Treball de Fi de Màster

Màster en Enginyeria de l'Energia

Design of a controller for a building from the tertiary sector associated to electric vehicles

REPORT

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Abstract

Currently the transport sector is dominated by the fossil fuels, bringing a high dependence on this specific source. The introduction of the electric vehicle offers an opportunity for avoiding this dependence, as there is more diversification on the energy sources for this new type of transport. However, its introduction also brings new challenges and risks, a new type of load appears and it cannot be left unmanaged because the electricity demand will increase significantly.

In order to confront these issues energy management systems will be required together with the load forecast, both will play an important role in a near future for ensuring the correct operation of the grid. In this work, the energy consumption from a building from the tertiary sector which has introduced bidirectional chargers is studied.

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1. Introduction

The fields of electromobility, renewables and energy efficiency are under an increasing attention nowadays due to the rapid growth of the global energy and the environmental deterioration. Its implementation are the key for the modernization of future energy systems and buildings.

The need of reducing the dependency on the fossil fuels, also the scarcity of fuel and the volatility of the prices have motivated the electric vehicles to be considered as effective resources in transportation. For that reason, many countries are already underway designing new polices in order to foment the introduction of electric vehicles for reducing the oil consumption and the CO2 emissions. As stated in the Paris Declaration on Electro-Mobility and Climate Change and Call to Action, a target of more than 100 million electric cars is expected by 2030 (1). This growing phenomena leads to a new type of load that cannot be left unmanaged. If the charging processes are not coordinated, several problems of safety and operation will arise within the grid system.

In (2) the impact of the penetration of the PEVs is studied, and it is established that depending on the vehicle characteristics and the distribution grid the peak load can be increased by 10% to 35%. It is true that the electrification of the transportation sector will bring new challenges that the system will need to confront, and smart technologies will be required in a near future. However, it will also offer new opportunities to the operation and planning of the power systems.

In recent years, several researchers have dealt with these issues. Some studies from the literature reviewed explore the solution of changing the normal consumption patterns with demand side resources, as a response to changes in electricity prices over time. There is several research on energy management systems in smart buildings and households in order to smooth its energy consumption profiles with the introduction of the EVs.

An example is in (1), where the so-called vehicle to building (V2B) concept is introduced and the objective is to control the power consumption of the building by scheduling the charging and discharging processes of the EVs batteries. In (3) there is also the evaluation of an energy management system introducing also the photovoltaic uncertainty in addition to the stochastic electric vehicles' driving schedule.

The research is also focused on the possibility of supplying power to the electric grid with the energy stored within the EVs batteries. This phenomena is commonly known as vehicle-to-grid (4).

In this project the association of the electric mobility with buildings through the bidirectional power flows between them is explored. The idea is to design an energy management system so as to optimize the charge and discharge processes of the connected vehicles in order to optimize the final cost, either from the building and the EV user, and also be able to forecast the energy consumption of that building in a near future.

2. State of the art

In almost all the literature reviewed there is the combination of some of the following solutions for the near future regarding the problems mentioned before, such as renewable energy, the introduction of the electric vehicle, energy storage solutions, micro grids… In this project some of these studies are reviewed, focusing principally on the implementation of energy management systems for controlling the introduction of the electric vehicles in buildings.

As previously commented there is expected an increase on the electricity demand due to the raise of use of PEVs. If this increase is not controlled challenges on the operation and management of the power grid will arise, bringing possible voltage imbalances in the distribution network. For that reason the interest on PEVs has raised significantly, not only because of the need of controlling the charging and discharging processes, also for the possibility of use them as ancillary services, a high number can be treated as energy storage systems which permit to smooth peak periods of consumption.

In (5) the authors have analysed the current most significant measures for the peak load shaving. A significant literature review about the three major strategies for peak load shaving is presented. Demand side management (DSM), energy storage systems (ESS) and the integration of electric vehicles (EV) to the grid are deeply discussed and several real projects and researches are highlighted, however the fact of using renewable energy sources is not taken into account.

The authors in (6) have analysed the problems mentioned above, and taking into account different conditions they have presented three algorithms for scheduling the PEV charging in a public building. In the first one the electricity prices are predetermined, they are known in advance the day before, whereas in the other algorithms the price is known one hour before. However, in the first and second simulations the PEVs are assumed atomic loads. The third scenario is more realistic as the PEV charging is assumed interruptible, i.e. non atomic loads.

In (1) a mathematical model in Matlab is implemented in order to peak shave and valley fill the energy consumption of a university building by means of scheduling the charging and discharging processes from the electric vehicle parking lot of the building. In this model real data of the parking lot occupancy and the power consumption of the building are used.

In (3) an additional value is added, the integration of a PV system. The authors in this study have evaluated the operation of an EMS in a building taking into account the bidirectional energy trading from an EV fleet from an office building and the uncertainty of the PV installation together with a storage system. A MILP framework-based model is implemented and it is concluded that the daily costs associated to the energy consumption from the building are much lower with the stochastic approach.

In (7) the authors have explored the potential of the introduction of the EVs for optimizing the energy management of a building. A MILP is also presented in this paper with the objective of minimizing the final energy bill, either for the user and the building. And effectively, the results show that the contracted power can be reduced and there is benefit for the EV users. In (8) a vehicle-to-building control strategy is also developed in order to use the electric vehicles as flexible resources in order to reduce the daily operating costs related to the energy consumption.

The researchers are not only focused on large buildings, the authors in (9) have proved that there is a potential cost reduction for heating a house and charging an electric vehicle if a smart energy management system is implemented. The simulations have verified that the cost reduction is so significant and it can reach a 13% (9). Therefore, it can be a promising path for cost reduction.

Another work related to the individual users of the EVs is in (10). The principal aim of this project was to develop an electric vehicle intelligent energy management system which enables the user of the electric vehicle to contribute to the frequency regulation. The so called prosumer term appears in this study because the user does not only act as a consumer, also acts as a producer. The innovative ability of this system is that it can automate the energy management of the battery taking into account the next trip mileage, in a way that permits to create economic benefit by shifting the charging or discharging processes to off-peak or peak hours.

In order to satisfy the EV charging demand it is necessary to have a reliable and robust system, as this new load is different from the current building loads, for example at household level, the fact of charging a single EV can increase the electricity consumption by 50% as established in (11). For that reason the knowledge of the day-ahead demand is decisive for the correct operation of the network.

In large buildings it is expected in a near future the introduction of charging stations within its parking lots. This fact can lead to important unbalances and possible penalizations if the charging and discharging processes are not coordinated, as it may increase the peak power consumptions considerably. For that reason scheduling strategies can be a promising solution so as to optimize its final energy costs as it will permit to accurate an estimation of the consumption taking into account different parameters.

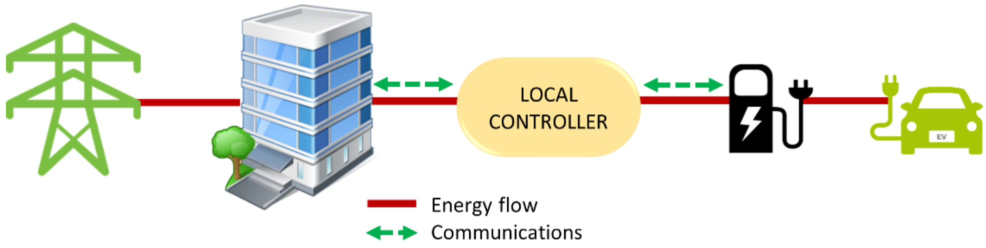

***Figure 1**: Configuration of a Smart building with charging stations*

In most of the literature reviewed different predicting methods are proposed, however these ones are usually based on traffic patterns and the characteristics of the EVs and charging processes, instead of historical data.

In (12) a review on how the Data Science has been used to deal with the most difficult problems related to the energy management within the building sector is presented. The current increase on energy consumption requires an important improvement of the current energy management procedure. Nowadays we have technology at our disposal which permits to collect high amounts of data. The current companies are taking advantage of it by developing solutions based on Data Mining and Data Science.

Data science consists on building algorithms and models in order to found patterns, also discover useful insights in order to do predictions with a high amount of data. The first step of this process is recollect all the data that could be useful. The next step is apply filters and clean the data, leaving the relevant information. However, the introduction of new data is also possible in order to provide further knowledge to the model.

Once the data is ready, it is necessary to decide which method or technique is going to be more effective. The different techniques, most used in Energy Management and Efficiency are classified into four groups: Classification, Clustering, Regression and Association Rule Mining (12).

This work reviews the data science techniques which have been used in this project, which can be classified into the classification and regression problems. However, before going deep into the different techniques it is interesting to analyse the different platforms and programming tools which are available currently in the market. In the following picture these ones are collected:

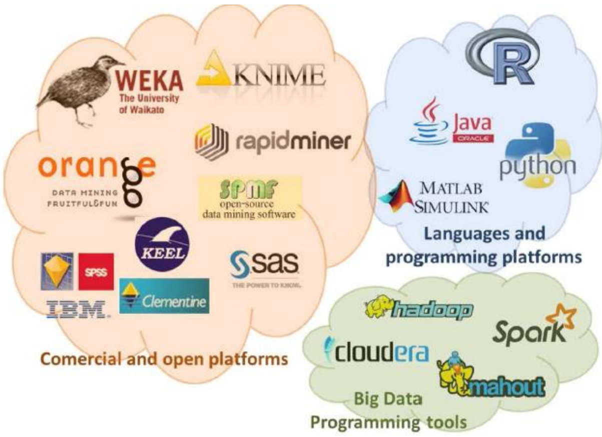

Figure 2: *Platforms and programming tools for data science implementation (12) .*

In this work the RapidMiner software has been used, as it is explained in Section 4, this software provides template-based frameworks, this means that there is not the necessity of writing code, the different processes or techniques are integrated into different blocks or workflows, in the programme called processes. Due to the ease that this programme offers, the fact that no writing code has been needed, this work doesn't study in deep the mathematical formulation of the different techniques described as follows.

The first technique is the Generalized Lineal Model, as stated in (13) this model is formed by three elements: the linear predictor, the link function and the error distribution. Regarding the linear prediction is a normal linear model. Then the link function converts values of the linear predictor into the range of the outcome variable (13). After, an error distribution (i.e Binomial or Poisson) shows how the observations varies from the expected values (13).

Then, the Deep Learning technique, as stated in (14), consists on non-linear modules which are organized into different multiple layers. The initial attributes are transformed into lower layers, in this way complex functions can be obtained (14). In order to make this more comprehensive, the following picture represents a scheme of this technique:

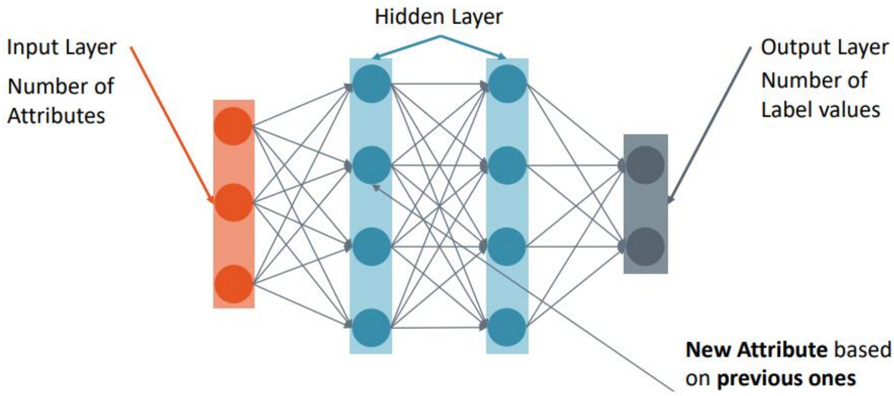

***Figure 3**: Deep Learning scheme (15)*

The next technique is Random Forests, this technique can be used into regression problems or classification problems. This technique is based on classification and regression trees (16). As shown in the next figure, this technique consists on, from the initial data set, different samples are divided by randomly selecting different observations and learning randomized binary decision trees. Finally these ones are aggregated, as shown in the picture, providing the solution (16).

