Techno-economic analysis of charging posts to be installed in a hub for electric vehicles

Catarina Gião Beja Ventura
catarinagbventura@tecnico.ulisboa.pt

Instituto Superior Técnico, Universidade de Lisboa, Portugal

December 2019

Abstract

Electric mobility is expanding at a rapid pace. Now that battery capacity and price are lesser issues, charging facilities will inevitably become the focus of attention. The aim of this thesis is to perform a techno-economic analysis of three different scenarios. Firstly, a fast-charging station using solely the national grid network for the charging facilities, secondly a photovoltaic based fast charging station together with the national grid network, and lastly a photovoltaic based fast charging station together with a storage system and the grid. By using an optimization method, the genetic algorithm, the model is analyzed for Lisboa, Faro, and Porto, by varying the number of the charging points, the number of photovoltaic panels and the number of batteries in order to obtain the optimal number for each one where the net present value is maximized. Its main conclusion is that the optimal solution which maximizes the net present value of the project is always the scenario resorting to a storage system and PV panels, and the grid network as of last resort. For instance, the optimal solution for Lisboa is: charging points - 12; batteries - 6; photovoltaic panels - 4955; net present value - 6.315.087€.

Keywords: Energy management, Electric mobility, E-Hub, Fast charging station, Net Present Value

1. Introduction

From all technological innovations likely to impact and disrupt the power sector, the rise of electric vehicles (EV) and the evolution of the autonomous versions thereof are among the most noteworthy. The International Energy Agency[1] (IEA) projects a global fleet of 60 million EVs in 2025 and more than a multiplication by 2 by 2040, reaching up to 140 million[1]. These transformative changes are now becoming more visible with a rising uptake of EVs as both their acquisition and maintenance costs fall. Therefore, charging facilities, charging duration and power supply issues will inevitably become focuses of attention[2]. The main goal of this thesis is to analyze and suggest the optimal and desirable number of fast charging posts and batteries for the storage system, as well as the number of photovoltaic (PV) panels required to be installed in a hub for electric vehicles in the three main cities of Portugal: Lisboa, Porto, and Faro. Thus, three main scenarios will be analyzed in this model which gather an economic and social performance in order to get the maximum net present value (NPV) by means of a genetic algorithm. The three scenarios are the following:

- Scenario 1: Grid;
- Scenario 2: Grid + solar energy;
- Scenario 3: Grid + solar energy + battery.

[1] Autonomous organization which works to ensure reliable, affordable and clean energy for its 30 member countries and beyond.

For the sake of clarity, a charging point refers to a device suited for charging a battery electric vehicle (BEV) and that only charges one BEV at a time.

2. Model Framework

Figure 1 presents a scheme of the developed model which connects all variables, sub-models, and distributions carried out for the optimization algorithm. The first sub-model, the queuing model, allows identifying the daily arrival distribution for the charging station, the waiting time tolerance of EV customers and the service time of each charged EV, as well as the maximum, tolerated service time for each EV. Following this, the second sub-model in accordance to the market share of EVs in Portugal, the correspondent battery capacities for each arrival EV considered for the charging station and the arrival EV distribution, returns the annual energy demand. From these two sub-models, the consumption profile of the EV fast-charging station was created. The development of the solar photovoltaic model is focused on creating the production profile required to meet the consumption profile for every city, taking into account its global horizontal irradiation. However, most of the time solar energy is not sufficient to fulfill the requirements and meet the consumption profile because of its intermittent nature. Therefore, the inclusion of the storage system model allows the creation of an alternative way to supply energy to EV customers. The energy management model includes these two models, as well as an algorithm returning for each hour the energy source type of the EV fast-charging station: grid network, solar panels or storage system. It likewise returns the amount of energy sold to the grid and the energy which is stored in the battery storage system. Following this, the economic assessment is completed, considering:

- The capital expenditure (CAPEX);
- The operational expenditure (OPEX), both, for the batteries, PVs and charging points;
- The sold-to-the-grid energy prices;
- The purchased-from-the-grid energy prices;
- The revenue from EV customers' usage.

From this analysis, the NPV, the internal rate of return (IRR) and the payback period is obtained taking into account a lifetime of 20 years. In addition, the optimal scenario is returned (scenario 1, 2 or 3). With these models in place, the genetic algorithm is performed.

