implemented with two independent type-I FRBS. One FRBS decides the capability of the EV to be charged and another decides the energy that the EV can deliver to the grid. The decision of both FRBS is based on the initial energy available in the EV (SoC) and the TRD. The EMS recollects the outputs of the controllers in a fleet to decide the final scheduling. The availability of the renewable energy is considered in this decision. The work in [30] proposes a type-II FRBS to decide the power flows in a microgrid with uncontrollable and controllable loads (as EVs), renewable energy sources, energy storage and fuel power generators. The goal is to decide the setting point of the controllable elements to maximize the use of renewable energy sources while achieving a uniform load curve. Only the charging of the EVs is considered in the algorithm.

Decentralized controllers offer a more robust and scalable solution for EV management. Considering only charging flows, the work in [26] describes a decentralized fuzzy controller. The FRBS is designed with three and five membership functions for the SoC and the electricity price respectively. These parameters are the inputs from which the charging power is derived. A similar approach is found in [29], but the inputs are the energy price and the SoC required by the user. The algorithm considers previous and future performances to provide a command of power as constant as possible. With the goal of improving the grid performance, the algorithm in [27] also defines a type-I FBRS but with the SoC and the grid voltage as inputs. The algorithm is executed continuously to decide the percentage change of the charging current.

Other advanced controllers are defined to manage the V2G flows. In the paper [28], a grid frequency controller is presented to regulate V2G operations exclusively, without operating in the charging process. When discharging its battery, the EV uses its local type-I FRBS controller. This system considers the frequency deviation (Δf) in the grid and the EV SoC to determine the power flow. There are also bidirectional controllers that decide the power flow in both senses. In [37], the type-I fuzzy controller makes the charging and discharging decision for grid frequency regulation. This preliminary decision is sent to a second optimization algorithm to determine the amount of energy to charge/discharge. This system considers the frequency deviation (Δf) in the grid and the Area Control Error (ACE) as explained in [38]. The use of the ACE restricts its use as a fully decentralized algorithm. A different approach is described in [39], in which the type-I fuzzy logic controller is used to determine the convenience of charging or discharging an EV in a particular charging station. In this way, the user can decide where to plug his EV among the charging stations close to its location. The decision is mainly based on the electricity prices and the amount of the power flow is not adjusted to the specific conditions of the grid.

The papers described previously only consider available measurements from the grid or the battery status. However, it is possible to incorporate other parameters such as estimations or preferences of the users' behavior. In this sense, the authors in [31] proposes a fuzzy controller for an improved integration of the EVs considering the grid parameters and the user's preferences. Specifically, the inputs of the FRBS are the voltage deviation of the grid, the time of use (TOU) as a demand response mechanism, the required SoC and the time remaining for departure. These last inputs, modeling the user's behavior, are a novelty in comparison with previous controllers. In a similar approach, the fuzzy controller proposed in [32] uses the voltage deviation, the required SoC and the time for departure to regulate the charging/discharging power of the EV. The last two parameters are combined to generate the input referred to as charging urgency.

Table 1 shows a summary of the characteristics of the different controllers implemented in the cited references following a decentralized approach. As can be observed, when considering the user's preferences, the algorithms already proposed assume that the data are exact definitions. However, the user could generate them with rough estimations, which are prone to variability. In this paper, we evaluate the convenience of using type-II fuzzy logic controllers to cope with the above-mentioned uncertainty. In the present approach, we use a cascade controller over a total of five inputs: voltage, SoC, V2G – with five membership functions-electric energy cost and TRD – with only three membership functions. Because of the use of the cascade controller, the number of rules for the fuzzy controller is reduced from 225 to 90 (15 for the first controller and 75 for the second controller). In this way we reduce significantly the computational power and resources that are necessary to obtain the power flow. Furthermore, it is possible to take into account a large number of parameters at the same time, which in previous studies have only been taken into account separately.

3. Control design

The goal of the proposed controller is to regulate the amount of power and connection mode for an EV (charge/discharge) in a decentralized way. The local controller installed in each EV works taking into account the following parameters: (i) grid voltage (V), (ii) energy cost ($Cost$), (iii) initial energy available in the EV (SoC), and (iv) the available recharging period based on the EV's owner estimation about his departure time (TRD). We have to remark that these input variables vary over time. However, some of them are more stable than others. Consequently, the output of the system varies over time as input does but with a non-direct mathematical function. For an effective operation, the proposed controller is based on a two-level cascade fuzzy controller design. In the first level, the controller decides about the suitability of each EV to supply or consume energy based on the grid voltage condition and the energy price costs. This level, referred to as Sense of the Power Flow (SPF), decides the connection mode of the EV (charge/discharge) and its priority, as it is a number ranging from −1 to 1. In the second level, called Percentage of Power (PP), the controller determines the percentage of power that the EV is going to consume or supply. It must be noted that the owners/drivers make no decisions about the charging/discharging process in the EV that will run the proposed controller, limiting their intervention to set the parameter TRD when they plug the EV to the grid. This action would be accomplished by using a mobile app or the control console of the car, as shown in Fig. 1.

The PP stage have three inputs: The output of the SPF controller (V2G), the SoC and the TRD. As can be observed, the SPF level uses information from the grid whereas PP relies on the EV's SoC level and the expected user's behavior. In this way, SPF will decide whether energy is consumed/supplied and PP the amount of energy exchanged. Figs. 2 and 3 show the diagram of then two stages of the proposed controller: the SPF stage and the PP stage.

The proposed controller will be designed with two approaches so that we will derive type-I and type-II fuzzy controllers. The main difference between the two controllers is that the fuzzy sets of inputs in type-II are more complex and are used in applications where the degree

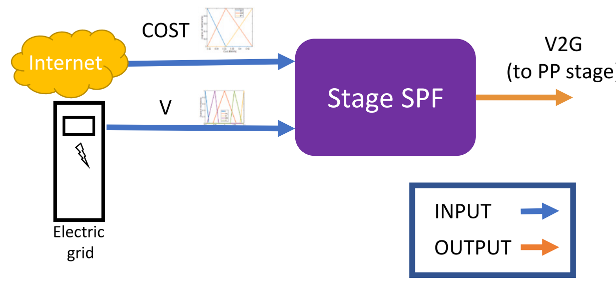


Fig. 2. SPF stage of the proposed cascade fuzzy control.

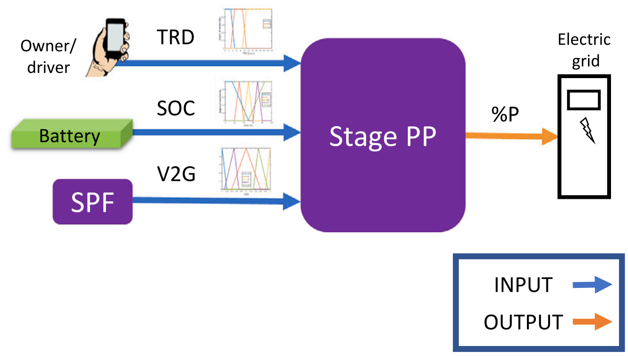


Fig. 3. PP Stage of the proposed cascade fuzzy control.

of uncertainty is higher. The convenience of the type-II fuzzy controller will be evaluated for the specific scenario under study.

Both fuzzy controllers use the *"Takagi–Sugeno–Kang (TKS)"* method. This method is different from the Mamdani one because the output of a TKS fuzzy system is defined as a set of linear functions, whereas in a Mamdani system the output is just modeled with one or more independent variables [40].

