Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems

J.A. Domínguez-Navarro, R. Dufo-López, J.M. Yusta-Loyo, J.S. Artal-Sevil, J.L. Bernal-Agustín
Electrical Engineering Department. Zaragoza University
C/María de Luna 3, 50018 Zaragoza, Spain
E-mails: {**jadona, rdufo, jmyusta, jsartal, jlbernal}@unizar.es**

Abstract. The development of electric vehicles (EVs) depends on several factors: the EV's acquisition price, autonomy, the charging process and the charging infrastructure. This paper is focused on the last factor: the design of an EV fast-charging station. In order to improve the profitability of the fast-charging stations and to decrease the high energy demanded from the grid, the station includes renewable generation (wind and photovoltaic) and a storage system. Unlike other papers, this one uses a detailed model of the charging process that considers the arrival time and state of charge of electric vehicles. First, the Monte Carlo method is used to model the EV demand and the renewable generation. Later, a genetic algorithm (GA) optimizes the installation and operation of the EV fast-charging station. It finds the optimal solution that maximizes the profit measured by its net present value (NPV). Several cases are studied to analyse the influence of renewable energies and storage systems. The obtained results show that a mix of renewable energies and storage systems attains the best cost efficient solution.

Keywords

Electric vehicle (EV), fast-charging station, Monte Carlo method, genetic algorithm and renewable energy.

Acronyms

$Cbuy_h$: buy price at electrical market at hour h (€),

Cch: cost of a charger (€).

Cm_t: maintenance cost of storage system at year t (€/year).

Cpv: square meter cost of photovoltaic panels (€/m^2).

$Cr\&m_t$: replace and maintenance of storage system at year t (€).

$Csale_h$: sale price at electrical market at hour h (€),

Cs_h: energy price station at hour h (€),

$Csto$: cost of storage system (€/kWh).

Cw_k: cost of the wind generator k (€).

$ECsto_h$: energy charged from storage system at hour h (kWh).

$EDsto_h$: energy discharged from storage system at hour h (kWh).

Eev_h: energy supplied to EV customers at hour h (kWh).

$Eg2s_h$: energy consumed from grid at hour h (kWh),

$EMAXev_h$: maximum energy demanded by EV customers at hour h (kWh).

Eph_h: energy supplied by photovoltaic generators at hour h (kWh).

$Es2g_h$: energy supplied to grid at hour h (kWh),

$Esoc_h$: energy level in storage system at hour h (kWh).

$Esoc_{h-1}$: energy level in storage system at hour $h-1$ (kWh).

$Esto_{inst}$: nominal energy capacity of the installed storage system (kWh).

$ETHsto_k$: total energy throughput of battery k that is equal to the life cycle by battery capacity (kWh).

Ew_h: energy supplied by wind generators at hour h (kWh).

h: an hour index.

I: initial investment (€).

i: interest rate.

$INFLOW_h$: cash inflow (income) at hour h (€).

n: the number of years considered in the study (year).

NCF_t: net cash flow at year t (€).

NPV: net present value (€).

nw: the number of types of wind generators considered in the study.

$OUTFLOW_h$: cash outflow (expenses) at hour h (€).

Pch_{inst}: rated power of the EV fast-charging supplier (kW).

$PCsto_h$: power of charge for storage system at hour *h* (kW).

$PDsto_h$: power of discharge for the storage system at hour *h* (kW).

Pev_h: power of the EV fast-charging supplier at hour *h* (kW).

$Pg2s_h$: power consumed from grid at hour *h* (kW),

Pgc_{max}: power limit in the grid connexion point (kW).

Pph_h: power supplied for photovoltaic generator at hour *h* (kW).

Pph_{inst}: rated power of the installed photovoltaic generator (kW).

$Ps2g_h$: power supplied to grid at hour *h* (kW),

$Psto_{inst}$: rated power of the installed storage system (kW).

Pw_h: power supplied for wind generator at hour *h* (kW).

Pw_{inst}: rated power of the installed wind generator (kW).

Qch: number of chargers installed.

Qw_k: number of wind generators of type *k*.

SOC: state of charge of the battery (p.u.).

SOC_{min}: minimum state of charge of the battery (p.u.).

Spv_{inst}: surface installed of photovoltaic panels (m^2).

t: a year index.

tev_k: waiting time for each vehicle (min).

tev_{max}: maximum waiting time; 0 (min), in our case.

y_k: *binary decision variable.*

1. Introduction

In the next few years, the number of electric vehicles (EVs) is expected to increase exponentially, due to the squandering of oil and the environmental impact associated with its use. For that reason, there is a tendency to coordinate efforts to reduce urban pollution and greenhouse gas emissions. At present, one of the most important problems in EV development is the shortage of charging infrastructure [1]. Drivers can charge their EVs at home, but the charge time is quite long. To promote the EV development, it is necessary to install fast-charging station in which the EV battery can be charged in around 15 minutes. By contrast, the disadvantage of fast charging is the high power demand and its impact on the grid. In order to address this, renewable sources and storage systems can be installed in these stations [2]. Review of studies about the appropriate system design for an EV station's installation and its operation can found in [3-9].

Several authors have analysed the impact of EV station operation within the electrical network. They present different methods to level the load curve. Xu et al. [10] showed a coordinate charging strategy to improve the effects of EV charging in the electrical demand curve as well as the profit of the EV stations. Zhang and Qian [11] presented a methodology to charge EVs during night time. Cao et al. [12] proposed an intelligent charging method for EV in response to time-of-use price that alleviates the stress in the network during the peak periods. Fazelpour et al. [13] developed an algorithm with two phases to integrate smart parking with a plug-in hybrid EV. First, the algorithm optimizes the size and location of renewable energy installations through the grid. Then, it optimizes the characteristics of EV charging. This reduces the power losses and improves the voltage profile in the network.

Some papers address the problem of locations for these EV stations and even their sizing but with simplifications about their demand and operation. Sadeghi-Barzani et al. [14] used a mixed integer non-linear optimization approach to locate fast-charging stations in a city; they considered the development and electrification costs, EV energy loss, and electric grid loss as objectives. In the model, they only defined the number of EVs arriving at the station, but they did not consider the arrival time or the occupation of the station. Wang et al. [15] presented a multiobjective planning model for EV charging stations to reduce power losses and voltage deviations in the distribution system. They considered a fixed demand and did not consider the operation of the charging process. Sungwoo and Kwasinski [16] used a spatial and temporal model of EV charging demand to locate the EV station. They used a fluid dynamic traffic model and queueing theory. Xiang et al. [17] developed a model to determine the siting and sizing of charging stations. They considered the interactions with the electrical grid, but they did not consider other types of energy sources.

A few authors have developed models for the design of EV charging stations, in which they used several simplifications in the design. Vermaak et al. [18] developed a model to calculate the size of a charging station with renewable energy, but the demand is constant and it has no connection to the grid. They optimized the results with Homer software. Hafez et al. [19] presented the optimal design of an EV charging station to minimize the lifecycle cost. They considered renewable energy, connexion to the grid and batteries, but they did not consider the arrival time; the optimization was also done with Homer software. Fathabadi [20] showed the electronic design of an EV charging station with PV and wind generators, but they did not determine the size of the EV station. He focused on the design of the converters and control algorithm. He used a daily curve to model demand, PV and wind generation.

In designs of EV charging stations, the demand models used have been very simple, with constant demand [18] and load profile [19, 20]. These load profiles do not consider when the charging of each vehicle begins and ends; rather, they are only an average value for each hour. More complex models exist the operation of EV charging stations. Bae and Kwasinski [21] used a model based on an M/M/s queueing theory, based on the state-transition algorithm used in Shrestha and Hansen [22]. Zhou and Liu [23] use an M/M/s queue based on a cell-transmission traffic model, and Viswanathan et al. [24] used real-world traffic data.

The energy management systems used in the designs of EV charging stations are also very simple. In [18], Vermaak et al. prioritized the charging of the EV and used a battery pack to store energy form renewable sources when there are no vehicles in the station. A similar form of management is used by Hafez et al. [19], but they also included a thermal load that feeds when there is excess renewable energy generation. In [20], Fathabadi developed a MPPT technique to track the maximum power points of PV and wind systems. Other, more complex methods have been found for operating EV charging stations. Authors seek to achieve different objectives in the EV charging process, including to maximize profits [25-27], minimize total energy costs for users [28-32], reduce power losses in the network [31, 33], minimize the generation costs [34, 35], minimize the peak load [36], avoid congestion in the distribution network [37] or regulate the frequency [38].

Most of the previous papers are focussed on the operations or the impact on the grid, while only a few papers address the design of EV charging stations. Among the papers about design, they do not consider the charging dynamic (the arrival time and state of charge of each electric vehicle) because they have to adapt the input data into an optimization program such as Homer that is not built to solve this kind of problem.

The originality of this paper is as follows:

- The study focusses on an EV charging station design problem with characteristics of an EV charging station operation problem.
- EV power demand is represented by an Erlang B queuing model, which until now has only been used in papers that discuss the optimization of EV operations.
- The EV operations include the purchase and sale of energy in the electricity market, which until now has only been used in papers that discuss the optimization of EV operations.
- This design problem includes a wide variety of energy sources: renewable generators, the grid and batteries.
- A genetic algorithm was adapted to deal with the complexity of the design problem.

The rest of the paper is organized as follows. The mathematical modelling of the optimization problem to design the EV station is explained in detail in Section 2. The probabilistic input data are described in Section 3. Then, the genetic algorithm's characteristics are shown in Section 4. Finally, three cases are studied and compared to show the changes in the design in Section 5, and Section 6 concludes the paper.

2. Mathematical modelling

The EV fast-charging station considered in this work consists of several chargers to fill the batteries of the EVs' clients as well as renewable generators and storage units to improve their profitability and reduce their impact in the electrical grid. The variables to be found in the charging station design problem consists of the optimal number and rated power of the chargers, the installed power of the renewable generators (wind and photovoltaic), the power and energy of the batteries and the contracted power in the grid connection point needed to feed the charging station.

The objective function (1) that the problem maximizes is the net present value (NPV), which is the difference between the present values of cash inflows (3) and the present values of cash outflows (4), including the cost of replacing and maintaining batteries (5) and the initial inversion (6) over a period of time (in this case, 20 years).

The optimization problem is also subject to several constraints:

- Energy balance in the whole charging station (7). Each hour, the sum of the photovoltaic and wind energy generated, the energy consumed or purchased from the grid and the energy discharged from the batteries must be equal to the sum of the energy supplied to the electric vehicles, the energy charged in the batteries and the power sold or supplied to the network.

- Stored energy in the batteries at hour h (8). The energy stored in the station's batteries at hour h must be equal to the energy stored at hour h − 1, plus the energy charged during hour h, minus the energy discharged during hour h.

- Limit of the power supplied by the wind generators (9). The power generated by the wind generators must be less than the installed wind power.

- Limit of the power supplied by the photovoltaic panels (10). The power generated by the photovoltaic generators must be less than the installed photovoltaic power.

- Limit of the discharge and charge power of the storage systems (11) and (12). The charge or discharge power in the station's batteries must be equal to or less than the nominal power of the installed converter.

- Limit of the discharge and charge energy of the storage systems (13) and (14). The discharge energy in the batteries at hour h must be equal to or less than the stored energy in the batteries at hour h – 1 and the charge energy in the batteries at hour h must be equal to or less than the difference between the battery capacity and the stored energy in the batteries at hour h – 1.

- Limit of the stored energy in the storage systems (15) and (16). The energy stored in the station's batteries must be equal to or less than the battery capacity and equal to or greater than the minimum state of charge allowed in the batteries.

- Limit of the supplied and consumed power from the grid at the connection point (17) and (18). The power supplied to or consumed from the network must be equal to or less than the contracted power at the point of connection to the network.

- Limit of the EV-supplied power at every EV fast-charging supplier (19). The power supplied by each charger must be equal to or less than its rated power.

- Limit of the EV-supplied energy at hour h (20). The energy supplied by the EV station must be equal to or less than the maximum energy demanded by EV consumers. The energy supplied may be lower than the energy demanded when a generation deficit from renewable sources can not be compensated.

- Limit of the waiting time for each EV (21). This restriction defines the maximum time that a consumer will wait his or her turn. If the waiting time is longer, the consumer will leave the station. In our case, we consider that if the chargers are busy, the consumer will leave.

The model evaluates the charging station's behaviour for 8760 hours per year. Some parameters of the model, such as the EV demand and the wind and photovoltaic generation, are represented with their probability distributions. The sequential Monte Carlo method was used to simulate the operation of the charging station. In section 3, every variable considered in the model is explained, and the algorithm used is explained in section 4.

Maximize:

$$NPV = \sum_{t=1}^{n} \frac{NCF_t}{(1+i)^t} - I \tag{1}$$

Subject to:

- Net cash flow at each year t,

$$NCF_t = \sum_{h=1}^{8760} (INFLOW_h - OUTFLOW_h) - Cr\&m_t, \tag{2}$$

$$INFLOW_h = Eev_h \cdot Cs_h + Es2g_h \cdot Csale_h, \tag{3}$$

$$OUTFLOW_h = Eg2s_h \cdot Cbuy_h, \tag{4}$$

$$Cr\&m_t = \frac{\sum_{h=1}^{8760} EDsto_h \cdot}{ETHsto} \cdot Csto \cdot Esto_{inst} + Cm_t; \tag{5}$$

- Initial inversion,

$$I = Cch \cdot Qch \cdot Pch_{inst} + \sum_{k=1}^{nw} (Cw_k \cdot Qw_k \cdot y_k) + Cpv \cdot Spv_{inst} + Csto \cdot Esto_{inst}; \tag{6}$$

- Energy balance in the charging station at hour h,

$$Eph_h + Ew_h + Eg2s_h + EDsto_h = Eev_h + Es2g_h + ECsto_h; \tag{7}$$

- Stored energy in the batteries at hour h,

$$Esoc_h = Esoc_{h-1} + ECsto_h - EDsto_h; \tag{8}$$

- Limit of the power supplied by the wind generators,

$$Pw_h \leq Pw_{inst}; \tag{9}$$

- Limit of the power supplied by the photovoltaic panels,

$$Pph_h \leq Pph_{inst}; \tag{10}$$

- Limit of the discharge and charge power of the storage systems,

$$PDsto_h \leq Psto_{inst}, \tag{11}$$

$$PCsto_h \leq Psto_{inst}; \tag{12}$$

- Limit of the discharge and charge energy of the storage systems,

$$EDsto_h \leq Esoc_{h-1}, \tag{13}$$

$$ECsto_h \leq Esto_{inst} - Esoc_{h-1}; \tag{14}$$

- Limit of the stored energy in the storage systems,

$$Esoc_h \leq Esto_{inst}, \tag{15}$$

$$Esoc_h \geq SOC_{min} \cdot Esto_{inst}; \tag{16}$$

- Limit of the supplied and consumed power from the grid at the connection point,

$$Ps2g_h \leq Pgc_{max}, \tag{17}$$

$$Pg2s_h \leq Pgc_{max}; \tag{18}$$

- Limit of the EV-supplied power at every EV fast-charging supplier,

$$\boldsymbol{Pev_h \leq Pch_{inst}}; \tag{19}$$

- Limit of the EV-supplied energy at hour h,

$$\boldsymbol{Eev_h \leq EMAXev_h}; \text{ and} \tag{20}$$

- Limit of the waiting time for each EV,

$$\boldsymbol{tev_k \leq tev_{max}} \tag{21}$$

Where y_{kw} are binary variables.

3. Input data models

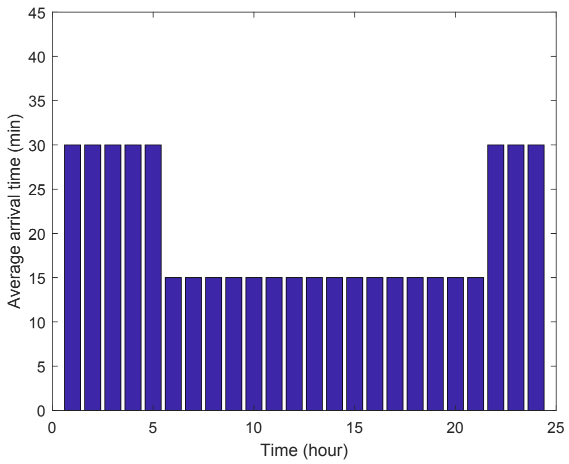
A. Electric vehicle demand

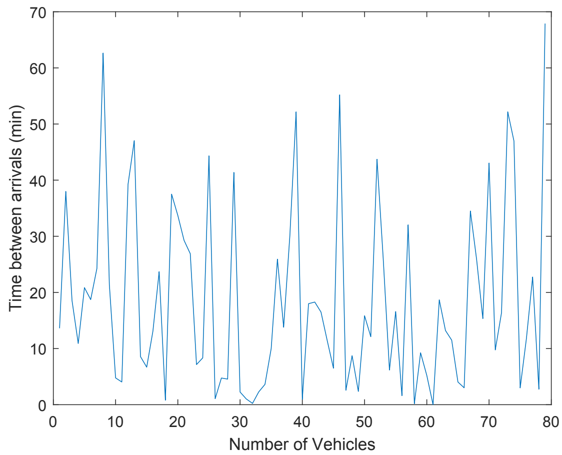
As introduced before, the first step is to model the EV demand at the charging station. This EV demand depends on the flow of electrical vehicles that arrive at the charging station and on the capacity and state of charge of their batteries. But we also consider that the charging station has a finite number of chargers and that when a consumer arrives at the station and no chargers are free, he or she will leave the charging station. This kind of system can be regarded as an Erlang B queueing model or M/M/c/c [39].

The first step consists of determining when each vehicle will arrive at the charging station. This can be modelled as a modulated Poisson process [40]. The time (*ta*) passed between the arrivals of two consecutive vehicles (21) is determined by an exponential distribution [11]. This distribution is defined by parameter λ, which is the average arrival time or time between two arrivals. As this time can change from hour to hour, a different λ_h is considered for each hour h. For this study, the arrival time selected is shown in Figure 1(a).

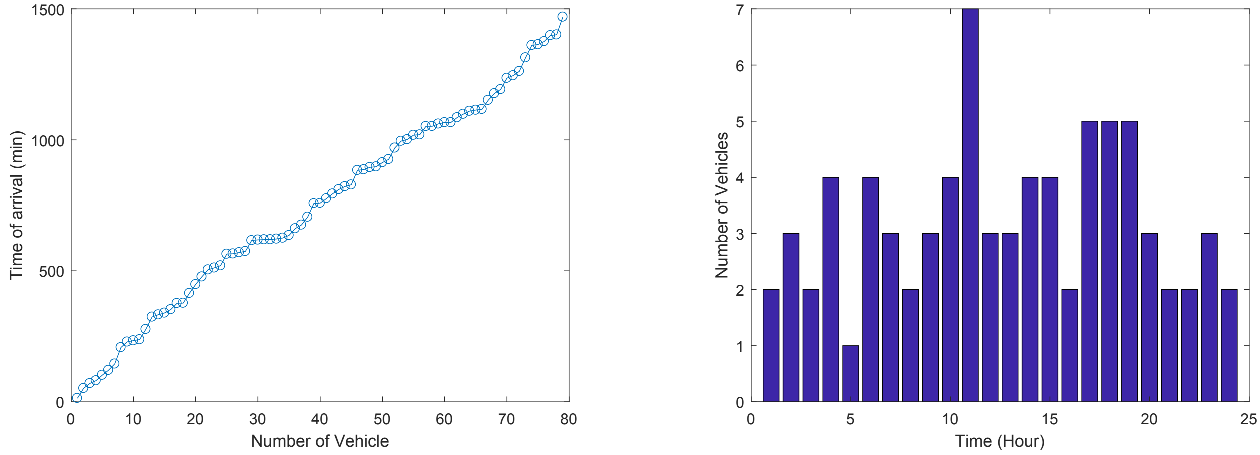
$$\boldsymbol{ta_h(x) = 1 - e^{-\lambda_h x}} \tag{21}$$

The electrical vehicle arrivals are simulated with the sequential Monte Carlo method, SMC [41]. A list of random numbers is obtained in the interval [0, 1], and every number gives us the arrival time of the next vehicle to introduce into the x parameter of the equation (21). Figure 1 gives an example of this sequence.





