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# Using Fuzzy Queuing Theory to Analyze the Impact of Electric Vehicles on Power Networks

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***Abstract*—Electric vehicles are a promising technology for reducing CO2 emissions and dependence on fossil fuels. Their market is expected to grow quickly in the next years with the increased concern about global warming and the advances in technology. However, due to their large batteries, with high energy capacity, their impact on power networks remains uncertain. Several studies have been carried out trying to predict this impact. In this paper we propose a more realistic approach based on modeling electric-vehicle recharging as a queueing problem. Vehicles arrive following a nonhomogeneous Poisson process with fuzzy arrival rate and their energy requirements follow an exponential distribution. To solve this queueing problem we will use a simulation procedure that will provide realistic quality measures about the performance of the system. Additionally, we present a case study on the impacts of electric vehicles on the Spanish power network. In particular we will analyze two possible scenarios corresponding to the expected situation for years 2014 and 2020.**

## I. Introduction

Electric vehicles (EVs) have recently become a popular topic of research and development. This is mainly due to the fact that EVs promise to reduce dependence on foreign oil, reduce emissions, and help to utilize generation capacity that is idle during off-peak hours [1]. There are three main types of EVs: fully EVs, fuel cell EVs, and hybrid EVs [2]. Fully EVs and fuel cell EVs are driven only using electric power, on the other hand, hybrid EVs use also an internal combustion engine [3]. Independently of their type, all EVs will rely upon batteries with high energy storage capacity and with large charging requirements. As the number of EVs increases, these charging requirements will become stronger and, eventually, can provoke considerable impacts on electric power system design and operation.

For this reason it is necessary to analyze the potential impact of EVs on power consumption and generation. First studies on the field supposed that recharging will mainly occur during off-peak hours, or that the number of vehicles will grow slowly enough to allow an appropriate planning. The work of [4] and [5] are clear examples where it is supposed that energy producers will control recharge habits. However, it is important to notice that, generally, drivers will control the timing of recharging. Obviously, in this case, drivers will plug their EVs whenever it is more convenient for them, which may not coincide with the timing preferred by producers, that is, off-peak hours. In this sense, the work of [1] is a more realistic study where also the economic impacts for the electrical utilities are analyzed. However, all these analyses use simple mathematical approaches to approximate EVs' energy requirements and simple assumptions, like considering that all vehicles will recharge at the same time and with completely depleted batteries. We believe that this suppositions are not realistic and that a more detailed study should be performed. In this regard, the use of Fuzzy Queueing theory can help us to obtain more accurate forecasts of future behavior.

Queueing theory (QT) is the mathematical study of waiting lines. Queues are formed when "clients" arrive to a "place" asking for a service to a "server", which has limited resources. If the server is not immediately available, the client has to wait, forming a waiting line. QT allows us to study different processes associated to queues like arriving at the queue, waiting in it and being served. Additionally, QT can answer important questions about the performance of the system. Some examples are: What is the average waiting time for a client? What is the average service time for a client? How much time does expend each client in the system (waiting + service time)? How many clients are waiting to be served? or what is the probability for a client to be waiting for a free server? QT has a wide range of applications, including traffic flow, telecommunications or facility design.

One possible drawback of QT is that its parameters have to be known exactly. And most of the times they have to be estimated by experts, so we can assume that there will be some uncertainty in their values [6]. Fuzzy Queueing Theory (FQT) provides the tools to deal with this uncertainty. In particular, in the problem addressed by this paper we can find many sources of uncertainty, as the variables that deal with clients' arrivals or with the recharging time needed by each user. For this reason we propose to use FQT to estimate the impacts of EVs in the generation and transportation of electricity. In order to do that we present a methodology based on simulations of a fuzzy queueing system. In this system arrivals will be modeled as a nonhomogenous Poisson process with fuzzy arrival rate, and service times will follow an exponential distribution with fuzzy parameter. Additionally we will use this methodology in a real environment, the forecast of the impact of EVs on the Spanish electric network.

The remainder of the paper is organized as follows. In Section II we explain the possible impacts of EVs on power networks. Then, in Section III we introduce QT and its fuzzy extension. After that, in Section IV, we define how the problem of recharging EVs is modeled using FQT. Next, in Section V the simulation process is introduced. In Section VI a case study on the impact of EVs on Spanish power network is presented, and in Section VII the obtained results are shown. Section VIII closes the paper with the conclusions.

## II. EVs and their impact on power generation and transportation

EVs and PHEVs (plug-in hybrid electric vehicles) are a potentially significant technology for reducing vehicle emissions and reliance on petroleum for transportation. EVs are expected to be able to travel around 150 km without recharge and PHEVs around 60 km. There is a significant potential market for this kind of vehicles, depending on vehicle cost and the future cost of petroleum. In fact, the economic incentive to purchase an EV is the low cost of electricity compared to fuel.