The fuzzy logic systems are characterized by the membership functions of the inputs. The input variables are related to each other by the so-called rules to obtain the output. The rules are stored in the knowledge base (KB). Thus, in a fuzzy system the inputs are fuzzified with the fuzzy sets defined in the membership functions, combined with each other with the KB rules and finally the output is obtained and defuzzified to get a final crisp value. Fuzzy controllers are used in many engineering fields, such as humidity control [41], automotive [42] or wireless sensor networks [43].

The next two subsections explain the type-I fuzzy controllers for SPF and PP subsystems. The last subsection will explain the modifications required for the type-II fuzzy logic system.

3.1. Stage SPF

The first level, the SPF stage, works with two inputs in the fuzzy controller: price of electricity ($Cost$) and grid voltage (V). The $Cost$ variable has three membership functions or fuzzy sets quantified as a specific price interval: (i) Down Time (DT), zone with low energy cost, (ii) Off-Peak (OP), zone with medium energy cost, (iii) and Peak Time (PT), zone with high energy cost. These three ranges for the energy costs are typical in current power systems. The input fuzzy sets of the $Cost$ variable are shown in Fig. 4.

The grid voltage V has five membership functions divided into Low (L), Medium Low (ML), Medium (M), Medium High (MH), and High (H). The Fig. 5 includes the shape of those fuzzy sets.

The output of this controller stage is the connection mode to choose by the EV (V2G/G2V) and its corresponding priority. The output is divided into five different levels: (i) very negative (VN), (ii) negative

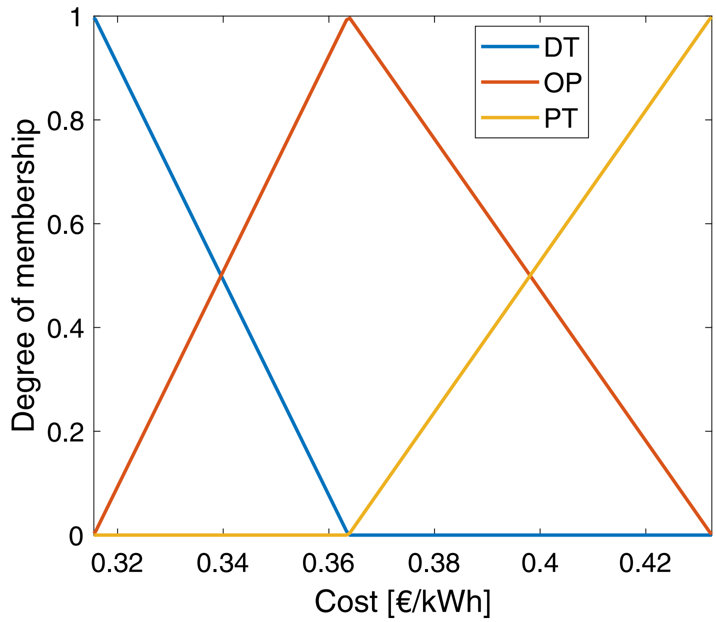


Fig. 4. Fuzzy type-I membership functions of $Cost$ variable for SPF.

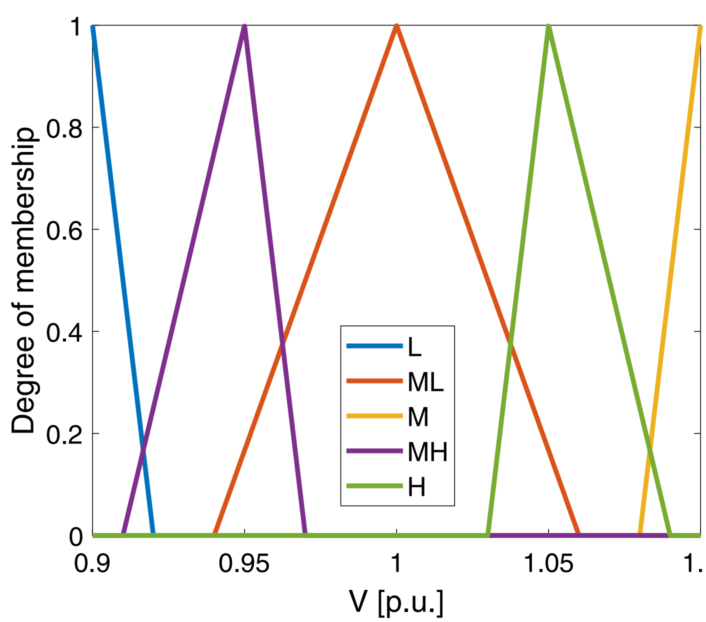


Fig. 5. Type-I fuzzy logic membership functions of V variable for SPF.

(N), (iii) maintain (M), (iv) positive (P) and (v) very positive (VP). The very negative level indicates a full discharge of the EV in the electric grid; negative is for a medium discharge; in 'maintain' level the EV does not charge nor discharge, and finally both positive and very positive levels imply charging the EV as the opposite to negative and very negative ones. The output of the SPF controller is summarized in Table 2. The SPF knowledge base is described in Table 3.

The knowledge base rules are defined in a clear and precise way that make them easy to understand. The design of the fuzzy rules is based on expert knowledge. Expert knowledge consists of using the practical experience of the research team to configure all the parameters of the fuzzy system. Thus, fuzzy rules have been developed from the study of the behavior of EV charging/discharging processes and the variables that can be measured by the controller to achieve a realistic decision for V2G or G2V modes.. For example, if $Cost$ is DT (low price) and V is L (lower than the reference value), then the output of the controller is VP, i.e. the battery should be charged with a very high probability. The output of this stage is the $V2G$ input of the next one. The rules can be explained as follows: with the first premise, the user is getting benefits, with the second one, the load in the grid is increased so that the voltage can also be elevated.

Table 2
Output of SPF controller.

Output	Value
Very negative	−1
Negative	−0.5
Maintain	0
Positive	0.5
Very positive	1

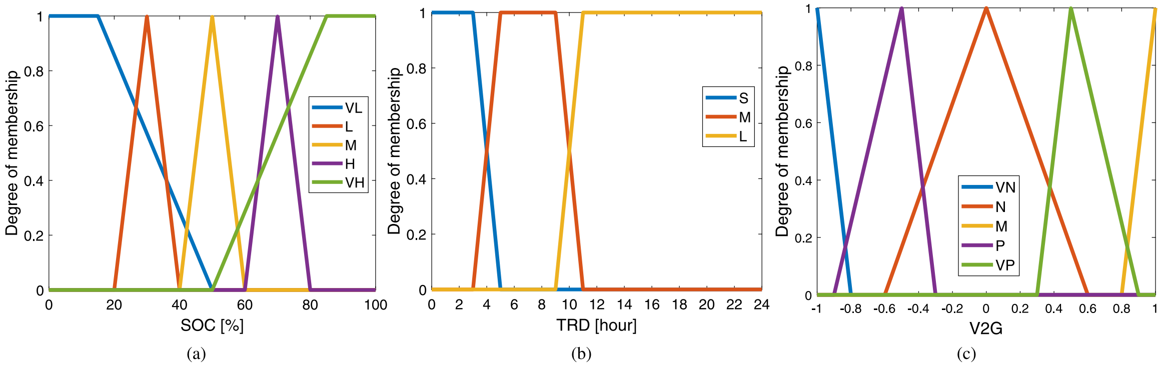


Fig. 6. Type-I membership functions of PP. (a) SoC, (b) TRD, (c) V2G.

Table 3
KB of SPF controller.