3. Optimization Method: Genetic Algorithm

A genetic algorithm is used in order to find the optimal number of charging points, the number of batteries and the number of PV needed to feed the

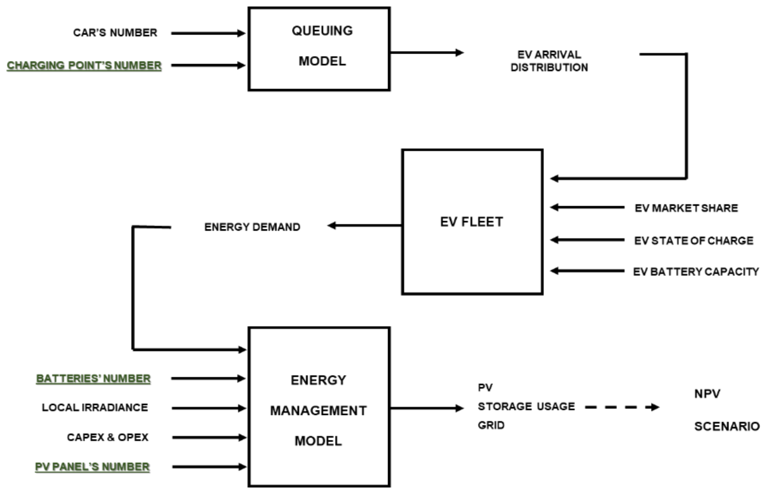

Figure 1 - Model framework

charging station, as underlined in green in Figure 1. The genetic algorithm is based on natural selection principles:

- Fitness function;
- Chromosome structure;
- Crossover and mutation rates.

The chromosome is a candidate solution, composed of genes representing the variable for optimization. In this case, the number of charging points, batteries and PV installed[3]. The fitness function that the project maximizes is the NPV, defined as the difference between the present values of cash inflows and the present values of cash outflows, including the initial investment over a period of 20 years and the lifetime of the project. The optimization problem is also subject to several constraints, such as:

$$Espv_h + Ecg_h + Edsto_h = Eev_h + Esg_h + Ecsto_h \quad (1)$$

$$Esoc_h = Esoc_{h-1} + Ecsto_h - Edsto_h \quad (2)$$

$$Edsto_h \leq Esoc_{h-1} \quad (3)$$

$$Ecsto_h \leq Esto_c - Esoc_{h-1} \quad (4)$$

$$Esoc_h \leq Esto_c \quad (5)$$

$$Esoc_h \geq SOC_{min} \times Esto_c \quad (6)$$

$$MAXev_h \geq Eev_h \quad (7)$$

$$Tw \leq Tw_{max} \quad (8)$$

$$Tc \leq Tc_{max} \quad (9)$$

The previous equations are integrated in time for every hour in order to have average energies.

3.1. Chromosome and its constraints

The genes from the chromosome included in the genetic algorithm need to be constrained by thresholds. These genes are constrained by the limits presented in Table 1. For this work, it is assumed that a single charging point has a power of 50 kW.

Table 1 - Limits of the genes

	Range	Variation
Number of charging points	1 - 20	1
Number of batteries	0 - 20	1
Number of PV panels	0 - 5000	1

The number of charging points ranges between 1 (at least one charging point is necessary for the study) and 20 (taking into account EV arrival distribution with an average of 23 EV arrivals per hour in the last year of the project lifetime, 20 years). The variation of the number of charging points is randomly performed, with a step of 1. The number of batteries ranges between 0 and 20. The minimum is zero as there is a chance that the optimal solution doesn't include a storage system. Since the power of the fast charging point is 50 kW, as mentioned previously, we assume that the battery could charge EVs for around 1 hour non-stop. Therefore 50 kW.h of maximum capacity would be needed, although a scenario with 20 fast-charging points would mean 20 times higher maximum capacity: 1000 kW.h. Therefore, by using a limit of 1000 kW.h, it is meant that a maximum of 20 batteries is used.

4. Model Development

4.1. Market share in Portugal

Analyzing the market share and according to the European Alternative Fuels Observatory (EAFO)[4], in Figure 2 is outlined the top 10 sold cars in Portugal until August 2019. The following figures present an example of the simulation for a configuration with 900 PV panels, 4 batteries and 4 charging points in Lisboa and for 24 hours. In the simulation process, a random number set up from a randomly uniform function is given from 0 to 100

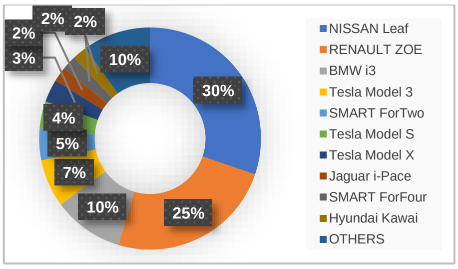

Figure 2 - EV market share in Portugal in August 2019[4]

and compared with the accumulated probability, i.e. the cumulative frequency. To obtain the type of vehicle that arrives at the charging station according to the top 10 of Figure 2. Figure 3 presents the number of cars by type arriving at the electric vehicles (EV) charging station.