As was previously stated, EVs can have a large impact on power networks. A key factor to understand this impact is to analyze the power demand on the grid from charging EVs. This demand will be a function of the voltage and amperage of the connection to the grid. At 120 volts AC, a 15 amp circuit would be about a 1.4 kW load, while a 30 amp circuit would be about 3.5 kW. The capacity of the battery will then determine the length of time it will take to recharge the battery, given the connection strength. The length of time can be estimated as $time = capacity/power$.

Electric power systems are designed to respond to instantaneous consumer demand, which constantly varies as a function of time of day and season, depending on the requirements for heat, light, and other services provided by electricity. Fig. 1 shows an hourly demand curve from the Spanish power network. This curve illustrate the significant variation in electric demand during the day. This variation creates significant burdens on the generating utility and also costs. These costs result from underutilized baseload power plants, large capacity requirements for peak demand, and demands of power plant cycling [4].

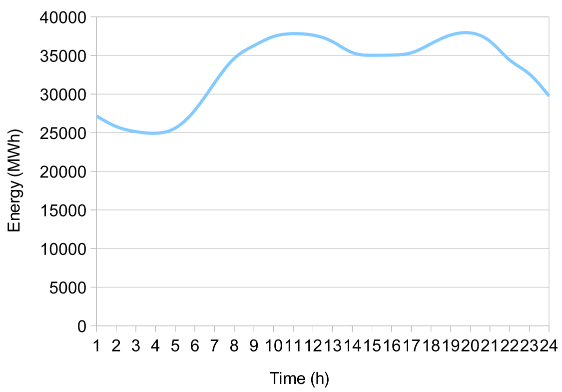


Fig. 1. Typical Hourly Electric Demand Patterns.

From a global perspective - concerning the power network of a whole country or state - the impact of EVs can be measured in two senses. First, EVs can cause an increment in the maximum demand of a day, which can exceed the maximum capacity of the network, provoking power cuts in the worst case. On the other hand, if too many users plug in their EVs at the same time the network could be saturated, once again producing blackouts in the worst case.

The local perspective, that is related to the networks of cities or neighborhoods, will not be analyzed in this paper.

## III. Queueing theory and fuzzy queueing theory

Queues are a usual phenomenon in our daily life. We find them when we visit the doctor, in the supermarket, in traffic lights, etc. They arise when some shared resources have to be used to serve a high number of clients. The study of queues is important because it provides theoretical evidence about what is the quality of service that can be expected from a given resource, and also about the way in which the access to this resource can be designed to provide a given quality of service to clients.

To analyze the quality of the service provided by the queueing system we have to study four different factors:

- The arrival rate, that is, the velocity of new arrivals.
- The service rate, that is, the velocity at which clients are served.
- The variability of the inter-arrival times.
- The variability of the service requirements.

It is intuitively clear that the quality of service is inversely related with items 1, 3 and 4, and directly related with item 2.

Another factor that has to be considered is queue discipline, meaning the way in which clients are selected from the queue. One of the most used is first-come first-served (FCFS) but is not the only possible one. For example, customers can be chosen in a last-come first-served (LCFS) way.

In the simplest case, arrivals are modeled as a Poisson process, which means that users arrive continuously and that inter-arrival times are independent and follow identically distributed exponential random variables with parameter $\lambda$. Where $\lambda$ represents the arrival rate. Additionally, services also follow an exponential distribution with parameter $\mu$, where $1/\mu$ represents the average service time. And there is only one server. In this case, illustrated in Fig. 2, calculating performance measures is quite simple.

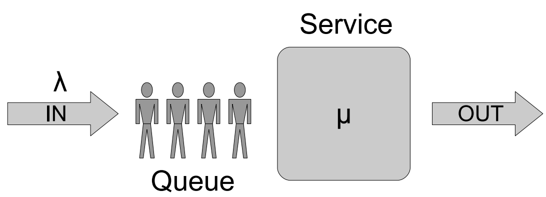


Fig. 2. A simple queueing system.

However, all these assumptions are not valid for the problem that is being studied. In particular, even if arrivals are continuous and independent, inter-arrival times are not identically distributed exponential random variables, that is, they are nonhomogeneous. The distribution can change during the day, for example, we can expect that many more people will start charging their EVs when they arrive at home after a working day, than late at night. This simple change makes the analysis of the system much more difficult, making necessary to face complex differential equations that require approximate methods like that of [7].