Cost\V	L	ML	M	MH	H
DT	VP	P	N	N	VN
OP	VP	P	M	N	VN
PT	VP	P	P	M	M

Table 4
Rules for V2G(VN) of fuzzy controller 2.

V2G VN					
TRD\SoC	VL	L	M	H	VH
S	VP	VP	VP	VP	P
M	VP	VP	VP	P	P
L	VP	VP	P	P	P

3.2. Stage PP

The second fuzzy control stage has as inputs the $V2G$, output of the previous control, the SoC of each EV, and the TRD. The $V2G$ input variable has five membership functions which are, very negative (VN), negative (N), maintain (M), positive (P), and very positive (VP). The SoC input is also defined with five membership functions, very low (VL), low (L), medium (M), high (H), and very high (VH). Finally, TRD has only three membership functions, short (S), medium (M) and long (L).

The degree of membership in the variables of this fuzzy control is defined with triangular membership functions for values L, M, and H in SoC and membership functions of $V2G$. However, VL and VH signals in SoC and TRD are trapezoidal membership functions as illustrated in Fig. 6.

The final output of this fuzzy controller, which is obtained from this stage, is the power level of charge/discharge per unit (P), who is defined in five levels: very negative (VN) and negative (N) for discharging, maintain (M), and finally positive and very positive for charging. Their singleton values are equal to the previous output, so the values in the Table 2 also refer to this output.

The rule base for the PP stage is defined in five different tables (Tables 4–8), each one for one membership function of the input variable V2G. In these tables, it can be seen the final singletons outputs of the two level cascade controller which are: very positive (VP), positive (P), maintain (M), negative (N) and very negative (VN).

3.3. Type-II Fuzzy logic

This section will explain the differences in controllers when using type-II fuzzy logic. As it was previously explained, this type of fuzzy logic is used in applications where uncertainty is very high. One of the goal of this paper is to evaluate the convenience of this type of fuzzy logic systems. The main difference in type-II fuzzy logic is in the shape of the membership functions. In this case, the fuzzy sets become surfaces to handle uncertainty. The fuzzy sets are formed with the so-called footprint of uncertainty (FOU) that are associated through the rules included in the knowledge base in the same way as in type-I. The output is also obtained in a similar way, through combinations of the inputs and outputs with knowledge rules. Now, the mathematical functions to obtain the output are more complex.

Table 5
Rules for V2G(V) of fuzzy controller 2.

V2G N					
TRD\SoC	VL	L	M	H	VH
S	VP	VP	VP	P	P
M	VP	VP	P	P	M
L	VP	P	P	M	M

Table 6
Rules for V2G(M) of fuzzy controller 2.

V2G M					
TRD\SoC	VL	L	M	H	VH
S	VP	VP	VP	P	M
M	VP	P	P	P	M
L	P	P	P	M	M

Table 7
Rules for V2G(P) of fuzzy controller 2.

V2G P					
TRD\SoC	VL	L	M	H	VH
S	VP	VP	P	M	N
M	VP	P	M	M	N
L	P	P	M	N	VN

Table 8
Rules for V2G(VP) of fuzzy controller 2.

V2G VP					
TRD\SoC	VL	L	M	H	VH
S	VP	VP	P	N	VN
M	P	P	M	N	VN
L	M	N	VN	VN	VN

We keep the same input variables but it is necessary to define the uncertainty in them with the FOU surfaces. Specifically, we assume that errors could be mainly associated to the measurements of the grid voltage (in SPF) and the TRD (in PP) of each EV. These variables show a high uncertainty which is produced by the error in the voltage meter, and the real use of the EVs. For the voltage case, we have defined the FOU based on a 3.2% of tolerance, which has been defined as the maximum tolerance error measures in adverse conditions, specified in

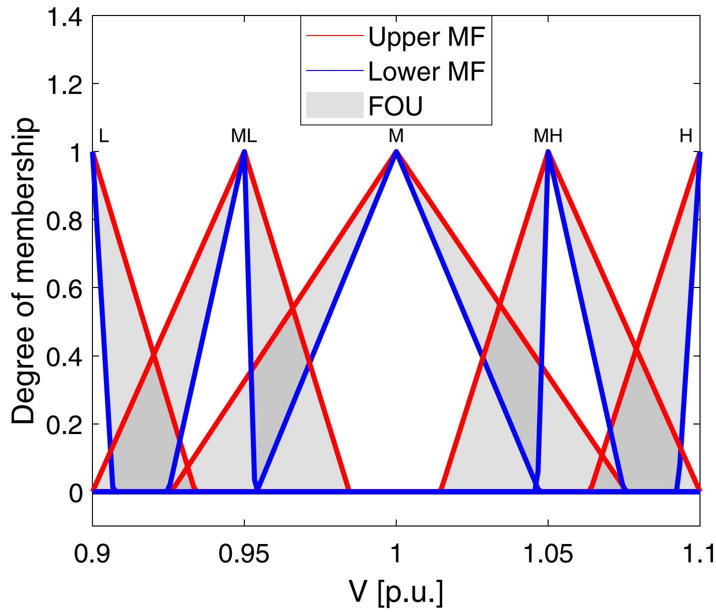


Fig. 7. System membership functions for V in SPF using type-II fuzzy logic.

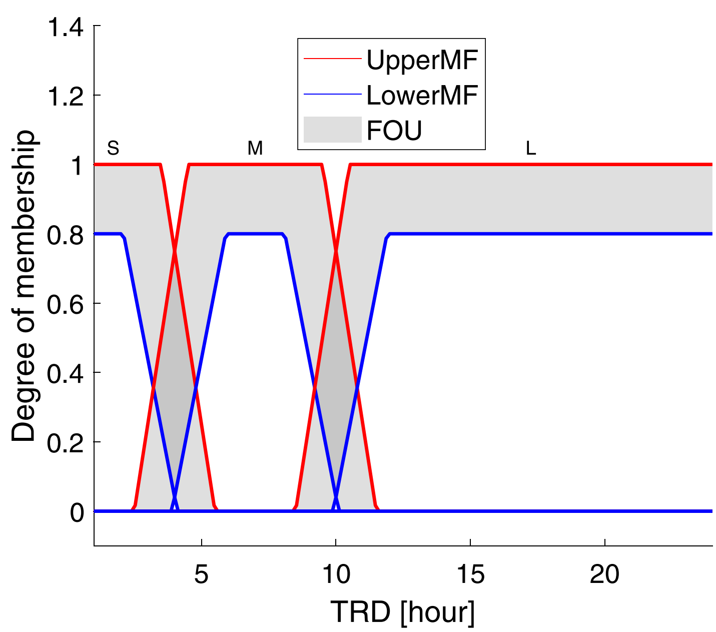


Fig. 8. System membership functions for TRD in PP using type-II fuzzy logic.

UNE-EN IEC 61557-12:2022 [25]. Fig. 7 shows the tolerance which is distributed in a +1.6% to upper MF and a −1.6% to lower MF. Concerning the TRD input variable, it has a value set by the user, who may have an unpredictable behavior. In this case, it is supposed an uncertainty interval of one half an hour before and after the user estimated departure, Fig. 8. With this approach, they are quantified two different possibilities in the time of use of each EV. The rest of the inputs have been defined using a general FOU of 0.2 because they show a good behavior of the system in the design tests that have been accomplished.

Finally, the output of type-II fuzzy systems is obtained by calculating the centroid derived by combining the inputs and outputs with the rules of the knowledge base. The final chosen method to compute the centroid of type-II parameters is the enhanced iterative algorithm based on stopping condition (EIASC), which had been previously tested in [44,45]. This method shows a better performance than other available algorithms because it requires less processing resources.