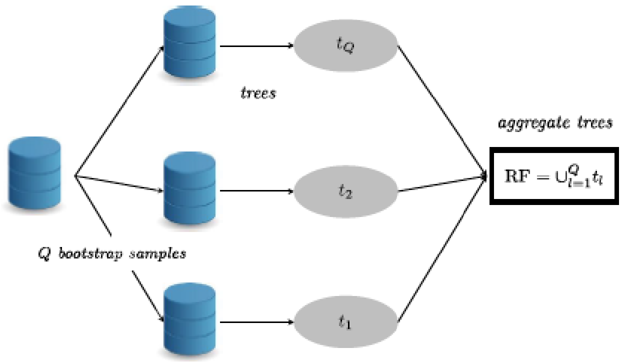

***Figure 4:** Random Forest scheme (16)*

The final technique analysed in this study is the Gradient Boosted Decision Trees, this technique, like it has been observed in Random Forest, uses an ensemble of multiply trees, also for classification and regression problems. The difference from the previous technique is that in this case, this model constructs a series of decision trees, in random forest the construction is in parallel. The idea of this model is that the training of each tree permits to correct the mistakes it may arise in the previous ones, therefore, as much trees are added to the model less errors are made (15) (17)

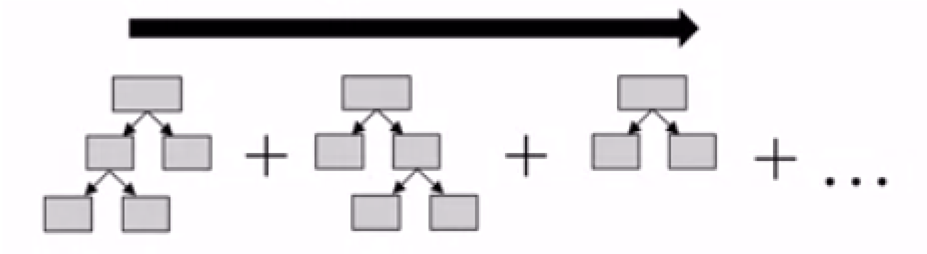

***Figure 5**: Gradient Boosted Decision Trees scheme (17)*

Some studies where machine learning techniques have been used in energy management problems also have been analysed in this work. For example, in (18) a charging strategy is presented in order to minimize the energy costs from the transport companies due to the increase in usage of electric buses. In order to achieve an effective usage it is crucial to know the energy demand from the electric buses a priori. For that reason a neural network predictor is done in this work in order to predict the energy demand for the next day, and it is based on historical energy usage and meteorological data. Once the energy demanded is estimated, an optimal charging strategy can be implemented.

In (19) a comparison between three modelling techniques for predicting the energy consumption in Hong Kong is done. The compared methodologies are the regression analysis, the decision tree and neural networks. This study has concluded that the decision tree model is the more accurate in comparison with the other ones.

In (20) a short-term energy load prediction model for buildings is presented and the method used is an artificial neural network. In order to obtain the output values, the system uses the values of temperature, the hours of the day and the energy consumed in each one. The results obtained have presented a better precision in comparison with the literature reviewed within this work.

In (21) also a short-term EV load forecast model using an artificial intelligence technique is presented, in particular the model used is Support Vector Machines. The data used for this analysis is national statistical data. The objective of the study is forecast the day-ahead demand of the EV load and then compare it with the current demand and also with the forecast output of a Monte Carlo technique. The results shown in the paper have demonstrated that the SVM proposed model presents a higher accuracy and it is more effective.

3. Methodology

The aim of this section is to describe the problem studied in this project and analyse the current situation of the EV integration in Catalunya. In section 3.1 there is a general description of the Spanish electric system and the initiatives which have been implemented during these last years in Catalunya for the introduction of the electric vehicle. In the next sections the building is described together with the description of the electric vehicle. Finally, one of the objectives of this project is firstly analyse the annual consumption of that building in order to optimize the contracted power, therefore, the optimization problem used for obtaining this annual data is described.

3.1. Current state of the EV

This work faces up the expected impact due to the penetration of the electric vehicles, mainly on buildings. The idea is to smooth its energy consumption by designing an energy management system so as to optimize the charge and discharge processes from the electric vehicles connected to the buildings so as to optimize the final energy costs and ensure the correct operation of the grid.

At this point it is interesting to analyse the context in which this project is, as we are working in Spain it is necessary to analyse the electric market, the way in which the price it is obtained, as well as the electric vehicles' implementation within the country. In the following sections these topics are briefly explained.

3.1.1. The Spanish electric system

The aim of this section is to briefly describe the parameters which form the price of the electricity we consume and how this one is obtained. In this project it has been considered an index price, which is obtained from the electric pool and varies all along the year. There are other ways such as buying futures which establish a fixed electricity price during a specific period of time.

So considering the case of study, if an electricity bill is analysed, three main components are found:

- The costs from the electrical market.
- The regulated costs which are associated to the electricity supply.
- The taxes.

In the following table all the costs associated to the cost's blocs mentioned above are detailed:

Costs from the electrical market	•Pool •Fee from the stakeholder •Technical restrictions and operation services
Regulated costs	•Energy access fee •Power access fee •Payment for capacity •Loses from transport and distribution •Payment of the operator •Rent of the meter box
Taxes	•Municipal tax •Electrical tax •IVA

Table 1: *Costs associated to the electricity price.*

However, all these costs are not detailed in the electricity bill, they are grouped. Firstly, the power access fee is found. This fee has an annually fixed price per kW, and for each tariff it has a different value.

In low voltage, the case in which this project works, there are three ranges of tariffs depending on the contracted power. In the following table the different tariffs are defined with its respective prices for the power access fee.

Tariff	Contracted power	Cost (€/kW year)		
2.0A	P ≤ 10kW	38.043426		
2.0DHA				
2.0DHS				
2.1A	10kW < P ≤ 15kW	44.44471		
2.1DHA				
2.1DHS				
3.0A	P > 15kW	P1	P2	P3
		40.728885	24.43733	16.291555

Table 2: *Power access fee (22)*

After the power access fee there are the costs associated to the energy consumed. On the one hand there is the energy access fee, this price is fixed per each kWh consumed, and it also depends on the contracted tariff, as it is shown in the following table:

Tariff	Contracted power	Cost (€/kWh)			
		Without DH	P1	P2	P3
2.0A	P ≤ 10kW	0.044027	-	-	-
2.0DHA		-	0.062012	0.002215	-
2.0DHS		-	0.062012	0.002879	0.000886
2.1A	10kW < P ≤ 15kW	0.05736	-	-	-
2.1DHA		-	0.074568	0.013192	-
2.1DHS		-	0.074568	0.017809	0.006596
3.0A	P > 15kW	-	0.018762	0.012575	0.00467

Table 3: *Energy Access fee (22)*

On the other hand there are the other terms mentioned before, except from the electrical tax, the VAT and the rent of the meter box. All these costs are expressed in €/kWh, and with the new meter box the idea is to invoice the energy consumed per each hour, that is a price for each hour of the day.

Some stakeholders show its hourly prices at their websites, in the following graphic the hourly prices from two days of May from a Spanish company are represented. Underlining that there is not the energy access fee in these prices.

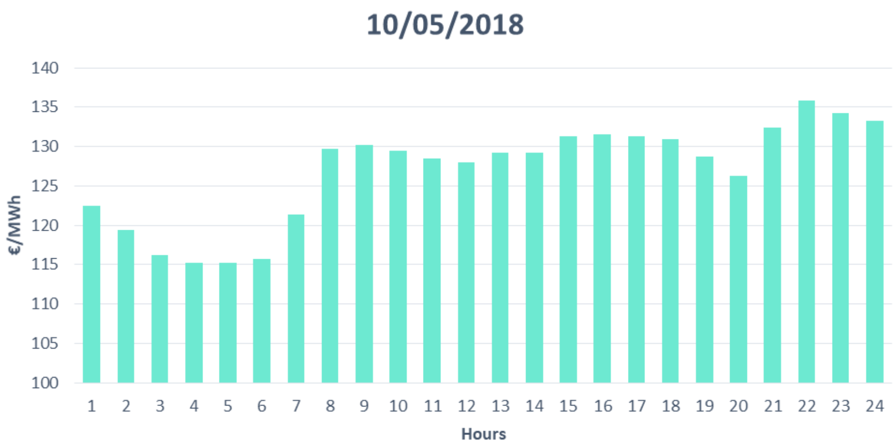

Figure 6: *Electricity hourly Price – 10/05/2018 (23)*

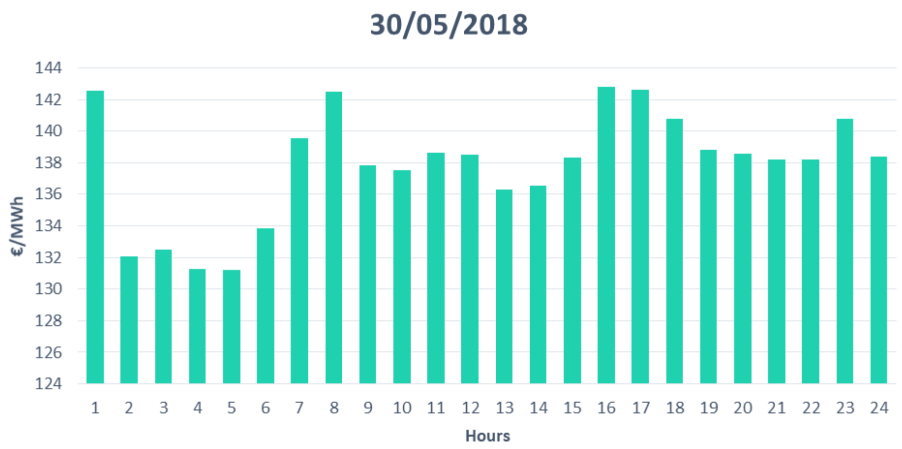

Figure 7: *Electricity hourly Price – 30/05/2018 (23)*

Finally, there are the electrical tax, the rent of the meter box and the VAT, explained in the following points:

- The electrical tax is a regulated cost defined by the Spanish government. This tax is applied to the sum of the power and energy costs, specifically is the 5.112696% of that sum (24).
- The rent of the meter box has to be paid if the meter box is not of property. Its price depends on the type of installation, i.e. monophasic or triphasic.
- The VAT (value-added tax), each country has its standard rates, here in Spain it is 21%.

Once the different parameters are identified, it is interesting to analyse which types of contracts the users from that study can have with the transmission agents. Firstly there are the houses from the different workers from the companies, usually in these cases, the contracted power is less than 10kW, and this means that the users can contract the tariffs 2.0A, 2.0DHA and 2.0DHS. The difference between them is the price of the access fee depending on the hours of the day. Then there are the companies where it is considered a contracted power higher than 15kW, this means the 3.0A contracted tariff.

3.1.2. The electric vehicles' implementation in Catalunya

The aim of this section is to briefly describe the strategies the government has followed during these years in order to promote the electrical vehicle, in this work the initiatives carried out in Catalonia are briefly described.

Firstly in 2010 the IVECAT ("Estratègia d'Impuls del Vehicle Elèctric a Catalunya") was approved, different targets were established within this agreement. The idea was to increase the electric vehicle fleet together with the development of a charging point network by establishing public charging points and also offering grants for the private ones. Moreover, this initiative proposed to adapt the current legislation so as to avoid possible barriers for the development of the EV, ensuring always the benefits for the environment (25). The final evaluation of that plan was defined as positive apart from the number of vehicles which were predicted by the end of 2015 (26)

After that plan, in 2012 the government approved the PECAC ("Pla d'energia i canvi climatic 2012-2020), where the energy policies proposed by the government are gathered. The aim was to achieve a progressive reduction of the consumption of fossil fuels during the period 2012-2020. That plan is referred to all the sectors, however, the transport sector takes and important role. There is an emphasis on the utilisation of the efficient, hybrid, electric and public vehicles and a strategy for the implementation of the electric vehicle is presented (27).

Carrying on with the idea to achieve that goals the government in 2016 approved the PIRVEC ("Pla d'Acció per al Desplegament d'Infraestructura de Recàrrega per als Vehicles Elèctrics 2016-2019"), this plan wants to make possible the cooperation between the public and the private sector so as to achieve the following objectives:

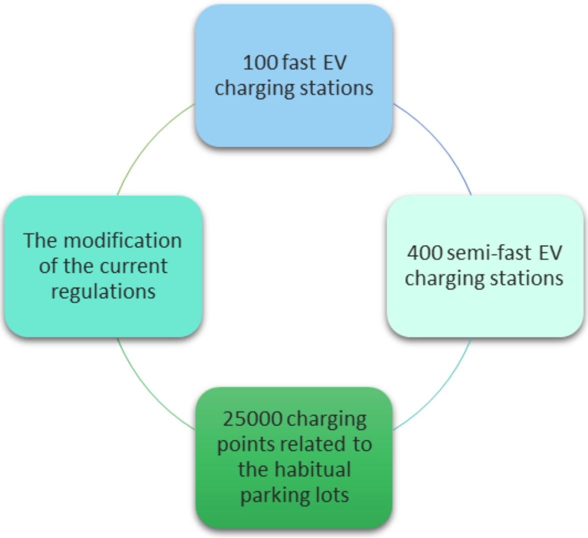

Figure 8: *PIRVEC objectives (28)*

Regarding the introduction of the electric vehicles within the buildings, the matter of this work, recently the European Union presented a new directive, the 2018/844. This one is focused on the buildings and it presents the necessary infrastructure for fomenting the e-mobility apart from other issues related to the energy consumption of the buildings.