In addition, in the majority of real cases it is not realistic to use crisp values for the parameters of the exponential distributions. Under this consideration, it is advisable to extend queueing methods using fuzzy logic, obtaining fuzzy queueing theory. However, few studies on this topic have been published [8]. One of the first attempts to introduce uncertainty in QT is the work of [9] where the authors discuss elementary queueing systems in which arrivals and departures follow a possibility pattern. This work was extended by [10] to fuzzy queueing systems. Later, Chen et al. [11] proposed a mathematical programming method to analyze queueing problems with fuzzy cost coefficients and arrival rates, and [8] analyzed queueing systems where the length of the queue is limited and both arrival and service rates are fuzzy numbers. Unfortunately, all this methods are not able to deal with nonhomogeneous arrivals, which is one of the main characteristics of the problem analyzed on this paper. However, it is still possible to find approaches able to do that, like that of [12]. In this article, the authors define a procedure which allows the use of nonhomogeneous fuzzy arrivals. In particular, this approach proposes to use simulations of the execution of the queueing system in order to obtain the quality measures that describe it. Due to the possibilities opened by this last approach we will adapt it to the problem faced in this article.

## IV. Modeling EVs Recharging Process as a Queueing Problem

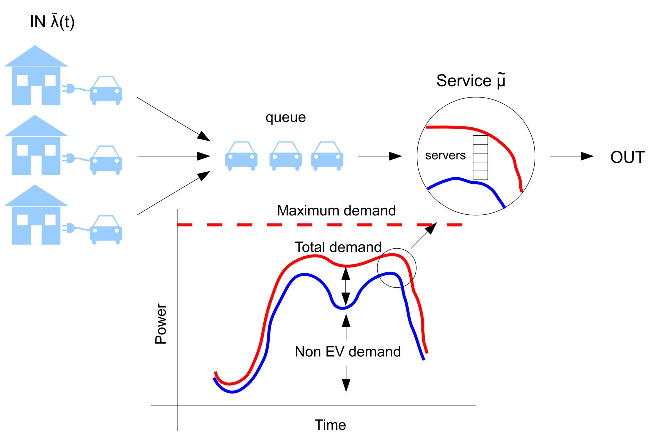


Fig. 3. EVs' recharging process modeled as a queueing problem ($\tilde{\lambda}$ and $\tilde{\mu}$ represent the fuzzy numbers used for arrival rate and service rate respectively).

The process of recharging EVs can be easily modeled as a queueing problem. We can consider the plugging in of a EV as the arrival of a new client, the service required is the recharge of the energy already spent by the EV, and the service time is the time needed by the system to provide this energy. The number of servers available is not constant and depends on five factors: total demand of power (including both non-EV demand and EV demand), maximum variability allowed for total demand, maximum demand allowed, number of EVs that need recharging and power required by each users. In particular, the servers are created dynamically depending on the demand. A new server will be created if there are EVs waiting in the queue and the constraints on demand and demand variability are not violated during all its recharging process. Similarly when a user leaves a server and there are no users waiting, a server is eliminated. To model the process in this way we have to assume that there is a central controller able to delay recharges and which knows the energy required by each user. The scheme of the process is showed in Fig. 3.

## V. Simulation of the Recharging Process

The simulation process used in this work is inspired by the one proposed in [12]. The main contribution of this new process is the possibility of dynamically generating servers that fulfill the previously stated requirements. Before start explaining the process it is necessary to introduce the notation used in this paper and define some operations.

### A. Notation and definitions

We denote a fuzzy subset of $\mathbb{R}$ as $\tilde{a}$ which is defined by a function $\xi_{\tilde{a}} : \mathbb{R} \to [0,1]$, called a *membership function*. The $\alpha$-level set of $\tilde{a}$, denoted $\tilde{a}_\alpha$, is defined by $\tilde{a}_\alpha = \{x \in \mathbb{R} : \eta_{\tilde{a}}(x) \geq \alpha\}$, for all $\alpha \in \{0,1]$. We denote $\tilde{a}_\alpha = [\tilde{a}^L_\alpha, \tilde{a}^R_\alpha]$.