4. Evaluation

The evaluation of the proposed decentralized techniques is performed within a realistic scenario. The grid scheme is shown in Fig. 9. The grid is based on a representative radial distribution as the one used in [33]. It is composed of a 33-kV substation in node 1, which supplies energy to three branches. Each branch is composed of four demand nodes, which have different demand power (active and reactive). They are at nodes from 5 to 15. At node 16, we have located the fleet of EVs.

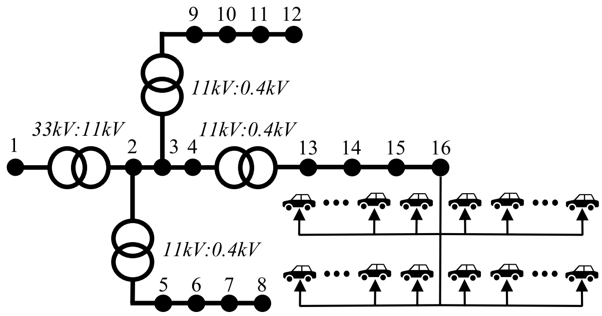


Fig. 9. Representative distribution power system for evaluation.

The maximum capacity of the power generator that supplies energy via the substation in node 1 is 5 MW and 3.5 MVar. This means that the usual system demand combined with the EV charge demand must not exceed the above mentioned limits.

To model the variation of the energy demand of nodes 5–15, a factor h is included in the consumption of the nodes. This parameter fluctuates between 0.6 and 1 according to the variation of the Spanish load demand. It means that the lower load has $h = 0.6$ whereas the higher load has $h = 1$. To decide which "h" value should be applied at each instant, we consider a representative load curve as a reference. Specifically, the curve is generated from the electricity Spanish demand data during 2021 [46]. In order to obtain a representative curve of the entire year, we have proceeded as follows. First, we have collected the 365 curves of energy demand for 2021 from [46]. Next, we estimated a representative load curve of the year using the k-means algorithm so that we can obtain a more realistic load variation than the one derived from an arithmetic mean [47]. The curve generated represents the consumption variations during a day. The main objective is not only to test the capability of the fuzzy control algorithms to work under static load conditions, but we also want to check how it adapts to the load variations.

Concerning the EV demand, three load profiles were considered. Initially, three basic user profiles are generated (Pro_i with $i \in \{1, 3\}$). The three profiles have been designed based on the three main patterns for the working times that can be found in Spain. The first profile is based on a full-time job with a half-day split timetable. In the second profile, an intensive full-time has been considered. Finally, in the third profile, it has been taken into account a full-time night schedule.

Each user profile is characterized with the following features:

- Initial SoC. This is the state of the charge that the battery of the EV has at the beginning of the day (0 h).
- Minimum SoC. This is the lower limit allowed for the SoC of the EV battery. This can be imposed whether technically to prevent early battery degradation or according to the user's preferences. For our evaluation, this lower limit is set between 20% and 25%, which is the minimum SoC level that the manufacturers usually recommend to extend battery life [48,49].
- Charge rate limit (C^{rate}_{limit}). It represents the maximum amount of energy that can flow from/to the battery in a period of time. For the computation of this parameter, we first calculate the maximum power flow in each EV as: (1)

$$C^{rate}_j = \frac{P_j}{V_j Ahr_j} \tag{1}$$

where C^{rate}_j is the current applied or extracted from the EV battery when it is charged or discharged, P_j corresponds to the power required/available to charge/discharge the j battery in W; V_j is the voltage level in the battery j and Ahr_j is the current load in the battery j.
The maximum value obtained for C^{rate}_j is the one considered as C^{rate}_{limit}, which is included in Table 9.

Table 9
User profiles.

Profile	Initial SoC [%]	Minimum SoC [%]	C^{rate}_{limit}
Pro_1	50	20	4
Pro_1^-	50	20	4
Pro_1^+	50	20	4
Pro_2	50	25	3
Pro_2^-	50	25	3
Pro_2^+	50	25	3
Pro_3	70	20	5
Pro_3^-	70	20	5
Pro_3^+	70	20	5

- Time remaining until departure (TRD). This parameter defines the time until the user estimates that they will use the EV. It is necessary to pay attention to this parameter in order to guarantee that the user has enough SoC for their personal use when they have planned to start driving.

To model realistic drivers' behavior, the set of basic profiles is extended with Pro_i^+ and Pro_i^-, leading to nine final charging profiles. For Pro_i^+, the TRD is delayed two hours when compared with Pro_i. For Pro_i^-, the TRD is overtaken by two hours in comparison with the TRD of Pro_i. In Table 9, the features of the nine profiles are summarized In addition, Table 10 shows the interval of time at which the EVs are plugged/unplugged to the power system in order to model the driver profiles for testing purposes. It is worth mentioning that having an EV plugged does not imply it is charging or discharging as it was advanced in the explanation of the scheduling algorithms that are tested in this paper. Moreover, the controller of each EV only runs if the vehicle is plugged, so when the EV is unplugged that controller remains idle.

Each profile has 20 EVs, and the maximum number of EVs connected simultaneously is 160. In order to generate a more realistic scenario, we model that the SoC of the EVs decreases in a proportional way to the time it is unplugged from the grid, being the discharge current proportional to the SoC. In this way, it is assumed that the longer period an electric vehicle is unplugged, the more distance it has traveled and therefore the greater the discharge of the electric vehicle has taken place.

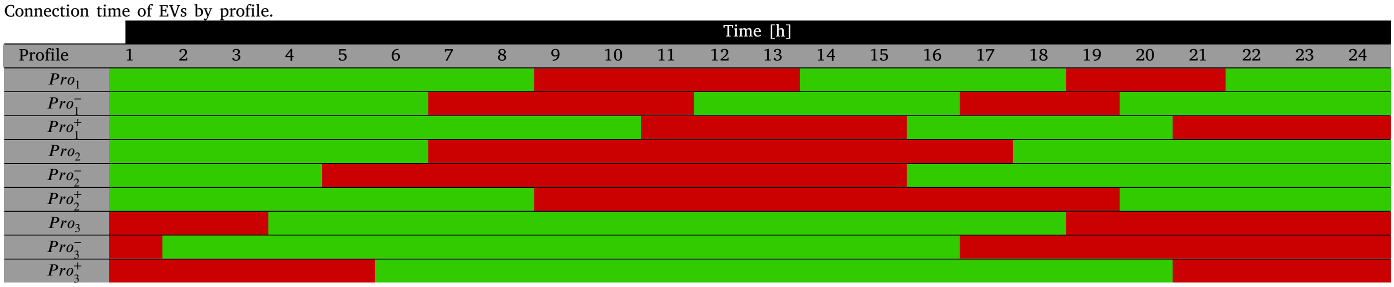
The resolution method used for the power flow is Newton–Raphson, which has the capability to converge with few iterations and with high precision. Considering the whole load (EVs and others), we have evaluated the EV scheduling algorithms for a period of three days according to the following metrics:

- ISE (Integral Square Error) of the voltage curve, which can be computed as [50]:

$$ISE = \int_0^T [V_r - V(t)]^2 dt \quad t \in \forall T \tag{2}$$

where $V_r = 1$ is the ideal voltage in the grid in p.u., and $V(t)$ is the voltage (p.u.) in the grid in each instant of the simulation. Please, take into account that voltage varies with the load and, consequently, with the control of the charge/discharge of EVs. For our computation, $T = 72$ h as we are considering the scheduling in three days. The ideal situation is that the value of ISE is always 0. This implies that the actual voltage in the grid is the same as the reference one, which leads to a better grid operation.
- Energy cost. It is defined as the sum of the costs of charging minus the revenues for discharging of all EV users during the simulation period. In our scenario, we are considering a realistic market operation in which prices change during the day. Fig. 10 shows the variation of this price in a representative scenario of the year 2021, which is obtained from the ESIOS transparency website [51]. For a simplicity purpose, we assume that the prices for selling and buying energy are the same at each instant of time.