The novelty this directive presents is the requirement of the member states to establish a minimum number of charging points at the non-residential buildings if these ones have more than a specific number of parking spaces. These requirements have to be accomplished before 2025 (29).

Regarding the situation in Catalonia, since June from 2015 the buildings of new construction have to include the necessary electrical infrastructure for the charge of the electric vehicles. This obligation is defined at the ITC-BT-52 and has to be applied to the new buildings with horizontal property. Moreover, it is also obligatory for the private sector, such as companies, cooperatives, offices… to have charging points for a percentage of the parking spaces in new buildings.

3.2. Presentation of the building

Before presenting the building, first it is interesting to explain the objective of that work. The aim as mentioned before is to design an energy management system for the building so as to charge and discharge the connected vehicles for optimizing its energy consumption. First an annual analysis is required in order to optimize the contracted power taking into account the charging and discharging processes it would have been. Once this term is defined, the idea is to forecast the energy consumption one day ahead so as to programme the charging and discharging processes for the following day, as the prices of the electricity are known one day in advanced.

Therefore, the historical data of the consumption of more than one year was needed, for that reason a building from the USA was chosen. It is a national laboratory and its consumption is an open source (30).

Some considerations are taken into account, first its localization as it is considered Catalunya and then the number of workers which own an electric vehicle. It has been considered that in this laboratory there are five chargers so five workers own an electric vehicle. Moreover, there is a turn of work for each worker and it is considered that these workers don't work during the weekend. Knowing this information it is interesting to know their daily routine in order to programme the charging and discharging processes, in the following section their routines are explained.

Regarding the consumption of the building, in the following graphic it is represented the consumption of a week from March. This consumption is without the introduction of the electric vehicle at the building:

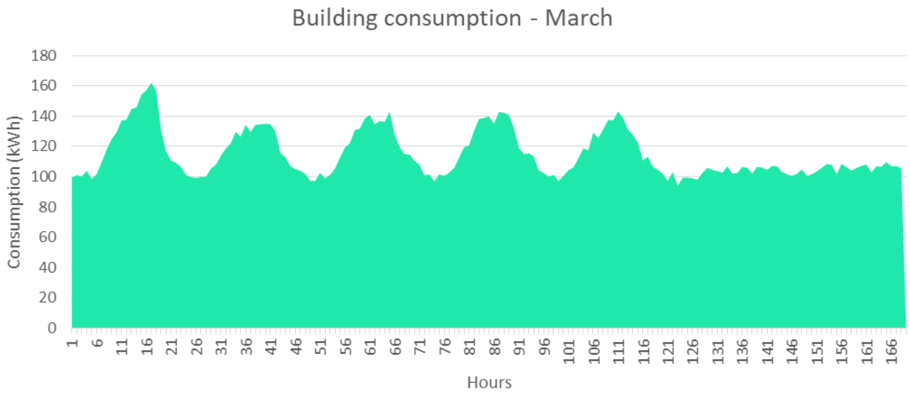

Figure 9: *Laboratory building consumption - March*

3.3. Routine's generation

The aim of this section is to briefly describe how the data of the routine of the workers has been obtained. This project has departed from the project *Tools for the assessment of business models around the exploitation of bidirectional electric vehicle chargers*, that project consisted on analysing the consumption from two different buildings where the workers from these two buildings had different routines. For that reason a Matlab software was created which creates the supposed routines of that workers. In this project this programme has been used for creating the routines of the laboratory workers.

As previously commented, in this building it has been considered that five workers have an electric vehicle, each of these workers has a different schedule and it is considered that on weekends they don't work.

The first step for obtaining that routine it is the specification of the necessary input data, which is (31):

- The number of workers for each turn.
- The schedule of each worker.
- The capacity of the vehicles' battery
- The consumption per km of the vehicles.
- The maximum charging/discharging power from the vehicles.
- The charger power of the houses.
- The maximum and minimum values of SOC for the vehicles.

In this work there has been considered only one type of electric vehicle, so all the characteristics mentioned above are the same ones for all the workers, that is the battery capacity, the discharging and charging power and the SOC.

Regarding the routine generated, the program works as follows. First, a routine for each day is made along a week, and this week is repeated along the year. This means that all the Mondays, for example, from a year have the same routine, it is not an unrealistic situation and it can be a good approximation as more or less the people tend to repeat the same activities along the days.

This routine has been done with Matlab and once it is executed it provides:

- A vector called availability which indicates with ones the hours when the worker is at the laboratory and zeros if he/she is not there.
- The data from the characteristics of the electric vehicles, as stated before all the workers have the same data as all vehicles have been considered equals.
- A vector called home that specifies with ones the hours when the worker is at home
- The consumption per hours of the electric vehicles from each worker, that is, when there are displacements, this is another vector called Vehicle Usage.

It has been considered the following schedules for the five workers:

Schedule

Worker 1	8h-16h
Worker 2	9h-19h
Worker 3	10h-18h
Worker 4	8h-18h
Worker 5	9h-18h

Table 4: *Worker's schedule*

Regarding the routine's generated by the Matlab programme only one day routine from two workers is represented in the following scheme.

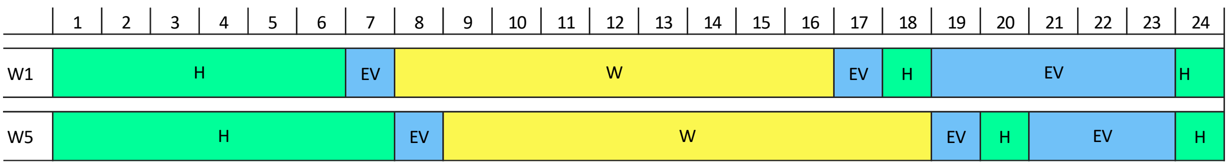

Figure 10: *Worker's routine (31)*

In that figure it is important to outline that the hours where it is specified EV, it doesn't mean that during these hours the vehicle is consuming, it means that the worker is out of home and work and in some hours there is consumption from the EV.

3.4. Vehicle's characteristics

The chosen vehicle for this work is the Renault Zoe. It has been chosen this vehicle as it is an affordable one. There are different versions of that vehicle, the chosen one is the version Q90. It presents a battery capacity of 41kWh and its technology is lithium-ion, regarding the consumption this car consumes 133Wh/km as average (32). This value is the one considered in this work, regardless of the km driven by the workers the considered consumption is the 133Wh per km.

Another important data are the periods of charging, there are different timings depending on the type of borne, for a borne of 16A (3.7kW) 15h and 30min are needed, whereas with a borne of 63A (43kW), the maximum, 65min are needed (32).

In the following table there is a summary of the most relevant data:

RENAULT ZOE	
BATTERY	
Useful Capacity (kWh)	41
Technology	Lithium-ion
Voltage	400
Number of modules/cells	12/192
Weight	305
CONSUMPTION	
Normalized consumption (Wh/km)	133

Table 5: *Renault ZOE battery characteristics (32)*

3.5. Optimization problem – Mathematical formulation

In this section, the used optimization algorithm for the analysis of the annual consumption of the building is described. This optimization problem has departed from (31) and some modifications have been introduced during this work. The main objective is to minimize the total cost which is composed by the electricity bill, from the building and the houses from the users and the penalization for discharging the batteries, so as to obtain the supposed charging and discharging processes it would have been. With all this information it is possible to determine the optimal contracted power.

Together with that minimization some technical restrictions are also implemented. The different hypothesis considered in this work have been explained during the previous sections, such as the fact that the workers have always the same routine, the consumption of the vehicles is always the same for each km done….

First it has been established the number of EVs which is the same as the number of workers, then the time periods are defined from t1 to t8760, which corresponds to the hours of a year, the time period studied in this work. Then, also the sets from the building, the price and consumption, are defined together with the characteristics of the EVs.

Once the sets are defined, the data obtained from the routine's generation from the Matlab software (31) is defined in the program as parameters. The vectors obtained in the previous sections, the availability at home and in the building are defined, together with the electricity price and the hourly consumption of the building of study. Moreover, the vector of usage of the EVs is also defined, and finally the characteristics of the electric vehicles, as previously commented, in this work it has been taken into account the hypothesis that all the workers have the same model of vehicle.

Then the scalar values are also introduced, in the previous sections all these values have been defined, such as the costs of the access fees of the different tariffs…

The next step is the definition of the variables. On the one hand there is the free variable which is the total cost of the system, then the positive variables, such as the charging rate of each EV at each hour, the hourly energy consumption of the building from the network, the state of charge of the batteries from each vehicle and each hour, among others. On the other hand, there are the binary variables, in this study it has been defined an indicator which defines if the EV at each time it is charging or discharging. If this indicator is 1 it means that the EV is charging and 0 if it is discharging. Some variables only depend on time and others depend on the time and each vehicle.

Then, the objective function and the different constraints are introduced.

3.5.1. Objective function

In the first equation the objective function is assessed.

$$\begin{aligned}\mathrm{Cost} = &\sum_{t=1}^{T}\left(\mathrm{M\_DAM}_t \cdot (\mathrm{price}_t + \mathrm{fee}_{eb})\right) + \mathrm{P}_{con} \cdot \mathrm{fee}_{pb} \\ &+ \sum_{t=1}^{T}\sum_{n=1}^{N} \mathrm{frac\_bat\_degrad}_{n,t} \cdot \mathrm{V} + \sum_{t=1}^{T}\left(\mathrm{c\_tot\_h}_t \cdot (\mathrm{price}_t + \mathrm{fee}_{eh})\right)\end{aligned} \tag{1}$$

As it is observed in the equation, this one is composed mainly in two parts. Firstly, the cost associated to the building is defined, and then the cost which corresponds to the users. Analysing the cost assumed by the laboratory, three main parts are identified.

- The electricity cost of the building, which corresponds to the first part of the equation. The hourly energy consumed by the building from the network is multiplied by the electricity cost and the energy access fee.

  $$\sum_{t=1}^{T}\left(\mathrm{M\_DAM_t} \cdot (\mathrm{price_t} + \mathrm{fee_{eb}})\right)$$

  Where:
  - M_DAM_t: is the building energy consumed from the grid [kWh].
  - $Price_t$: is the cost of electricity for the building in the DAM at time t [€/kWh].
  - $Feee_b$: is the energy access fee of the building [€/kWh].

- The cost related to the contracted power, which corresponds to the multiplication of the power with the power access fee.

  $$\mathrm{P_{con}} \cdot \mathrm{fee_{pb}}$$

  Where:
  - P_{con}: is the contracted power [kW]
  - Fee_{pb}: is the power access fee of the building [€/kW]

- The degradation cost of the batteries due to the discharging processes. This cost corresponds to the multiplication of the fractional battery degradation with the lifetime value of the battery.

  $$\sum_{t=1}^{T}\sum_{n=1}^{N}\mathrm{frac\_bat\_degrad}_{n,\mathrm{t}} \cdot \mathrm{V}$$

  Where:
  - $Frac\_bat\_degrad_{ev,t}$: is the fractional battery degradation.
  - V: is the lifetime value of the battery [€].

Then, the final part of the objective function, corresponds to the cost the user of the electric vehicle has to assume when he/she is charging its vehicle at home.

$$\sum_{t=1}^{T}\left(\mathrm{c_{tot_{h_{\mathit{t}}}}} \cdot (\mathrm{price_t} + \mathrm{fee_{eh}})\right)$$

Where:

- $C\_tot\_h_t$: Corresponds to the total energy charged at the different homes from all workers for each time t [kWh].
- $Price_t$: is the cost of electricity for the houses in the DAM at time t [€/kWh].
- Fee_{eh}: is the energy access fee [€/kWh].