Let $\oslash$ be a binary operation between two fuzzy numbers $\tilde{a}$ and $\tilde{b}$. Then, following [13], if $0 \notin \tilde{b}_\alpha$ for all $\alpha \in [0,1]$, then $\tilde{a} \oslash \tilde{b}$ is also a fuzzy number and for any $\alpha \in [0,1]$, we have:

$$(\tilde{a} \oslash \tilde{b})_\alpha = \Big[min\left\{\tilde{a}^L_\alpha/\tilde{b}^L_\alpha, \tilde{a}^L_\alpha/\tilde{b}^R_\alpha, \tilde{a}^R_\alpha/\tilde{b}^L_\alpha, \tilde{a}^R_\alpha/\tilde{b}^R_\alpha\right\}, \\ max\left\{\tilde{a}^L_\alpha/\tilde{b}^L_\alpha, \tilde{a}^L_\alpha/\tilde{b}^R_\alpha, \tilde{a}^R_\alpha/\tilde{b}^L_\alpha, \tilde{a}^R_\alpha/\tilde{b}^R_\alpha\right\}\Big]$$

Furthermore, we use $\tilde{1}_{\{m\}}$ to indicate a fuzzy singleton with value $m$.

Finally, we denote $\mathcal{F}(\mathbb{R})$ the set of all fuzzy numbers. And define the function $\eta : \mathcal{F}(\mathbb{R}) \to \mathbb{R}$, which is called *defuzzification function* if $\eta(\tilde{1}_{\{m\}}) = m$ for any singleton $\tilde{1}_{\{m\}}$. Thus, every fuzzy number $\tilde{a} \in \mathcal{F}(\mathbb{R})$ is defuzzified into a real number $\eta(\tilde{a})$.

### B. A nonhomogeneous Poisson process with fuzzy arrival rate

As was previously indicated, we will model arrivals as a nonhomogeneous Poisson process where the arrival rate is dependent on time and defined using a fuzzy number.

In particular, we will define the arrival rate as $\tilde{\lambda}(t)$. Additionally, $\tilde{\lambda}(t)$ has to be bounded, meaning that $\eta(\tilde{\lambda}(t)) \leq \eta(\tilde{\lambda})$ for all $t \geq 0$. Let us suppose that an event of the Poisson process that occurs at time $t$ is counted with probability

$\eta(\tilde{\lambda}(t))/\eta(\tilde{\lambda})$. Then the process is defined as a nonhomogeneous Poisson process with fuzzy intensity function $\tilde{\lambda}(t)$ [12]. Once we have defined the process we can use the simulation procedure shown in Algorithm 1 in order to generate inter-arrival times.

**Algorithm 1:** Pseudo-code used to generate inter-arrival times.

```
Input: t: current time, λ̃(t): nonhomogeneous
       arrival rate, λ̃: maximum arrival rate.
Output: next interarrival time.
begin
    s = t;
    repeat
        u = generate random number;
        s = s + η(1̃_{-ln u} ⊘ λ̃);
        v = generate random number;
    until v ≤ η(λ(s))/η(λ);
    return s-t;
end
```

## C. The simulation process

We consider the following queueing system. Customers (EVs) will arrive following a nonhomogeneous Poisson process with fuzzy arrival rate that will be simulated using the previously defined procedure. Once a client arrives, it will wait in the queue or not depending on if it is possible or not to create a new server for it. As aforementioned, this is subject to the restrictions on maximum demand and maximum demand change. When a user is finally assigned to a server it is allowed to use it until its batteries are fully recharged, after this time the server is free. A free server can be used by another customer if by doing that no restriction about demand and demand variability is violated, otherwise is destroyed. If the server is destroyed and there are customers waiting in the queue, then we create a new server as soon as no restriction is violated by that. Similarly, if a new client arrives and is impossible to create a new server, we create it as soon as possible. The process to generate a new server is a bit complicated because of the fact that non-EV demand is not constant in time. For this reason we need an iterative process that recalculates the moment in which creating a new server is not violating restrictions until it is stable.

Concerning queue policy we will use a slight modification of FCFS. In particular, we choose the first user in the queue that does not violate any restriction. This policy guarantees that the queue will not be blocked by users with very demanding requirements, and thus, waiting time is reduced. At the same time, it is fair with those users that arrived first, because as soon as they do not violate any condition they start charging.

Regarding the time needed by each user to recharge its batteries - service time - we will assume that it is exponentially distributed, with a fuzzy parameter $\tilde{\mu}$. Then,we can generate a new service time using $\eta(\tilde{1}_{\{-\ln u\}} \oslash \tilde{\mu})$, where $u$ is a randomly generated number.

Simulation process will finish when simulation time reaches a specified limit. After this point, no more arrivals will be allowed, but servers will continue serving those clients that arrived before the limit.

The full simulation process can be seen on Algorithms 2, 3, 4, 5 y 6. In this algorithms, variables $t$, $T$, $t_A$, $t_D$ and $t_N$ respectively represent, current time, end time, next arrival time, next departure time and the time when a new server will be created. Furthermore, $Queue$ represents the list of tasks in the queue, and $Service$ the list of tasks that are being served. Finally, $\tilde{\lambda}(t)$ and $\tilde{\mu}$ are the parameters used to model users arrivals and service time respectively.