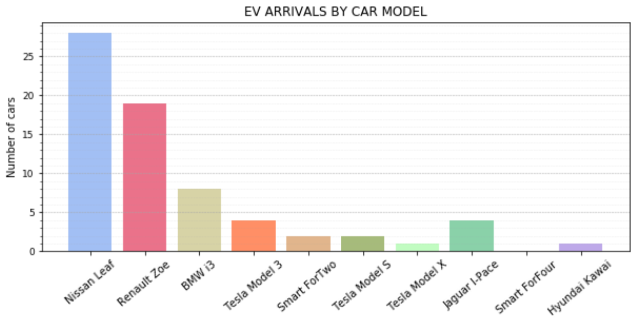

Figure 3 - Number of cars by model

4.2. Battery capacity

By knowing which type of vehicle is arriving at the charging station (from the top 10 presented in Figure 2) a value of battery capacity ranging from 17,6 to 100 kW.h is considered.

4.3. State of Charge (SOC)

The charging demand of an EV is determined by the initial battery State of Charge (SOC) and its charging characteristics. The SOC of an EV battery is defined from the average (μ) and typical deviation (σ) of the logarithm of the SOC[5]. Therefore, it can be modeled by the lognormal distribution (10) assuming a mean value of 40% and a standard deviation of 10%. A random number from 0 to 1 is simulated for the SOC of each car arriving at the station and Figure 4 presents it according to the lognormal distribution.

$$SOC = \frac{1}{SOC_{initial} \times \sigma \times \sqrt{2\pi}} . e^{\frac{-(\ln(SOC_{initial}) - \mu)^2}{2\sigma^2}} \qquad (10)$$

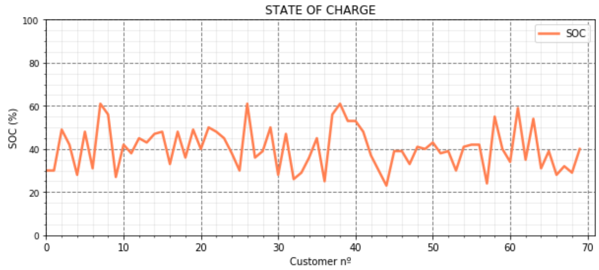

Figure 4 - SOC for every EV arrival

4.4. EV arrival distribution

The arrival distribution represents the EV customers' arrival into the queuing system. They usually arrive randomly, and the arrivals are independent of each other, i.e. it is unknown whether an EV will arrive and if the next EV will arrive one minute later or one hour later. Therefore, it can be modeled by a Poisson distribution with x arrivals in a specific time period where λ=3 (11).

$$P(X = x) = \frac{\lambda^x * e^{-\lambda}}{x!} \qquad (11)$$

In the simulation process, a random number following the Poisson distribution is taken to obtain the number of EV arrivals for each hour presented in Figure 5.

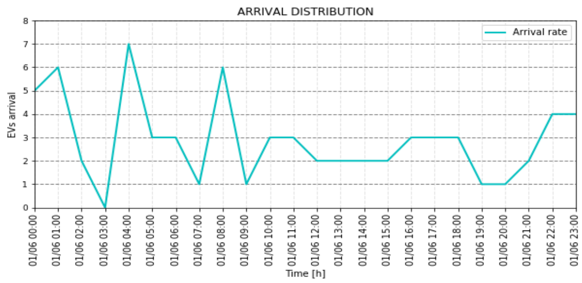

Figure 5 - EVs arrival distribution

Throughout the lifetime of the project – 20 years, the mean of EV arrivals is increased by one, i.e. in the present year the arrival distribution has a mean of 3 arrivals per hour and the next year is assumed an arrival distribution with a mean of 4 arrivals per hour. In the last year, will be an arrival distribution with a mean of 23 arrivals per hour.

4.5. Waiting time

The maximum waiting time in the waiting line is assumed to be 40 minutes. Therefore, in case all chargers are busy, the customer will wait up to 40 minutes to recharge the car. After this period, the EV customer will leave the EV fast-charging station and will not charge the vehicle. Additionally, the model assumes that, for each hour, whatever the number of EV arrivals, will arrive at the beginning of the hour, i.e. if 2 EVs arrive at midnight, it is assumed that both arrive at midnight sharp.