3.5.2. Restrictions and definitions

The next equations, after defining the objective function, correspond to the restrictions and also the definitions of the different variables of the problem.

Energy building

Equation (2) establishes the energy consumed in the building from the network at each time t, the equation is:

$$\mathrm{M\_DAM_t} = \mathrm{B\_cons_t} + \mathrm{c\_tot\_b_t} - \mathrm{d\_tot\_b_t} \qquad (2)$$

Where:

- B_cons_t: is the building load [kWh]
- $c\_tot\_b_t$: is the total energy charged by the electric vehicles in the building at time t [kWh]
- $d\_tot\_b_t$: is the total energy discharged by the electric vehicles in the building at time t [kWh]

This equations establishes that the energy consumed from the network has to be equal to the load of the building, plus the energy used for charging the batteries minus the energy discharged from the batteries.

In this project it has been assumed the hypothesis that it cannot be energy sold to the grid, for that reason equation (3), establishes that restriction:

$$\mathrm{B_{cons_t}} \geq \mathrm{d\_tot\_b_t} \qquad (3)$$

The building load has to be greater than the energy discharged from the electric vehicles.

Continuing with the restrictions the building consumption has to accomplish, all the supply points connected to the distribution network have to accomplish that the contracted power has to be lower than the consumption peaks it can be during the hours. In some tariffs, it is allowed to surpass it, as then it will be economical penalizations at the bill. In this work this option has not been taken into account, for that reason, the contracted power has to be lower than the energy consumed at each hour:

$$P_{con} \geq M\_DAM_t \tag{4}$$

Charging and discharging processes, at work and at home

The following equations are the ones which establish the charging and discharging processes of the electric vehicles.

Equation (5) defines the energy charged to each vehicle at each time t, when these ones are parked at the company building. In order to accomplish that situation, the car has to be at the company in order to be charged. Moreover, the energy charged each hour has to be lower than the maximum power the EV can bear. Therefore, the equation is:

$$c\_n\_t_{n,t} \leq cd\_n\_t_{n,t} \cdot Av_{n,t} \cdot C\_n\_max_n \tag{5}$$

Where:

- $c\_n\_t_{n,t}$: is the energy charged at each vehicle at each hour in the company building [kWh]
- $cd\_n\_t_{n,t}$: is a binary variable mentioned at the beginning of this section. It establishes a 1 if the battery is charging and 0 if it is discharging.
- $Av_{n,t}$: corresponds to the vector availability, obtained from the routine's generation. It is also a binary parameter, it is 1 when the car is parked at the building and 0 if it is not.
- $C\_n\_max_n$: is the maximum power the electric car can bear when it is connected to the charging station [kW].

Equation (6) corresponds to the contrary situation, when the battery from the electric car is discharged at the building. The equation is:

$$d\_n\_t_{n,t} \leq (1 - cd\_n\_t_{n,t}) \cdot Av_{n,t} \cdot D\_n\_max_n \tag{6}$$

Where:

- $d\_n\_t_{n,t}$: is the energy discharged to the building from each electric vehicle at each time period [kWh]
- $D\_n\_max_n$: is the maximum power the electric vehicle can bear when the battery is discharged [kW], it is the same value as $C\_n\_max_n$.

Comparing both equations, in that case if the EV is being discharged, it means that $cd\_n\_t_{n,t}$ has to be 0, but $Av_{n,t}$ has to be 1, as the EV is parked within the building.

Equation (5) and (6) define the charging and discharging processes only when the electric vehicle is parked at the laboratory. For that reason, another equation is needed for defining the charging periods of the EVs when they are parked at their respective houses. This situation is defined in equation (7).

$$c\_n\_t\_h_{n,t} \leq H_{n,t} \cdot C\_n\_max_n \tag{7}$$

Where:

- $H_{n,t}$: corresponds to the vector home, obtained from the routine's generation. It is also a binary parameter, it is 1 when the car is parked at home and 0 if it is not.

As observed in the objective function, this one is calculated with the total values of the charging and discharging processes, so the following equations, (8), (9) and (10) determine the total energy that it is charged and discharged each hour, at the building and at the different houses.

$$c\_tot\_b_t = \sum_{n=1}^{N} c\_n\_t_{n,t} \tag{8}$$

$$d\_tot\_b_t = \sum_{n=1}^{N} d\_n\_t_{n,t} \tag{9}$$

These two equations determine the total energy that it is charged and discharged at the laboratory building for each hour.

$$c\_tot\_h_t = \sum_{n=1}^{N} c\_n\_t\_h_{n,t} \tag{10}$$

Finally, equation (10) determines the total energy charged by the electric vehicles at their respective houses each hour.

Another important factor related to the charging and discharging processes from the electric vehicles is the limitation of these processes due to the maximum power the charging stations can support. For that reason, there are three more restrictions for the periods in which the batteries are being charged or discharged.

In equation (11) and (12) it is established that the energy charged and the energy discharged at each hour has to be lower than the maximum power of the charging station.

$$c\_n\_t_{n,t} \leq c\_b\_max \tag{11}$$

$$d\_n\_t_{n,t} \leq d\_b\_max \tag{12}$$

Where:

- c_b_max: is the maximum power supported by the charging station from the building, when charging [kW].
- d_b_max: is the maximum power supported by the charging station from the building, when

discharging, this value is the same as c_b_max [kW].

The same restriction is applied to the charging stations from the different houses, in equation (13).

$$\mathrm{c\_n\_t\_h}_{\mathrm{n,t}} \leq \mathrm{c\_h\_max} \tag{13}$$

Where:

- c_h_max: is the maximum power supported by the charging station from the houses, when charging [kW].

The battery degradation

As it is known the batteries from the electric vehicles have a limited life, several researches are underway in order to model and predict the lifetime degradation and the behaviour of the BEV batteries. For that reason, in this study it has been necessary to penalize in a way the moments in which the batteries from the electric vehicles are being discharged. Therefore, a cost has been added to the objective function related to the discharging processes, this one has been defined at the beginning of the section as the multiplication of the fractional life utilization of a battery and the battery value (33)

The fractional life utilization of the battery is defined in equation (14), it has been extracted from (33), and it establishes the fraction of degradation fixed per kWh.

$$\mathrm{frac\_bat\_degrad}_{\mathrm{n,t}} = \frac{\mathrm{d\_n\_t}_{\mathrm{n,t}}}{\mathrm{CL}_{\mathrm{nom}} \cdot \mathrm{DoD} \cdot 2 \cdot \mathrm{B\_n}} \tag{14}$$

Where:

- CLnom: is the nominal cycle life from the batteries.
- DoD: is the nominal depth of discharge [%].
- B_n: is the nominal capacity of the battery.

State of charge of the batteries

The last equations for define are the ones related to the state of charge of the vehicles. In this work it has been assumed the fact that during all the day the state of charge of the batteries is known for each hour. The two first restrictions to take into account are, the state of charge has to be lower than the maximum value and higher than the minimum, these two restrictions are defined in equation (15).

$$\mathrm{SOC\_n\_min} \leq \mathrm{SOC\_n\_t}_{\mathrm{n,t}} \leq \mathrm{SOC\_n\_max} \tag{15}$$

Where:

- SOC_n_min: is the minimum SOC of the battery.
- SOC_n_max: is the maximum SOC of the battery.
- SOC_n_$t_{n,t}$: is the SOC of the battery at each hour and from each vehicle.

The next restriction needed to accomplish is the fact that, the SOC at time "t" has to be equal to the SOC at time "t-1" plus the energy which can be charged at time "t", at the building or at their respective houses, minus the energy that it can be discharged at time "t" and minus the energy consumed at time "t", due to a displacement for example. That is for t>1, and this condition is defined in equation (16).

$$\mathrm{SOC\_n\_t}_{\mathrm{n,t}} = \mathrm{SOC\_n\_t}_{\mathrm{n,t-1}} + \left(\frac{\mathrm{c\_n\_t}_{\mathrm{n,t}} \cdot \eta_{bc} + \mathrm{c\_n\_t\_h}_{\mathrm{n,t}} \cdot \eta_{hc} - \frac{\mathrm{d\_n\_t}_{\mathrm{n,t}}}{\eta_{bd}} - US_{n,t}}{\mathrm{B\_n}} \right) \qquad (16)$$

Where:

- η_{bc}: is the charging efficiency of the bidirectional charging station from the building.
- η_{bd}: is the discharging efficiency of the bidirectional charging station from the building.
- η_{ch}: is the charging efficiency of the unidirectional charging station from the houses.
- $US_{n,t}$: is the vector obtained from the routine's generation programme, where it is specified in each hour the consumption of each vehicle [kWh].

These are the equations used in the optimization problem. Once this is executed the program provides the time periods when the vehicles it would have been charged or discharged and the optimal contracted power for the building.

4. Study case and results discussion

The aim of this section is to demonstrate how the energy management system proposed in this study works, in the following figure a scheme is represented in order to understand it better:

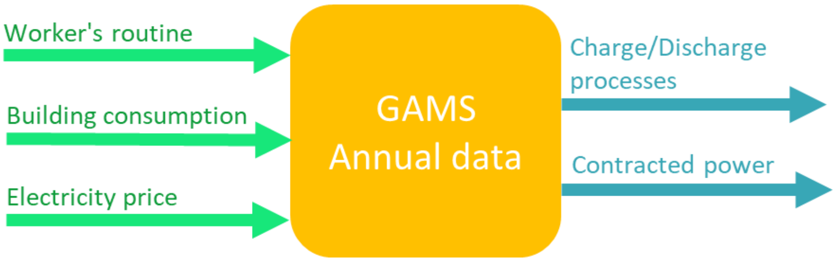

Figure 11: *Study case scheme – Annual analysis*

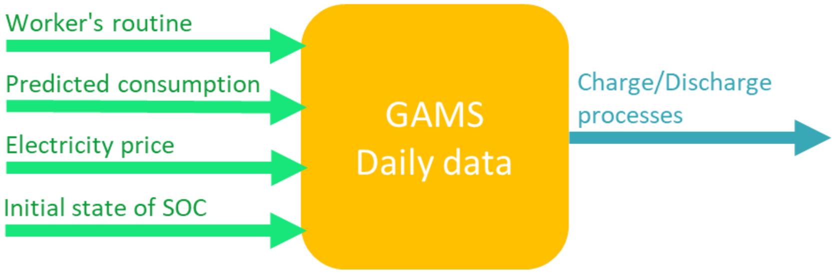

Figure 12: *Study case scheme – Daily analysis*

Firstly, the data obtained from the mathematical model described in the previous section is presented, which corresponds to the Annual analysis, Figure 11. Using the mathematical model described in the previous section the overall consumption of the building is presented considering the charging and discharging periods from the electric vehicles. Then this charging and discharging processes are also presented together with the state of charge of the electric vehicles. All these mentioned data is represented in weekly periods as it is not visual if all the annual data is represented. And finally the obtained contracted power is obtained.

In Table 1 in the Annex the input data used in the optimization problem is summarized.

In the next two sections the daily analysis is presented, Figure 12. First the method used for predicting the consumption of the building is determined. Once this one is obtained the optimization problem described in the previous section is modified because in this part of that study the problem works with only 24h and it takes into account the last state of charge of the EVs. With all that, the forecasting of the charging and discharging processes of the batteries, so the complete consumption of the building, is obtained.

4.1. Annual analysis

As it has been commented along the different sections of this work, it has been considered that in this building there are five workers who own an electric vehicle, and each worker has a different schedule, this means its personal routine. In the section where the consumption of the building was presented, Figure 9, the consumption was without the introduction of the EVs. In the following graphic the consumption of the building during two weeks of July is represented with the introduction of the electric vehicles.