Table 10
Connection time of EVs by profile.



Electric vehicle plugged to the power system.
Electric vehicle unplugged from the power system.

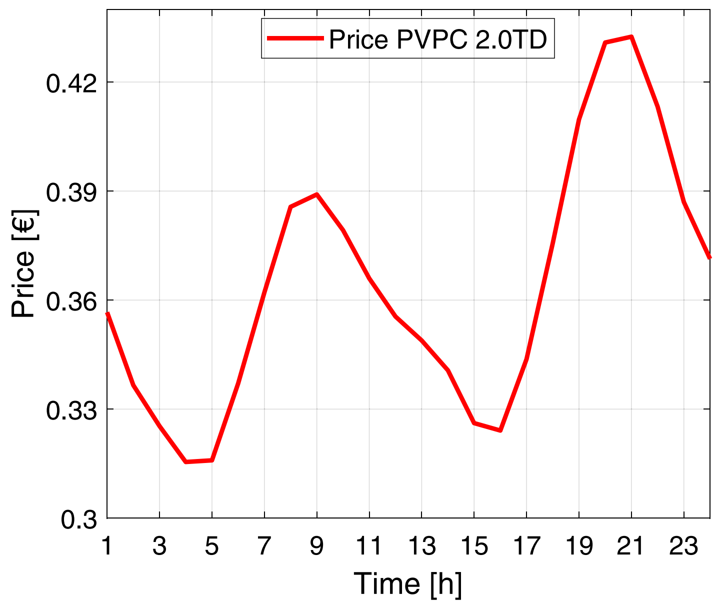


Fig. 10. Average daily price 2021 in Spain, rate PVPC 2.0TD.
Source: Data extracted from [52].

- Percentage of battery discharged. Batteries are vulnerable elements, which suffer from degradation when discharged are frequent. When evaluating a scheduling algorithm, it is vital to consider how much the battery is discharged.

With the use of these metrics, we are considering both the grid operation and the drivers' satisfaction. The scheduling algorithms evaluated are: (i) average charging rate (ACR) [53], (ii) Fuzzy type-I proposed cascade controller, (iii) Fuzzy type-II proposed cascade controller, (iv) Fuzzy type-I control [32] based in the parameter Charging Urgency (CU), (v) a smart charging Fuzzy type-I controller (SC) that takes into account the SoC and the energy cost [26] and (vi) Fuzzy type-I (ADC) described in [31] with a pre-processing of the inputs related to the grid performance and the user's preference. Section 2 describes ACR, SC and ADC in detail.

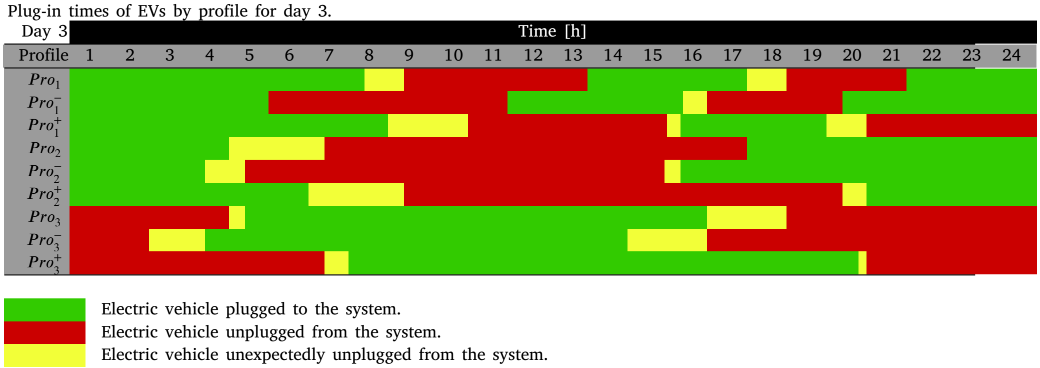
The simulation scenario is modeled to take into account uncontrollable situations, such as measurement errors in the grid voltage or personal circumstances of the users, which cause them to leave earlier than planned and arrive later, making greater use of the vehicle's battery. As an example of the periods used, the third day is shown in Table 11. In this table, the yellow areas correspond to periods when the vehicle arrives later or leaves earlier than programmed.

In Fig. 11 are shown the average system energy cost with the different controllers and the minimum SoC before departure that the EVs have during the simulation time. The dashed lines represent the limit of the SoC before departure (red), and the average energy cost for all the controllers (blue). The limit of minimum SoC has been established to ensure an enough energy amount which can guarantee that in an unexpected situation such as an non-programmed trip, the driver does not need to stop to charge the EV. This is a common requirement set by EV drivers. In order to consider that the solution obtained with the controller is an optimal solution, the minimum SoC must be over the red dashed line, and the average energy cost must be down the blue dashed line. It can be observed that the proposal based on type-II fuzzy logic is capable to comply with these requirements. The minimum SoC is reduced greatly with CU and ADC as they do not guarantee this restriction. However, the energy cost is much lower than in the other controllers. For those keeping a minimum SoC, type-II fuzzy logic controller leads to a reduced cost. Thus, only with the type-II fuzzy logic controller, it is guaranteed that a sufficient battery level is available before departure, while at the same time the energy cost is lower than the daily average. The algorithms ACR and SC only schedule charging processes and, it can be seen that incorporating V2G operations reduce the energy cost.

Fig. 12 shows the ISE evolution. Including a scheduling algorithm reports in a reduction of the ISE error, which is beneficial for the grid. ACR presents a slight improvement when compared with the type-II fuzzy logic controller, but this is achieved at a higher cost.

Although the energy cost and the minimum SoC are relevant for the user, it is also important to consider the degradation that the battery suffers in the V2G operations. Batteries are sensitive electronic devices

Table 11
Plug-in times of EVs by profile for day 3.



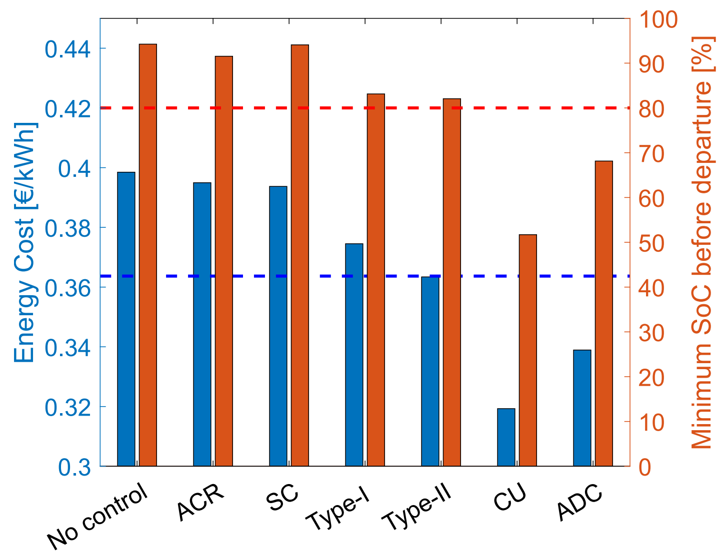


Fig. 11. Average energy cost and SoC before departure.