**Algorithm 2:** Pseudocode for the simulation

```
begin
    inicializar();
    while t < T do
        if t_A < t_D AND t_A < t_S then
            handleNewArrival();
        end
        else
            if t_D < t_S then
                handleNewDeparture();
            end
            else
                handleNewServer();
            end
        end
    end
end
```

**Algorithm 3:** Pseudocode for the handling of arrivals.

```
begin
    Generate service time using exponential
    distribution with parameter μ̃;
    Add task to Queue;
    t_A=Generate next arrival time using
    exponential distribution with parameter λ̃(t);
    t_N=GenerateNewServer();
end
```

**Algorithm 4:** Pseudocode for the handling of departures.

```
begin
    Store task data;
    Remove task from Service;
    if Queue is not empty then
        Search in queue the first task which will
        not make total demand exceed maximum
        allowed demand during all its duration;
        Remove task from Queue;
        Add task to Service;
    end
    else
        Reduce number of servers;
    end
    t_D=finish time of the next finishing task;
end
```

During the simulation we will store information that will allow us to obtain the following quality measures:

- Each user's waiting time.
- Each user's service time.

**Algorithm 5:** Pseudocode for the handling of a new server.

**begin**
```
    Search in queue the first task which meets
    demand restrictions;
    Remove task from Queue;
    Add task to Service;
    Increment number of servers;
    if Queue is not empty then
        t_N = GenerateNewServer();
    end
end
```

**Algorithm 6:** Pseudocode for the generation of a new server.

**begin**
```
    lastAllocationDemand = Obtain NoEV Demand at
    the time when last task was allocated using
    predictor;
    lastAllocationDemand += Number of servers *
    Power used by a server;
    demandAfterAdding = currentDemand + Power used
    by a server;
    while possible time is not stable do
        possible time =
        t + (demandAfterAdding - lastAllocationDemand) / maximumdemandincrement;
        demandAfterAdding = prediction of demand
        at time possible time + (Number of server
        + 1) * Power used by a server;
    end
    return possible time;
end
```

- Electric power supplied to the clients at some specific control points, in order to approximate the one supplied at every moment.
- Size of the queue at some specific control points, in order to approximate the size at every moment.
- Number of servers at some specific control points, in order to approximate the number at every moment.

## VI. A CASE STUDY: IMPACT OF EVS ON SPANISH ELECTRIC NETWORK

In the previous sections we have introduced a simulation process able to analyze the impact of EVs on electricity generation and transportation. The main reason to develop such process was the necessity of an unbiased methodology able to generate very detailed data about the future impact of EVs on the Spanish electric network. In particular, the problem that motivated this study was the design of an intelligent battery charger. The main objectives of the charger are: to recharge the battery in a reasonable period of time, and to avoid an overload of the electric network. In order to fulfill the last requirement, the charger has to be aware of both the non EV and the EV electricity demand at every moment. However, the main problem is that it will not be able to communicate with any agent capable of providing this information. For this reason it is very important to obtain very detailed data about the behavior of users and network load at every moment. The results obtained in this case study will be of prime importance to decide how the charger has to react at every moment.

In order to perform the simulation of this case study it is important to obtain accurate values for each of its parameters. In the following subsections we will indicate which values are going to be used and how they were obtained. Specifically we will need information about: non EV demand, arrival rates and service time.

Note that, in this study, we want to obtain a global picture of the impact of EVs on Spain. For this reason, we will use global information concerning the whole Spain. This approach could be complemented in the future with more detailed simulations for each zone.

### A. Prediction of non EV demand

The first parameter that we are going to study is the electric demand in environments where EVs are not present. REE is the Spanish organization in charge of controlling power networks. This organization periodically publishes information about hourly demand regarding every day. From this historical data, we extracted data concerning last five years. After that we applied fuzzy clustering grouping hourly data on a day basis, that means that we will obtain clusters grouping days with similar demand patterns. The prototypes of the clusters obtained are shown on Fig. 4.

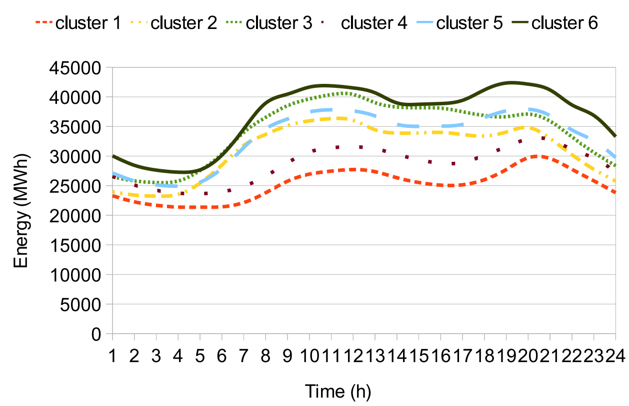


Fig. 4. Prototypes of demand clusters.