(a) (b)



(c) (d)

Figure 1. Simulation of arrival times of EVs over the temporal horizon of 1 day. (a) Average arrival time (min), (b) time between arrivals (min), (c) time of arrival (min) and (d) number of vehicles per hour.

In the second step, the energy needed to fill the battery is calculated for every vehicle that arrives. For this, it is necessary to determine the capacity and state of charge of the EV's battery. The battery capacity is associated with the vehicle type. It is supposed that the types of vehicles that can come to the station include motorbikes, cars and vans. The battery selection is associated with a discrete distribution found in the registration data obtained from the Traffic General Direction of Spain [42] about these type of vehicles; see Table 1.

Table 1. Probability of battery capacity.

	Battery capacity (kWh)	Probability (%)	Accumulated probability (%)
Bike	3.6	0.115	0.115
Small private car	16	0.370	0.485
Large private car	25	0.380	0.865
Van	63	0.135	1

The state of charge (SOC) of the EV battery can be modelled by the lognormal distribution and is defined by the average (μ) and typical deviation (σ) of the logarithm of the SOC variable [11]. Parameter E represents the initial SOC of an EV battery and varies from 0 to 1. Fig. 2 shows the lognormal distribution of SOC used, for which the μ and σ parameters of equation (22) are 3 and 0.6, respectively:

$$\boldsymbol{SOC(E;\mu,\sigma)} = \frac{\mathbf{1}}{\boldsymbol{E\sigma\sqrt{2\pi}}}\cdot \boldsymbol{e}^{-(\boldsymbol{lnE}-\boldsymbol{\mu})^{2}/2\boldsymbol{\sigma}^{2}} \tag{22}$$

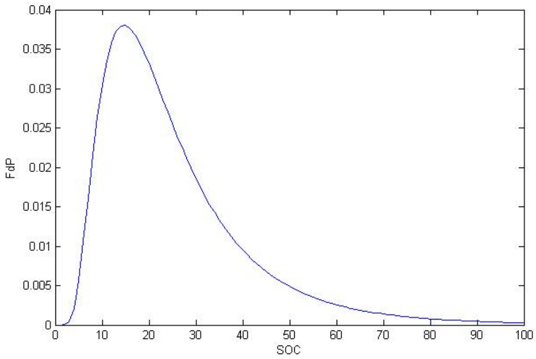


Fig. 2 Lognormal distribution of battery SOC.

In the simulation process, a random number from the interval [0, 1] is compared with the accumulated probability found in Table 1 to obtain the type of vehicle that arrives at the charging station and to determine the maximum capacity of its battery. In the same way, another random number is introduced into parameter E of equation (22) for every EV that arrives to charging station to obtain its battery SOC.

In the third step, once the SOC and the battery capacity have been calculated, the charging time can be obtained for each vehicle by means of this simplified equation:

$$\boldsymbol{t_{charge}} = \frac{\boldsymbol{Battery\_Capacity} * (\mathbf{1} - \boldsymbol{SOC})}{\boldsymbol{P_{charger}}}. \quad (23)$$

Equation (21) obtains the arrival times, and equation (23) calculates the charging time. With these data, the vehicles are distributed to the different chargers. The charging simulation of Li-ion batteries has been simplified and modelled as constant power load [43-45]. At times when all of the chargers are busy, if a new vehicle arrives, it does not wait, and it is lost. As the charging periods are relatively long, consumers normally do not wait if they see that all of the chargers are busy and will go to the next charging station [39].

Finally, taking into account the fast charging power and the number of chargers supplying power, *m*, the total demand of the EV station, is:

$$\boldsymbol{P_{station}(t)} = \sum_{\boldsymbol{k=1}}^{\boldsymbol{m}} \boldsymbol{P_{charger,k}(t)}. \quad (24)$$

Figure 3 shows an example of the temporal evolution of demand over one day in an example with three chargers as well as the total demand at the station. The load profile of a service station is not a smooth demand curve throughout the day, since the events are discrete.

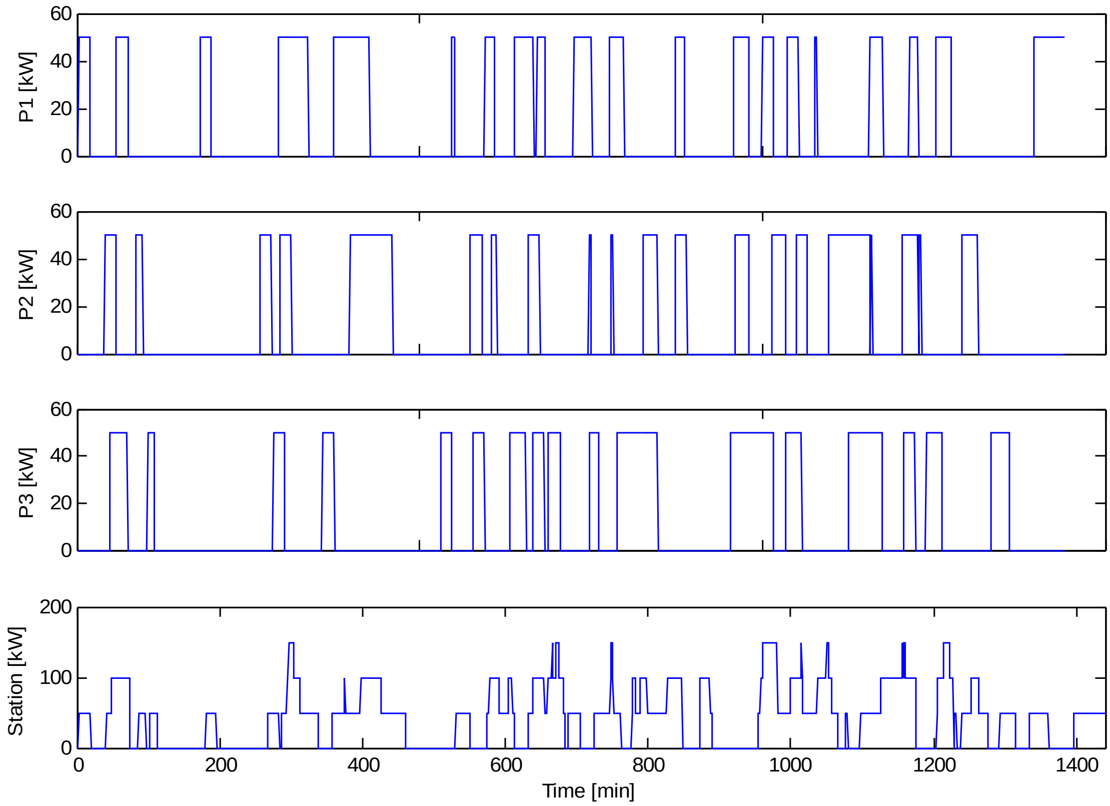


Figure 3. Demand at each charger and total of the station in a day.

B. *Wind energy generation*

The wind speed is modelled by a Weibull distribution (25). The parameters needed to calculate it are the scale factor (c) and the shape factor (k), which depend on the location.

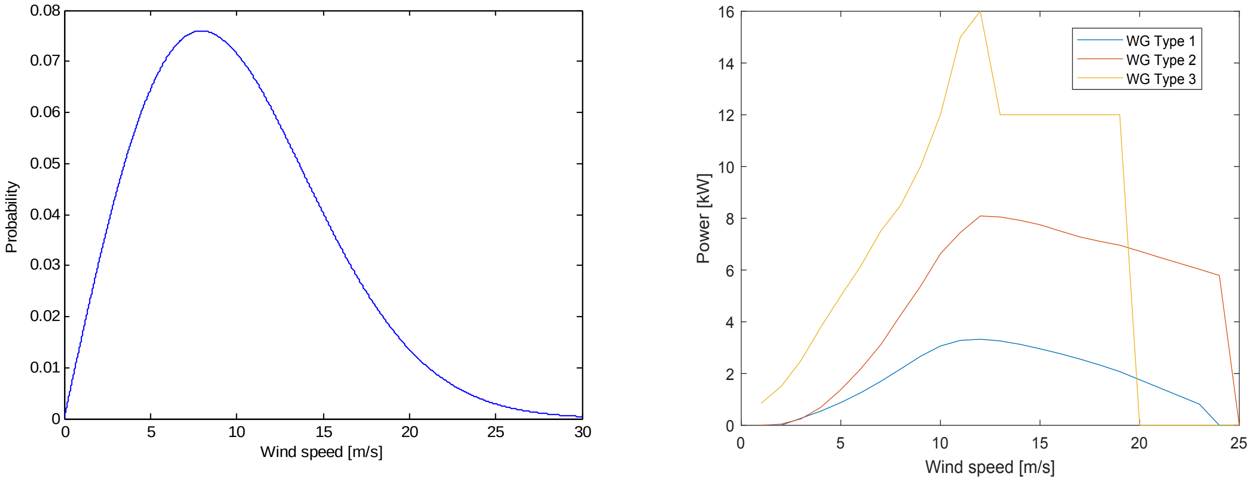
$$\boldsymbol{p(v) = \frac{k}{c} \cdot \left(\frac{v}{c}\right)^{k-1} \cdot e^{-\left(\frac{v}{c}\right)^{k}}} \tag{25}$$

$$\boldsymbol{c = v_m \cdot \left(0.568 + \frac{0.433}{k}\right)^{-1/k}} \tag{26}$$

In the simulation process, it is possible to obtain the hourly evolution of the wind speed from a series of random numbers, introducing each random number p in the inverse of the Weibull distribution.

$$\boldsymbol{v = -c[\ln(1-p)]^{1/k}} \tag{27}$$

Once the speed is obtained, the power that turbine can generate with this speed can be obtained from the wind generator power curve. Wind resources are modelled with the Weibull distribution for an average wind speed (v_m = 6 m/s) and a shape factor (k = 2). The power curve for three turbines, as utilized in this paper, can be seen in Figure 4.



(a) (b)

Figure 4(a) Weibull distribution for wind speed and (b) power curve for the wind generator.

C. Photovoltaic solar energy.

The hourly output power of the photovoltaic panels, Ppv_h, can be evaluated by the next equation [13, 46]:

$$\boldsymbol{Ppv_h = G_i \cdot A \cdot \eta,} \tag{28}$$

where G_i is the global solar irradiance at the tilted surface, A is the installed surface and η is the efficiency of the system (17% in our case) that considers losses due to spectral sensitivity of the PV cells among others effects [47].

The data on global solar irradiance on an inclined plane were obtained from PVGIS (Photovoltaic Geographical Information System) tools [48]. It computes the real-sky global irradiance adding the beam, diffuse and reflected components on an inclined plane.

$$\boldsymbol{G_i = B_i + D_i + R_i} \tag{29}$$

The inputs are latitude, longitude and altitude from the location and the slope angle and orientation of the solar panels. The output is the estimation of real-sky global irradiance on the solar panels. In Figure 5, it is the hourly global irradiance for 41º latitude north, 0º longitude and 200 m of altitude; the solar panels are oriented towards the south and have an inclined angle of 40º.

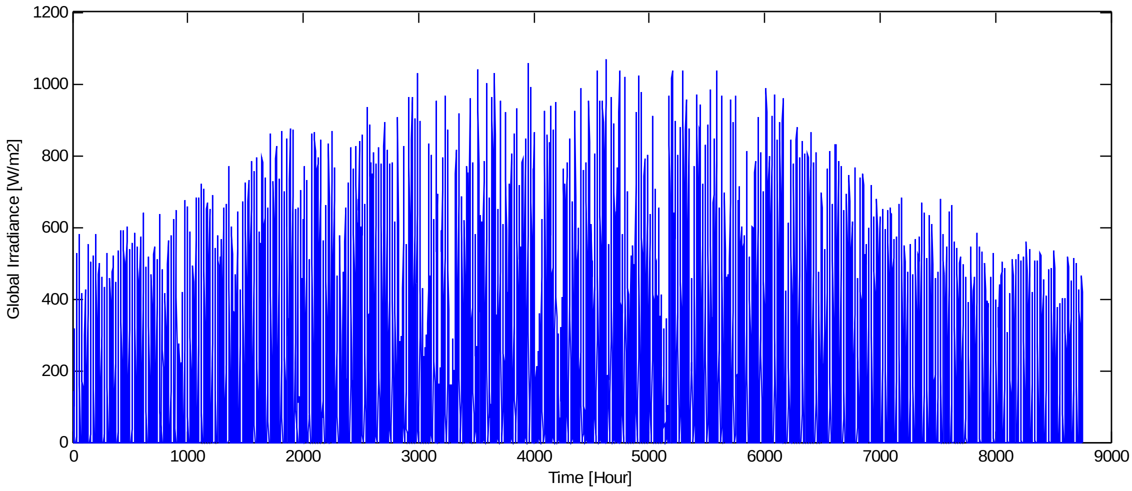


Figure. 5. Hourly global irradiance on a surface inclined 40º.

D. Energy prices.

In Spain, EV charging stations must go to the electricity market or make a bilateral contract with a retailer for contracted power greater than 10 kW.

In the electricity market, the hourly price is determined by the point at which the supply and demand curves meet, according to the marginal pricing model. At this price, one has to add a generation toll and taxes to sell energy to the network. To buy from the network, one has to add the costs of the technical constraints and system operator management, the payments for capacity and interruptibility, the costs of the tolls and the losses in the transport of energy through the networks and taxes. In our case, the variation in the purchase price and sale price of energy as a result of the terms indicated above has been calculated at 0.0828 and 0.0022 €/kWh, respectively. The sale price of energy to electric vehicles has been estimated by adding 0.04 €/kWh to the purchase price of energy as a benefit.

Fig. 6 shows the real purchase and sale prices of energy in the market, the sale price of energy to electric vehicles, and the annual average values of these curves. The difference between the purchase price of energy from the network (blue line) and the sale price to the network (red line) is due to the difference between tolls and taxes that must be paid when buying and selling. The sale price for electric vehicles (yellow line) takes into account the desired benefit and taxes.

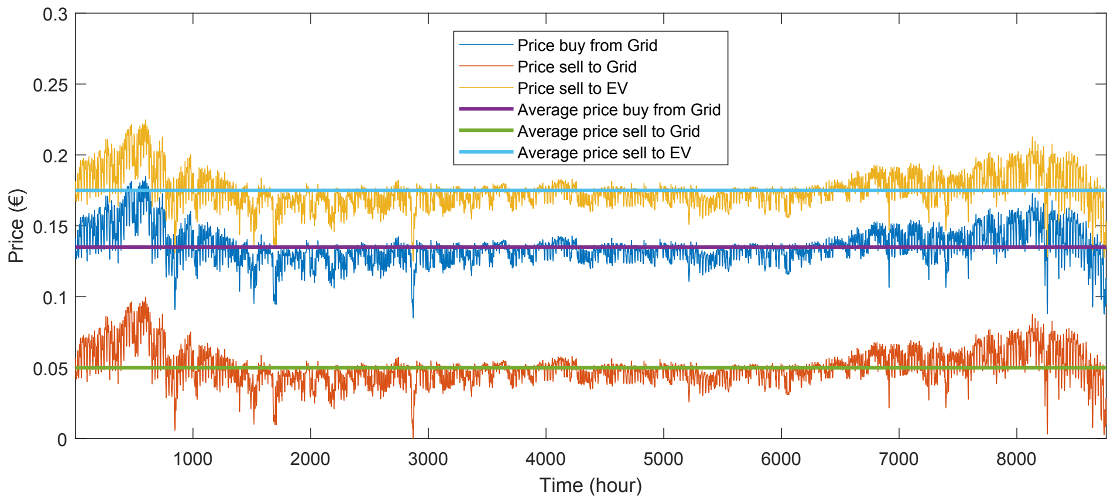


Figure 6. Hourly prices of energy

4. Optimization Algorithm

Genetic algorithms (GAs) [49, 50] are optimization methods widely used to solve real-world problems and are based on natural selection principles. Pseudocode of the optimization algorithm is shown in Figure 7. Here, the main characteristics of the proposed algorithm are explained, specifically the fitness function, chromosome structure and crossover and mutation rates.

```
Program EV_station_optimization;
Begin:
Step 1: Generate an initial population (t=0) with nsol feasible solutions
randomly.
Step 2: Evaluate these nsol solutions of the population (t=0) with the
Fitness_function program.
For t=1 to max_generations
      Step 3: Select the best solutions from population(t) as parents.
      Step 4: Apply crossover on parents, creating population(t+1)
      Step 5: Apply mutation into population(t+1)
      Step 6: Evaluate population(t+1) with the fitness function
EndFor;
End.
```

Figure 7. EV station optimization

A. Chromosome: Optimization variables

A chromosome represents each individual, as shown in Figure 8; this is composed of the variables that the optimization program can change in the design process. These variables are associated with the charging station's structure: the number and power of chargers, number and type of wind generators, surface occupied by photovoltaic panels, storage system capacity and transfer capacity of the connexion to the grid. All of the variables are real, except for the number of chargers and the number and type of wind generators, which are integers. In addition, these variables are constrained by the limits presented in Table 2 for design reasons.

Qch	Qw_{kw}	kw	Pch_{inst}	Spv_{inst}	$Esto_{inst}$	Pgc_{max}

Figure 8. Structure of a chromosome.

Table 2. Range of optimization variables.

Variable	Description	Variable type	Lower limit	Upper limit
Qch	Number of chargers	Integer	1	10
Qw_{kw}	Number of wind generators	Integer	0	4
kw	Type of wind generator	Integer	1	3
Pch_{inst}	Charger power	Real	44	220
Spv_{inst}	Surface occupied by photovoltaic panels	Real	0 m^2	1875 m^2
$Esto_{inst}$	Storage system capacity	Real	0 kWh	500 kWh
Pgc_{max}	Transfer capacity of the connexion to the grid	Real	0 kW	600 kW

B. Crossover and mutation operators

The chromosome has three integer-type genes and four real-type genes. The crossover operator used for the three genes of integer type creates a random binary vector and selects the genes from the first parent if the vector has a 1 and the genes from the second parent if the vector has a 0; then, it combines the genes to create the two children. If the binary vector is [1 0 1] and the parents are Parent1 = [a b c] and Parent2 = [1 2 3], then the children are Child1 = [a 2 c] and Child2 = [1 b 3].