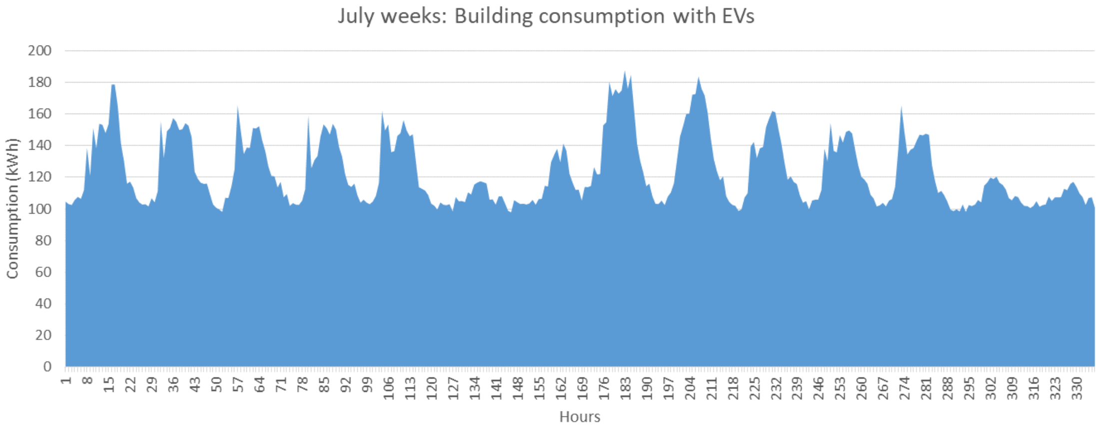

Figure 13: *Building consumption with EVs*

Two more graphics from the year have been analysed, one from March and other from December, these graphics are represented in the Annex. As it is observed the consumption of the building remains similar during the year, following more or less the same routine. However, the introduction of the EV causes significant variations along the year. Comparing the consumption from July and from March it is appreciated that in March the picks of consumption are more significant.

Another important aspect from this study are the charging and discharging periods from the batteries of the electric vehicles, the optimization problem provides the hours when the vehicles of the workers are being charged or discharged depending on the situations. Firstly, the charging processes are represented. There has been analysed also three periods of time from the year, in the following graphic a week from July is represented. The others, from March and December, are in the Annex.

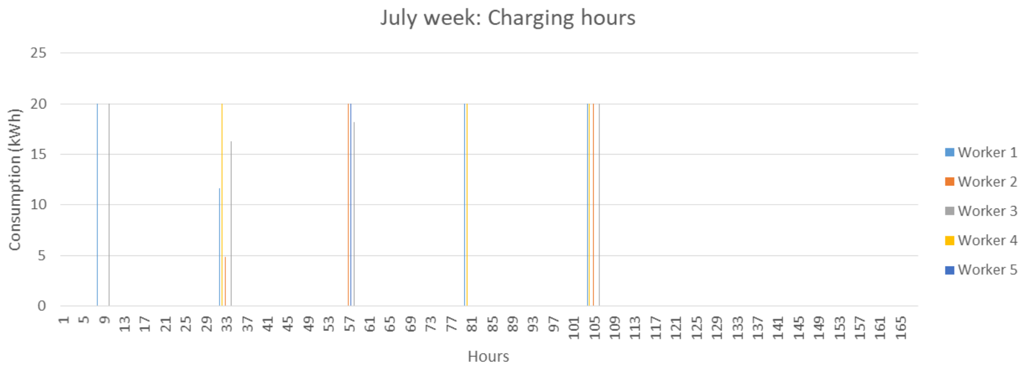

Figure 14: *Charging hours of the workers EVs*

As it is appreciated, the workers during the year take advantage of the possibility of charging its electric vehicles at the building as it is observed in this graphic and the ones from the Annex, although the workers follow the same routine during each week of the year, the charging periods are not repeated all along the year.

In this study the possibility of charging the electric vehicles at their respective houses is also included. However, the result obtained is that there wouldn't have been charging processes at the different houses.

Regarding the discharging periods, this situation is less usual in this scenario due to the penalization for discharging the batteries explained in Section 3.5.2. The same procedure has been followed for analysing the discharging periods. And the result obtained is that there are only discharging processes on December as shown in the following graphic:

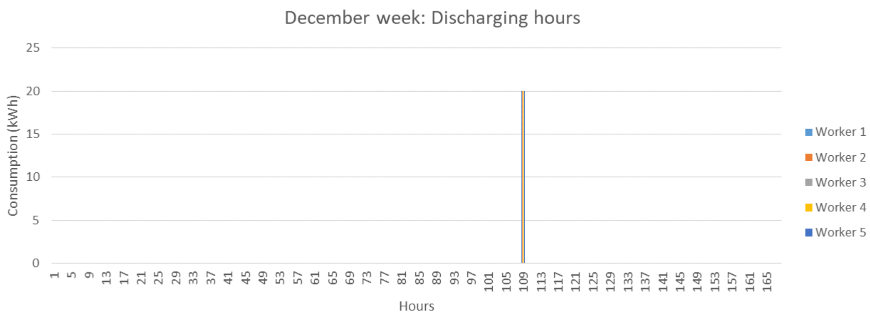

Figure 15: *Discharging hours of the workers EVs*

Therefore, knowing the charging and discharging periods and the consumption of the electric vehicles, the programme also provides the SOC of each vehicle from each worker, in this work it is also represented the SOC from worker 1 during a week of July in the following graphic.

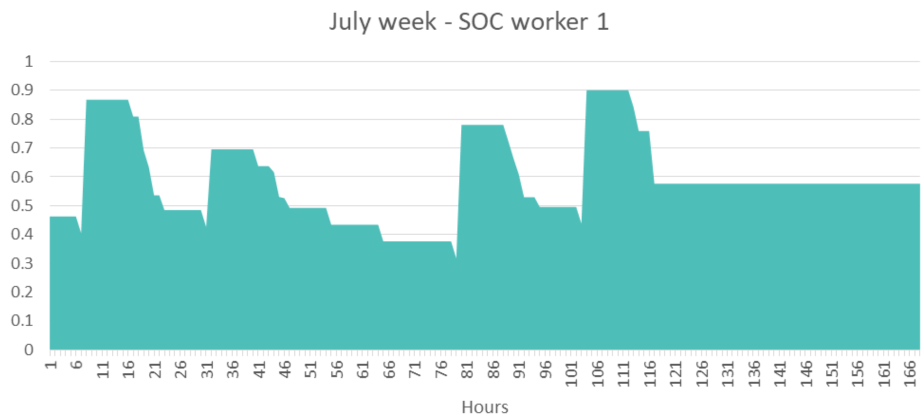

Figure 16: *SOC worker 1*

Comparing it with the Figure 14**:** Charging hours of the workers EVs it is possible to verify the charging hours of the electric vehicle.

One of the aim of this work is to do this annual analysis in order to optimize the contracted power, in this case the result obtained is 419.46 kW, as it is the maximum pic during the whole year. In this study there has not been considered penalizations in this term, but a future improvement would be its introduction, as the contracted power would have been more optimized.

4.2. Machine learning application for the daily consumption

Once the annual analysis is done, the next step is to work with the daily data, here is where the machine learning methods are analysed in order to obtain the suitable one for this case of study. Before this analysis first it is interesting to see why these predictive models are taken an important role in these times.

As it has been described in the state of the art of this project, the replacement of the diesel, so the substitution of the petrol cars by electric vehicles within a period of time, has raised the necessity to ensure that the buildings, principally from the tertiary sector, can deal with this increase of the electricity demand without being prejudicial for them.

For that reason, once the electric vehicles are integrated within the building, it is necessary a management system so as to avoid the large load increase and also be capable to predict it. For achieving these goals the design of an appropriate infrastructure is a must. As observed during this work, with the optimization problem the system is capable to distribute the charging periods in order to reduce the final electricity bill together with the reduction of the peak power demand.

A part from that, a predictive model it is also needed, an important part of the buildings from the tertiary sector have a large consumption, and if this one is not well predicted, it may arise important disturbances in the network that can be translated into considerable penalizations in the final electricity bill.

Currently, here in Spain with the IET/290/2012, all the old meters are being changed with the new intelligent ones, at the end of this year all the meters have to be changed. The advantage of this new implementation is that the consumption is registered hourly, so big amounts of data will be generated, as it has been done with the optimization problem from the previous section. With the hourly consumption it is easier to create profiles of consumption and easier to make estimations of the future consumption. However, the processing of such amounts of data is a difficult task. For that reason, the machine learning techniques have increased considerably during the last years.

The aim of this section is to use these techniques in order to manipulate and to study all the data obtained in the previous section. The idea is that, with the historical data, the price of the electricity… establish a model that can be capable to predict the consumption of the building for a specific day of the year.

In order to achieve that goal it has been used the data science software RapidMiner. This software provides template-based frameworks which avoid the necessity of writing code, it results more intuitive and easier to learn. The programme permits to load the data, transform it, visualize it and do the necessary analysis in an intuitive way. It provides a GUI for designing and executing the workflows, or as it is known in the program, the processes. These processes are available within the programme as blocks and it is not necessary to write any code, as shown in the following picture:

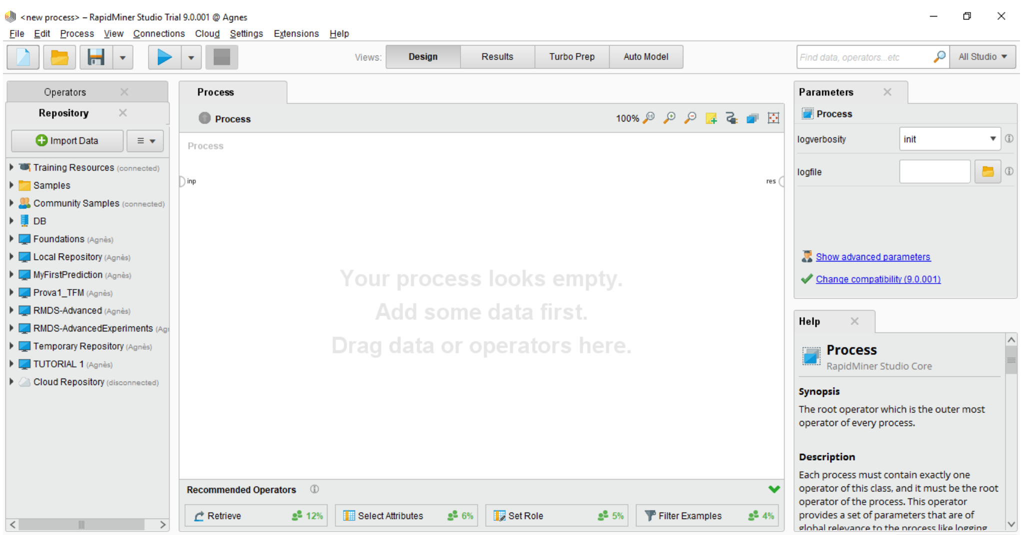

Figure 17: *Graphical user interface RapidMiner.*

The first step in order to create the model for forecasting the consumption, is the preparation of the data we want to use. That is so important, as the quantity and the quality of the chosen data will determine on how good the predictive model would be. The data used in this project is the historical hourly consumption and the historical hourly temperature of that zone. Therefore, a matrix with the following information has been gathered:

- The day of the week (Monday, Tuesday…).
- The number of the day.
- The number of the month.
- The number of the year.
- The different hours.
- The hourly temperature.
- The hourly consumption of the building (historical data).

This is the data which is supposed to know in advance for forecasting the consumption which will be used in the optimization problem for forecasting the charging and discharging periods. In order to do the prediction of a specific day, it is necessary to have all the data, except from the consumption. Therefore, one day of the consumption has been omitted as it is the day which is going to be predicted, so the programme is going to be trained with the rest of the data. Once the prediction is done, this can be compared with the real data the following day, when the real consumption of the building is going to be known.

In this building the 09/01/2015 is the day that is going to be predicted. So, in the dataset commented above the consumption of this day has been deleted.

The following step is the preparation of the training data, once this one is gathered sometimes this one needs some adjusting or manipulation, such as normalization, in this case. Observing the data set from this work, if these examples are plotted, which sometimes is done for pattern recognition, what it is obtained is the following graphic.

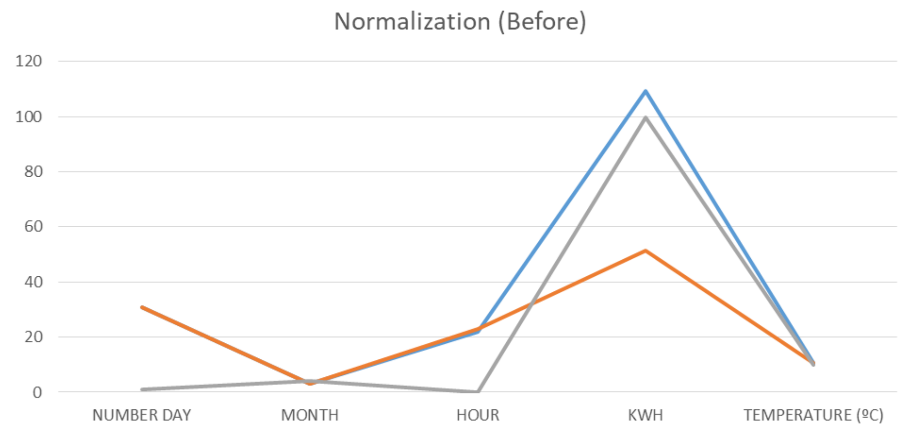

Figure 18: *Normalization (Before)*

The problem, observed in the graphic, is that if all the data is represented in the same y scale, then the consumption is the one that dominates because is the one that has the large value, it is not possible to determine how affect and what is going on with the rest of the data set. In order to deal with this issue normalization has been applied to the data set, with this procedure all the attributes are normalized to the same y scale, and the distortion within the model is avoided.