For this simulation we will use cluster 6 which represents scenarios of a very high demand. The prototype of this cluster will be used to predict demand as a set of fuzzy rules, where the input is the time of the day and the output the prototype values.

### B. Arrival rate $\tilde{\lambda}(t)$

Arrival rate is one of the most important parameters in our simulation. As was previously said it is time dependent and will be modeled using fuzzy sets. To do that we will use a study performed by the Spanish Ministry of Public Works, named Movilia [14]. The purpose of the study is the analysis of the mobility patterns of the citizens that reside in Spain. Additionally it studies the characteristics and the causes of this patters. An important piece of information provided by

TABLE I
PERCENTAGES OF DISPLACEMENT BY TIME FRAME.

| From 4:01 to 7:00 | From 7:01 to 8:00 | From 8:01 to 9:00 | From 9:01 to 12:00 | From 12:01 to 15:00 | From 15:01 to 18:00 | From 18:01 to 21:00 | From 21:01 to 0:00 | From 0:01 to 4:00 |
|---|---|---|---|---|---|---|---|---|
| 3.6% | 6.5% | 8.7% | 14.4% | 20.9% | 21.4% | 19.2% | 4.7% | 0.8% |

Movilia are the percentages of displacement grouped by time frame, that can be seen on Table I.

Moreover, we can suppose that most of the recharges will take place either at home or at the workplace, and immediately after arriving to those places. For this reason we need to focus on those displacements with destination home or workplace. Fortunately Movilia also indicates the percentage of displacements with these destinations with regard to the total number of displacements. These data are shown on Table II.

Furthermore, we need to assume that EV users will behave as the average Spanish citizen. Thus they will travel 3.3 times a day. With all this data, and considering $n$ as the number of EVs in Spain, we will be able to calculate an approximation of the number of vehicles recharging divided by time frames. The methodology is quite simple, we just need to multiply $n$, the number of trips a day, the percentage of displacement per time frame and the percentage of displacement heading home and work. Using this approximation we can generate the fuzzy arrival rates

### C. Service rate $\tilde{\mu}$

Another important parameter is the time needed by each user to fully charge its batteries. This time, that we will call $\tilde{ct}$, depends on battery capacity, $\tilde{c}$, and on the power that we can provide to the charger $\tilde{p}$. As an estimate we can calculate it as $\tilde{ct} = \tilde{c} \oslash \tilde{p}$.

Thus, it is necessary to estimate how much energy is consumed by a user. To do that we need data about: distance traveled per day and consumption per unit of distance. The first question can be answered using information from Movilia, for the second one we can use the specifications provided for the EVs that are or will be available in the near future. In particular, we consider only one type of EV whose consumption is the worst among all specifications. Additionally, we need to specify the power provided by the charger, 3.5 kW.

With this information we can calculate the fuzzy set that models average service time and that is shown in Fig. 5. To finish, service rate is calculated as $\tilde{1}_{\{1\}} \oslash \tilde{ct}$.

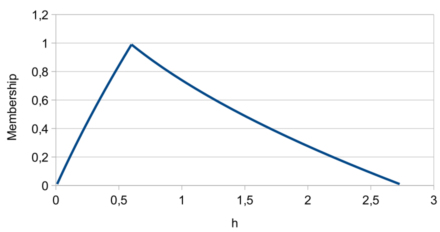


Fig. 5. Fuzzy set that models average service time.

### D. Other parameters

There remain two parameters that have to be specified in order to carry out the final simulations. Regarding maximum power demand, we will use the maximum historical value of the last five years, 48.34 GW. Concerning maximum demand variability the value utilized is 7.1 GW/h, which, once again, corresponds to the maximum historical data of the last five years.

## VII. RESULTS

In this section we will analyze two possible scenarios. The first one corresponds to the expected scenario for 2014. According to the forecast of the Spanish Ministry of Industry, Tourism and Commerce [15], in 2014 there will be around 250000 EVs in Spain. So the first simulation will use this estimate. On the other hand, for the second one, we will use the prediction for year 2020, which foresees around 2500000 EVs [16]. Each one of the simulations will consist of five days.