4.6. Service Time

The duration of stay of the EVs (12) in the fast-charging stations, depends upon the EVs' SOC, market share and battery capacities. It is assumed that the maximum charging time is 25 minutes.

$$Tc = \frac{Bcapacity_k \times \left(\frac{SOC_{full} - SOC_{initial_k}}{100}\right)}{P_{charger}} \qquad (12)$$

4.7. EV Energy demand

For every EV arrival, it is associated with the battery capacity of the model arriving and its SOC at the moment. The energy required for each EV and provided by the fast charging station is:

$$Eev_k = Bcapacity_k \times \left(\frac{SOC_{full} - SOC_{initial_k}}{100}\right) \qquad (13)$$

Figure 6 presents the energy required by each EV customer for every hour.

4.8. Solar photovoltaic model

To get the power of the PV module, a python library was used in the program: pvlib[6]. It collects local irradiance estimation data using a Data Source of historical radiation from NREL for Lisboa, Porto, and Faro. Considering this, it is necessary to know for each city its latitude, longitude, and altitude.

Table 2 - Latitude, longitude and altitude data[6]

	Lisboa	Porto	Faro
Latitude (º)	38,73	41,16	37,03
Longitude (º)	- 9,14	- 8,63	- 7,93
Altitude (m)	57	115	80

Figure 6 presents the energy consumption and the PV production profile. The energy production from PV panels is continuous throughout the day, although it is represented in the figure as a constant value for each hour, to be easily compared with the consumption values.

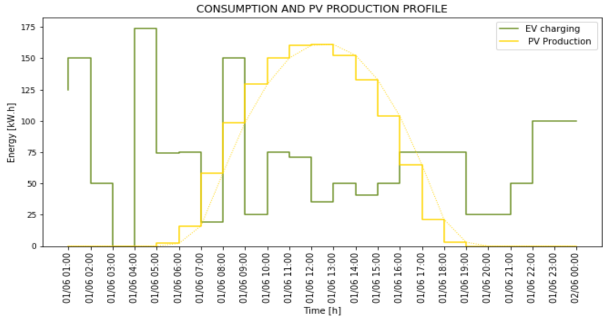

Figure 6 - Energy consumption and PV production profile

4.8.1. Storage system model

The stored energy cannot be higher than the battery capacity and it cannot be lower than its minimum allowed SOC, as it may cause damage and reduce its lifespan. For this kind of battery, a minimum SOC of 10% can be used[7]. In this case, the value is 5 kW.h, taking into account that each battery has 50 kW.h capacity. Figure 7 presents the schematic diagram of the fast-charging station connected to the utility grid, PV system, and storage system. The PV array produces electricity, which can be directed from the controller to the battery storage, to the EVs (used immediately) or sold to the grid. Whenever there is not enough solar power, the battery can supply power to the load if it has enough energy stored otherwise if there is not, the electric vehicles can also be charged by the power bought back from the grid network.