The normalization method recommended by the programme is the Z-transformation, the calculation it does with the data set is, first it determines the average and it subtract it, then it divides by the standard deviation. Therefore, the mean value gets 0 with a standard deviation of 1. Analysing the values obtained, it is possible to determine that the negative values are under the average and the positive ones above the average. So the magnitudes are scaled by the standard deviation, as shown in the following graphic:

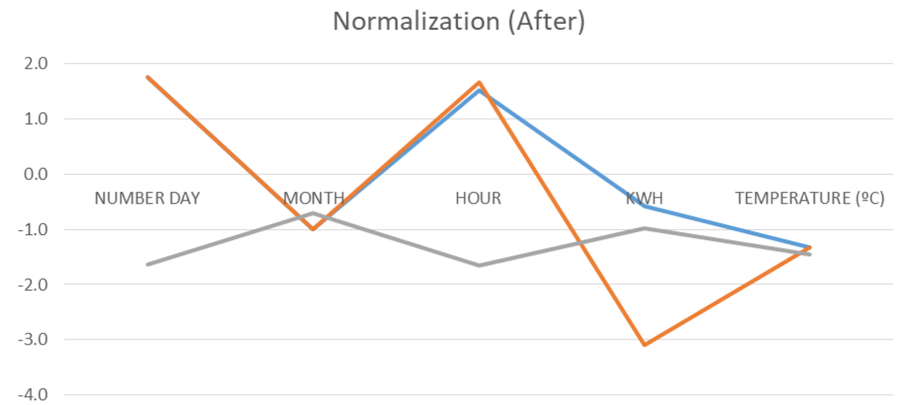

Figure 19: *Normalization (After)*

The next step in the workflow is choosing the model. In this study four models have been analysed in order to see which one is the most suitable, these ones are:

- The Generalized Linear Model
- Deep Learning
- Random Forest
- Gradient Boosted Trees

These models are techniques used in regression problems, in this section these ones are not deeply described as their description is able at the section of the state of the art.

Therefore, the next step has been the training of the model with the historical data, before 09/01/2015, and the prediction of the consumption.

However, before continuing it is necessary to define in a few words the indicator used in this work for analysing which method is the suitable one, this indicator is the Root Mean Square Error (RMSE). This indicator is a statistical calculation used for determining the differences between the predicted values from a model and the current values, in this study the data from the dataset. If this value is large it means that the model is not so accurate.

This measure is defined as the square root of the mean squared error (15):

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{T}\left(x_{\mathrm{observ}_t} - x_{\mathrm{model}_t}\right)^2}{T}} \qquad (17)$$

As previously commented, there has been added to the dataset the historical hourly temperature from San Francisco where the building is located. Although it is considered that it is located in Catalonia, is more accurate if the temperature from there is used for the prediction (34), as usually the temperature is related to the consumption. In the following graphic the temperature registration, only from a week of March, is represented:

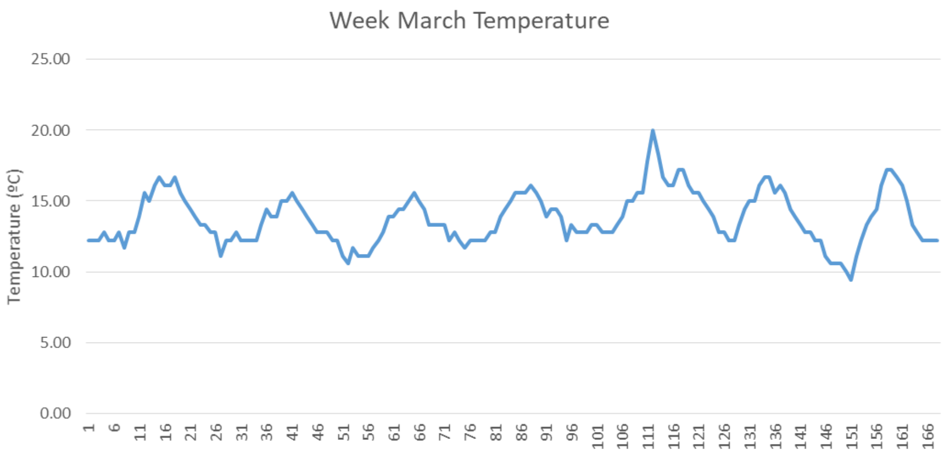

Figure 20: *March Temperature*

Therefore, with these modifications the models have been done. In that case the results are graphically shown for each of the studied model.

However, first the Root Mean Square Error is presented for each of the studied techniques:

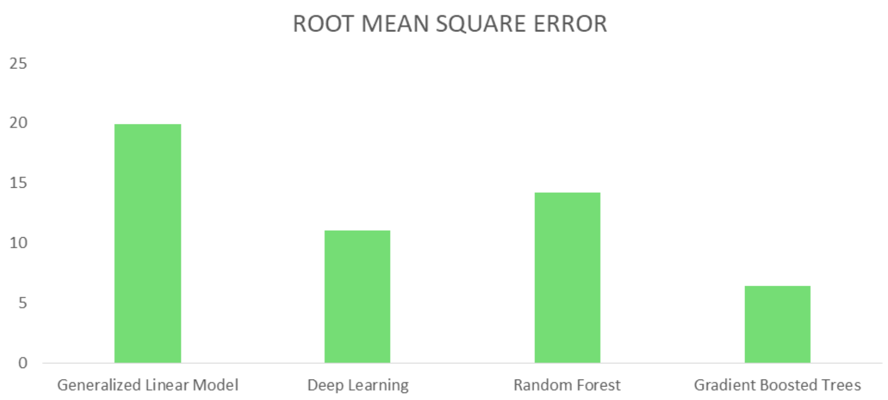

Figure 21: *RMSE*

As it is appreciated in the graphic the Generalized Linear model and the Random Forest model have a worse result in comparison with the other ones, so probably, these two models are not the suitable ones for the problem studied in this project. Regarding the Deep Learning and the Gradient Boosted Trees a better result has been obtained.

In order to make these results more visual, in the following sections each of the solutions obtained in each model are represented.

4.2.1. Generalized Linear Model

Regarding the Generalized Linear Model, this technique has been the less accurate one, as observed in the previous section. In order to confirm the commented results above, in the following graphic the consumption predicted and the real consumption of the 09/01/2015 are graphed.

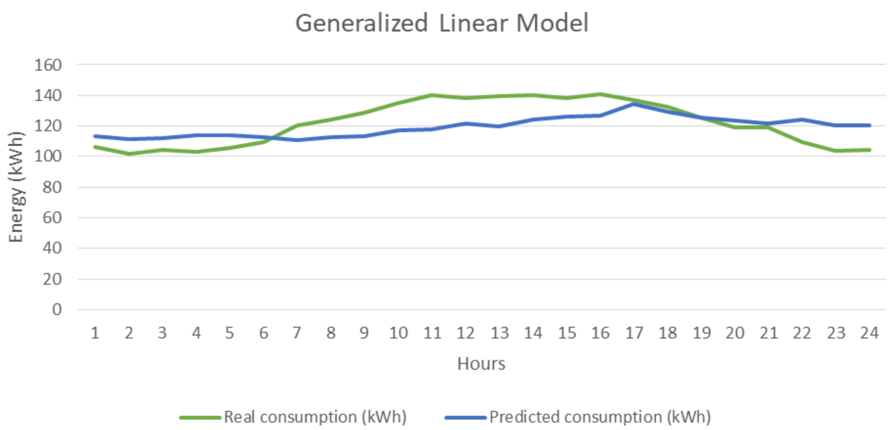

Figure 22: *Generalized Linear Model*

As it is appreciated in the graphic, in effect, the prediction of the energy consumption is significantly different from the real one. It couldn't be used in a real case as it would cause significant penalization in the electricity bill due to the deviations and the charging and discharging processes wouldn't be well optimized.

4.2.2. Deep Learning

The Deep Learning technique is the second model studied in this project. As it has been observed in Figure 21: RMSE is the second model which its prediction is the more accurate.

In order to observe the prediction done by this model and compare it with the real consumption, in the following graphic the two curves are represented:

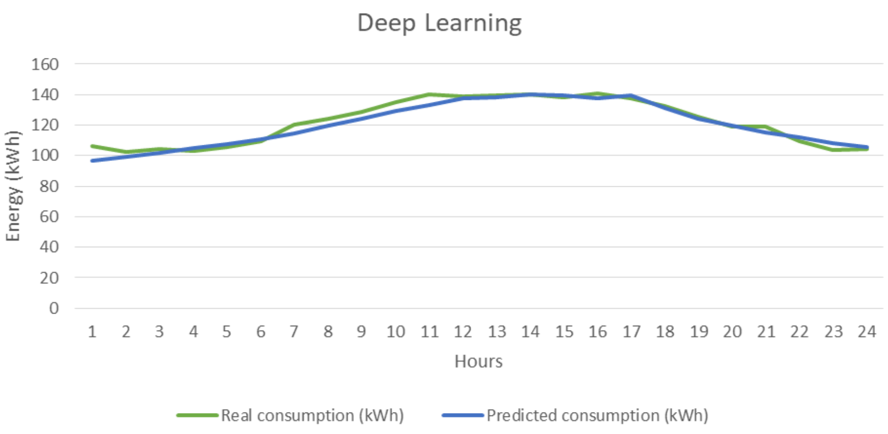

Figure 23: *Deep Learning Model*

As it is appreciated, effectively, this method is more suitable than the previous one, as it is appreciated in the graphic the predicted consumption is more adjusted to the real one. It would be a better model in a real world case as demonstrated in the RMSE and the graphic of consumption.

4.2.3. Random forest

The next analysed technique is the Random Forest model. As observed previously, this technique presents the second highest value of RMSE comparing with the other models, so it is not the suitable one. In the following graphic it is also concluded that supposition.

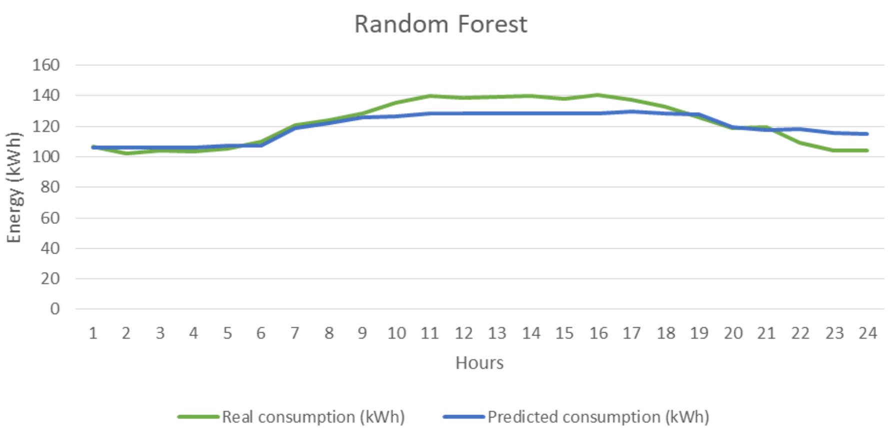

Figure 24: *Random Forest Model*

As it is observed in the graphic, the predicted consumption varies significantly from the real one.

4.2.4. Gradient Boosted Trees

The final analysed technique is the Gradient Boosted Trees, as it is appreciated in Figure 21: RMSE is the model which has the lower RMSE. In the following graphic it is demonstrated that it is the most suitable model due to the low error obtained.