### A. Scenario 1: 250,000 EVs

The results of the simulation concerning the first scenario are shown in Figs. 6, 7 and 8. In Fig. 6 we show electricity demand during the simulation, comparing demand without EVs and total demand (non EV + EV). The results illustrate that the impact caused by 250,000 EVs is minimal from a global perspective. Fig. 7 indicates the number of customers that are using a server and also those that are waiting in the queue. As was expected, the number of servers oscillates during the simulation, being the highest peak around 15:00, when the largest number of clients go back home. However, the most interesting result in this figure is queue length. As can be seen, the number of users waiting in the queue is nearly zero, during all the simulation. This result is clarified in Fig. 8, where we show how much time each user spent waiting in the queue. In particular, each point represents one user. The maximum waiting time is around 25 seconds, which is not a large amount of time.

As was previously explained, the main reason to perform this simulations was to use the data generated in the design of an intelligent charger. However, this results indicate that it is not necessary to provide the charger with this intelligence, at least in a global scenario with 250,000 EVs. The local implications of EVs are left out of the analysis of this paper. In the next section we will treat this problem in a more demanding scenario, with a number of EVs ten times larger.

### B. Scenario 2: 2,500,000 EVs

In this subsection we analyze the predicted scenario for year 2012. The results are shown in Figs. 9, 10 and 11. Fig. 9

TABLE II
PERCENTAGES OF TRIPS HEADING HOME AND WORKPLACE.

| | From 4:01 to 7:00 | From 7:01 to 8:00 | From 8:01 to 9:00 | From 9:01 to 12:00 | From 12:01 to 15:00 | From 15:01 to 18:00 | From 18:01 to 21:00 | From 21:01 to 0:00 | From 0:01 to 4:00 |
|---|---|---|---|---|---|---|---|---|---|
| Home | 4.6% | 2.0% | 6.6% | 31.7% | 67.7% | 38.8% | 67.1% | 74.9% | 83.6% |
| Workplace | 85.0% | 65.6% | 30.4% | 9.4% | 10.1% | 11.6% | 1.9% | 3.4% | 4.7% |

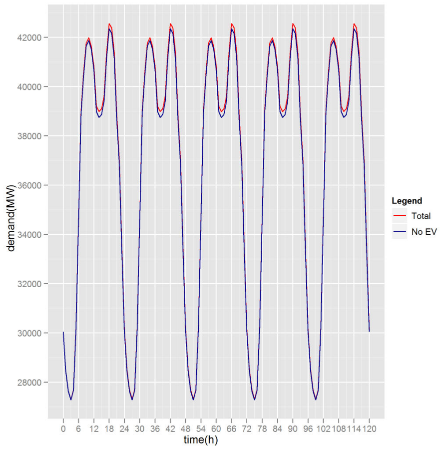


Fig. 6. Non EV and total demand for scenario 1.

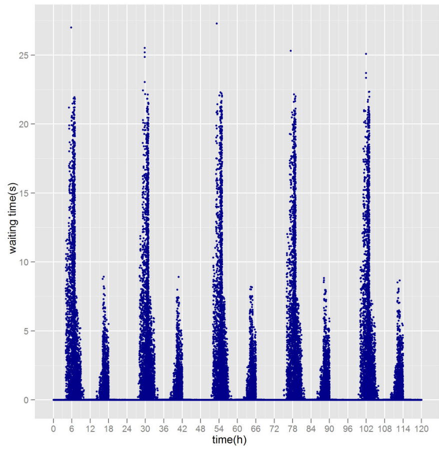


Fig. 8. Waiting time for users in scenario 1.

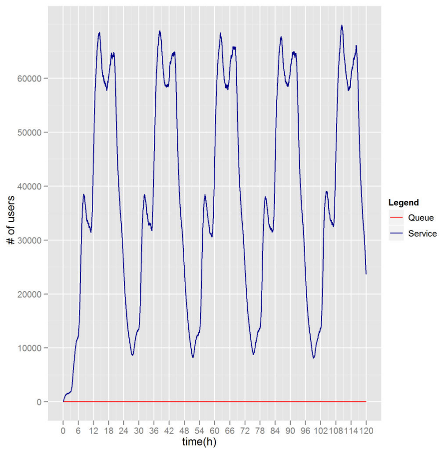


Fig. 7. Users being served and in queue for scenario 1.

shows the results related to demand. Compared to the previous scenario, the impact of 2,500,000 EVs is much bigger, an is even able to fill the first off-peak valley, corresponding to a time between 12:00 am and 18:00 pm. However, the second valley remains unfilled, mainly because most of the EVs finish recharging quite quickly and not many vehicles arrive as this valley corresponds to night hours. With respect to the number of servers and queue size, shown on Fig. 10, the results are similar to those obtained in scenario 1. The pattern followed by the number of servers is analogous to the previous one but for the number of servers that is 10 times larger. On the other hand, the increment in the number of EVs does not dramatically affect queue size, whose values remain very low. Once again these results are explained more deeply in Fig. 11, where we show how much time was waiting each user. Compared to results obtained for scenario 1, we can observe how the number of users that have to wait is larger, which can be appreciated in the increase of the density of points. However, the most important sign, maximum waiting time, remains invariable around 25 seconds. As we previously pointed out this waiting time can be considered small.