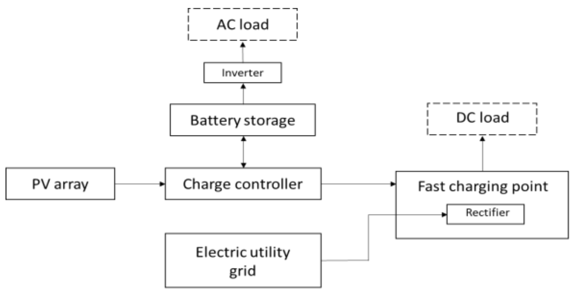

Figure 7 - Schematic diagram of a fast-charging station

4.8.2. Energy management model

The flow chart in Figure 9 presents the logic behind the used energy management model. The energy management model is evaluated for each hour. During rush hours, the energy purchased from the grid is more expensive, therefore the model firstly evaluates if it is a peak hour or not in order to choose between grid and storage system (if not empty of energy) as an energy source. If it is full hour/ empty hour/ super empty hour then, it verifies if there is available PV energy. If so, it charges EVs from PV energy, and if there is an energy surplus, it charges the storage system. In case the storage system is full, it sells the energy to the grid network. If there is not enough PV energy, it performs the charges thanks to the grid network. The difference from the rush hours is that, when there is not enough PV energy, instead of charging from the grid, charges are performed from the storage system. In the case of neither the battery nor the PV are able to provide energy, the grid network is used as the last resort. Figure 8 presents the energy supplied by the battery, the PV and by the grid in the upper part of the graph, demonstrating the three different technologies used throughout the day to supply the EV fast-charging station. In the bottom part, it presents the energy sold to the grid and the energy stored in the battery. These are presented as negative values in order to improve readability. It is assumed that the battery is half-charged at the beginning of the day. The energy is stored throughout the day while it is not rush hour, up to its maximum capacity and the surplus is sold to the grid. When the rush hours are reached, the battery is discharged, and the energy consumed by the EVs is only provided by the battery. During the daytime, the energy provided to EVs is mostly done by PV. During the nighttime, the grid network is preferred, since there is no PV production and is empty and super empty hours and the system cannot use the storage system to provide energy.

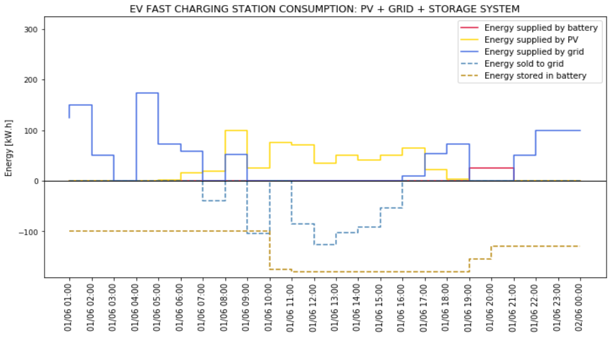

Figure 8 - EV fast-charging station consumption

4.9. Energy Prices

The energy pricing of the fast-charging station considers the medium voltage schedule [8] and the Energias de Portugal (EDP) medium voltage energy tariffs [9] when using the national grid network. It is possible to verify, what increases superbly the amount paid for grid network usage is the power charges. This may make the storage system use a more affordable price scenario during nighttime and the PV system use a more affordable price scenario during the daytime even though there is an investment for these systems. The remuneration price of the amount of electricity supplied to the national grid network by the EV fast-charging station covered by the provisions of the following article [10] is calculated according to the following expression:

$$Csg_h = Esg_h \times OMIE \times 0.9 \qquad (14)$$

Where:

- OMIE = 0,05729 (€/kW.h) given by [11] for 2018 – the resulting value of the simple arithmetic average of the closing prices of the Iberian Energy Market Operator (OMIE) for Portugal;

The price for charging EVs is composed of the charging energy (0,21 €/kW.h), the station usage (0,15€ + 0,09€/kW.h) as well as the fees and taxes. The model only takes into account the charging energy and the station usage, as fees and taxes are not revenue for the project since they are directed as a debt to the state. [9] presents the energy tariffs.