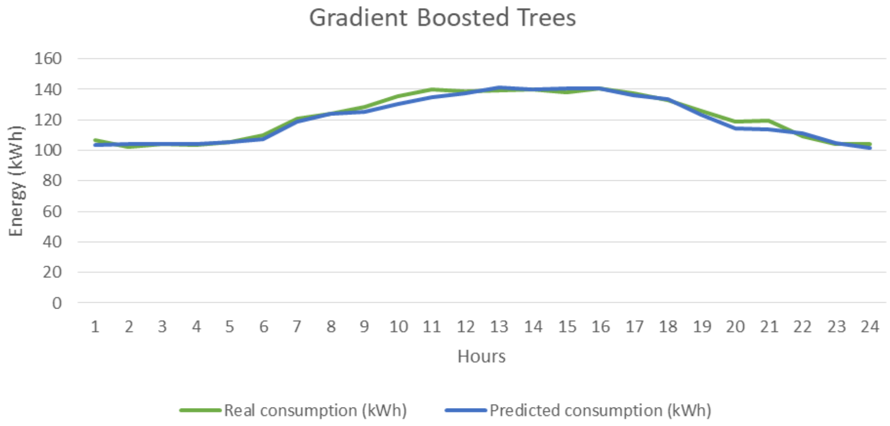

Figure 25: *Gradient Boosted Trees Model*

As it is appreciated is the model which has provided the most accurate prediction, therefore, it would be the chosen model in a real world case. So in the following section, the daily optimization of the charging and discharging processes, this model is the one used in order to programme these daily processes.

4.3. Daily analysis

As it has been observed during this work this energy management system consists principally on three parts. First, an annual analysis is required, taking into account the consumption of the building an optimization problem has been presented in order to optimize the charging and discharging processes of the electric batteries that it would have been during the year 2014 so as to obtain an optimal power to be contracted. The second part, has been the selection of the model which will be used in this section for doing the daily predictions of the consumption of the building, the suitable one has been the Gradient Boosted Trees Model.

Therefore, with these two completed parts the next step has been the modification of the optimization problem so as to work with only daily data.

In order to make it more comprehensive the Figure 12 is repeated in this section:

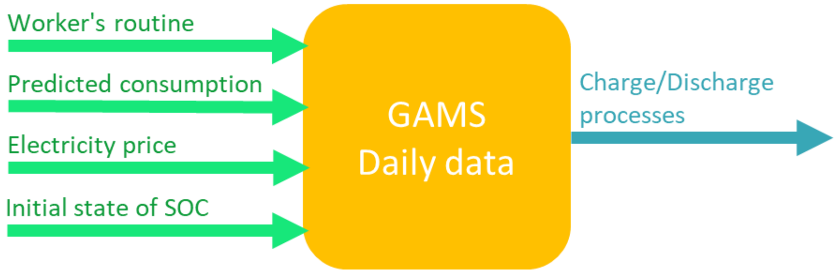

Figure 12: Study case scheme – Daily analysis

As it is appreciated, in this case the input data changes a bit. Regarding the worker's routine the same vectors explained in the previous sections are required, the difference is that in this case there is only needed the data from a day and not a year, the same with the electricity price.

What changes a bit is the consumption, in this case this programme doesn't work with the real data, it works with the predicted consumption done the day before so as to programme one day in advanced the charging and discharging processes of the batteries. However, in order to do it correctly the state of charge of the different batteries from the last hour of the day before is also needed, in this programme instead of starting taking into account that the battery is charged, it starts considering the last value obtained of the SOC.

In this section the day 09/01/15 is the one which will be predicted, as it is the example used in the previous sections, so first the predicted consumption without the electric vehicles is presented in the following graphic, the one obtained in the previous section:

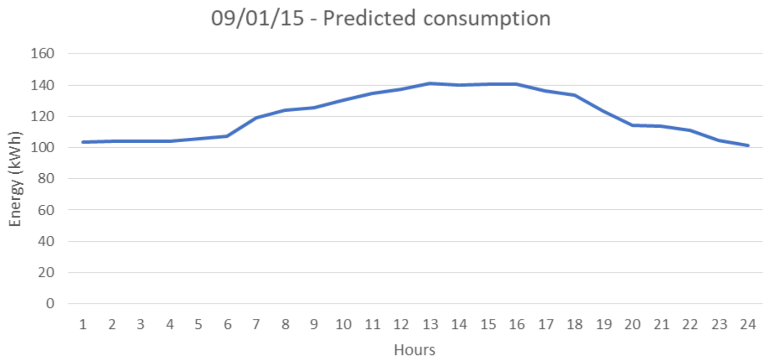

Figure 26: *Predicted consumption 09/01/15*

The value obtained of the SOC from the previous day is 0.3 for the five workers, and considering the routines described in the previous sections the results obtained for that day are represented in the following graphics.

First it is interesting to analyse the final consumption of the building, so considering the impact of the electric vehicles:

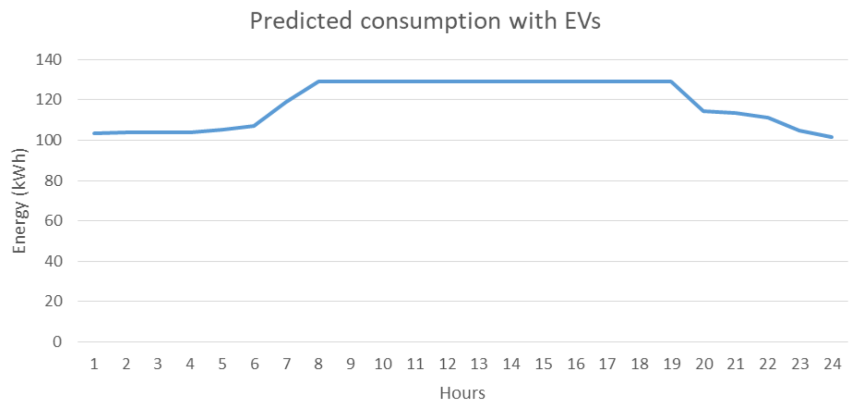

Figure 27: *Predicted consumption with EVs*

As it is appreciated in this figure if the optimization problem is done daily, more discharging periods appear if it is compared with the previous figure, during the hours when the workers are at the building the consumption has reduced a bit.

The next figure to analyse are the charging periods, in the following graphic there are represented the hours when each car is charged at the building, as observed only two workers during this day would charge their vehicles:

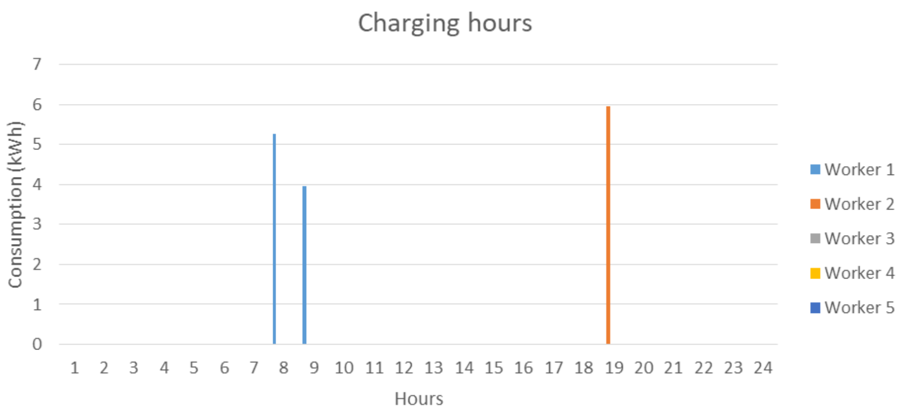

Figure 28: *Charging hours*

Regarding the charging hours at the different houses of the workers, as it is appreciated in the graphic, because of the state of charge of the different vehicles starts at 0.3, the workers need to charge their vehicles at home before going to work:

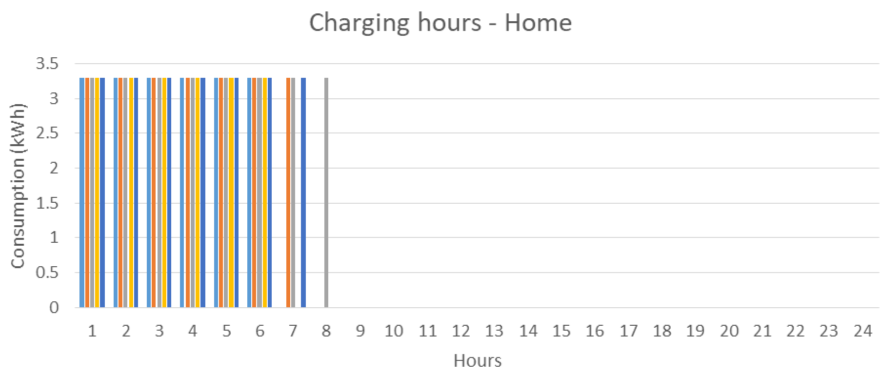

Figure 29: *Charging hours - Home*

Then there are the discharging periods in the following graphic, these ones are represented for each vehicle.

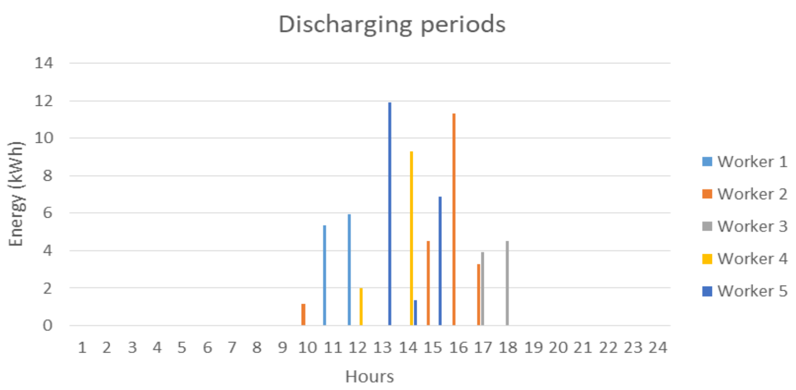

Figure 30: *Discharging hours*

As it is not usual to observe discharging processes due to the added penalization, it is interesting to see the curve of the electricity price:

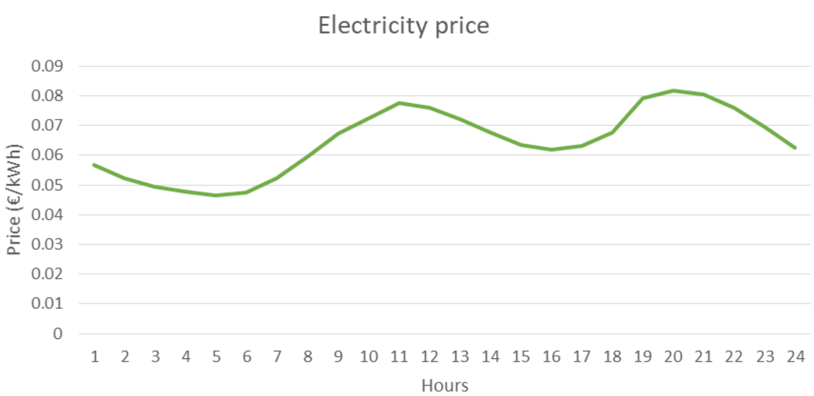

Figure 31: *Electricity price*

Observing this graphic and the graphic of the consumption of the building the discharging processes correspond to the hours when there is more consumption and the price of the electricity is also higher.

The final step in this section is to check if the predicted consumption of the building varies significantly from the real one considering the EVs. For doing that verification the daily optimization has been done changing only the consumption of the building for the real one. This would have been the verification to do the following day once it would have passed.

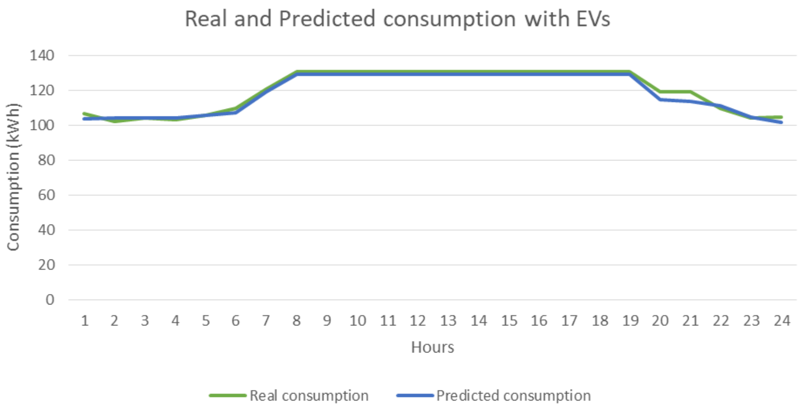

Figure 32: *Real and predicted consumption with EVs*

As it is appreciated in the figure if the prediction is done correctly it is viable and effective to programme the charging and discharging processes of the electric vehicles as the electricity price is known one day in advance. Therefore, the idea is to do the different processes explained in this work every day along the year, so every day the idea is to programme the charging and discharging processes of the electric vehicles taking into account the routines of the workers.