The crossover operator used for the four real-type genes creates every gene k of the child from two parents, parent1 and parent2, using the next function:

$$\text{child}(k) = \text{parent1}(k) + \text{Ratio} * (\text{parent2}(k) - \text{parent1}(k)), \quad (30)$$

where Ratio is, in our case, equal to 0.8.

The mutation operator is applied to a small number of chromosomes. First, a random number between 0 and 1 is generated, and if this number is less than a threshold—in our case, 0.001—then a mutation is applied to this chromosome. Then, an integer random number between 1 and the number pf genes indicates the gene at which the mutation is applied. Finally, for integer-type genes, that gene is changed by an integer random number generated between the limits of this gene. For real-type genes, a real random number is generated between the limits of this gene.

```
If gene(k) is integer
    then gene(k) = randi([Lower limit, Upper limit]);
If gene(k) is real
    then gene(k) = Lower limit + (Upper limit – Lower limit) * rand();
```
(31)

C. Fitness function: Profitability

The fitness function is the same objective function that NPV (1) described in the mathematical model. The initial outlay corresponds to the cost of installing each energy system element. Incomes are associated with the energy supplied to customers who recharge their vehicles and with the surplus energy sold to the grid. On the other hand, expenses correspond to the energy bought from the grid, the maintenance of the EV station and the replacement of batteries.

To evaluate this fitness function, the energy management of the EV station during a year must be simulated. This energy management is simpler than other forms of energy management that can be found in papers on the operation problems of EV stations. Note that this paper treats the design problem, which is already complex enough. The renewable generation is prioritized to feeding the EV chargers. If the energy available at the charging station is higher than the demand of the EV chargers, this energy will be stored. Once the battery's maximum capacity is reached, this surplus energy will be supplied to the electrical grid. If the limit of the grid connexion is reached and it is not possible to inject energy into the grid, then the renewable generation will be reduced. When there is a deficiency of energy to feed the EV chargers, that energy will be provided by storage systems firstly and, as a last resort, by the grid. The calculations of the batteries' life and maintenance have also been included in equation (5).

The EV station's operations were simulated with a sequential Monte Carlo method. The operations were simulated hourly during a year. First, the algorithm calculates the hourly EV demand from the probability distributions of arrival time, battery capacity and battery SOC. Second, the energy generated by wind and solar generators is calculated. Third, the energy flows among the generators, battery, EV chargers and grid are calculated. The problem's restrictions must be checked when calculating the energy flows. Finally, the value of the fitness function is calculated, as can be seen in Figure 9.

The costs of energy sold to and purchased from the network were calculated based on the cost of hourly energy in the electricity market plus the corresponding tolls for the use of the electricity grid, and the cost of the energy sold to EVs was the electric market cost plus a profit, as explained in section 3-d.

```
Program Fitness_function;
Begin:
For h=1 to 8760 do
    Step 1: EV demand calculation
        - Generate random numbers.
        - Obtain the arrival time of EVs.
        - Obtain the kind of EV and battery capacity.
        - Obtain the battery's SOC.
    Step 2: Renewable energy calculation
        - Generate random numbers.
        - Obtain the energy generated by wind generators.
        - Obtain the energy generated by solar modules.
    Step 3: Energy balance
        - Calculate the energy flows among devices that meet
        the devices' restrictions.
Endfor;
    Step 4: Evaluation of the fitness function NPV.
End.
```

Figure 9. Evaluation of the fitness function

5. Study case

A. Description of case

This work explains a model to optimize the design of EV charging stations. Data for modelling EV demand and wind and solar resources can be found in the "Input data models" section, limits for decision variables that optimize the algorithm are shown in Table 2 and economic data used in the objective function can be found in Table 3. Lithium ion batteries have been considered in the storage system with a minimum SOC level of 10% or 0.1 p.u.

Table 3. Economic costs.

	Installation cost		Buy/sell energy
Wind Generators	650 €/kW	Sell energy to EV	0.175 €/kWh
Solar PV panels	100 €/m^2	Sell energy to grid	0.055 €/kWh
EV Charger	500 €/kW	Buy energy from grid	0.135 €/kWh
Battery (Li-ion)	150 €/kWh	Contracted power to grid	0.121 €/kW month
	Other parameters		
Time of the cash flow	20 years	Maintenance	1000 €/year
Discount rate	2.69 %	Cycle life	2000 cycles

The first three cases were defined to study different patterns of feeding the station, the fourth case to study different arrival patterns of vehicles to the station, the fifth case to compare the performance with other heuristic algorithms and the sixth case to study the transfer capacity of the connexion to the grid.

Case I. The EV station feeds only from the grid. In this case, the EV station is connected to the grid, and all of the energy needed is purchased from the grid. The energy price has two terms: the contracted power and the energy consumed. This case is the baseline for the comparisons.

Case II. The EV station feed only from renewable energy. In this case, the EV station is isolated from the grid and is only fed by solar and wind renewable energy. Due to the uncertainty of renewable energy, batteries are installed to guarantee the service of the EV station. The design has limits for the solar and wind power installed that will depend on the location; in this case, the limits are in Table 2.

Case III. The EV station feeds from a mix of renewable energy and the grid. In this case, the EV station has renewable energy and a connexion to grid. This design is the most flexible because it has the advantages of both worlds: cheap energy from the renewable energy and safe feeding from the grid. Additionally, it is allowed to sell the excess energy to the grid [51].

Case IV. Similar to case III, but now with more detailed data. In this case, a different average arrival time is considered for every hour (see Figure 10), compared to the previous cases, in which only two periods were considered (see Figure 1(a)). In addition, it uses the hourly prices of the Spanish electric market and the hourly network access tolls (see Figure 6), rather than the average prices (see Table 3).

Case V. Similar to case IV, but now with a new algorithm: the particle swarm optimization. This case allows the performance of these algorithms to be compared, in terms of both computational time and accuracy.

Case VI and VII. Similar to case IV, but the capacity of power transfer to the grid is limited.

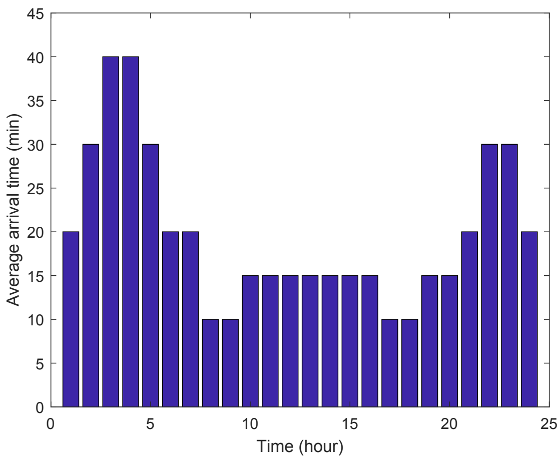


Figure 10. Average arrival time (min)

B. Results

The optimal solutions obtained for the design of EV stations are described and examined from economic and technical perspectives. The characteristics of the designed EV stations are shown in Table 4, and the economic results can be found in Table 5.

Table 4 gives the number of chargers installed (N. chargers), the power of each charger (Charger power), the maximum power of the connexion between the grid and the EV station (Grid power), the type of wind generator installed (Type Wgen), the number of wind generators installed (N. Wgen), the surface of solar PV panels installed (Solar surface), the capacity of batteries installed (Battery) and the computational time in minutes necessary to reach the solution (Computational time (min)) with a Intel Core i5 and 4 GB of RAM.

Table 4. Optimal configuration for each case.

Case	N. chargers	Charger power (kW)	N. Wgen	Type Wgen	Solar surface (m^2)	Battery (kWh)	Grid power (kW)	Computational time (min)
I	4	44.26	0	0	0	0	128.33	104
II	5	44.25	4	3	1456.38	379.57	0	136
III	5	46.11	4	3	1871.95	329.51	298.36	153
IV	5	46.00	4	3	1873.48	122.27	255.70	218
V	5	46.54	4	3	1874.21	125.32	243.74	82
VI	5	46.39	4	3	1867.00	190.20	200.00	80
VII	5	44.00	4	3	1867.49	111.52	100.00	75

Table 5 gives the net present value (NPV), internal rate of return (IRR), profit investment ratio (PIR), investment, the cost of battery replacements, cost of maintenance, cost of buying energy from the grid, income from selling energy to the grid and income from selling energy to EV drivers. The PIR index is the ratio between the present value of future cash flows and the initial investment and can be used to rank the projects.

Table 5. Economic results for each case.

Case	NPV (€)	IRR (years)	PIR (p.u.)	Investment (€)	Battery replacement (€)	Maintenance (€/year)	Cost of buying energy from the grid (€/year)	Income from selling energy to the grid (€/year)	Income from selling energy to EV owners (€/year)
I	166,397.66	5	2.879	88,532.09	0	1000	60,190.72	0	78,025.01
II	787,027.28	4	3.234	352,215.83	43,662.11	1000	0	0	78,248.50
III	990,445.25	4	3.533	390,897.26	37,903.48	1000	4138.58	15,087.07	83,167.25
IV	1,025,950.37	4	3.852	359,692.62	13,696.84	1000	15,521.45	14,752.55	93,522.74
V	1,020,344.70	4	3.821	361,569.00	25,767.62	1000	14,509.18	15,238.30	94,010.32
VI	1,006,539.27	4	3.718	370,218.69	42,232.98	1000	12,087.09	12,975.53	93,067.81
VII	955,624.17	4	3.711	352,477.82	12,492.59	1000	15,101.23	10,098.22	92,388.38

C. Comparison of cases I, II and III

As can be seen in Table 4, the number and power of chargers are similar in the first three cases because they mainly depend on the demand characteristics. However, the number of chargers is lower in case I, in which the EV station is fed only from the grid, with a more expensive energy price than that of free renewable energy.

The contracted power to the grid, in the grid power column, is greater in case III than in case I, which seems like a contradiction because case I is fed only from the grid, whereas case III can be fed from both the grid and renewable energy. Nevertheless, there is no contradiction because the EV station in case I buys energy from the grid and the EV station in case III sells energy to the grid.

The comparison between the installed renewable power in cases II and III shows that in case III, the maximum power of renewable energy (wind and solar) is installed based on the constraints from the four type 3 wind generators and 1871.95 m^2 of solar panels, while 1456.38 m^2 is installed in case II, which is less than the 1871.95 m^2 allowed. The reason is that in case II, the installed power is only needed to feed the demand because the energy that is not sold to electric vehicles is wasted, and the solution in case III installs all renewable energy possible, to sell this energy to the grid and get profits.

Finally, the solution for case II needs more storage capacity than the solution of case III because case II only uses uncertain renewable energy to feed the EV station, while case III can also use the connexion to the grid.

The computational time column shows the time necessary to reach the solution. These times are long because the evaluation of the fitness function requires simulation of the EV charging station's operations by the Monte Carlo method. Furthermore, optimizing the design problem of an EV charging station with a genetic algorithm is also complex.

From an economic standpoint, the best solution is obtained in case III, with better value in the NPV than that of case II and the same IRR. In case III, the EV station has a mixed strategy, with renewable energies and connexion to the grid. This strategy permits income to be obtained from selling energy to EV owners and to the grid.

Investment is much greater in cases II and III than in case I, due to the installation costs of renewable generators and batteries; see Figure 11 and Table 5. However, these cost are compensated quickly by the operational costs and cost of the energy used. This energy is bought from the grid in case I, with a cost around 60,190.72 €/year, compared to a small cost in case III of about 4,138.58 €/year and practically free in case II. The rest of the energy used in cases II and III is supplied from renewable sources.

From an environment standpoint and when considering the impact on the grid, case II is better because it uses only renewable energy and has no impact on the grid. It does not have energy interchanges with the grid.

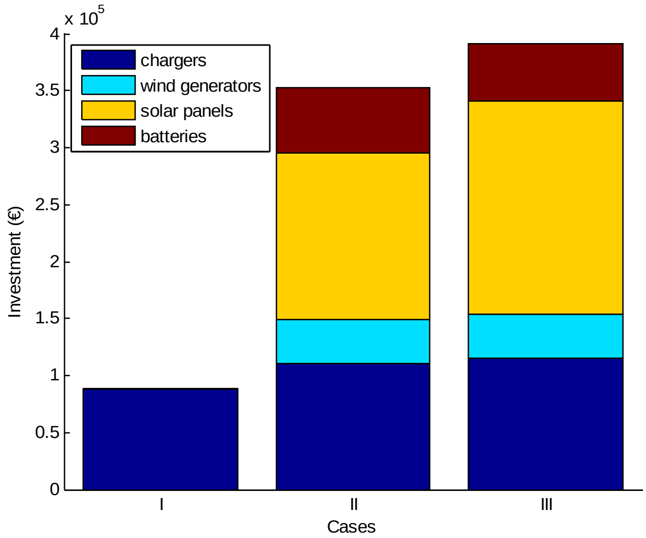


Figure. 11. Components of investment.

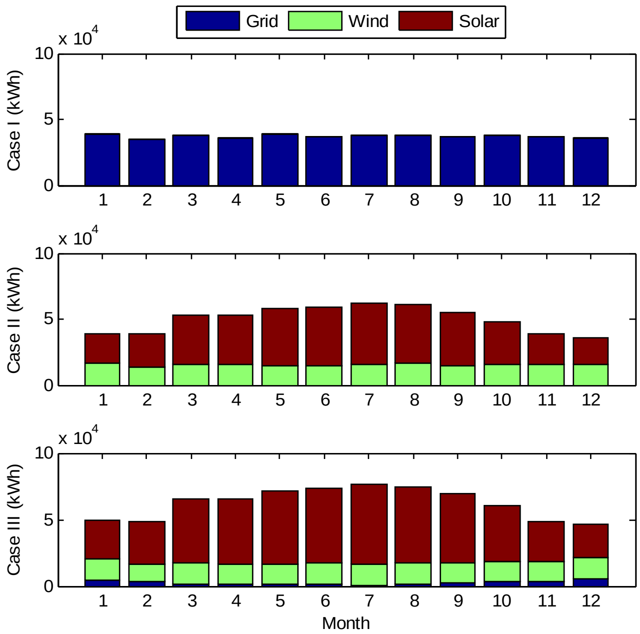


Figure. 12. Origin of the monthly energy used in each case.

Figure 12 shows the monthly energy used (sold to EV owners and the grid) in each case. The starting point in the optimization process is the hypothetical demand generated by the EVs at the location of the charging station, which is the same in all three cases. However, the real demand that each station is capable of satisfying is different, depending on the number of chargers assigned to it by the optimization of its configuration as well as the availability of energy at each moment according to the energy supply configuration that the optimization assigned to it. Case I has four chargers, so there will be consumers who will not stop when all of the chargers are occupied. Case II has five chargers, so it can serve more consumers, but in some cases, energy deficits can occur due to fluctuations in renewable energy or excess energy being wasted. Case III involves five chargers, but the optimization program calls for more installed solar renewable generation because the surplus energy can be sold to the grid.

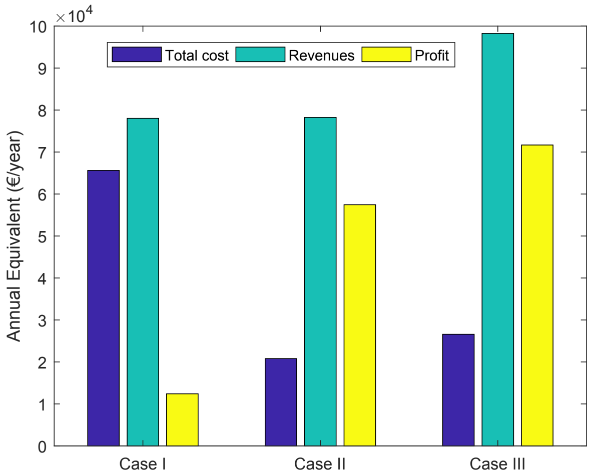
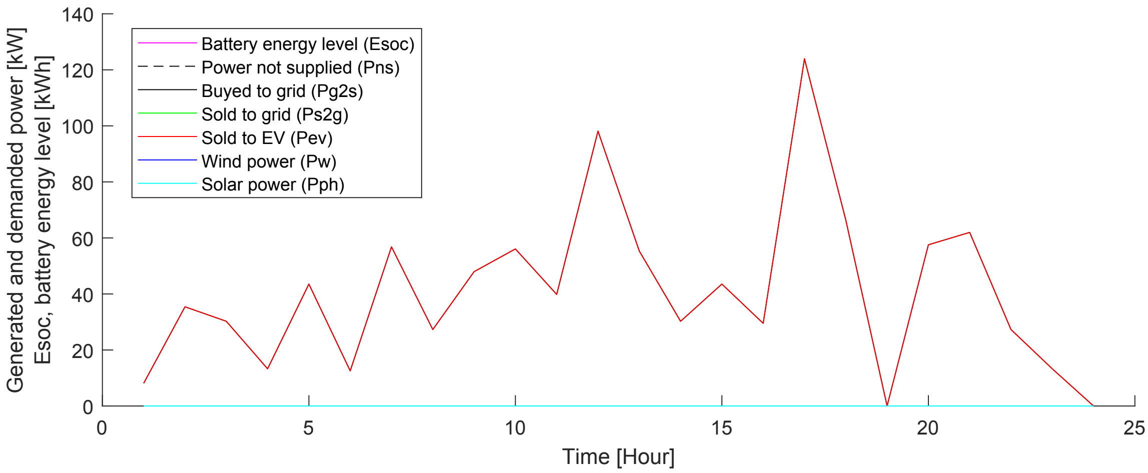


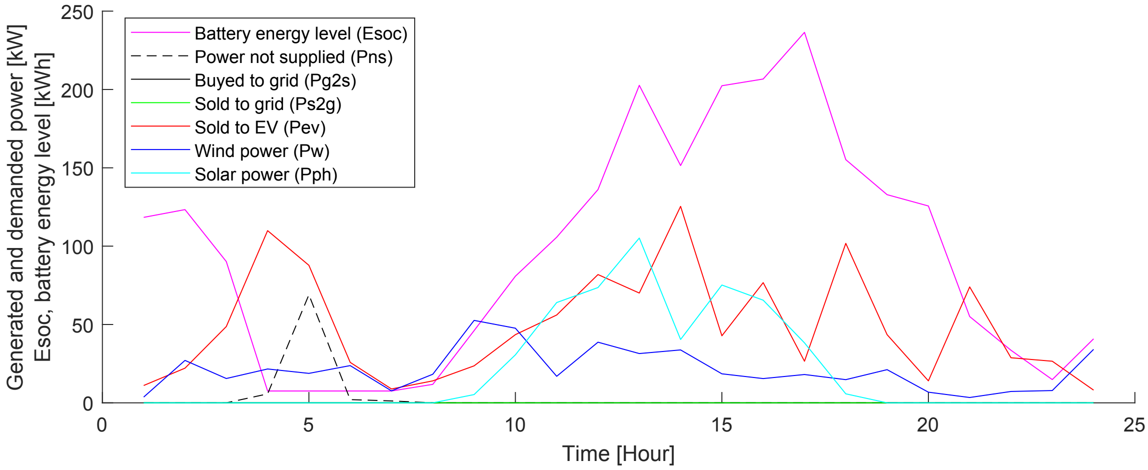
Figure. 13. Comparison in annual equivalent values.