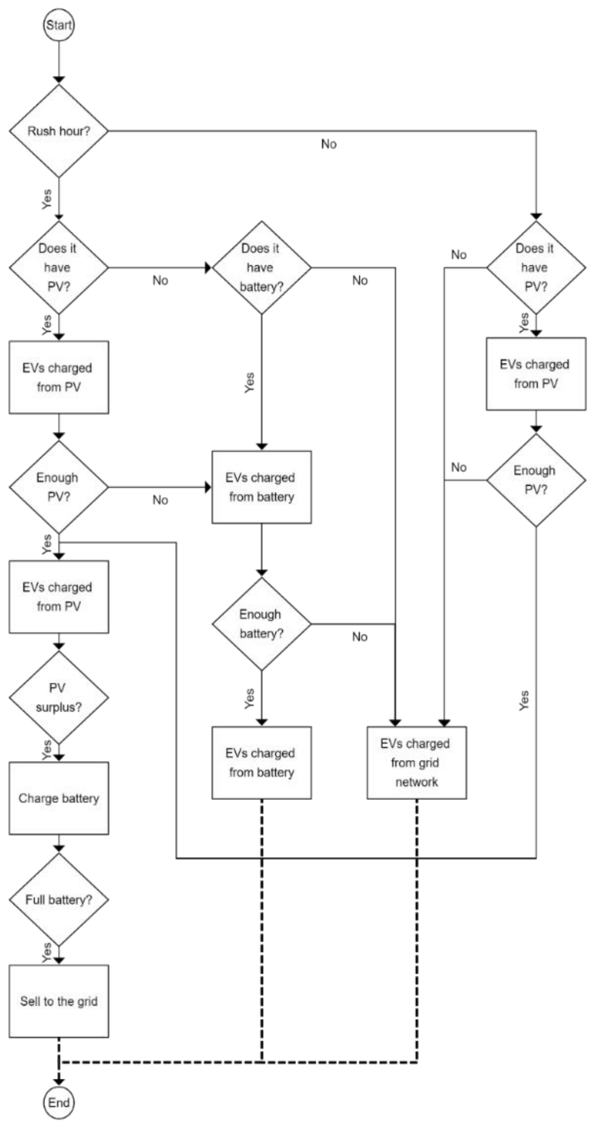

Figure 9 - Energy management model

4.10. Economical assessment

4.10.1. Net Present Value, Internal Rate of Return and Payback period

The net present value (15) is the value of all cash flows (positive and negative) over the entire life of a project investment. The net cash inflows taken into account are the revenue from energy sold to EVs and energy sold to the grid. The net cash outflows consider the energy purchased from the grid and the OPEX from the batteries, PV panels, and the charging points every year. The initial investment takes into account the CAPEX from the batteries, PV panels, and the charging points.

$$NPV = \sum_{t=1}^{n} \frac{NCF_t}{(1+i)^t} - I \qquad (15)$$

The internal rate of return (IRR) is a metric used to estimate the profitability of potential investments. The higher is the IRR of a project, the more desirable is to undertake it. The formula relies on the same as NPV formula, presented below:

$$0 = NPV = \sum_{t=1}^{n} \frac{NCF_t}{(1+IRR)^t} - I \qquad (16)$$

The payback period (17) is the time where the initial outlay of investment is expected to be recovered through the cash inflows generated by the investment. The payback period is an indicator of the risk inherent of a project. In order to calculate the payback period of an investment one must calculate the cumulative cash flow for each year.

$$Payback\ period = t + \frac{C_t}{C_{t+1}} \qquad (17)$$

4.10.2. CAPEX and OPEX

The charging points type considered the QC45 with a DC output with power up to 50 kW and dual port[12]. Its purchase value is around 29.000€[13]. As the charging point for this thesis is considered as a device suited for charging only one EV at a time, and as the QC45 model suits up to 2 charging places at the same time, we consider in the model that its purchase price is 14.500€. In addition, it is considered the installation costs accounting as 15% of the purchasing cost, 2.175€. Therefore, the correspondent CAPEX of one charging point is Ccp = 16.675€. The CAPEX value of PV panels is given by the following formula taking into account the PV capacity[14]:

$$Cpv = 102 \times PV_{capacity} - 75 \qquad (18)$$

The CAPEX value of the storage is given by the following formula taking into account that every battery for the lifetime of the project as to be replaced at least once[7]:

$$Csto = 2 \times (Bcapacity_{sto} \times SC_{battery} + P_{NOM} \times SC_{equipment}) \qquad (19)$$

The OPEX value for the fast charging points is given by the following formula, according to [9] where it defines the price for the contracted power of 0,0508

€/kW per day and accounting with 1% of the investment, which is used for maintenance and other general technical problems:

$$Ccp_t = Pcharger \times 0{,}0508 \times 365 + 0{,}01 \times Ccp \qquad (20)$$

The OPEX value for PV panels is given according to [15] where it defines the initial cost for larger systems as 0.5% as a reasonable expectation of PV system operation and maintenance (O&M) costs. The OPEX value for the storage system is given according to [7] where it defines, 3% of the initial system cost per year for the batteries O&M costs.

5. Results and Discussion

5.1. Parameter optimization

Two different analyses were performed, the convergence value of the NPV in order to stop the genetic algorithm being the main difference between them of 1% and 0.1% for Lisboa. The obtained optimal configurations are a set of chargers' numbers, the number of PV installed and the number of batteries installed and the corresponding NPV value. The two analyses were evaluated and assumed various combinations of population size and number of generations. Each combination was performed three times in order to verify the repeatability of the genetic algorithm's results. For combinations with smaller population sizes, 20 and 50, the three performed simulations always returned the same results. The larger the population size, the greater the probability of not returning the same solution and as a consequence the most difficult to find the optimal solution, since there will be more mutations in the solution space. The population size of 20 has the lowest resulting NPV. Therefore, the population size of 20 is not the optimal size for the genetic algorithm optimization. It is possible to validate that the IRR and payback period variations are significantly related to the number of batteries installed. The greater the number of batteries installed, the lower the IRR and the higher the payback period, since these are very expensive. The NPV, except for the population of 20, varies less than 2%, while the computational time increases considerably. The NPV difference presented for every solution is within $\pm$4% for this convergence value of the NPV.