5. Budget

The aim of this section is to briefly detail the hypothetical costs associated to the realization of this project. As it has been a simulation the considered costs are the licenses used of the different softwares and the expended hours:

- Regarding the costs associated to the used materials there are:

MATERIAL COSTS

	Real Cost	Annual Cost	Project Cost
Laptop	1.100 €	183 €	16 €
Matlab License	800 €	800 €	68 €
Gams License	1.600 €	1.600 €	137 €
RapidMiner License	0 €	0 €	0 €
		TOTAL	**221 €**

Table 6: *Material Costs*

As it is appreciated first it has been considered the real cost of the licenses and the cost of buying a computer. In the case of the computer it has been considered that its lifetime it is 6 years, so the annual cost has been determined. Having the annual costs the project cost has been calculated taking into account that 750h are required for the 30 ECTS.
Regarding the RapidMiner License as it has been used for an educational purpose the license is free.
Therefore the total cost is 221€.

- Regarding the dedicated hours:

STUDENT COST

	Hours	Price	TOTAL
Student	750	8 €/h	**6.000 €**

Table 7: *Student cost*

As it is appreciated the total cost for the realization of the project would be approximately 6221€.

6. Environmental impact

As it has been observed along the previous sections the aim of this work has been the design of an energy management system so as to optimize the charging and discharging processes of the electric vehicle's batteries within a building from the tertiary sector. The introduction of these vehicles is strictly related to the decrease of the fossil fuel dependency, i.e. a reduction of the current CO_2 emissions.

As it has been observed in the previous sections the fact of connecting the EVs to the building through the bidirectional chargers permits to discharge the batteries from these vehicles so as to decrease the pics of consumption of the building. Usually these peaks are produced during the peak hours of the day when in the electrical system there are also considerable peaks of consumption. Commonly during these periods of time there is required the technologies which provide quick responses and it coincides sometimes with the generation plants which use fossil fuels. For that reason, the fact of discharging the EVs batteries contributes to the CO_2 reduction as it causes less generation.

In this study the ideal case would have been the calculation of the reduction of the CO2 emissions due to the discharge of the batteries considering the daily forecast in a real case. However, as it has been analyzed a hypothetical day of 2015, it has been considered that the supposed energy discharged during that day, 69,2kWh, would have been energy no generated.

From (35) it has been observed that the carbon intensity of the electricity production in Spain is always changing depending on the technologies that are working at each time, for that reason a mean value has been obtained, 333 gCO_2eq/kWh.

Therefore, in a day the reduced CO_2 emission would have resulted in 23.044 gCO_2eq/kWh.

Enegy discharged (kWh)	69,2
Carbon intensity (gCO_2eq/kWh)	333
TOTAL (gCO_2eq/kWh)	**23.044**

Table 8: *Reduction CO2 emissions.*

This value can change every day depending on the energy discharged and the value of the carbon intensity of that day.

Conclusions

The present project aims to analyse the association of the electric mobility with buildings from the tertiary sector through the exploitation of bidirectional power flows. For doing this, first a review on the current implementation of energy management systems for controlling its introduction is deeply analysed. It has been observed that high efforts are focussed on these issues, focusing on new strategies for peak shaving and valley filling the energy consumption by scheduling the charging and discharging processes from the electric vehicles.

It is important to analyse this new phenomena, these vehicles are a new type of load that cannot be left unmanaged, because several problems of safety and operation can arise in the grid system.

In this work a building from the tertiary sector has been studied, in particular a laboratory. First it has been established that five workers own an electric vehicle and then the routine this workers follow along a year has been created with the software from (31).

With all the data generated from that programme and the consumption of the building an optimization problem has been done in order to analyse the hours when the batteries from the electric vehicles would have been charged or discharged during the year 2014 in that building so as to obtain an optimal contracted power. With this, it has been possible to know the hourly consumption it would have been in this building during this year. Observing that results, it has been observed that the consumption of the building varies along the different months of the year but the variation is not so significant.

It is also interesting the fact that although there has been established a constant routine for the different workers, the charging and the discharging periods of the electric vehicles, at home or at the building, does not follow a routine it varies along the year.

As observed in the literature review, the fact of having and energy management system which is able to distribute the charging and discharging processes during the different hours of the day, is an important step for controlling the possible increases of the electricity demand. As mentioned before, the EV charging demand is different from the residential one, for that reason for ensuring the stability of the network the knowledge of the day-ahead demand is necessary.

For that reason the second part of that work has been the design of an energy management system which permits to predict the consumption of the building of the following day, in order to do that first it has been necessary to do the prediction of the consumption of the building without the EVs. So four machine learning techniques have been analysed with the historical consumption of the building: the Generalized Linear Model, the Deep Learning, the Random Forest and the Gradient Boosted Trees. The results have demonstrated that the last model is the most reliable one for the prediction of the consumption.

Therefore, that model has been the chosen one for predicting the consumption of the building every day and use this approximation of the consumption for optimizing the charging and discharging processes of the batteries for the following day, the results have demonstrated that if this prediction is well done, it is a viable and effective way for controlling the consumption of the building.

Acknowledgement

I would like to thank my tutor Francisco for his support and help during this work and for guiding me through it, this project has resulted so interesting to do.

Finally, I would like also to thank my workmates for cheering me up.

ETSEIB

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Treball de Fi de Màster

Màster en Enginyeria de l'Energia

Design of a controller for a building from the tertiary sector associated to electric vehicles

APPENDIX

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Convocatòria: Gener 2019

Escola Tècnica Superior
d'Enginyeria Industrial de Barcelona

A. Appendix

INPUT DATA

price	Specific values for each hour of the year (€/kWh)	Cost of the electricity consumed from the network
B_cons	Specific values for each hour of the year (kWh)	Consumption of the building without Evs
C_n_max	43 kW	Maximum power charging form the EV battery (kW)
C_n_min	0 kW	Minimum power charging form the EV battery (kW)
D_n_max	43 kW	Maximum power discharging form the EV battery (kW)
D_n_min	0 kW	Minimum power discharging form the EV battery (kW)
B_n_V	41 kW	Capacity of the EV battery (kWh)
SOC_n_max	1	Maximum state of charge of the battery
SOC_n_min	0.3	Minimum state of tharge of the battery
A	Specific values for each hour of the year, this is binary	The vector which specifies if the worker is at work (1) or not (0)
H	Specific values for each hour of the year, this is binary	The vector which specifies if the worker is at home (1) or not (0)
US	Specific values for each hour of the year (kWh)	Houry usage of the EVs
ηbc	0.95	Charging efficiency of the building charger
ηbd	0.95	Disharging efficiency of the building charger
ηhc	0.95	Charging efficiency of the home charger
c_b_max	20 kW	Maximum charging power building chargers (kW)
d_b_max	20 kW	Maximum discharging power building chargers (kW)
c_h_max	3.3kW	Maximum charging power home chargers (kW)
fee_pb	100 €/kW	Power access fee of the building (€/kW)
fee_eb	0.012 €/kWh	Energy access fee of the building (€/kWh)
fee_eh	0.044 €/kWh	Energy access fee of home (€/kWh)

V	1000 €/KWh	Lifetime value of the battery (€/kWh)

Table 9: *Input data – Optimization problem*

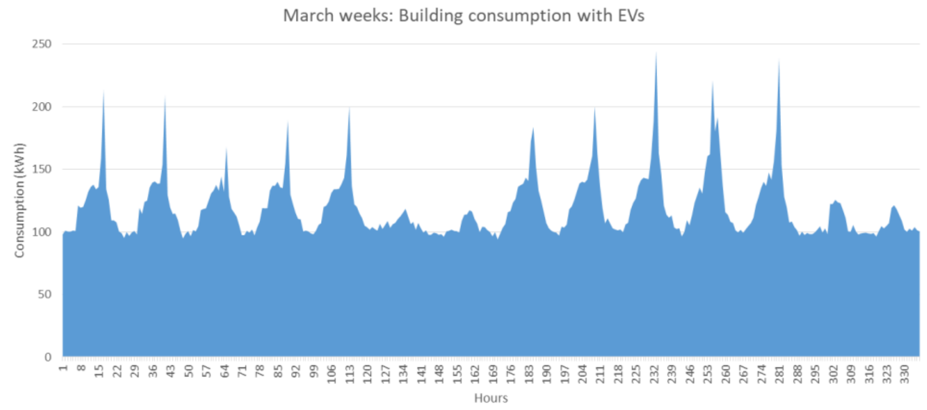

Figure 33: *Building consumption with EVs – March*

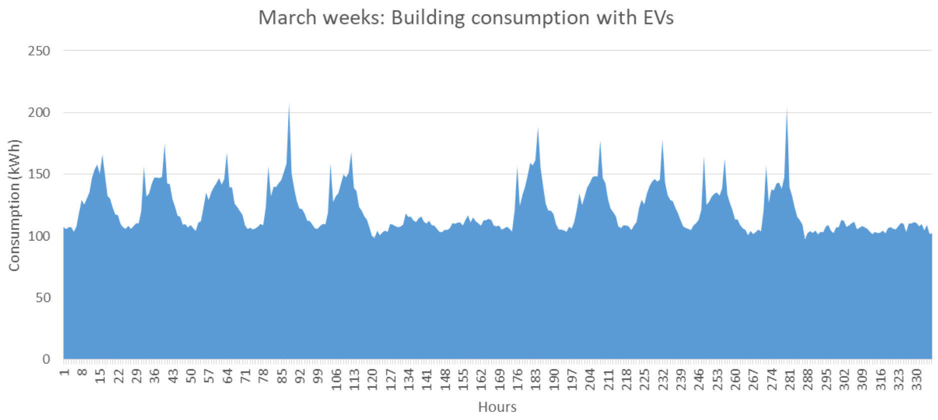

Figure 34: *Building consumption with EVs – December*

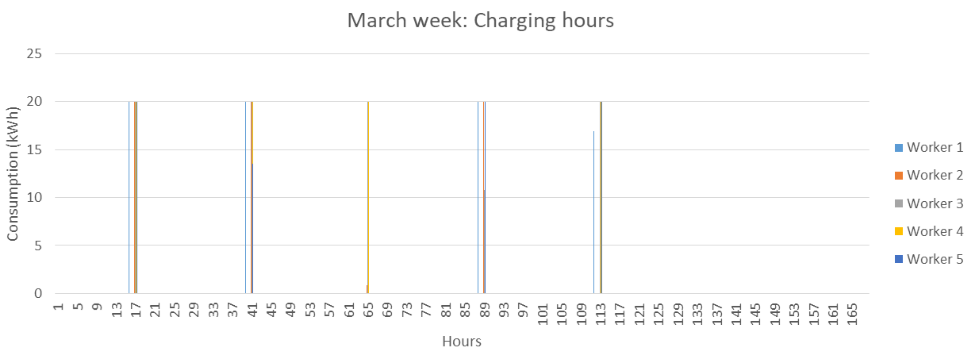

Figure 35: *Charging hours of the workers EVs– March*

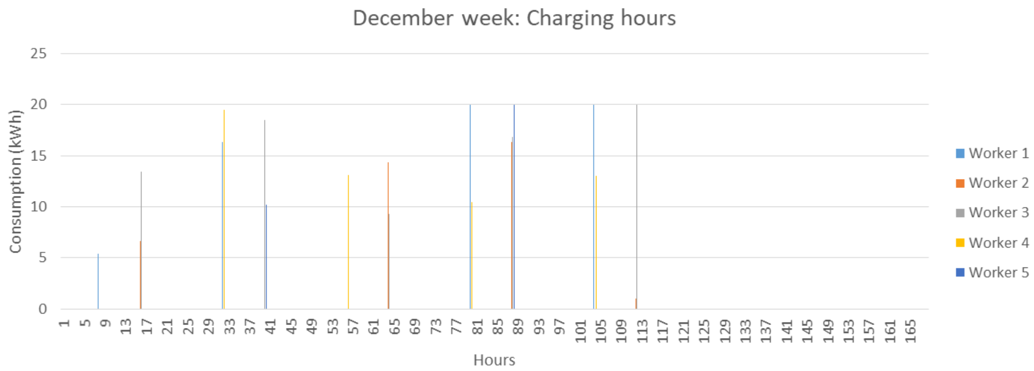

Figure 36: *Charging hours of the workers EVs - December*