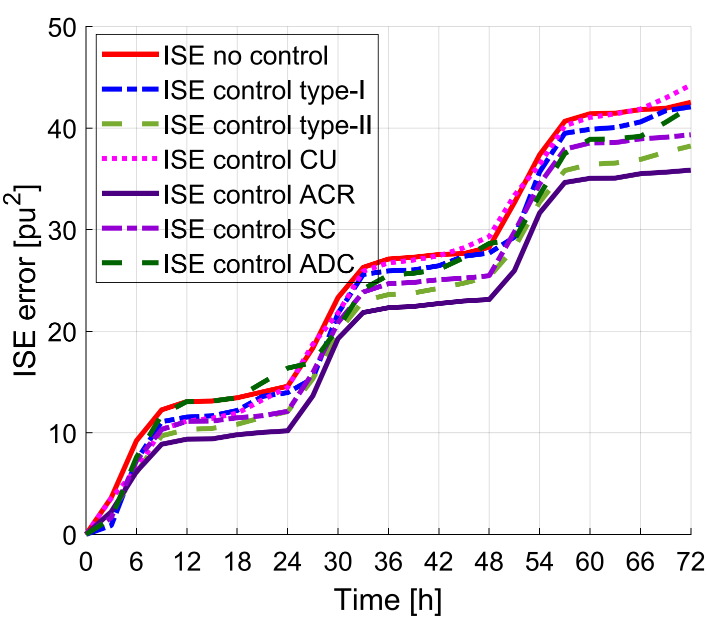


Fig. 12. ISE evolution with different controllers.

and deep discharging makes their capacity diminish. Consequently, dispatching algorithms that result in high discharging levels will shorten the useful battery lifetime [54]. Paying attention to the percentage of battery discharge in the control algorithms, the overall balance varies

Table 12
Battery percentage discharged by day and profile.

Profile	Battery discharged [%]			
	Type-I Fuzzy	Type-II Fuzzy	CU	ADC
Pro_1	14.389	4.187	20.514	48.754
Pro_1^-	49.659	20.214	75.422	104.12
Pro_1^+	1.918	4.111	0.127	14.669
Pro_2	71.648	30.332	65.864	71.563
Pro_2^-	35.352	30.432	50.238	80.013
Pro_2^+	65.191	12.403	65.610	71.817
Pro_3	2.383	0	0	42.482
Pro_3^-	0.134	0	0	39.080
Pro_3^+	5.157	4.004	0	52.291

differently depending on the controllers as can be seen in Table 12. Please, note that ACR and SC are not included in this analysis as they do not consider V2G operations. The controller supported by type-II fuzzy logic achieves a reduced energy cost and an acceptable minimum SoC while provoking reduced discharges. Its capability to cope with uncertainty leads to a better performance if we compare it with the proposal based on type-I fuzzy logic. In CU and ADC the increase of the percentage of discharge is significant. We can state that our controller results in relevant advantages in the short and long term.

5. Conclusions

This paper focuses on developing two distributed V2G scheduling algorithms to satisfy grid and users' requirements. The type-I fuzzy logic controller supposed a simpler approach than type-II fuzzy to cope to the stability and cost problem that show a good performance in experiments shown in the previous section. By using a type-II fuzzy logic controller, the scheduling algorithm is able to cope with uncertainty, intrinsically present in the grid measurements and in the user's behavior. The algorithm has been designed in a two-cascade approach in order to simplify the knowledge base.

The evaluation of the algorithms shows that type-I and type-II fuzzy logic controller achieves a better balance in terms of energy cost and percentage of battery discharged while ensuring a minimum SoC for the user, whereas other approaches used in the experiments tend to a SoC of 0% which cannot feasible in real applications. V2G operations lead to a significant reduction in the energy cost, but they have to be carefully planned to prevent early battery degradation.

Finally, it can be concluded that with the proposed controller it can be reduced the charge energy cost at the same time that improves the stability in the grid. This method would help the sustainability of EVs because it would be reduced the waste of energy, storing energy in a distributed way and when the energy is needed it can be get from EVs.

CRediT authorship contribution statement

Alicia Triviño: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Conceptualization. **Alejandro López:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Investigation, Formal analysis, Data curation. **Antonio J. Yuste:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Juan C. Cuevas:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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References

[1] D.S. Bhandarkar, Vehicular pollution, their effect on human health and mitigation measures, Veh. Eng. (VE) 1 (2013) 33–40.
[2] E. Gryparis, P. Papadopoulos, H.C. Leligou, C.S. Psomopoulos, Electricity demand and carbon emission in power generation under high penetration of electric vehicles. A European union perspective, Energy Rep. 6 (2020) 475–486, http://dx.doi.org/10.1016/j.egyr.2020.09.025, URL https://www.sciencedirect.com/science/article/pii/S2352484720313378. Technologies and Materials for Renewable Energy, Environment and Sustainability.
[3] E.U. Soykan, M. Bagriyanik, G. Soykan, Disrupting the power grid via EV charging: The impact of the SMS phishing attacks, Sustain. Energy Grids Netw. 26 (2021) 100477, http://dx.doi.org/10.1016/j.segan.2021.100477, URL https://www.sciencedirect.com/science/article/pii/S2352467721000485.
[4] J. Delgado, R. Faria, P. Moura, A.T. de Almeida, Impacts of plug-in electric vehicles in the portuguese electrical grid, Transp. Res. D 62 (2018) 372–385, http://dx.doi.org/10.1016/j.trd.2018.03.005, URL https://www.sciencedirect.com/science/article/pii/S1361920916306095.
[5] S. Faddel, A.T. Al-Awami, O.A. Mohammed, Charge control and operation of electric vehicles in power grids: A review, Energies 11 (4) (2018) http://dx.doi.org/10.3390/en11040701, URL https://www.mdpi.com/1996-1073/11/4/701.
[6] B.K. Sovacool, J. Kester, L. Noel, G. Zarazua de Rubens, Actors, business models, and innovation activity systems for vehicle-to-grid (V2G) technology: A comprehensive review, 2020, http://dx.doi.org/10.1016/j.rser.2020.109963.
[7] A. Torkey, H. Abdelgawad, Framework for planning of EV charging infrastructure: Where should cities start? Transp. Policy 128 (2022) 193–208, http://dx.doi.org/10.1016/j.tranpol.2022.09.015, URL https://www.sciencedirect.com/science/article/pii/S0967070X22002578.
[8] J. Tian, Y. Lv, Q. Zhao, Y. Gong, C. Li, H. Ding, Y. Yu, A charging plan generation method for EV clusters considering the operation of regional distribution network, Energy Rep. 8 (2022) 135–143, http://dx.doi.org/10.1016/j.egyr.2022.10.117, URL https://www.sciencedirect.com/science/article/pii/S2352484722020522. 2022 7th International Conference on Green Energy Technologies.
[9] X. Liu, Z. Bie, Optimal allocation planning for public EV charging station considering AC and DC integrated chargers, Energy Procedia 159 (2019) 382–387, http://dx.doi.org/10.1016/j.egypro.2018.12.072, URL https://www.sciencedirect.com/science/article/pii/S1876610218313675. Renewable Energy Integration with Mini/Microgrid.
[10] P. Patil, K. Kazemzadeh, P. Bansal, Integration of charging behavior into infrastructure planning and management of electric vehicles: A systematic review and framework, Sustainable Cities Soc. 88 (2023) 104265, http://dx.doi.org/10.1016/j.scs.2022.104265, URL https://www.sciencedirect.com/science/article/pii/S2210670722005704.
[11] M. İnci, M.M. Savrun, Ö. Çelik, Integrating electric vehicles as virtual power plants: A comprehensive review on vehicle-to-grid (V2G) concepts, interface topologies, marketing and future prospects, J. Energy Storage 55 (2022) 105579, http://dx.doi.org/10.1016/j.est.2022.105579, URL https://www.sciencedirect.com/science/article/pii/S2352152X22015675.
[12] N. Erdogan, F. Erden, M. Kisacikoglu, A fast and efficient coordinated vehicle-to-grid discharging control scheme for peak shaving in power distribution system, J. Mod. Power Syst. Clean Energy 6 (2018) 555–566, http://dx.doi.org/10.1007/s40565-017-0375-z.
[13] K.M. Tan, S. Padmanaban, J.Y. Yong, V.K. Ramachandaramurthy, A multi-control vehicle-to-grid charger with bi-directional active and reactive power capabilities for power grid support, Energy 171 (2019) 1150–1163, http://dx.doi.org/10.1016/j.energy.2019.01.053, URL https://www.sciencedirect.com/science/article/pii/S0360544219300556.
[14] A.K. Verma, B. Singh, D.T. Shahani, Vehicle to grid and grid to vehicle bidirectional power flow at unity power factor with DC ripple compensation, in: 2012 IEEE 7th International Conference on Industrial and Information Systems, ICIIS, 2012, pp. 1–6, http://dx.doi.org/10.1109/ICIInfS.2012.6304811.
[15] Y. Liu, D. Jin, S. Jiang, W. Liang, J. Peng, C.-M. Lai, An active damping control method for the LLCL filter-based SiC MOSFET grid-connected inverter in vehicle-to-grid application, IEEE Trans. Veh. Technol. 68 (4) (2019) 3411–3423, http://dx.doi.org/10.1109/TVT.2019.2899166.
[16] Q. Lin, H. Yi, M. Chen, Minimizing cost-plus-dissatisfaction in online EV charging under real-time pricing, IEEE Trans. Intell. Transp. Syst. 23 (8) (2022) 12464–12479, http://dx.doi.org/10.1109/TITS.2021.3114537.