Figure 13 permits the three cases to be compared in terms of annual equivalent values. Case I has a large total cost because the operational costs are high. Case III has the highest revenue because it sells energy to the grid and therefore has the highest profit.

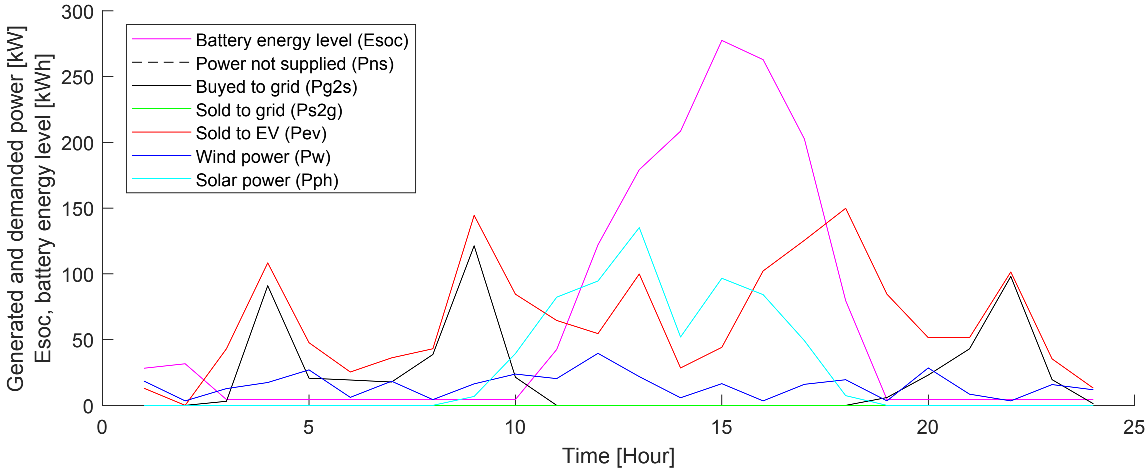
Operation of the EV station every day differs according to the available energy sources, as shown in Figure 14. It shows the hourly power that each element generates or demands and, in the case of batteries, their energy level. In case I, all of the energy sold to electrical vehicles is provided from the grid. In case II, all energy is provided from wind and solar sources, but the batteries are needed to give service to all EVs, and at some hours (around 5 a.m. on this day), the EV station cannot supply all of the energy demanded by the EVs. In case III, the EV station uses the grid to supply energy to EVs when renewable sources are not enough.



(a) Case I: EV station feeds only from the grid.



(b) Case II: EV station feeds only from renewable energy.



(c) Case III: EV station feeds from a mix of renewable energy and the grid.

Figure. 14. Daily operation of the EV station.

D. Comparison between cases III and IV

Next, cases III and IV are compared. Case IV is the same as case III but with a more detailed modelling. It has different mean arrival times for every hour (Fig. 10) and uses hourly energy prices from the Spanish market for one year (Fig. 6).

As can be seen when comparing the optimal configurations of both cases in Table 4, these configurations are similar, with the only notable difference being in the size of the batteries. More vehicles arrive during day hours because the average arrival times decreased by a few hours; therefore, the renewable energy generated is used to feed the vehicles instead of being stored.

From the comparison of the economic results obtained in both cases, it can also be seen that the differences are small. More income would come from energy being sold to consumers, at 93,522.74 €/year in case IV compared to 83,167.25 €/year in case III, and less income would come from energy being sold to the network, at 14,752.55 €/year in case IV compared to 15,087.07 €/year in case III. Since the capacity of the batteries in case IV is lower, at 122.27 kWh compared to 329.51 kWh in case III, the investment and the cost of replacing them are lower but more energy has to be bought from the grid.

E. Comparison between cases IV and V

The comparison of the GA used in this work with another heuristic algorithm allows us to have an idea of our GA's performance. In this case, our GA has been compared with the particle swarm optimization algorithm [50, 52]. The results obtained in case IV, with the genetic algorithm, and case V, with particle swarm optimization, show that the results are very similar, but the new algorithm is faster.

F. Comparison among cases V, VI and VII

In these cases, the transfer power between the station and the network has been limited. By limiting the transferred power, its impact on the network is limited. The energy sold both to the network from renewable energy and to consumers decreases.

6. Conclusions

A GA using technique and economic factors optimized the design of EV fast-charging stations. Probabilistic distributions modelled the EV demand and renewal generation more realistically. Specifically, the EV demand model was improved when adding more details (arrival time, EV battery capacity, SOC and the EV distribution during the day).

The first three simulated cases confirmed that an EV charging station can be profitable. The main inconvenience is the high power that EV fast charges demand. The installation of renewable generators can improve a station's profitability, but it needs a connexion to the grid or a storage system to balance the intermittence of renewable energy.

The comparison among the last three cases confirmed that the utilization of renewable energies and storage systems would reduce the impact on the electrical grid.

The required investment is high; however, the development of technology is trending towards decreases in costs, which is a particularly interesting aspect in the case of batteries, both for the storage system and for EVs. This fact favours distributed generation, to achieve more sustainable energy management.

Acknowledgement

The authors would like to thank the support of Government of Aragon with FEDER funds.

References

[1] http://www.ieahev.org/by-country/spain-charging-infrastructure/.

[2] G. Mauri and A. Valsecchi, "The role of fast charging stations for electric vehicles in the integration and optimization of distribution grid with renewable energy sources," CIRED 2012 Workshop: Integration of Renewables into the Distribution Grid, Lisbon, 2012, pp. 1-4.doi: 10.1049/cp.2012.0815

[3] M. Amjad, A. Ahmad, M.H. Rehmani, T. Umer, A review of EVs charging: From the perspective of energy optimization, optimization approaches, and charging techniques, Transp. Res. Part D Transp. Environ. 62 (2018) 386–417. doi:10.1016/j.trd.2018.03.006.

[4] J. García-Villalobos, I. Zamora, J.I. San Martín, F.J. Asensio, V. Aperribay, Plug-in electric vehicles in electric distribution networks: A review of smart charging approaches, Renew. Sustain. Energy Rev. 38 (2014) 717–731. doi:10.1016/J.RSER.2014.07.040.

[5] S. Habib, M. Kamran, U. Rashid, Impact analysis of vehicle-to-grid technology and charging strategies of electric vehicles on distribution networks – A review, J. Power Sources. 277 (2015) 205–214. doi:10.1016/J.JPOWSOUR.2014.12.020.

[6] I. Rahman, P.M. Vasant, B.S.M. Singh, M. Abdullah-Al-Wadud, N. Adnan, Review of recent trends in optimization techniques for plug-in hybrid, and electric vehicle charging infrastructures, Renew. Sustain. Energy Rev. 58 (2016) 1039–1047. doi:10.1016/J.RSER.2015.12.353.

[7] K.M. Tan, V.K. Ramachandaramurthy, J.Y. Yong, Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques, Renew. Sustain. Energy Rev. 53 (2016) 720–732. doi:10.1016/J.RSER.2015.09.012.

[8] W. Su, H. Eichi, W. Zeng, M.-Y. Chow, A Survey on the Electrification of Transportation in a Smart Grid Environment, IEEE Trans. Ind. Informatics. 8 (2012) 1–10. doi:10.1109/TII.2011.2172454.

[9] Q. Wang, X. Liu, J. Du, F. Kong, Smart Charging for Electric Vehicles: A Survey From the Algorithmic Perspective, IEEE Commun. Surv. Tutorials. 18 (2016) 1500–1517. doi:10.1109/COMST.2016.2518628.

[10]Z. Xu, Z. Hu, Y. Song, Z. Luo, K. Zhan and J. Wu, "Coordinated charging strategy for PEVs charging stations," *2012 IEEE Power and Energy Society General Meeting*, San Diego, CA, 2012, pp. 1-8. doi: 10.1109/PESGM.2012.6345045

[11]Peng Zhang and Kejun Qian, “A Methodology for Optimization of Power Systems Demand due to Electric Vehicle Charging Load.”, IEEE Transactions On Power Systems, Vol. 27, No. 3, pp 1628-1636, 2012.

[12]Cao Y, Tang S, Li C, Zhang P, Tan Y, Zhang Z, et al. An optimized EV charging model considering TOU price and SOC curve. IEEE Trans Smart Grid 2012;3 (1):388–93. http://dx.doi.org/10.1109/TSG.2011.2159630.

[13]Fazelpour, Farivar, Majid Vafaeipour, Omid Rahbari, and Marc A. Rosen. 2014. “Intelligent Optimization to Integrate a Plug-in Hybrid Electric Vehicle Smart Parking Lot with Renewable Energy Resources and Enhance Grid Characteristics.” Energy Conversion and Management 77. Elsevier Ltd: 250–61. doi:10.1016/j.enconman.2013.09.006.

[14]P. Sadeghi-Barzani, A. Rajabi-Ghahnavieh and H. KazemiKaregar: “Optimal fast charging station placing and sizing”. Applied Energy, 125 (2014) 289-299.

[15]Wang G, Xu Z, Wen F, Wong KP. “Traffic-constrained multiobjective planning of electric-vehicle charging stations”. IEEE Trans Power Deliv 2013;28:2363–72.

[16]Sungwoo Bae and Alexis Kwasinski. “Spatial and Temporal Model of Electric Vehicle Charging Demand”. IEEE Transactions On Power Systems, Vol. 3, No. 1, March 2012.

[17]Xiang, Yue, Junyong Liu, Ran Li, Furong Li, Chenghong Gu, and Shuoya Tang. 2016. “Economic Planning of Electric Vehicle Charging Stations Considering Traffic Constraints and Load Profile Templates.” Applied Energy 178. Elsevier Ltd: 647–59. doi:10.1016/j.apenergy.2016.06.021.

[18]Vermaak, Herman Jacobus, and Kanzumba Kusakana. 2014. “Design of a Photovoltaic-Wind Charging Station for Small Electric Tuk-Tuk in D.R.Congo.” Renewable Energy 67. Elsevier Ltd: 40–45. doi:10.1016/j.renene.2013.11.019.

[19]Hafez, Omar, and Kankar Bhattacharya. 2017. “Optimal Design of Electric Vehicle Charging Stations Considering Various Energy Resources.” Renewable Energy 107. Elsevier Ltd: 576–89. doi:10.1016/j.renene.2017.01.066.

[20]Fathabadi, Hassan. 2017. “Novel Wind Powered Electric Vehicle Charging Station with Vehicle-to-Grid (V2G) Connection Capability.” Energy Conversion and Management 136. Elsevier Ltd: 229–39. doi:10.1016/j.enconman.2016.12.045.

[21]S. Bae, A. Kwasinski, Spatial and Temporal Model of Electric Vehicle Charging Demand, IEEE Trans. Smart Grid. 3 (2012) 394–403. doi:10.1109/TSG.2011.2159278.

[22]S. Shrestha, T.M. Hansen, Spatial-temporal stochasticity of electric vehicles in an integrated traffic and power system, in: 2016 IEEE Int. Conf. Electro Inf. Technol., IEEE, 2016: pp. 0227–0232. doi:10.1109/EIT.2016.7535245.

[23]Zhili Zhou, Tachun Lin, Spatial and Temporal Model for Electric Vehicle rapid charging demand, in: 2012 IEEE Veh. Power Propuls. Conf., IEEE, 2012: pp. 345–348. doi:10.1109/VPPC.2012.6422675.

[24]V. Viswanathan, D. Zehe, J. Ivanchev, D. Pelzer, A. Knoll, H. Aydt, Simulation-assisted exploration of charging infrastructure requirements for electric vehicles in urban environments, J. Comput. Sci. 12 (2016) 1–10. doi:10.1016/j.jocs.2015.10.012.

[25]C. Hutson, G.K. Venayagamoorthy, K.A. Corzine, Intelligent Scheduling of Hybrid and Electric Vehicle Storage Capacity in a Parking Lot for Profit Maximization in Grid Power Transactions, in: 2008 IEEE Energy 2030 Conf., IEEE, 2008: pp. 1–8. doi:10.1109/ENERGY.2008.4781051.

[26] Sekyung Han, Soohee Han, K. Sezaki, Development of an Optimal Vehicle-to-Grid Aggregator for Frequency Regulation, IEEE Trans. Smart Grid. 1 (2010) 65–72. doi:10.1109/TSG.2010.2045163.

[27] E. Sortomme, M.A. El-Sharkawi, Optimal Charging Strategies for Unidirectional Vehicle-to-Grid, IEEE Trans. Smart Grid. 2 (2011) 131–138. doi:10.1109/TSG.2010.2090910.

[28] I.K.A. Aswantara, K.S. Ko, D.K. Sung, A centralized EV charging scheme based on user satisfaction fairness and cost, in: 2013 IEEE Innov. Smart Grid Technol. (ISGT Asia), IEEE, 2013: pp. 1–4. doi:10.1109/ISGT-Asia.2013.6698730.

[29] D.T. Nguyen, L.B. Le, Joint Optimization of Electric Vehicle and Home Energy Scheduling Considering User Comfort Preference, IEEE Trans. Smart Grid. 5 (2014) 188–199. doi:10.1109/TSG.2013.2274521.

[30] D. Wu, D.C. Aliprantis, L. Ying, Load Scheduling and Dispatch for Aggregators of Plug-In Electric Vehicles, IEEE Trans. Smart Grid. 3 (2012) 368–376. doi:10.1109/TSG.2011.2163174.

[31] M.H.K. Tushar, C. Assi, M. Maier, M.F. Uddin, Smart Microgrids: Optimal Joint Scheduling for Electric Vehicles and Home Appliances, IEEE Trans. Smart Grid. 5 (2014) 239–250. doi:10.1109/TSG.2013.2290894.

[32] M.D. Galus, G. Andersson, Demand Management of Grid Connected Plug-In Hybrid Electric Vehicles (PHEV), in: 2008 IEEE Energy 2030 Conf., IEEE, 2008: pp. 1–8. doi:10.1109/ENERGY.2008.4781014.

[33] S. Acha, T.C. Green, N. Shah, Effects of optimised plug-in hybrid vehicle charging strategies on electric distribution network losses, in: IEEE PES T&D 2010, IEEE, 2010: pp. 1–6. doi:10.1109/TDC.2010.5484397.

[34] Jing Huang, V. Gupta, Yih-Fang Huang, Scheduling algorithms for PHEV charging in shared parking lots, in: 2012 Am. Control Conf., IEEE, 2012: pp. 276–281. doi:10.1109/ACC.2012.6314939.

[35] M. Gonzalez Vaya, G. Andersson, Centralized and decentralized approaches to smart charging of plug-in Vehicles, in: 2012 IEEE Power Energy Soc. Gen. Meet., IEEE, 2012: pp. 1–8. doi:10.1109/PESGM.2012.6344902.

[36] T.N. Le, S. Al-Rubaye, H. Liang, B.J. Choi, Dynamic charging and discharging for electric vehicles in microgrids, in: 2015 IEEE Int. Conf. Commun. Work., IEEE, 2015: pp. 2018–2022. doi:10.1109/ICCW.2015.7247477.

[37] S. Huang, Q. Wu, S.S. Oren, R. Li, Z. Liu, Distribution Locational Marginal Pricing Through Quadratic Programming for Congestion Management in Distribution Networks, IEEE Trans. Power Syst. 30 (2015) 2170–2178. doi:10.1109/TPWRS.2014.2359977.

[38] F.J. Soares, P.M.R. Almeida, J.A.P. Lopes, Quasi-real-time management of Electric Vehicles charging, Electr. Power Syst. Res. 108 (2014) 293–303. doi:10.1016/J.EPSR.2013.11.019.

[39] I.S. Bayram, G. Michailidis, M. Devetsikiotis, S. Bhattacharya, A. Chakrabortty, F. Granelli, Local energy storage sizing in plug-in hybrid electric vehicle charging stations under blocking probability constraints, 2011 IEEE Int. Conf. Smart Grid Commun. (2011) 78–83. doi:10.1109/SmartGridComm.2011.6102396.

[40] J. Kim, S.-Y. Son, J.-M. Lee, H.-T. Ha, Scheduling and performance analysis under a stochastic model for electric vehicle charging stations, Omega. 66 (2017) 278–289. doi:10.1016/j.omega.2015.11.010.

[41] F. Koyanagi, T. Inuzuka, Y. Uriu and R. Yokoyama, "Monte Carlo simulation on the demand impact by quick chargers for electric vehicles," 1999 IEEE Power Engineering Society Summer Meeting. Conference Proceedings (Cat. No.99CH36364), Edmonton, Alta., 1999, pp. 1031-1036 vol.2. doi: 10.1109/PESS.1999.787457

[42] Dirección General de Tráfico. Available on: http://www.dgt.es/es/seguridad-vial/estadisticas-e-indicadores/parque-vehiculos/

[43] F. Marra, Y.T. Fawzy, T. Bulo, B. Blazic, Energy storage options for voltage support in low-voltage grids with high penetration of photovoltaic, in: 2012 3rd IEEE PES Innov. Smart Grid Technol. Eur. (ISGT Eur., IEEE, 2012: pp. 1–7. doi:10.1109/ISGTEurope.2012.6465690.

[44] M.F. Shaaban, A.A. Eajal, E.F. El-Saadany, Coordinated charging of plug-in hybrid electric vehicles in smart hybrid AC/DC distribution systems, Renew. Energy. 82 (2015) 92–99. doi:10.1016/j.renene.2014.08.012.

[45] M.B. Arias, S. Bae, Prediction of electric vehicle charging-power demand in realistic urban traffic networks, Appl. Energy. 195 (2017) 738–753. doi:10.1016/j.apenergy.2017.02.021.

[46]F. Fazelpour, M. Vafaeipour, O. Rahbari, R. Shirmohammadi, Considerable parameters of using PV cells for solar-powered aircrafts, Renew. Sustain. Energy Rev. 22 (2013) 81–91. doi:10.1016/j.rser.2013.01.016.

[47]Smets, A., Jäger, K. et al. Solar Energy. Fundamentals, Technology, and Systems. Delft University of Technology, UIT Cambridge, England, 2014.

[48]PVGIS. Available on: http://re.jrc.ec.europa.eu/pvgis/solres/solrespvgis.htm

[49]T. Bäck, D. B. Fogel, Z. Michalewicz, Evolutionary Computation 1: Basic Algorithms and Operators, Institute of Physics Publishing, Bristol and Philadelphia, p. 339, 2000.

[50]Matlab User's Guide (online): https://es.mathworks.com/help/?s_tid=hp_ff_l_doc

[51]R. Dufo-López, J.S. Artal-Sevil, J.L. Bernal-Agustín, J.A. Domínguez-Navarro, Can electric vehicles reduce electricity bill? 2014 IEEE International Electric Vehicle Conference (IEVC) IEEExplore Digital Library. December 2014, Florence, Italy; pp.: 1-4.

[52]Kennedy, J.; Eberhart, R.C. (2001). Swarm Intelligence. Morgan Kaufmann. ISBN 1-55860-595-9.