The highest values for NPV were returned from the population size of 400 and 200, 6.316.301€ and 6.315.087€. However, the population size of 200 demonstrated more concise data since the three returned values of NPV from the three generations were the same. Likewise, the difference between the highest NPV value of the population size of 400 and 200 is only 1,214€ which represents negligible value for this kind of project. Therefore, the population size of 200 will be used to perform the following simulations for Porto and Faro.

5.2. Analysis of the three different cities

Below are presented the values for Lisboa, Faro, and Porto.

Table 3 - Economic analysis for the three different cities

	NPV (€)	IRR	Payback period (years)	Ideal configuration
Lisboa	6 315 087	0,592	2,06	[12 6 4955]
Porto	6 349 288	0,637	1,9	[14 4 5000]
Faro	6 342 947	0,562	2,17	[12 7 5000]

The varying parameter among the 3 cities is solely the global horizontal irradiation (GHI), which is higher for Faro, whereas the values for Lisboa and Porto are very similar. Therefore, the returned NPV values are not directly correlated with the GHI, since the higher values of NPV are from Porto and Faro. In addition, generally, the higher the PV production, the more energy is sold to the grid. However, the case of Faro has the highest number of installed batteries which decreases substantially the NPV and IRR, although Faro has a higher yearly energy production from PV which balances the difference between NPVs.

From Table 3 it is also possible to conclude that, the higher the number of charging points and the lower the number of batteries, the highest is the NPV. By having more charging points, there are more EVs charging throughout the year, increasing the revenue from the energy sold to EVs from the charging station. Likewise, by having a smaller number of batteries, its CAPEX decreases substantially, decreasing the investment made in the beginning. From Table 3 it is possible to verify that Porto was the city with the highest NPV returned of 6.349.288€, with an IRR of 0,637 and a payback period of 1,9 years. Thereby, the investment is returned in almost 2 years, and the business model has economic profitability of almost 64%. Faro has the second-highest NPV returned of 6.342.947€, although it has lower values for the IRR and higher value for the payback period compared to Lisboa.

By having an arrival distribution following the Poisson distribution it can happen that a lot of EV customers can arrive at the station during nighttime and a small percentage of EVs arriving during the daytime, or even during the rush hours. However, nowadays it is not common to have those types of distribution. Therefore, a constant arrival distribution is also simulated. The NPV returned values for the three different cities are considerably lower, almost 2 MM€. As a consequence, from the constant arrival distribution, the number of batteries for every city increases. This can be a reason for the lower returned NPV value. The Poisson and constant arrival distribution might not be taking into account daily similar values for the simulation, i.e. by having a Poisson distribution with a mean value of three and a constant distribution with a constant EV arrival of four EVs/hour from 7h-22h and one EV/hour from 22h-7h, it will most likely not return similar daily totals for EV arrivals. In general, as the NPVs are lower for the three cities, the payback periods are higher, and the IRR is lower.

6. Conclusions

The genetic algorithm performed for two different convergence criteria of 1% and 0,1% evaluated the optimal population size of 200 which performed and returned the best three NPV values concisely. By comparing among the returned NPV values for the different population size and generation limit combinations, it is possible to validate that the IRR and payback period variations are related to the number of batteries installed. The greater the number of batteries installed, the lower is the IRR and the higher is the payback period since these are very expensive. For this reason, charging posts and PV panels dictate the economic viability of the business model. Generally, a high number of PVs installed are associated with a high NPV returned. This is due to its low investment value and the significant decrease in the grid network usage, which is very expensive and increases the cash outflows. The higher the number of charging points and the lower the number of batteries, the highest is the NPV. With more charging points, there are more EVs charging throughout the year, increasing the revenue. Likewise, with fewer batteries, its CAPEX decreases substantially, decreasing the investment made in the beginning. For a constant arrival distribution, the NPV returned values for the 3 different cities are considerably lower. Concluding, the optimal scenario chosen is always scenario 3 with a storage system and photovoltaic panels installed. The optimal solution for Lisboa, Porto, and Faro is:

- Lisboa: charging points - 12; batteries - 6; PV - 4955; NPV - 6.315.087€;
- Porto: charging points - 14; batteries - 4; PV - 5000; NPV - 6.349.288€;

- Faro: charging points - 12; batteries - 7; PV - 5000; NPV - 6.342.947€.

Some areas that could be developed include:

- Integration of a multiplier factor depending on the hour of the day for the arrival distribution keeping the average value of Poisson;
- Associate a logistic curve to the arrival distribution considering the EVs growth in the following 20 years;
- Consider various maximum capacities for the batteries instead of a constant capacity.