[17] S. Hamdare, O. Kaiwartya, M. Aljaidi, M. Jugran, Y. Cao, S. Kumar, M. Mahmud, D. Brown, J. Lloret, Cybersecurity risk analysis of electric vehicles charging stations, Sensors 23 (15) (2023) http://dx.doi.org/10.3390/s23156716, URL https://www.mdpi.com/1424-8220/23/15/6716.

[18] E.S.F. Tantawy, G.M. Amer, H. M.Fayez, Scheduling home appliances with integration of hybrid energy sources using intelligent algorithms, Ain Shams Eng. J. 13 (4) (2022) 101676, http://dx.doi.org/10.1016/j.asej.2021.101676, URL https://www.sciencedirect.com/science/article/pii/S2090447921004548.

[19] C. Balasundar, C. Sundarabalan, J. Sharma, N. Srinath, J.M. Guerrero, Design of power quality enhanced sustainable bidirectional electric vehicle charging station in distribution grid, Sustainable Cities Soc. 74 (2021) 103242, http://dx.doi.org/10.1016/j.scs.2021.103242, URL https://www.sciencedirect.com/science/article/pii/S2210670721005199.

[20] M. Sridharan, Short review on various applications of fuzzy logic-based expert systems in the field of solar energy, Int. J. Ambient Energy (2021) 1–17, http://dx.doi.org/10.1080/01430750.2021.1927839, arXiv:https://doi.org/10.1080/01430750.2021.1927839.

[21] M. Fathi, J.A. Parian, Intelligent MPPT for photovoltaic panels using a novel fuzzy logic and artificial neural networks based on evolutionary algorithms, Energy Rep. 7 (2021) 1338–1348, http://dx.doi.org/10.1016/j.egyr.2021.02.051, URL https://www.sciencedirect.com/science/article/pii/S2352484721001499.

[22] M.S. Masaki, L. Zhang, X. Xia, Fuzzy logic control of plug-in supercapacitor storage for thermoelectric management of batteries, Renew. Energy Focus 43 (2022) 59–73, http://dx.doi.org/10.1016/j.ref.2022.08.010, URL https://www.sciencedirect.com/science/article/pii/S1755008422000710.

[23] M. Mrówczyńska, M. Skiba, M. Sztubecka, A. Bazan-Krzywoszańska, J. Kazak, P. Gajownik, Scenarios as a tool supporting decisions in urban energy policy: The analysis using fuzzy logic, multi-criteria analysis and GIS tools, Renew. Sustain. Energy Rev. 137 (2021) 110598, http://dx.doi.org/10.1016/j.rser.2020.110598, URL https://www.sciencedirect.com/science/article/pii/S1364032120308820.

[24] N. Khasanzoda, I. Zicmane, S. Beryozkina, M. Safaraliev, S. Sultonov, A. Kirgizov, Regression model for predicting the speed of wind flows for energy needs based on fuzzy logic, Renew. Energy 191 (2022) 723–731, http://dx.doi.org/10.1016/j.renene.2022.04.017, URL https://www.sciencedirect.com/science/article/pii/S0960148122004785.

[25] UNE-EN IEC 61557-12:2022/A1:2022, Asociación Española de Normalización, Génova, 6 - 28004 Madrid, 2022, p. 32, URL https://www.une.org/encuentra-tu-norma/busca-tu-norma/norma/?c=N0068056.

[26] M. Nour, S.M. Said, A. Ali, C. Farkas, Smart charging of electric vehicles according to electricity price, in: 2019 International Conference on Innovative Trends in Computer Engineering, ITCE, 2019, pp. 432–437, http://dx.doi.org/10.1109/ITCE.2019.8646425.

[27] J.-H. Teng, S.-H. Liao, C.-K. Wen, Design of a fully decentralized controlled electric vehicle charger for mitigating charging impact on power grids, IEEE Trans. Ind. Appl. 53 (2) (2017) 1497–1505, http://dx.doi.org/10.1109/TIA.2016.2622221.

[28] K. Janfeshan, M.A. Masoum, S. Deilami, V2G application to frequency regulation in a microgrid using decentralized fuzzy controller, in: Proceedings of 2014 International Conference on Modelling, Identification & Control, 2014, pp. 361–364, http://dx.doi.org/10.1109/ICMIC.2014.7020781.

[29] S. Hussain, S. Thakur, S. Shukla, J.G. Breslin, Q. Jan, F. Khan, Y.-S. Kim, A two-layer decentralized charging approach for residential electric vehicles based on fuzzy data fusion, J. King Saud Univ. - Comput. Inf. Sci. 34 (9) (2022) 7391–7405, http://dx.doi.org/10.1016/j.jksuci.2022.04.019, URL https://www.sciencedirect.com/science/article/pii/S1319157822001471.

[30] A. Beheshtikhoo, M. Pourgholi, I. Khazaee, Design of type-2 fuzzy logic controller in a smart home energy management system with a combination of renewable energy and an electric vehicle, J. Build. Eng. 68 (2023) 106097, http://dx.doi.org/10.1016/j.jobe.2023.106097, URL https://www.sciencedirect.com/science/article/pii/S2352710223002760.