Highlights:

- The study focusses on an EV charging station design problem with characteristics of an EV charging station operation problem.
- EV power demand is represented by an Erlang B queuing model, which until now has only been used in papers that discuss the optimization of EV operations.
- The EV operations include the purchase and sale of energy in the electricity market, which until now has only been used in papers that discuss the optimization of EV operations.
- This design problem includes a wide variety of energy sources: renewable generators, the grid and batteries.
- A genetic algorithm was adapted to deal with the complexity of the design problem.

Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems

J.A. Domínguez-Navarro, R. Dufo-López, J.M. Yusta-Loyo, J.S. Artal-Sevil, J.L. Bernal-Agustín
Electrical Engineering Department. Zaragoza University
C/María de Luna 3, 50018 Zaragoza, Spain
E-mails: {**jadona, rdufo, jmyusta, jsartal, jlbernal}@unizar.es**

Abstract. The development of electric vehicles (EVs) depends on several factors: the EV's acquisition price, autonomy, the charging process and the charging infrastructure. This paper is focused on the last factor: the design of an EV fast-charging station. In order to improve the profitability of the fast-charging stations and to decrease the high energy demanded from the grid, the station includes renewable generation (wind and photovoltaic) and a storage system. Unlike other papers, this one uses a detailed model of the charging process that considers the arrival time and state of charge of electric vehicles. First, the Monte Carlo method is used to model the EV demand and the renewable generation. Later, a genetic algorithm (GA) optimizes the installation and operation of the EV fast-charging station. It finds the optimal solution that maximizes the profit measured by its net present value (NPV). Several cases are studied to analyse the influence of renewable energies and storage systems. The obtained results show that a mix of renewable energies and storage systems attains the best cost efficient solution.

Keywords

Electric vehicle (EV), fast-charging station, Monte Carlo method, genetic algorithm and renewable energy.

Acronyms

$Cbuy_h$: buy price at electrical market at hour h (€),

Cch: cost of a charger (€).

Cm_t: maintenance cost of storage system at year t (€/year).

Cpv: square meter cost of photovoltaic panels (€/m^2).

$Cr\&m_t$: replace and maintenance of storage system at year t (€).

$Csale_h$: sale price at electrical market at hour h (€),

Cs_h: energy price station at hour h (€),

$Csto$: cost of storage system (€/kWh).

Cw_k: cost of the wind generator k (€).

$ECsto_h$: energy charged from storage system at hour h (kWh).

$EDsto_h$: energy discharged from storage system at hour h (kWh).

Eev_h: energy supplied to *EV* customers at hour h (kWh).

$Eg2s_h$: energy consumed from grid at hour h (kWh),

$EMAXev_h$: maximum energy demanded by *EV* customers at hour h (kWh).

Eph_h: energy supplied by photovoltaic generators at hour h (kWh).

$Es2g_h$: energy supplied to grid at hour h (kWh),

$Esoc_h$: energy level in storage system at hour h (kWh).

$Esoc_{h-1}$: energy level in storage system at hour $h-1$ (kWh).

$Esto_{inst}$: nominal energy capacity of the installed storage system (kWh).

$ETHsto_k$: total energy throughput of battery k that is equal to the life cycle by battery capacity (kWh).

Ew_h: energy supplied by wind generators at hour h (kWh).

h: an hour index.

I: initial investment (€).

i: interest rate.

$INFLOW_h$: cash inflow (income) at hour h (€).

n: the number of years considered in the study (year).

NCF_t: net cash flow at year t (€).

NPV: net present value (€).

nw: the number of types of wind generators considered in the study.

$OUTFLOW_h$: cash outflow (expenses) at hour h (€).

Pch_{inst}: rated power of the EV fast-charging supplier (kW).

$PCsto_h$: power of charge for storage system at hour *h* (kW).

$PDsto_h$: power of discharge for the storage system at hour *h* (kW).

Pev_h: power of the EV fast-charging supplier at hour *h* (kW).

$Pg2s_h$: power consumed from grid at hour *h* (kW),

Pgc_{max}: power limit in the grid connexion point (kW).

Pph_h: power supplied for photovoltaic generator at hour *h* (kW).

Pph_{inst}: rated power of the installed photovoltaic generator (kW).

$Ps2g_h$: power supplied to grid at hour *h* (kW),

$Psto_{inst}$: rated power of the installed storage system (kW).

Pw_h: power supplied for wind generator at hour *h* (kW).

Pw_{inst}: rated power of the installed wind generator (kW).

Qch: number of chargers installed.

Qw_k: number of wind generators of type *k*.

SOC: state of charge of the battery (p.u.).

SOC_{min}: minimum state of charge of the battery (p.u.).

Spv_{inst}: surface installed of photovoltaic panels (m^2).

t: a year index.

tev_k: waiting time for each vehicle (min).

tev_{max}: maximum waiting time; 0 (min), in our case.

y_k: *binary decision variable.*

1. Introduction

In the next few years, the number of electric vehicles (EVs) is expected to increase exponentially, due to the squandering of oil and the environmental impact associated with its use. For that reason, there is a tendency to coordinate efforts to reduce urban pollution and greenhouse gas emissions. At present, one of the most important problems in EV development is the shortage of charging infrastructure [1]. Drivers can charge their EVs at home, but the charge time is quite long. To promote the EV development, it is necessary to install fast-charging station in which the EV battery can be charged in around 15 minutes. By contrast, the disadvantage of fast charging is the high power demand and its impact on the grid. In order to address this, renewable sources and storage systems can be installed in these stations [2]. Review of studies about the appropriate system design for an EV station's installation and its operation can found in [3-9].

Several authors have analysed the impact of EV station operation within the electrical network. They present different methods to level the load curve. Xu et al. [10] showed a coordinate charging strategy to improve the effects of EV charging in the electrical demand curve as well as the profit of the EV stations. Zhang and Qian [11] presented a methodology to charge EVs during night time. Cao et al. [12] proposed an intelligent charging method for EV in response to time-of-use price that alleviates the stress in the network during the peak periods. Fazelpour et al. [13] developed an algorithm with two phases to integrate smart parking with a plug-in hybrid EV. First, the algorithm optimizes the size and location of renewable energy installations through the grid. Then, it optimizes the characteristics of EV charging. This reduces the power losses and improves the voltage profile in the network.

Some papers address the problem of locations for these EV stations and even their sizing but with simplifications about their demand and operation. Sadeghi-Barzani et al. [14] used a mixed integer non-linear optimization approach to locate fast-charging stations in a city; they considered the development and electrification costs, EV energy loss, and electric grid loss as objectives. In the model, they only defined the number of EVs arriving at the station, but they did not consider the arrival time or the occupation of the station. Wang et al. [15] presented a multiobjective planning model for EV charging stations to reduce power losses and voltage deviations in the distribution system. They considered a fixed demand and did not consider the operation of the charging process. Sungwoo and Kwasinski [16] used a spatial and temporal model of EV charging demand to locate the EV station. They used a fluid dynamic traffic model and queueing theory. Xiang et al. [17] developed a model to determine the siting and sizing of charging stations. They considered the interactions with the electrical grid, but they did not consider other types of energy sources.

A few authors have developed models for the design of EV charging stations, in which they used several simplifications in the design. Vermaak et al. [18] developed a model to calculate the size of a charging station with renewable energy, but the demand is constant and it has no connection to the grid. They optimized the results with Homer software. Hafez et al. [19] presented the optimal design of an EV charging station to minimize the lifecycle cost. They considered renewable energy, connexion to the grid and batteries, but they did not consider the arrival time; the optimization was also done with Homer software. Fathabadi [20] showed the electronic design of an EV charging station with PV and wind generators, but they did not determine the size of the EV station. He focused on the design of the converters and control algorithm. He used a daily curve to model demand, PV and wind generation.

In designs of EV charging stations, the demand models used have been very simple, with constant demand [18] and load profile [19, 20]. These load profiles do not consider when the charging of each vehicle begins and ends; rather, they are only an average value for each hour. More complex models exist the operation of EV charging stations. Bae and Kwasinski [21] used a model based on an M/M/s queueing theory, based on the state-transition algorithm used in Shrestha and Hansen [22]. Zhou and Liu [23] use an M/M/s queue based on a cell-transmission traffic model, and Viswanathan et al. [24] used real-world traffic data.

The energy management systems used in the designs of EV charging stations are also very simple. In [18], Vermaak et al. prioritized the charging of the EV and used a battery pack to store energy form renewable sources when there are no vehicles in the station. A similar form of management is used by Hafez et al. [19], but they also included a thermal load that feeds when there is excess renewable energy generation. In [20], Fathabadi developed a MPPT technique to track the maximum power points of PV and wind systems. Other, more complex methods have been found for operating EV charging stations. Authors seek to achieve different objectives in the EV charging process, including to maximize profits [25-27], minimize total energy costs for users [28-32], reduce power losses in the network [31, 33], minimize the generation costs [34, 35], minimize the peak load [36], avoid congestion in the distribution network [37] or regulate the frequency [38].

Most of the previous papers are focussed on the operations or the impact on the grid, while only a few papers address the design of EV charging stations. Among the papers about design, they do not consider the charging dynamic (the arrival time and state of charge of each electric vehicle) because they have to adapt the input data into an optimization program such as Homer that is not built to solve this kind of problem.

The originality of this paper is as follows:

- The study focusses on an EV charging station design problem with characteristics of an EV charging station operation problem.
- EV power demand is represented by an Erlang B queuing model, which until now has only been used in papers that discuss the optimization of EV operations.
- The EV operations include the purchase and sale of energy in the electricity market, which until now has only been used in papers that discuss the optimization of EV operations.
- This design problem includes a wide variety of energy sources: renewable generators, the grid and batteries.
- A genetic algorithm was adapted to deal with the complexity of the design problem.

The rest of the paper is organized as follows. The mathematical modelling of the optimization problem to design the EV station is explained in detail in Section 2. The probabilistic input data are described in Section 3. Then, the genetic algorithm's characteristics are shown in Section 4. Finally, three cases are studied and compared to show the changes in the design in Section 5, and Section 6 concludes the paper.

2. Mathematical modelling

The EV fast-charging station considered in this work consists of several chargers to fill the batteries of the EVs' clients as well as renewable generators and storage units to improve their profitability and reduce their impact in the electrical grid. The variables to be found in the charging station design problem consists of the optimal number and rated power of the chargers, the installed power of the renewable generators (wind and photovoltaic), the power and energy of the batteries and the contracted power in the grid connection point needed to feed the charging station.

The objective function (1) that the problem maximizes is the net present value (NPV), which is the difference between the present values of cash inflows (3) and the present values of cash outflows (4), including the cost of replacing and maintaining batteries (5) and the initial inversion (6) over a period of time (in this case, 20 years).

The optimization problem is also subject to several constraints:

- Energy balance in the whole charging station (7). Each hour, the sum of the photovoltaic and wind energy generated, the energy consumed or purchased from the grid and the energy discharged from the batteries must be equal to the sum of the energy supplied to the electric vehicles, the energy charged in the batteries and the power sold or supplied to the network.

- Stored energy in the batteries at hour h (8). The energy stored in the station's batteries at hour h must be equal to the energy stored at hour h − 1, plus the energy charged during hour h, minus the energy discharged during hour h.

- Limit of the power supplied by the wind generators (9). The power generated by the wind generators must be less than the installed wind power.

- Limit of the power supplied by the photovoltaic panels (10). The power generated by the photovoltaic generators must be less than the installed photovoltaic power.

- Limit of the discharge and charge power of the storage systems (11) and (12). The charge or discharge power in the station's batteries must be equal to or less than the nominal power of the installed converter.

- Limit of the discharge and charge energy of the storage systems (13) and (14). The discharge energy in the batteries at hour h must be equal to or less than the stored energy in the batteries at hour h – 1 and the charge energy in the batteries at hour h must be equal to or less than the difference between the battery capacity and the stored energy in the batteries at hour h – 1.

- Limit of the stored energy in the storage systems (15) and (16). The energy stored in the station's batteries must be equal to or less than the battery capacity and equal to or greater than the minimum state of charge allowed in the batteries.

- Limit of the supplied and consumed power from the grid at the connection point (17) and (18). The power supplied to or consumed from the network must be equal to or less than the contracted power at the point of connection to the network.

- Limit of the EV-supplied power at every EV fast-charging supplier (19). The power supplied by each charger must be equal to or less than its rated power.

- Limit of the EV-supplied energy at hour h (20). The energy supplied by the EV station must be equal to or less than the maximum energy demanded by EV consumers. The energy supplied may be lower than the energy demanded when a generation deficit from renewable sources can not be compensated.

- Limit of the waiting time for each EV (21). This restriction defines the maximum time that a consumer will wait his or her turn. If the waiting time is longer, the consumer will leave the station. In our case, we consider that if the chargers are busy, the consumer will leave.

The model evaluates the charging station's behaviour for 8760 hours per year. Some parameters of the model, such as the EV demand and the wind and photovoltaic generation, are represented with their probability distributions. The sequential Monte Carlo method was used to simulate the operation of the charging station. In section 3, every variable considered in the model is explained, and the algorithm used is explained in section 4.

Maximize:

$$NPV = \sum_{t=1}^{n} \frac{NCF_t}{(1+i)^t} - I \tag{1}$$

Subject to:

- Net cash flow at each year t,

$$NCF_t = \sum_{h=1}^{8760} \left(INFLOW_h - OUTFLOW_h\right) - Cr\&m_t, \tag{2}$$

$$INFLOW_h = Eev_h \cdot Cs_h + Es2g_h \cdot Csale_h, \tag{3}$$

$$OUTFLOW_h = Eg2s_h \cdot Cbuy_h, \tag{4}$$

$$Cr\&m_t = \frac{\sum_{h=1}^{8760} EDsto_h \cdot}{ETHsto} \cdot Csto \cdot Esto_{inst} + Cm_t; \tag{5}$$

- Initial inversion,

$$I = Cch \cdot Qch \cdot Pch_{inst} + \sum_{k=1}^{nw} \left(Cw_k \cdot Qw_k \cdot y_k\right) + Cpv \cdot Spv_{inst} + Csto \cdot Esto_{inst}; \tag{6}$$

- Energy balance in the charging station at hour h,

$$Eph_h + Ew_h + Eg2s_h + EDsto_h = Eev_h + Es2g_h + ECsto_h; \tag{7}$$

- Stored energy in the batteries at hour h,

$$Esoc_h = Esoc_{h-1} + ECsto_h - EDsto_h; \tag{8}$$

- Limit of the power supplied by the wind generators,

$$Pw_h \leq Pw_{inst}; \tag{9}$$

- Limit of the power supplied by the photovoltaic panels,

$$Pph_h \leq Pph_{inst}; \tag{10}$$

- Limit of the discharge and charge power of the storage systems,

$$PDsto_h \leq Psto_{inst}, \tag{11}$$

$$PCsto_h \leq Psto_{inst}; \tag{12}$$

- Limit of the discharge and charge energy of the storage systems,

$$EDsto_h \leq Esoc_{h-1}, \tag{13}$$

$$ECsto_h \leq Esto_{inst} - Esoc_{h-1}; \tag{14}$$

- Limit of the stored energy in the storage systems,

$$Esoc_h \leq Esto_{inst}, \tag{15}$$

$$Esoc_h \geq SOC_{min} \cdot Esto_{inst}; \tag{16}$$

- Limit of the supplied and consumed power from the grid at the connection point,

$$Ps2g_h \leq Pgc_{max}, \tag{17}$$

$$Pg2s_h \leq Pgc_{max}; \tag{18}$$

- Limit of the EV-supplied power at every EV fast-charging supplier,

$$\boldsymbol{Pev_h} \leq \boldsymbol{Pch_{inst}}; \tag{19}$$

- Limit of the EV-supplied energy at hour h,

$$\boldsymbol{Eev_h} \leq \boldsymbol{EMAXev_h}; \text{ and} \tag{20}$$

- Limit of the waiting time for each EV,

$$\boldsymbol{tev_k} \leq \boldsymbol{tev_{max}} \tag{21}$$

Where y_{kw} are binary variables.

3. Input data models

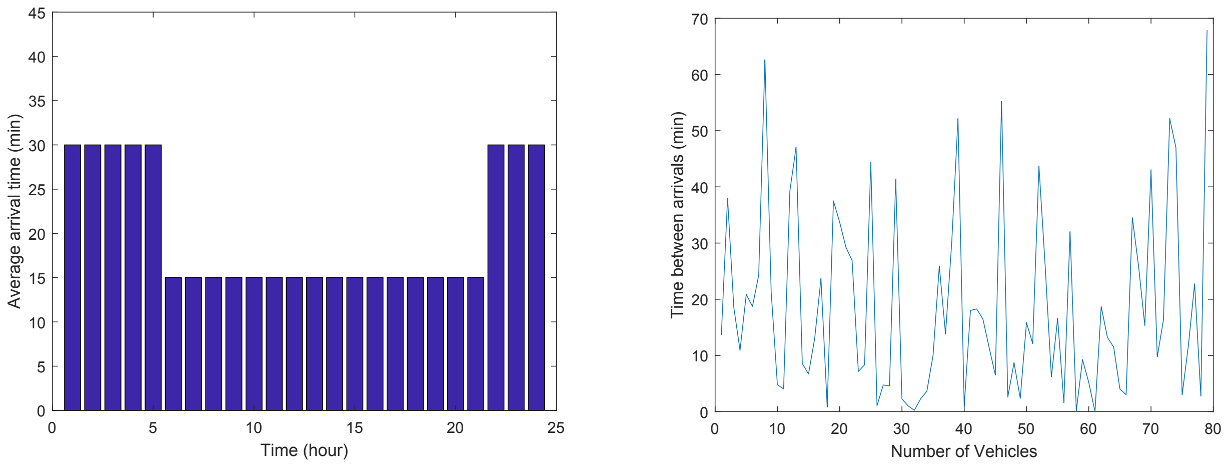
A. Electric vehicle demand

As introduced before, the first step is to model the EV demand at the charging station. This EV demand depends on the flow of electrical vehicles that arrive at the charging station and on the capacity and state of charge of their batteries. But we also consider that the charging station has a finite number of chargers and that when a consumer arrives at the station and no chargers are free, he or she will leave the charging station. This kind of system can be regarded as an Erlang B queueing model or M/M/c/c [39].