$Espv_h$	the energy supplied PV (kW.h)
Ecg_h	energy consumed from the grid (kW.h)
$Edsto_h$	energy discharged from the battery (kW.h)
Eev_h	the energy supplied to EVs (kW.h)
Esg_h	the energy supplied to the grid (kW.h)
$Ecsto_h$	energy charged to the battery (kW.h)
$Esoc_h$	the energy level in the battery (kW.h)
$Esto_c$	energy capacity of the battery (kW.h)
Eev_h	the energy supplied to EVs (kW.h)
Esg_h	the energy supplied to the grid (kW.h)
Ecg_h	energy consumed from the grid (kW.h)
Ncp	number of charging points installed
Npv	number of PV panels installed
Nsto	number of batteries
SOC_{min}	minimum SOC of the battery (p.u)
$MAXev_h$	energy demand by EVs (kW.h)
Tw	waiting time for each EV (min)
Tc	charging time for each EV (min)
t	year
h	hour
i	interest rate
$P_{charger}$	charger power (kW)
$SC_{battery}$	the specific cost of the battery (€/kW.h)
$SC_{equipment}$	battery complement cost (€/kW)

7. References

[1] F. Sioshansi, *Innovation and Disruption at the Grid's Edge. How Distributed Energy Resources are Disrupting the Utility Business Model*. 2017.

[2] Till Bunsen *et al.*, "Global EV Outlook 2019 to electric mobility," *OECD iea.org*, p. 232, 2019.

[3] "Optimization methods - genetic algorithm " .

[4] "Home | EAFO." [Online]. Available: https://www.eafo.eu/. [Accessed: 05-Apr-2019].

[5] "120. Generating log normal samples from provided arithmetic mean and standard deviation of the original population – Python for healthcare modeling and data science." [Online]. Available: https://pythonhealthcare.org/2019/02/07/120-generating-log-normal-samples-from-provided-arithmetic-mean-and-standard-deviation-of-original-population/. [Accessed: 01-Oct-2019].

[6] W. F. Holmgren, C. W. Hansen, and M. A. Mikofski, "Pvlib Python: a Python Package for Modeling Solar Energy Systems," *J. Open Source Softw.*, vol. 3, no. 29, p. 884, 2018.

[7] G. Lorenzi, R. da Silva Vieira, C. A. Santos Silva, and A. Martin, "Techno-economic analysis of utility-scale energy storage in island settings," *J. Energy Storage*, vol. 21, no. January 2019, pp. 691–705, 2019.

[8] "Horários Média Tensão - Inverno e Verão." [Online]. Available: https://www.edpsu.pt/pt/tarifasehorarios/horarios/Pages/HorariosMT.aspx. [Accessed: 11-Oct-2019].

[9] "Tarifas de Média Tensão." [Online]. Available: https://www.edpsu.pt/pt/tarifasehorarios/Pages/TarifaMT.aspx. [Accessed: 11-Oct-2019].

[10] "MINISTÉRIO DO AMBIENTE, ORDENAMENTO DO TERRITÓRIO E ENERGIA Decreto-Lei n.º 153/2014 de 20 de Outubro."

[11] "Inicio | OMIE." [Online]. Available: http://www.omel.es/pt/inicio. [Accessed: 21-Oct-2019].

[12] "Efacec Electric Mobility | EV QC45 Quick Charger." [Online]. Available: https://electricmobility.efacec.com/ev-qc45-quick-charger/. [Accessed: 21-Oct-2019].

[13] "Efacec QC45 - 50kW CHAdeMO/SAE Combo Dual Charger ChargePoint Enabled – Best EV Chargers." [Online]. Available: https://www.bestevchargers.com/products/efacec-ocpp-50kw-chademo-single-port?_pos=1&_sid=068930b86&_ss=r. [Accessed: 21-Oct-2019].

[14] C. H. Villar, D. Neves, and C. A. Silva, "Solar PV self-consumption: An analysis of influencing indicators in the Portuguese context," *Energy Strateg. Rev.*, vol. 18, pp. 224–234, 2017.

[15] N. Sandia, S. Alliance, S. Pv, and M. W. Group, "Best Practices in Photovoltaic System Operations and Maintenance 2 nd Edition NREL / Sandia / Sunspec Alliance SuNLaMP Best Practices in Photovoltaic System Operation and Maintenance 2 nd Edition," no. December, 2016.