[31] S. Faddel, O.A. Mohammed, Automated distributed electric vehicle controller for residential demand side management, IEEE Trans. Ind. Appl. 55 (1) (2019) 16–25, http://dx.doi.org/10.1109/TIA.2018.2866255.

[32] L. Chen, B. Chen, Fuzzy logic-based electric vehicle charging management considering charging urgency, in: 2019 IEEE Innovative Smart Grid Technologies - Asia, ISGT Asia, 2019, pp. 3441–3446, http://dx.doi.org/10.1109/ISGT-Asia.2019.8881748.

[33] M. Singh, P. Kumar, I. Kar, A multi charging station for electric vehicles and its utilization for load management and the grid support, IEEE Trans. Smart Grid 4 (2) (2013) 1026–1037, http://dx.doi.org/10.1109/TSG.2013.2238562.

[34] K. Sayed, A.G. Abo-Khalil, A. S. Alghamdi, Optimum resilient operation and control DC microgrid based electric vehicles charging station powered by renewable energy sources, Energies 12 (22) (2019) http://dx.doi.org/10.3390/en12224240, URL https://www.mdpi.com/1996-1073/12/22/4240.

[35] M.U. Jan, A. Xin, M.A. Abdelbaky, H.U. Rehman, S. Iqbal, Adaptive and fuzzy PI controllers design for frequency regulation of isolated microgrid integrated with electric vehicles, IEEE Access 8 (2020) 87621–87632, http://dx.doi.org/10.1109/ACCESS.2020.2993178.

[36] F.M. Shakeel, O.P. Malik, Fuzzy based energy management system for a micro-grid with a V2G parking lot, in: 2020 IEEE Electric Power and Energy Conference, EPEC, 2020, pp. 1–5, http://dx.doi.org/10.1109/EPEC48502.2020.9320112.

[37] S. Iqbal, S. Habib, N.H. Khan, M. Ali, M. Aurangzeb, E.M. Ahmed, Electric vehicles aggregation for frequency control of microgrid under various operation conditions using an optimal coordinated strategy, Sustainability 14 (5) (2022) http://dx.doi.org/10.3390/su14053108, URL https://www.mdpi.com/2071-1050/14/5/3108.

[38] S. Habib, M.M. Khan, F. Abbas, M. Numan, Y. Ali, H. Tang, X. Yan, A framework for stochastic estimation of electric vehicle charging behavior for risk assessment of distribution networks, Front. Energy 14 (2) (2020) 298–317, http://dx.doi.org/10.1007/s11708-019-0648-5.

[39] G.C. Lazaroiu, M. Roscia, Fuzzy logic strategy for priority control of electric vehicle charging, IEEE Trans. Intell. Transp. Syst. 23 (10) (2022) 19236–19245, http://dx.doi.org/10.1109/TITS.2022.3161398.

[40] M. Dhimish, V. Holmes, B. Mehrdadi, M. Dales, Comparing mamdani sugeno fuzzy logic and RBF ANN network for PV fault detection, Renew. Energy 117 (2018) 257–274, http://dx.doi.org/10.1016/j.renene.2017.10.066, URL https://www.sciencedirect.com/science/article/pii/S0960148117310273.

[41] M. Woźniak, J. Szczotka, A. Sikora, A. Zielonka, Fuzzy logic type-2 intelligent moisture control system, Expert Syst. Appl. 238 (2024) 121581.

[42] S. Gunjate, D.S.A. Khot, A systematic review of emergency braking assistant system to avoid accidents using pulse width modulation and fuzzy logic control integrated with antilock braking, Int. J. Automot. Mech. Eng. 20 (2) (2023) 10457–10479.

[43] A.J. Yuste-Delgado, J.C. Cuevas-Martínez, A. Triviño-Cabrera, Statistical normalization for a guided clustering type-2 fuzzy system for WSN, IEEE Sens. J. 22 (6) (2022) 6187–6195, http://dx.doi.org/10.1109/JSEN.2022.3150066.

[44] X. Liu, Y. Lin, S.-P. Wan, New efficient algorithms for the centroid of an interval type-2 fuzzy set, Inform. Sci. 570 (2021) 468–486, http://dx.doi.org/10.1016/j.ins.2021.04.032, URL https://www.sciencedirect.com/science/article/pii/S0020025521003595.

[45] D. Wu, M. Nie, Comparison and practical implementation of type-reduction algorithms for type-2 fuzzy sets and systems, in: 2011 IEEE International Conference on Fuzzy Systems, FUZZ-IEEE 2011, 2011, pp. 2131–2138, http://dx.doi.org/10.1109/FUZZY.2011.6007317.

[46] Análisis | ESIOS electricidad · datos · transparencia. URL https://www.esios.ree.es/es/analisis/1293?vis=1&start_date=31-01-2023T00%3A00&end_date=31-01-2023T23%3A55&compare_start_date=30-01-2023T00%3A00&groupby=minutes5&compare_indicators=545,544.

[47] S. Harris, R.C. De Amorim, An extensive empirical comparison of k-means initialization algorithms, IEEE Access 10 (2022) 58752–58768, http://dx.doi.org/10.1109/ACCESS.2022.3179803.

[48] E.D. Kostopoulos, G.C. Spyropoulos, J.K. Kaldellis, Real-world study for the optimal charging of electric vehicles, Energy Rep. 6 (2020) 418–426, http://dx.doi.org/10.1016/j.egyr.2019.12.008, URL https://www.sciencedirect.com/science/article/pii/S2352484719310911.

[49] X. Yu, Z. Lu, L. Zhang, L. Wei, X. Cui, L. Jin, Experimental study on transient thermal characteristics of stagger-arranged lithium-ion battery pack with air cooling strategy, Int. J. Heat Mass Transfer 143 (2019) 118576, http://dx.doi.org/10.1016/j.ijheatmasstransfer.2019.118576, URL https://www.sciencedirect.com/science/article/pii/S0017931019331710.

[50] R. De Oliveira, R. Guimarães Corrêa, W.H. Kwong, An IMC-PID tuning procedure based on the integral square error (ISE) criterion: A guide tour to understand its features, IFAC Proc. Vol. 28 (18) (1995) 87–91, http://dx.doi.org/10.1016/S1474-6670(17)45131-7, URL https://www.sciencedirect.com/science/article/pii/S1474667017451317. IFAC Workshop on Control Education and technology Transfer Issues, Curitiba, Brazil, 11-12 September.

[51] Bienvenido | ESIOS electricidad · datos · transparencia. URL https://www.esios.ree.es/es#.

[52] R.E. de España, Análisis | ESIOS electricidad · datos · transparencia. URL https://www.esios.ree.es/es/analisis/600?vis=1&start_date=06-02-2023T00%3A00&end_date=06-02-2023T23%3A00&compare_start_date=05-02-2023T00%3A00&groupby=hour&compare_indicators=1001,705.

[53] G.R. Chandra Mouli, M. Kefayati, R. Baldick, P. Bauer, Integrated PV charging of EV fleet based on energy prices, V2G, and offer of reserves, IEEE Trans. Smart Grid 10 (2) (2019) 1313–1325, http://dx.doi.org/10.1109/TSG.2017.2763683.

[54] T.A. Lehtola, A. Zahedi, Electric vehicle battery cell cycle aging in vehicle to grid operations: A review, IEEE J. Emerg. Sel. Top. Power Electron. 9 (1) (2021) 423–437, http://dx.doi.org/10.1109/JESTPE.2019.2959276.