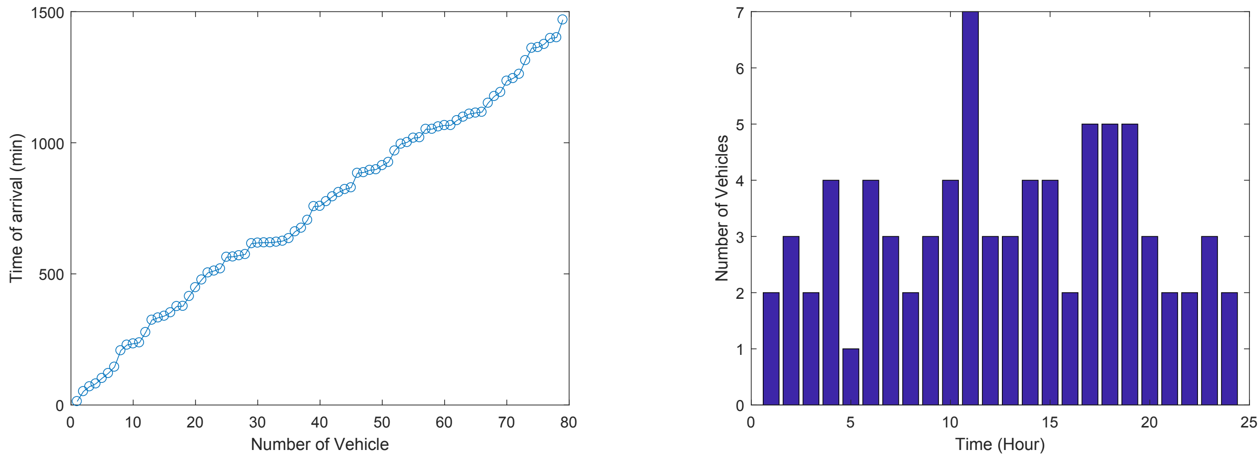
The first step consists of determining when each vehicle will arrive at the charging station. This can be modelled as a modulated Poisson process [40]. The time (*ta*) passed between the arrivals of two consecutive vehicles (21) is determined by an exponential distribution [11]. This distribution is defined by parameter λ, which is the average arrival time or time between two arrivals. As this time can change from hour to hour, a different λ_h is considered for each hour h. For this study, the arrival time selected is shown in Figure 1(a).

$$\boldsymbol{ta_h(x) = 1 - e^{-\lambda_h x}} \tag{21}$$

The electrical vehicle arrivals are simulated with the sequential Monte Carlo method, SMC [41]. A list of random numbers is obtained in the interval [0, 1], and every number gives us the arrival time of the next vehicle to introduce into the x parameter of the equation (21). Figure 1 gives an example of this sequence.



(a) (b)



(c) (d)

Figure 1. Simulation of arrival times of EVs over the temporal horizon of 1 day. (a) Average arrival time (min), (b) time between arrivals (min), (c) time of arrival (min) and (d) number of vehicles per hour.

In the second step, the energy needed to fill the battery is calculated for every vehicle that arrives. For this, it is necessary to determine the capacity and state of charge of the EV's battery. The battery capacity is associated with the vehicle type. It is supposed that the types of vehicles that can come to the station include motorbikes, cars and vans. The battery selection is associated with a discrete distribution found in the registration data obtained from the Traffic General Direction of Spain [42] about these type of vehicles; see Table 1.

Table 1. Probability of battery capacity.

	Battery capacity (kWh)	Probability (%)	Accumulated probability (%)
Bike	3.6	0.115	0.115
Small private car	16	0.370	0.485
Large private car	25	0.380	0.865
Van	63	0.135	1

The state of charge (SOC) of the EV battery can be modelled by the lognormal distribution and is defined by the average (μ) and typical deviation (σ) of the logarithm of the SOC variable [11]. Parameter E represents the initial SOC of an EV battery and varies from 0 to 1. Fig. 2 shows the lognormal distribution of SOC used, for which the μ and σ parameters of equation (22) are 3 and 0.6, respectively:

$$SOC(E;\mu,\sigma) = \frac{1}{E\sigma\sqrt{2\pi}} \cdot e^{-(\ln E-\mu)^2/2\sigma^2} \quad (22)$$

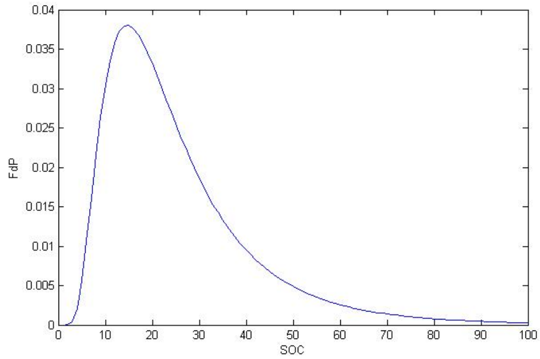


Fig. 2 Lognormal distribution of battery SOC.

In the simulation process, a random number from the interval [0, 1] is compared with the accumulated probability found in Table 1 to obtain the type of vehicle that arrives at the charging station and to determine the maximum capacity of its battery. In the same way, another random number is introduced into parameter E of equation (22) for every EV that arrives to charging station to obtain its battery SOC.

In the third step, once the SOC and the battery capacity have been calculated, the charging time can be obtained for each vehicle by means of this simplified equation:

$$\boldsymbol{t_{charge}} = \frac{\boldsymbol{Battery\_Capacity} * (\mathbf{1} - \boldsymbol{SOC})}{\boldsymbol{P_{charger}}}. \quad (23)$$

Equation (21) obtains the arrival times, and equation (23) calculates the charging time. With these data, the vehicles are distributed to the different chargers. The charging simulation of Li-ion batteries has been simplified and modelled as constant power load [43-45]. At times when all of the chargers are busy, if a new vehicle arrives, it does not wait, and it is lost. As the charging periods are relatively long, consumers normally do not wait if they see that all of the chargers are busy and will go to the next charging station [39].

Finally, taking into account the fast charging power and the number of chargers supplying power, *m*, the total demand of the EV station, is:

$$\boldsymbol{P_{station}(t)} = \sum_{\boldsymbol{k=1}}^{\boldsymbol{m}} \boldsymbol{P_{charger,k}(t)}. \quad (24)$$

Figure 3 shows an example of the temporal evolution of demand over one day in an example with three chargers as well as the total demand at the station. The load profile of a service station is not a smooth demand curve throughout the day, since the events are discrete.

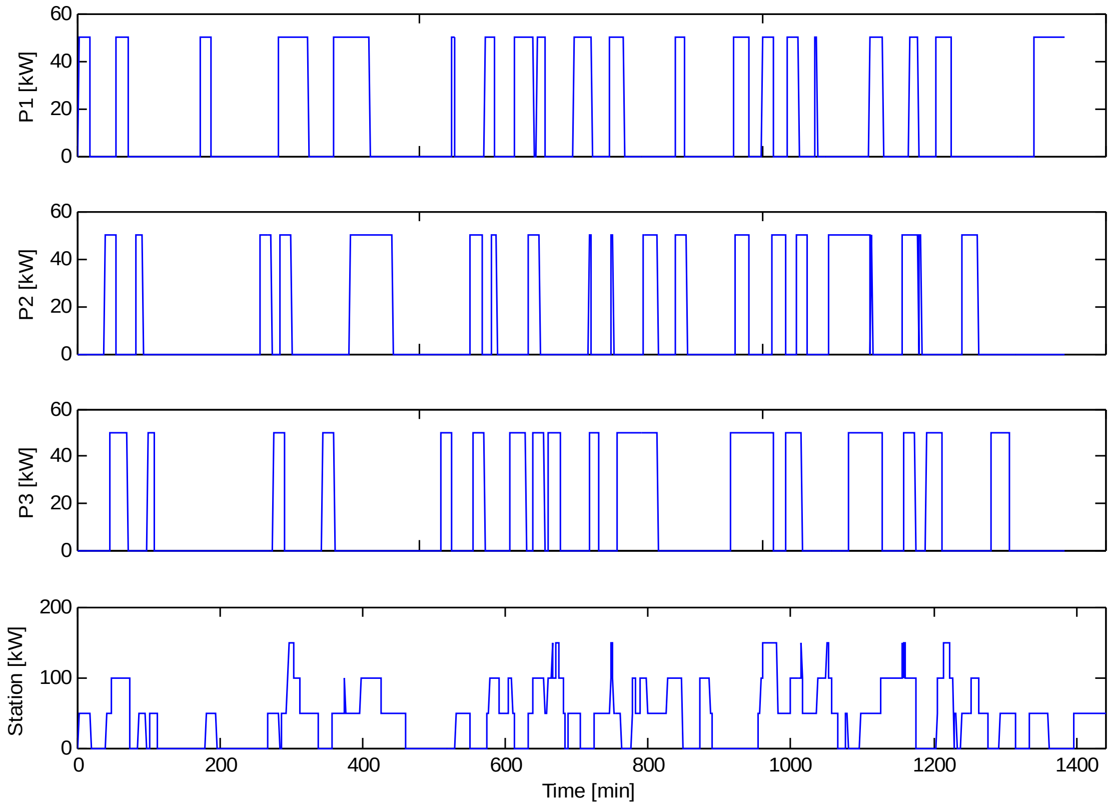


Figure 3. Demand at each charger and total of the station in a day.

B. Wind energy generation

The wind speed is modelled by a Weibull distribution (25). The parameters needed to calculate it are the scale factor (c) and the shape factor (k), which depend on the location.

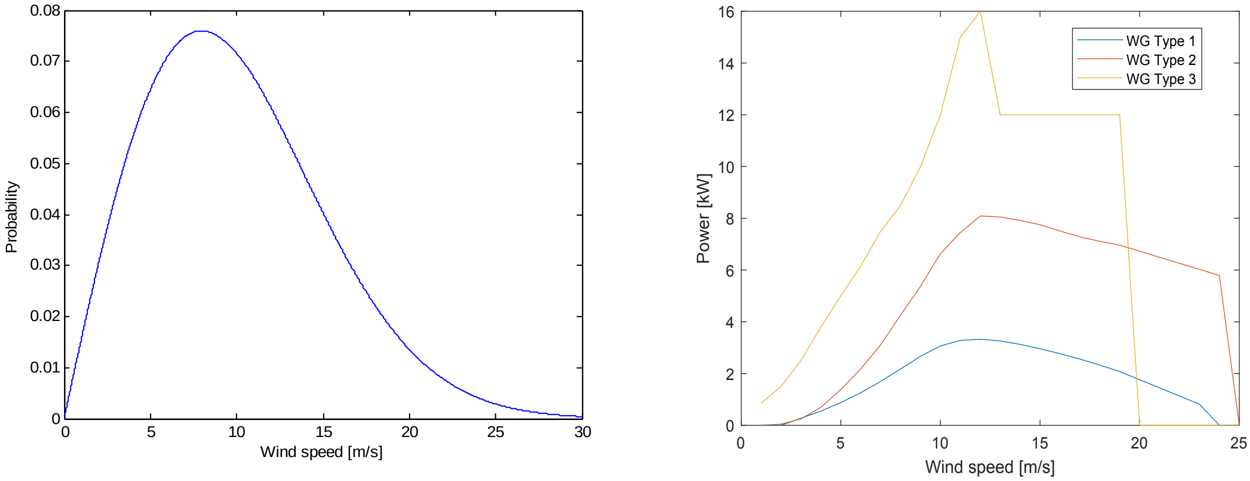
$$p(v) = \frac{k}{c} \cdot \left(\frac{v}{c}\right)^{k-1} \cdot e^{-\left(\frac{v}{c}\right)^{k}} \tag{25}$$

$$c = v_m \cdot \left(0.568 + \frac{0.433}{k}\right)^{-1/k} \tag{26}$$

In the simulation process, it is possible to obtain the hourly evolution of the wind speed from a series of random numbers, introducing each random number p in the inverse of the Weibull distribution.

$$v = -c[\ln(1-p)]^{1/k} \tag{27}$$

Once the speed is obtained, the power that turbine can generate with this speed can be obtained from the wind generator power curve. Wind resources are modelled with the Weibull distribution for an average wind speed (v_m = 6 m/s) and a shape factor (k = 2). The power curve for three turbines, as utilized in this paper, can be seen in Figure 4.



(a) (b)

Figure 4(a) Weibull distribution for wind speed and (b) power curve for the wind generator.

C. Photovoltaic solar energy.

The hourly output power of the photovoltaic panels, Ppv_h, can be evaluated by the next equation [13, 46]:

$$\boldsymbol{Ppv_h = G_i \cdot A \cdot \eta}, \tag{28}$$

where G_i is the global solar irradiance at the tilted surface, A is the installed surface and η is the efficiency of the system (17% in our case) that considers losses due to spectral sensitivity of the PV cells among others effects [47].

The data on global solar irradiance on an inclined plane were obtained from PVGIS (Photovoltaic Geographical Information System) tools [48]. It computes the real-sky global irradiance adding the beam, diffuse and reflected components on an inclined plane.

$$\boldsymbol{G_i = B_i + D_i + R_i} \tag{29}$$

The inputs are latitude, longitude and altitude from the location and the slope angle and orientation of the solar panels. The output is the estimation of real-sky global irradiance on the solar panels. In Figure 5, it is the hourly global irradiance for 41º latitude north, 0º longitude and 200 m of altitude; the solar panels are oriented towards the south and have an inclined angle of 40º.

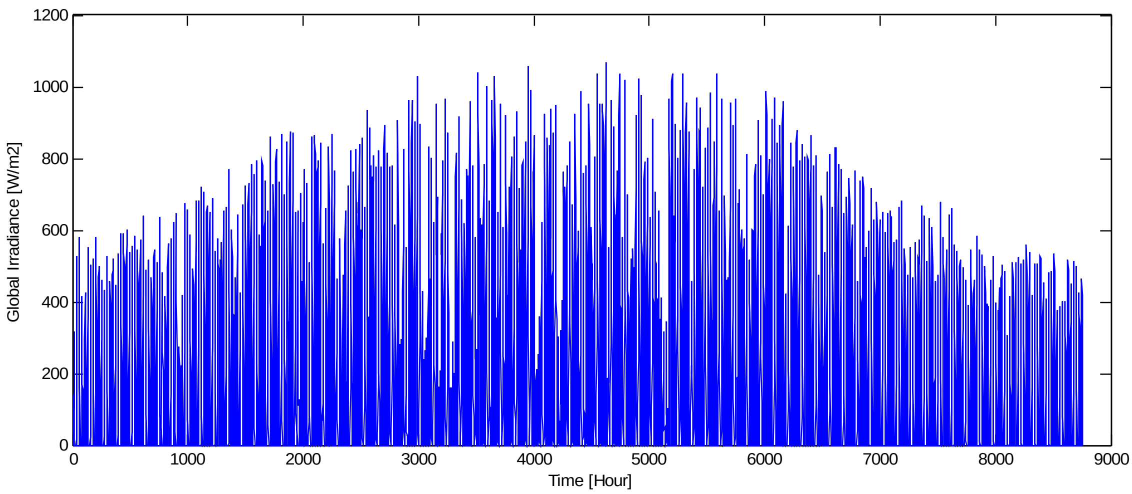


Figure. 5. Hourly global irradiance on a surface inclined 40º.

D. Energy prices.

In Spain, EV charging stations must go to the electricity market or make a bilateral contract with a retailer for contracted power greater than 10 kW.

In the electricity market, the hourly price is determined by the point at which the supply and demand curves meet, according to the marginal pricing model. At this price, one has to add a generation toll and taxes to sell energy to the network. To buy from the network, one has to add the costs of the technical constraints and system operator management, the payments for capacity and interruptibility, the costs of the tolls and the losses in the transport of energy through the networks and taxes. In our case, the variation in the purchase price and sale price of energy as a result of the terms indicated above has been calculated at 0.0828 and 0.0022 €/kWh, respectively. The sale price of energy to electric vehicles has been estimated by adding 0.04 €/kWh to the purchase price of energy as a benefit.

Fig. 6 shows the real purchase and sale prices of energy in the market, the sale price of energy to electric vehicles, and the annual average values of these curves. The difference between the purchase price of energy from the network (blue line) and the sale price to the network (red line) is due to the difference between tolls and taxes that must be paid when buying and selling. The sale price for electric vehicles (yellow line) takes into account the desired benefit and taxes.

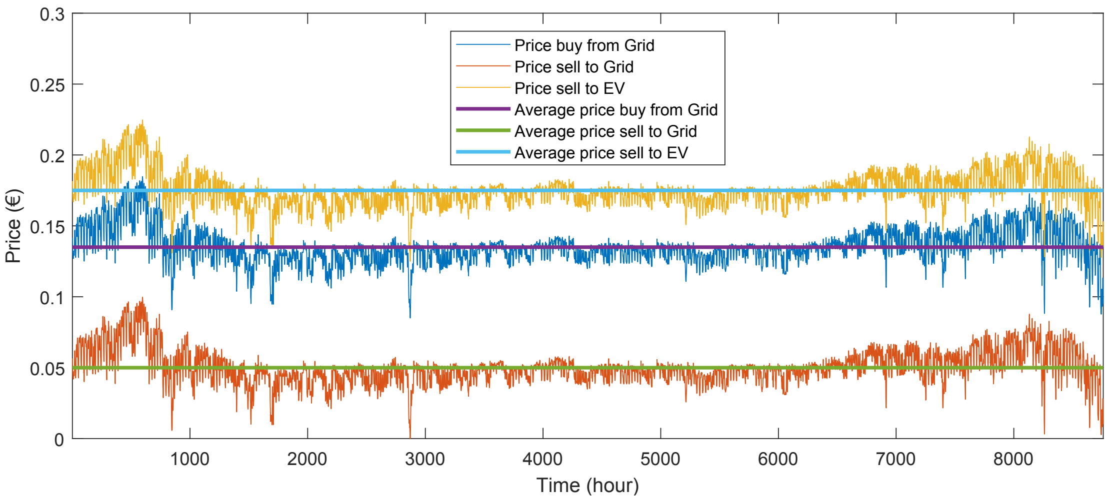


Figure 6. Hourly prices of energy

4. Optimization Algorithm

Genetic algorithms (GAs) [49, 50] are optimization methods widely used to solve real-world problems and are based on natural selection principles. Pseudocode of the optimization algorithm is shown in Figure 7. Here, the main characteristics of the proposed algorithm are explained, specifically the fitness function, chromosome structure and crossover and mutation rates.

```
Program EV_station_optimization;
Begin:
Step 1: Generate an initial population (t=0) with nsol feasible solutions
randomly.
Step 2: Evaluate these nsol solutions of the population (t=0) with the
Fitness_function program.
For t=1 to max_generations
      Step 3: Select the best solutions from population(t) as parents.
      Step 4: Apply crossover on parents, creating population(t+1)
      Step 5: Apply mutation into population(t+1)
      Step 6: Evaluate population(t+1) with the fitness function
EndFor;
End.
```

Figure 7. EV station optimization

A. Chromosome: Optimization variables

A chromosome represents each individual, as shown in Figure 8; this is composed of the variables that the optimization program can change in the design process. These variables are associated with the charging station's structure: the number and power of chargers, number and type of wind generators, surface occupied by photovoltaic panels, storage system capacity and transfer capacity of the connexion to the grid. All of the variables are real, except for the number of chargers and the number and type of wind generators, which are integers. In addition, these variables are constrained by the limits presented in Table 2 for design reasons.

Qch	Qw_{kw}	kw	Pch_{inst}	Spv_{inst}	$Esto_{inst}$	Pgc_{max}

Figure 8. Structure of a chromosome.

Table 2. Range of optimization variables.

Variable	Description	Variable type	Lower limit	Upper limit
Qch	Number of chargers	Integer	1	10
Qw_{kw}	Number of wind generators	Integer	0	4
kw	Type of wind generator	Integer	1	3
Pch_{inst}	Charger power	Real	44	220
Spv_{inst}	Surface occupied by photovoltaic panels	Real	0 m^2	1875 m^2
$Esto_{inst}$	Storage system capacity	Real	0 kWh	500 kWh
Pgc_{max}	Transfer capacity of the connexion to the grid	Real	0 kW	600 kW

B. Crossover and mutation operators

The chromosome has three integer-type genes and four real-type genes. The crossover operator used for the three genes of integer type creates a random binary vector and selects the genes from the first parent if the vector has a 1 and the genes from the second parent if the vector has a 0; then, it combines the genes to create the two children. If the binary vector is [1 0 1] and the parents are Parent1 = [a b c] and Parent2 = [1 2 3], then the children are Child1 = [a 2 c] and Child2 = [1 b 3].