As in scenario 1 our simulations indicate that, from a global perspective, EVs will not dramatically affect Spanish electric network. Of course, demand peaks will be higher - in the simulations an increase of the 6.3% was observed -, but we can expect that this growth will be gradual. In that case, electricity suppliers will be able to adapt the network in order to minimize the impacts. For this reason we consider that the design of an intelligent charger is not necessary to avoid network crashes.

## VIII. CONCLUSIONS

EVs can offer many advantages, like a reduction of the dependence on foreign oil, less emissions, and a better utilization of generation capacity during off-peak hours. However, their recharging process can pose some problems due to the high capacity of their batteries. For this reason it is important to study and anticipate the impacts on power networks. In this paper we have proposed a new methodology for this study. This methodology is based on a simulation process, that models arrivals of EV users as a nonhomogeneous Poisson process with fuzzy arrival rate. We believe that this approach is more formal than previous approaches and that the results provided are more realistic.

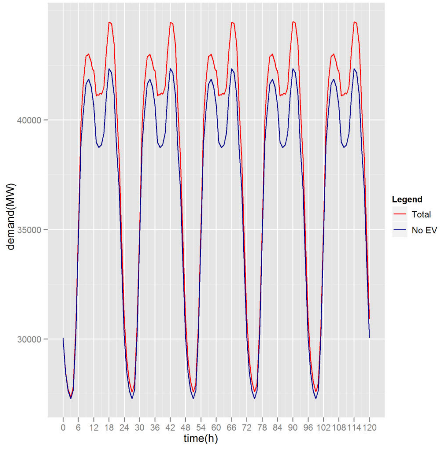


Fig. 9. Non EV and total demand for scenario 2.

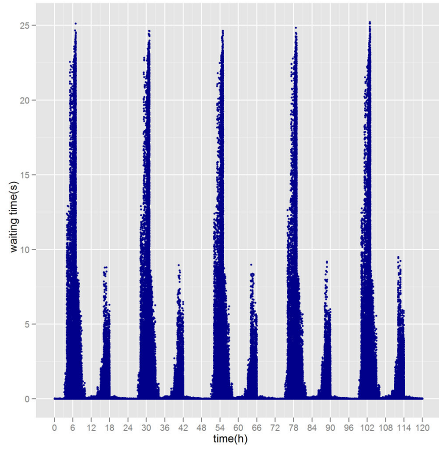


Fig. 11. Waiting time for users in scenario 2.

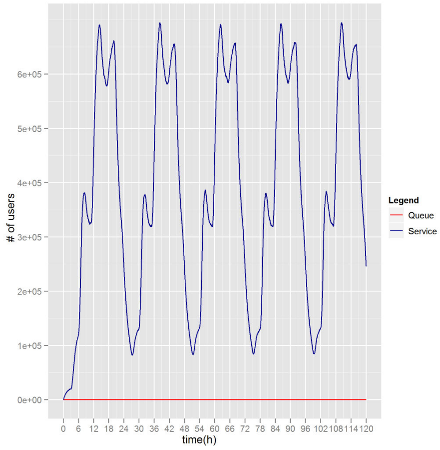


Fig. 10. Users being served and in queue for scenario 2.

In particular, we have applied this methodology to a real case study: the analysis of the impact of EVs on Spanish power network. This analysis was focused on the obtaining of realistic data that could be used in the creation of an intelligent charger able to prevent network saturation. To do that, chargers have to decide, depending on the moment, when it is convenient to start the recharging process, i.e. to define a waiting time. To carry out the simulations we used data provided publicly by the Spanish government.

Two scenarios have been studied. The first one corresponds to the environment forecast for year 2014, when a number of 250,000 EVs has been estimated. In this case, simulations have pointed out that the impact of EVs will be minor. Moreover, the waiting time necessary to avoid network instability is so small, that it can be discarded without risk. The second scenario represents the hypothetic situation in year 2020, when experts foresee around 2,500,000 EVs. As expected, the impact in this scenario is larger, increasing maximum power demand a 6.3%. Nevertheless, waiting times remain similar to those obtained in previous scenario and can also be discarded.

The results obtained in this paper suggest that the impact of EVs on the Spanish power network would not be as strong as expected. For this reason we believe that power suppliers will be able to anticipate it and act consequently.

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