The crossover operator used for the four real-type genes creates every gene k of the child from two parents, parent1 and parent2, using the next function:

$$\text{child}(k) = \text{parent1}(k) + \text{Ratio} * (\text{parent2}(k) - \text{parent1}(k)), \tag{30}$$

where Ratio is, in our case, equal to 0.8.

The mutation operator is applied to a small number of chromosomes. First, a random number between 0 and 1 is generated, and if this number is less than a threshold—in our case, 0.001—then a mutation is applied to this chromosome. Then, an integer random number between 1 and the number pf genes indicates the gene at which the mutation is applied. Finally, for integer-type genes, that gene is changed by an integer random number generated between the limits of this gene. For real-type genes, a real random number is generated between the limits of this gene.

If gene(k) is integer

    then gene(k) = randi([Lower limit, Upper limit]);

If gene(k) is real

    then gene(k) = Lower limit + (Upper limit – Lower limit) * rand(); (31)

C. Fitness function: Profitability

The fitness function is the same objective function that NPV (1) described in the mathematical model. The initial outlay corresponds to the cost of installing each energy system element. Incomes are associated with the energy supplied to customers who recharge their vehicles and with the surplus energy sold to the grid. On the other hand, expenses correspond to the energy bought from the grid, the maintenance of the EV station and the replacement of batteries.

To evaluate this fitness function, the energy management of the EV station during a year must be simulated. This energy management is simpler than other forms of energy management that can be found in papers on the operation problems of EV stations. Note that this paper treats the design problem, which is already complex enough. The renewable generation is prioritized to feeding the EV chargers. If the energy available at the charging station is higher than the demand of the EV chargers, this energy will be stored. Once the battery's maximum capacity is reached, this surplus energy will be supplied to the electrical grid. If the limit of the grid connexion is reached and it is not possible to inject energy into the grid, then the renewable generation will be reduced. When there is a deficiency of energy to feed the EV chargers, that energy will be provided by storage systems firstly and, as a last resort, by the grid. The calculations of the batteries' life and maintenance have also been included in equation (5).

The EV station's operations were simulated with a sequential Monte Carlo method. The operations were simulated hourly during a year. First, the algorithm calculates the hourly EV demand from the probability distributions of arrival time, battery capacity and battery SOC. Second, the energy generated by wind and solar generators is calculated. Third, the energy flows among the generators, battery, EV chargers and grid are calculated. The problem's restrictions must be checked when calculating the energy flows. Finally, the value of the fitness function is calculated, as can be seen in Figure 9.

The costs of energy sold to and purchased from the network were calculated based on the cost of hourly energy in the electricity market plus the corresponding tolls for the use of the electricity grid, and the cost of the energy sold to EVs was the electric market cost plus a profit, as explained in section 3-d.

```
Program Fitness_function;
Begin:
For h=1 to 8760 do
      Step 1: EV demand calculation
            - Generate random numbers.
            - Obtain the arrival time of EVs.
            - Obtain the kind of EV and battery capacity.
            - Obtain the battery's SOC.
      Step 2: Renewable energy calculation
            - Generate random numbers.
            - Obtain the energy generated by wind generators.
            - Obtain the energy generated by solar modules.
      Step 3: Energy balance
            - Calculate the energy flows among devices that meet
             the devices' restrictions.
Endfor;
      Step 4: Evaluation of the fitness function NPV.
End.
```

Figure 9. Evaluation of the fitness function

5. Study case

A. Description of case

This work explains a model to optimize the design of EV charging stations. Data for modelling EV demand and wind and solar resources can be found in the "Input data models" section, limits for decision variables that optimize the algorithm are shown in Table 2 and economic data used in the objective function can be found in Table 3. Lithium ion batteries have been considered in the storage system with a minimum SOC level of 10% or 0.1 p.u.

Table 3. Economic costs.

	Installation cost		Buy/sell energy
Wind Generators	650 €/kW	Sell energy to EV	0.175 €/kWh
Solar PV panels	100 €/m^2	Sell energy to grid	0.055 €/kWh
EV Charger	500 €/kW	Buy energy from grid	0.135 €/kWh
Battery (Li-ion)	150 €/kWh	Contracted power to grid	0.121 €/kW month
	Other parameters		
Time of the cash flow	20 years	Maintenance	1000 €/year
Discount rate	2.69 %	Cycle life	2000 cycles

The first three cases were defined to study different patterns of feeding the station, the fourth case to study different arrival patterns of vehicles to the station, the fifth case to compare the performance with other heuristic algorithms and the sixth case to study the transfer capacity of the connexion to the grid.

Case I. The EV station feeds only from the grid. In this case, the EV station is connected to the grid, and all of the energy needed is purchased from the grid. The energy price has two terms: the contracted power and the energy consumed. This case is the baseline for the comparisons.

Case II. The EV station feed only from renewable energy. In this case, the EV station is isolated from the grid and is only fed by solar and wind renewable energy. Due to the uncertainty of renewable energy, batteries are installed to guarantee the service of the EV station. The design has limits for the solar and wind power installed that will depend on the location; in this case, the limits are in Table 2.

Case III. The EV station feeds from a mix of renewable energy and the grid. In this case, the EV station has renewable energy and a connexion to grid. This design is the most flexible because it has the advantages of both worlds: cheap energy from the renewable energy and safe feeding from the grid. Additionally, it is allowed to sell the excess energy to the grid [51].

Case IV. Similar to case III, but now with more detailed data. In this case, a different average arrival time is considered for every hour (see Figure 10), compared to the previous cases, in which only two periods were considered (see Figure 1(a)). In addition, it uses the hourly prices of the Spanish electric market and the hourly network access tolls (see Figure 6), rather than the average prices (see Table 3).

Case V. Similar to case IV, but now with a new algorithm: the particle swarm optimization. This case allows the performance of these algorithms to be compared, in terms of both computational time and accuracy.

Case VI and VII. Similar to case IV, but the capacity of power transfer to the grid is limited.

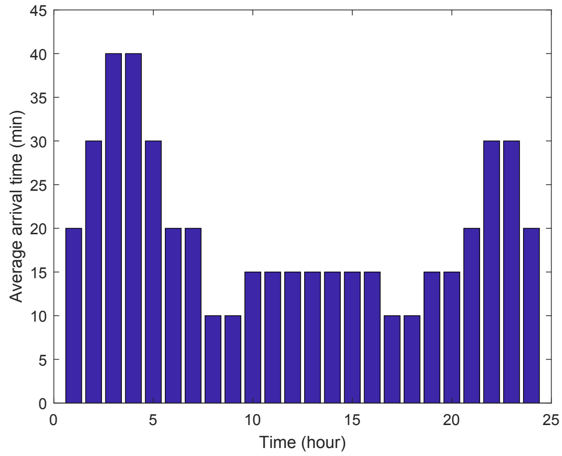


Figure 10. Average arrival time (min)

B. Results

The optimal solutions obtained for the design of EV stations are described and examined from economic and technical perspectives. The characteristics of the designed EV stations are shown in Table 4, and the economic results can be found in Table 5.

Table 4 gives the number of chargers installed (N. chargers), the power of each charger (Charger power), the maximum power of the connexion between the grid and the EV station (Grid power), the type of wind generator installed (Type Wgen), the number of wind generators installed (N. Wgen), the surface of solar PV panels installed (Solar surface), the capacity of batteries installed (Battery) and the computational time in minutes necessary to reach the solution (Computational time (min)) with a Intel Core i5 and 4 GB of RAM.

Table 4. Optimal configuration for each case.

Case	N. chargers	Charger power (kW)	N. Wgen	Type Wgen	Solar surface (m^2)	Battery (kWh)	Grid power (kW)	Computational time (min)
I	4	44.26	0	0	0	0	128.33	104
II	5	44.25	4	3	1456.38	379.57	0	136
III	5	46.11	4	3	1871.95	329.51	298.36	153
IV	5	46.00	4	3	1873.48	122.27	255.70	218
V	5	46.54	4	3	1874.21	125.32	243.74	82
VI	5	46.39	4	3	1867.00	190.20	200.00	80
VII	5	44.00	4	3	1867.49	111.52	100.00	75

Table 5 gives the net present value (NPV), internal rate of return (IRR), profit investment ratio (PIR), investment, the cost of battery replacements, cost of maintenance, cost of buying energy from the grid, income from selling energy to the grid and income from selling energy to EV drivers. The PIR index is the ratio between the present value of future cash flows and the initial investment and can be used to rank the projects.

Table 5. Economic results for each case.

Case	NPV (€)	IRR (years)	PIR (p.u.)	Investment (€)	Battery replacement (€)	Maintenance (€/year)	Cost of buying energy from the grid (€/year)	Income from selling energy to the grid (€/year)	Income from selling energy to EV owners (€/year)
I	166,397.66	5	2.879	88,532.09	0	1000	60,190.72	0	78,025.01
II	787,027.28	4	3.234	352,215.83	43,662.11	1000	0	0	78,248.50
III	990,445.25	4	3.533	390,897.26	37,903.48	1000	4138.58	15,087.07	83,167.25
IV	1,025,950.37	4	3.852	359,692.62	13,696.84	1000	15,521.45	14,752.55	93,522.74
V	1,020,344.70	4	3.821	361,569.00	25,767.62	1000	14,509.18	15,238.30	94,010.32
VI	1,006,539.27	4	3.718	370,218.69	42,232.98	1000	12,087.09	12,975.53	93,067.81
VII	955,624.17	4	3.711	352,477.82	12,492.59	1000	15,101.23	10,098.22	92,388.38

C. Comparison of cases I, II and III

As can be seen in Table 4, the number and power of chargers are similar in the first three cases because they mainly depend on the demand characteristics. However, the number of chargers is lower in case I, in which the EV station is fed only from the grid, with a more expensive energy price than that of free renewable energy.

The contracted power to the grid, in the grid power column, is greater in case III than in case I, which seems like a contradiction because case I is fed only from the grid, whereas case III can be fed from both the grid and renewable energy. Nevertheless, there is no contradiction because the EV station in case I buys energy from the grid and the EV station in case III sells energy to the grid.

The comparison between the installed renewable power in cases II and III shows that in case III, the maximum power of renewable energy (wind and solar) is installed based on the constraints from the four type 3 wind generators and 1871.95 m^2 of solar panels, while 1456.38 m^2 is installed in case II, which is less than the 1871.95 m^2 allowed. The reason is that in case II, the installed power is only needed to feed the demand because the energy that is not sold to electric vehicles is wasted, and the solution in case III installs all renewable energy possible, to sell this energy to the grid and get profits.

Finally, the solution for case II needs more storage capacity than the solution of case III because case II only uses uncertain renewable energy to feed the EV station, while case III can also use the connexion to the grid.

The computational time column shows the time necessary to reach the solution. These times are long because the evaluation of the fitness function requires simulation of the EV charging station's operations by the Monte Carlo method. Furthermore, optimizing the design problem of an EV charging station with a genetic algorithm is also complex.

From an economic standpoint, the best solution is obtained in case III, with better value in the NPV than that of case II and the same IRR. In case III, the EV station has a mixed strategy, with renewable energies and connexion to the grid. This strategy permits income to be obtained from selling energy to EV owners and to the grid.

Investment is much greater in cases II and III than in case I, due to the installation costs of renewable generators and batteries; see Figure 11 and Table 5. However, these cost are compensated quickly by the operational costs and cost of the energy used. This energy is bought from the grid in case I, with a cost around 60,190.72 €/year, compared to a small cost in case III of about 4,138.58 €/year and practically free in case II. The rest of the energy used in cases II and III is supplied from renewable sources.

From an environment standpoint and when considering the impact on the grid, case II is better because it uses only renewable energy and has no impact on the grid. It does not have energy interchanges with the grid.

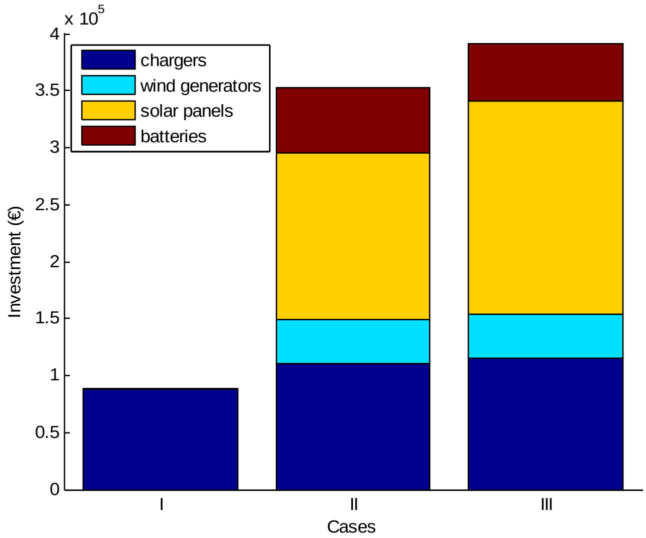


Figure. 11. Components of investment.

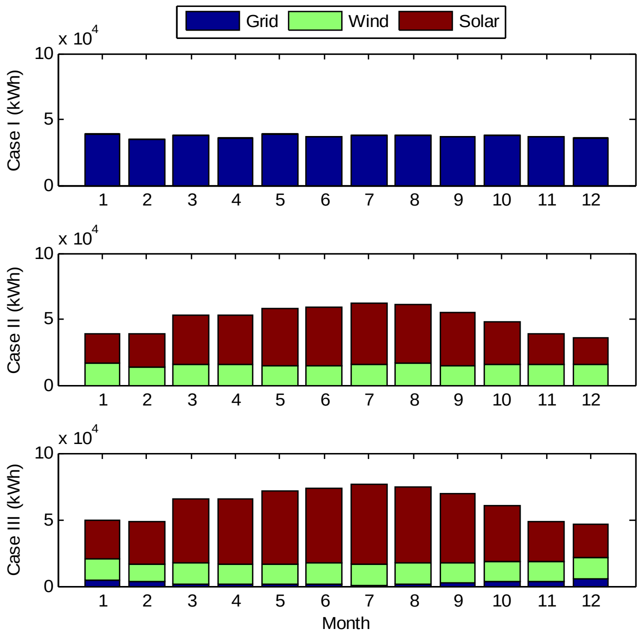


Figure. 12. Origin of the monthly energy used in each case.

Figure 12 shows the monthly energy used (sold to EV owners and the grid) in each case. The starting point in the optimization process is the hypothetical demand generated by the EVs at the location of the charging station, which is the same in all three cases. However, the real demand that each station is capable of satisfying is different, depending on the number of chargers assigned to it by the optimization of its configuration as well as the availability of energy at each moment according to the energy supply configuration that the optimization assigned to it. Case I has four chargers, so there will be consumers who will not stop when all of the chargers are occupied. Case II has five chargers, so it can serve more consumers, but in some cases, energy deficits can occur due to fluctuations in renewable energy or excess energy being wasted. Case III involves five chargers, but the optimization program calls for more installed solar renewable generation because the surplus energy can be sold to the grid.

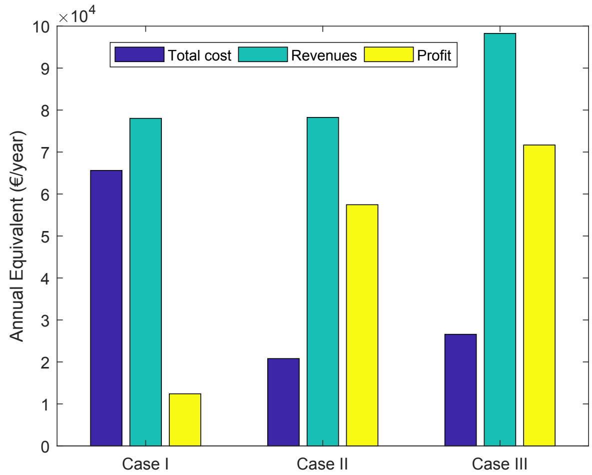
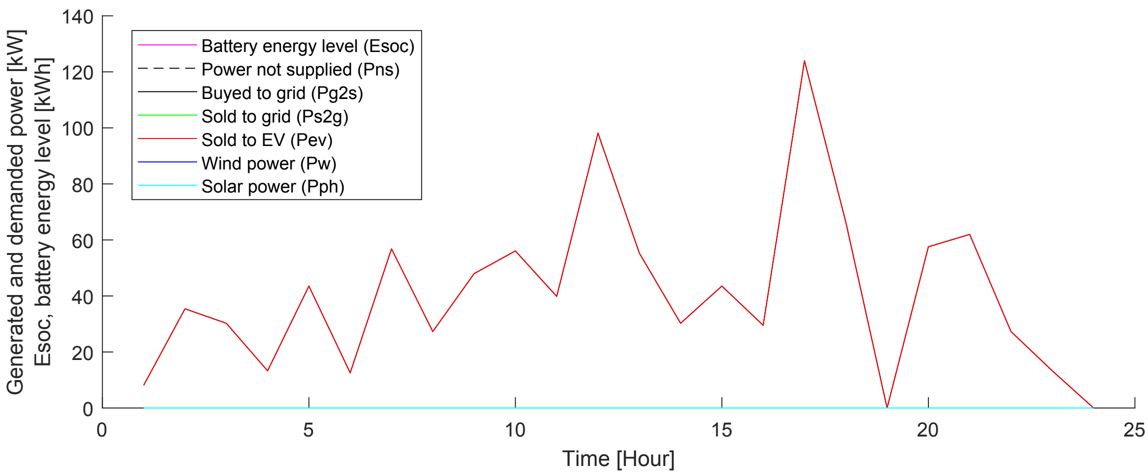


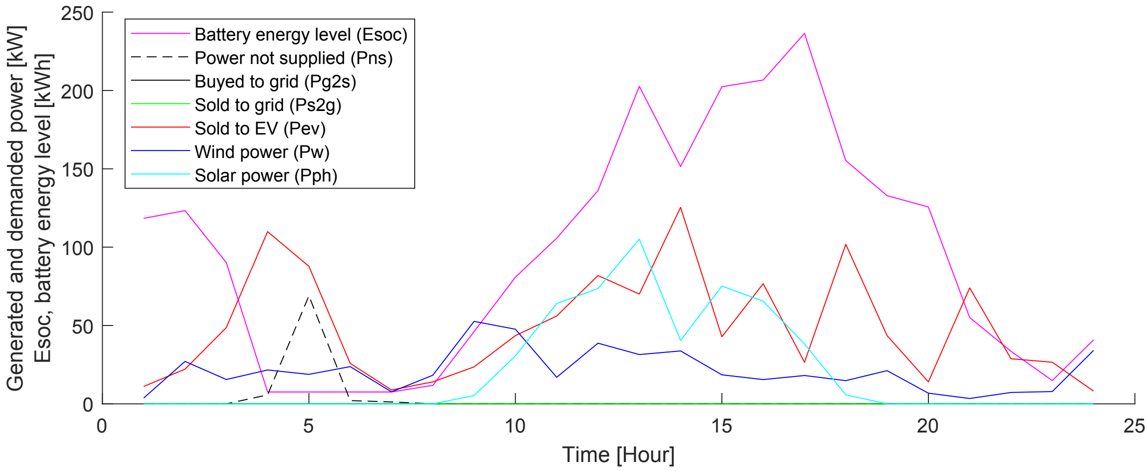
Figure. 13. Comparison in annual equivalent values.

Figure 13 permits the three cases to be compared in terms of annual equivalent values. Case I has a large total cost because the operational costs are high. Case III has the highest revenue because it sells energy to the grid and therefore has the highest profit.

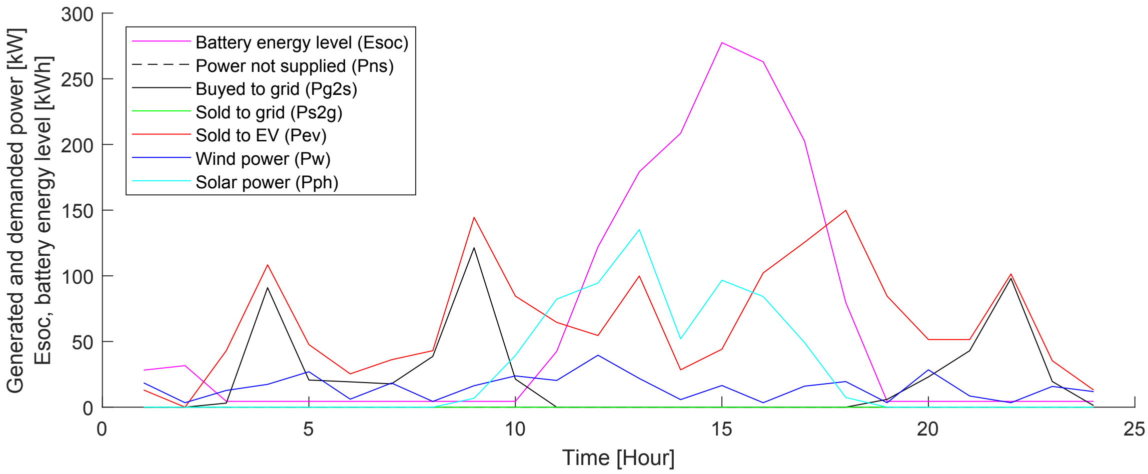
Operation of the EV station every day differs according to the available energy sources, as shown in Figure 14. It shows the hourly power that each element generates or demands and, in the case of batteries, their energy level. In case I, all of the energy sold to electrical vehicles is provided from the grid. In case II, all energy is provided from wind and solar sources, but the batteries are needed to give service to all EVs, and at some hours (around 5 a.m. on this day), the EV station cannot supply all of the energy demanded by the EVs. In case III, the EV station uses the grid to supply energy to EVs when renewable sources are not enough.



(a) Case I: EV station feeds only from the grid.



(b) Case II: EV station feeds only from renewable energy.



(c) Case III: EV station feeds from a mix of renewable energy and the grid.

Figure. 14. Daily operation of the EV station.

D. Comparison between cases III and IV

Next, cases III and IV are compared. Case IV is the same as case III but with a more detailed modelling. It has different mean arrival times for every hour (Fig. 10) and uses hourly energy prices from the Spanish market for one year (Fig. 6).

As can be seen when comparing the optimal configurations of both cases in Table 4, these configurations are similar, with the only notable difference being in the size of the batteries. More vehicles arrive during day hours because the average arrival times decreased by a few hours; therefore, the renewable energy generated is used to feed the vehicles instead of being stored.

From the comparison of the economic results obtained in both cases, it can also be seen that the differences are small. More income would come from energy being sold to consumers, at 93,522.74 €/year in case IV compared to 83,167.25 €/year in case III, and less income would come from energy being sold to the network, at 14,752.55 €/year in case IV compared to 15,087.07 €/year in case III. Since the capacity of the batteries in case IV is lower, at 122.27 kWh compared to 329.51 kWh in case III, the investment and the cost of replacing them are lower but more energy has to be bought from the grid.

E. Comparison between cases IV and V

The comparison of the GA used in this work with another heuristic algorithm allows us to have an idea of our GA's performance. In this case, our GA has been compared with the particle swarm optimization algorithm [50, 52]. The results obtained in case IV, with the genetic algorithm, and case V, with particle swarm optimization, show that the results are very similar, but the new algorithm is faster.

F. Comparison among cases V, VI and VII

In these cases, the transfer power between the station and the network has been limited. By limiting the transferred power, its impact on the network is limited. The energy sold both to the network from renewable energy and to consumers decreases.

6. Conclusions

A GA using technique and economic factors optimized the design of EV fast-charging stations. Probabilistic distributions modelled the EV demand and renewal generation more realistically. Specifically, the EV demand model was improved when adding more details (arrival time, EV battery capacity, SOC and the EV distribution during the day).

The first three simulated cases confirmed that an EV charging station can be profitable. The main inconvenience is the high power that EV fast charges demand. The installation of renewable generators can improve a station's profitability, but it needs a connexion to the grid or a storage system to balance the intermittence of renewable energy.

The comparison among the last three cases confirmed that the utilization of renewable energies and storage systems would reduce the impact on the electrical grid.

The required investment is high; however, the development of technology is trending towards decreases in costs, which is a particularly interesting aspect in the case of batteries, both for the storage system and for EVs. This fact favours distributed generation, to achieve more sustainable energy management.

Acknowledgement

The authors would like to thank the support of Government of Aragon with FEDER funds.

References

[1] http://www.ieahev.org/by-country/spain-charging-infrastructure/.

[2] G. Mauri and A. Valsecchi, "The role of fast charging stations for electric vehicles in the integration and optimization of distribution grid with renewable energy sources," CIRED 2012 Workshop: Integration of Renewables into the Distribution Grid, Lisbon, 2012, pp. 1-4.doi: 10.1049/cp.2012.0815

[3] M. Amjad, A. Ahmad, M.H. Rehmani, T. Umer, A review of EVs charging: From the perspective of energy optimization, optimization approaches, and charging techniques, Transp. Res. Part D Transp. Environ. 62 (2018) 386–417. doi:10.1016/j.trd.2018.03.006.

[4] J. García-Villalobos, I. Zamora, J.I. San Martín, F.J. Asensio, V. Aperribay, Plug-in electric vehicles in electric distribution networks: A review of smart charging approaches, Renew. Sustain. Energy Rev. 38 (2014) 717–731. doi:10.1016/J.RSER.2014.07.040.

[5] S. Habib, M. Kamran, U. Rashid, Impact analysis of vehicle-to-grid technology and charging strategies of electric vehicles on distribution networks – A review, J. Power Sources. 277 (2015) 205–214. doi:10.1016/J.JPOWSOUR.2014.12.020.

[6] I. Rahman, P.M. Vasant, B.S.M. Singh, M. Abdullah-Al-Wadud, N. Adnan, Review of recent trends in optimization techniques for plug-in hybrid, and electric vehicle charging infrastructures, Renew. Sustain. Energy Rev. 58 (2016) 1039–1047. doi:10.1016/J.RSER.2015.12.353.

[7] K.M. Tan, V.K. Ramachandaramurthy, J.Y. Yong, Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques, Renew. Sustain. Energy Rev. 53 (2016) 720–732. doi:10.1016/J.RSER.2015.09.012.

[8] W. Su, H. Eichi, W. Zeng, M.-Y. Chow, A Survey on the Electrification of Transportation in a Smart Grid Environment, IEEE Trans. Ind. Informatics. 8 (2012) 1–10. doi:10.1109/TII.2011.2172454.

[9] Q. Wang, X. Liu, J. Du, F. Kong, Smart Charging for Electric Vehicles: A Survey From the Algorithmic Perspective, IEEE Commun. Surv. Tutorials. 18 (2016) 1500–1517. doi:10.1109/COMST.2016.2518628.

[10]Z. Xu, Z. Hu, Y. Song, Z. Luo, K. Zhan and J. Wu, "Coordinated charging strategy for PEVs charging stations," *2012 IEEE Power and Energy Society General Meeting*, San Diego, CA, 2012, pp. 1-8. doi: 10.1109/PESGM.2012.6345045

[11]Peng Zhang and Kejun Qian, “A Methodology for Optimization of Power Systems Demand due to Electric Vehicle Charging Load.”, IEEE Transactions On Power Systems, Vol. 27, No. 3, pp 1628-1636, 2012.

[12]Cao Y, Tang S, Li C, Zhang P, Tan Y, Zhang Z, et al. An optimized EV charging model considering TOU price and SOC curve. IEEE Trans Smart Grid 2012;3 (1):388–93. http://dx.doi.org/10.1109/TSG.2011.2159630.

[13]Fazelpour, Farivar, Majid Vafaeipour, Omid Rahbari, and Marc A. Rosen. 2014. “Intelligent Optimization to Integrate a Plug-in Hybrid Electric Vehicle Smart Parking Lot with Renewable Energy Resources and Enhance Grid Characteristics.” Energy Conversion and Management 77. Elsevier Ltd: 250–61. doi:10.1016/j.enconman.2013.09.006.

[14]P. Sadeghi-Barzani, A. Rajabi-Ghahnavieh and H. KazemiKaregar: “Optimal fast charging station placing and sizing”. Applied Energy, 125 (2014) 289-299.

[15]Wang G, Xu Z, Wen F, Wong KP. “Traffic-constrained multiobjective planning of electric-vehicle charging stations”. IEEE Trans Power Deliv 2013;28:2363–72.

[16]Sungwoo Bae and Alexis Kwasinski. “Spatial and Temporal Model of Electric Vehicle Charging Demand”. IEEE Transactions On Power Systems, Vol. 3, No. 1, March 2012.

[17]Xiang, Yue, Junyong Liu, Ran Li, Furong Li, Chenghong Gu, and Shuoya Tang. 2016. “Economic Planning of Electric Vehicle Charging Stations Considering Traffic Constraints and Load Profile Templates.” Applied Energy 178. Elsevier Ltd: 647–59. doi:10.1016/j.apenergy.2016.06.021.

[18]Vermaak, Herman Jacobus, and Kanzumba Kusakana. 2014. “Design of a Photovoltaic-Wind Charging Station for Small Electric Tuk-Tuk in D.R.Congo.” Renewable Energy 67. Elsevier Ltd: 40–45. doi:10.1016/j.renene.2013.11.019.

[19]Hafez, Omar, and Kankar Bhattacharya. 2017. “Optimal Design of Electric Vehicle Charging Stations Considering Various Energy Resources.” Renewable Energy 107. Elsevier Ltd: 576–89. doi:10.1016/j.renene.2017.01.066.

[20]Fathabadi, Hassan. 2017. “Novel Wind Powered Electric Vehicle Charging Station with Vehicle-to-Grid (V2G) Connection Capability.” Energy Conversion and Management 136. Elsevier Ltd: 229–39. doi:10.1016/j.enconman.2016.12.045.

[21]S. Bae, A. Kwasinski, Spatial and Temporal Model of Electric Vehicle Charging Demand, IEEE Trans. Smart Grid. 3 (2012) 394–403. doi:10.1109/TSG.2011.2159278.

[22]S. Shrestha, T.M. Hansen, Spatial-temporal stochasticity of electric vehicles in an integrated traffic and power system, in: 2016 IEEE Int. Conf. Electro Inf. Technol., IEEE, 2016: pp. 0227–0232. doi:10.1109/EIT.2016.7535245.

[23]Zhili Zhou, Tachun Lin, Spatial and Temporal Model for Electric Vehicle rapid charging demand, in: 2012 IEEE Veh. Power Propuls. Conf., IEEE, 2012: pp. 345–348. doi:10.1109/VPPC.2012.6422675.

[24]V. Viswanathan, D. Zehe, J. Ivanchev, D. Pelzer, A. Knoll, H. Aydt, Simulation-assisted exploration of charging infrastructure requirements for electric vehicles in urban environments, J. Comput. Sci. 12 (2016) 1–10. doi:10.1016/j.jocs.2015.10.012.

[25]C. Hutson, G.K. Venayagamoorthy, K.A. Corzine, Intelligent Scheduling of Hybrid and Electric Vehicle Storage Capacity in a Parking Lot for Profit Maximization in Grid Power Transactions, in: 2008 IEEE Energy 2030 Conf., IEEE, 2008: pp. 1–8. doi:10.1109/ENERGY.2008.4781051.

[26]Sekyung Han, Soohee Han, K. Sezaki, Development of an Optimal Vehicle-to-Grid Aggregator for Frequency Regulation, IEEE Trans. Smart Grid. 1 (2010) 65–72. doi:10.1109/TSG.2010.2045163.

[27]E. Sortomme, M.A. El-Sharkawi, Optimal Charging Strategies for Unidirectional Vehicle-to-Grid, IEEE Trans. Smart Grid. 2 (2011) 131–138. doi:10.1109/TSG.2010.2090910.

[28]I.K.A. Aswantara, K.S. Ko, D.K. Sung, A centralized EV charging scheme based on user satisfaction fairness and cost, in: 2013 IEEE Innov. Smart Grid Technol. (ISGT Asia), IEEE, 2013: pp. 1–4. doi:10.1109/ISGT-Asia.2013.6698730.

[29]D.T. Nguyen, L.B. Le, Joint Optimization of Electric Vehicle and Home Energy Scheduling Considering User Comfort Preference, IEEE Trans. Smart Grid. 5 (2014) 188–199. doi:10.1109/TSG.2013.2274521.

[30]D. Wu, D.C. Aliprantis, L. Ying, Load Scheduling and Dispatch for Aggregators of Plug-In Electric Vehicles, IEEE Trans. Smart Grid. 3 (2012) 368–376. doi:10.1109/TSG.2011.2163174.

[31]M.H.K. Tushar, C. Assi, M. Maier, M.F. Uddin, Smart Microgrids: Optimal Joint Scheduling for Electric Vehicles and Home Appliances, IEEE Trans. Smart Grid. 5 (2014) 239–250. doi:10.1109/TSG.2013.2290894.

[32]M.D. Galus, G. Andersson, Demand Management of Grid Connected Plug-In Hybrid Electric Vehicles (PHEV), in: 2008 IEEE Energy 2030 Conf., IEEE, 2008: pp. 1–8. doi:10.1109/ENERGY.2008.4781014.

[33]S. Acha, T.C. Green, N. Shah, Effects of optimised plug-in hybrid vehicle charging strategies on electric distribution network losses, in: IEEE PES T&D 2010, IEEE, 2010: pp. 1–6. doi:10.1109/TDC.2010.5484397.

[34]Jing Huang, V. Gupta, Yih-Fang Huang, Scheduling algorithms for PHEV charging in shared parking lots, in: 2012 Am. Control Conf., IEEE, 2012: pp. 276–281. doi:10.1109/ACC.2012.6314939.

[35]M. Gonzalez Vaya, G. Andersson, Centralized and decentralized approaches to smart charging of plug-in Vehicles, in: 2012 IEEE Power Energy Soc. Gen. Meet., IEEE, 2012: pp. 1–8. doi:10.1109/PESGM.2012.6344902.

[36]T.N. Le, S. Al-Rubaye, H. Liang, B.J. Choi, Dynamic charging and discharging for electric vehicles in microgrids, in: 2015 IEEE Int. Conf. Commun. Work., IEEE, 2015: pp. 2018–2022. doi:10.1109/ICCW.2015.7247477.

[37]S. Huang, Q. Wu, S.S. Oren, R. Li, Z. Liu, Distribution Locational Marginal Pricing Through Quadratic Programming for Congestion Management in Distribution Networks, IEEE Trans. Power Syst. 30 (2015) 2170–2178. doi:10.1109/TPWRS.2014.2359977.

[38]F.J. Soares, P.M.R. Almeida, J.A.P. Lopes, Quasi-real-time management of Electric Vehicles charging, Electr. Power Syst. Res. 108 (2014) 293–303. doi:10.1016/J.EPSR.2013.11.019.

[39]I.S. Bayram, G. Michailidis, M. Devetsikiotis, S. Bhattacharya, A. Chakrabortty, F. Granelli, Local energy storage sizing in plug-in hybrid electric vehicle charging stations under blocking probability constraints, 2011 IEEE Int. Conf. Smart Grid Commun. (2011) 78–83. doi:10.1109/SmartGridComm.2011.6102396.

[40]J. Kim, S.-Y. Son, J.-M. Lee, H.-T. Ha, Scheduling and performance analysis under a stochastic model for electric vehicle charging stations, Omega. 66 (2017) 278–289. doi:10.1016/j.omega.2015.11.010.

[41]F. Koyanagi, T. Inuzuka, Y. Uriu and R. Yokoyama, "Monte Carlo simulation on the demand impact by quick chargers for electric vehicles," 1999 IEEE Power Engineering Society Summer Meeting. Conference Proceedings (Cat. No.99CH36364), Edmonton, Alta., 1999, pp. 1031-1036 vol.2. doi: 10.1109/PESS.1999.787457

[42]Dirección General de Tráfico. Available on: http://www.dgt.es/es/seguridad-vial/estadisticas-e-indicadores/parque-vehiculos/

[43]F. Marra, Y.T. Fawzy, T. Bulo, B. Blazic, Energy storage options for voltage support in low-voltage grids with high penetration of photovoltaic, in: 2012 3rd IEEE PES Innov. Smart Grid Technol. Eur. (ISGT Eur., IEEE, 2012: pp. 1–7. doi:10.1109/ISGTEurope.2012.6465690.

[44]M.F. Shaaban, A.A. Eajal, E.F. El-Saadany, Coordinated charging of plug-in hybrid electric vehicles in smart hybrid AC/DC distribution systems, Renew. Energy. 82 (2015) 92–99. doi:10.1016/j.renene.2014.08.012.

[45]M.B. Arias, S. Bae, Prediction of electric vehicle charging-power demand in realistic urban traffic networks, Appl. Energy. 195 (2017) 738–753. doi:10.1016/j.apenergy.2017.02.021.

[46]F. Fazelpour, M. Vafaeipour, O. Rahbari, R. Shirmohammadi, Considerable parameters of using PV cells for solar-powered aircrafts, Renew. Sustain. Energy Rev. 22 (2013) 81–91. doi:10.1016/j.rser.2013.01.016.

[47]Smets, A., Jäger, K. et al. Solar Energy. Fundamentals, Technology, and Systems. Delft University of Technology, UIT Cambridge, England, 2014.

[48]PVGIS. Available on: http://re.jrc.ec.europa.eu/pvgis/solres/solrespvgis.htm

[49]T. Bäck, D. B. Fogel, Z. Michalewicz, Evolutionary Computation 1: Basic Algorithms and Operators, Institute of Physics Publishing, Bristol and Philadelphia, p. 339, 2000.

[50]Matlab User's Guide (online): https://es.mathworks.com/help/?s_tid=hp_ff_l_doc

[51]R. Dufo-López, J.S. Artal-Sevil, J.L. Bernal-Agustín, J.A. Domínguez-Navarro, Can electric vehicles reduce electricity bill? 2014 IEEE International Electric Vehicle Conference (IEVC) IEEExplore Digital Library. December 2014, Florence, Italy; pp.: 1-4.

[52]Kennedy, J.; Eberhart, R.C. (2001). Swarm Intelligence. Morgan Kaufmann. ISBN 1-55860-595-9.