UNIVERSIDAD DE VALLADOLID

ESCUELA DE INGENIERIAS INDUSTRIALES

Grado en Ingeniería en Organización Industrial

DEVELOPMENT OF A DYNAMIC PRICING ALGORITHM FOR THE APPLICATION OF ELECTRIC CAR CHARGING PROCESSES

Autor:

Lorenzo Calvo, Alicia

D. Eusebio de la Fuente López

Hochschule Magdeburg Stendal

Valladolid, agosto 2022.

TFG REALIZADO EN PROGRAMA DE INTERCAMBIO

TÍTULO: **DEVELOPMENT OF A DYNAMIC PRICING ALGORITHM FOR THE APPLICATION OF ELECTRIC CAR CHARGING PROCESSES**

ALUMNO: Alicia Lorenzo Calvo

FECHA: 04.08.2022

CENTRO: Fachbereich Ingenieurwissenschaften und Industriedesign

UNIVERSIDAD: Hochschule Magdeburg-Stendal

TUTOR: Dr.-Ing. Prof. WUST Przemyslaw Komarnicki y M.Sc. Marcel Hallmann

I Resumen

Actualmente, el creciente uso del automóvil, junto con la preocupación por el medio ambiente fomenta la investigación en los vehículos eléctricos. Por ello, la industria del VE ha crecido enormemente durante los últimos años, planteando nuevos problemas a la sociedad.

Este trabajo tiene como objetivo desarrollar un algoritmo basado en precios dinámicos para la carga de VE. Se trata de paliar la demanda en horas punta, beneficiando la economía del consumidor y de los operadores de recarga.
Primeramente, se introduce la base técnica de este proyecto. Después, se define la metodología utilizada para el modelo algorítmico, señalando las entradas, la función objetivo y los posibles algoritmos vinculados a la inteligencia artificial que pueden dar solución.

Finalmente, utilizando la herramienta MATLAB Simulink, se ha realizado una simulación implementando el algoritmo, analizando posteriormente su efectividad, llegando a determinadas conclusiones a partir de los resultados y proponiendo futuras líneas de trabajo relacionadas.

Palabras clave: Vehículos eléctricos, precios dinámicos, aprendizaje automático, estado de la red, algoritmo

Fachbereich Ingenieurwissenschaften
und Industriedesign

Institut für Elektrotechnik

Bachelorarbeit

DEVELOPMENT OF A DYNAMIC PRICING ALGORITHM FOR THE APPLICATION OF ELECTRIC CAR CHARGING PROCESSES

am 01.08.2022 vorgelegte Bachelorarbeit
von Alicia Lorenzo

Erstprüfer: Prof. Dr.-Ing. Prof. WUST Przemyslaw Komarnicki

Betreuer: M.Sc. Marcel Hallmann

Declaration of Authorship

I hereby declare that I have written this Bachelor's Thesis independently and only using the literature and aids indicated. The passages taken directly or indirectly from external sources are marked as such.

The thesis has not been submitted to any other examination authority in the same or a similar form and has not been published.

Magdeburg, 01.08.2022

………………………………………………………..

Place, Date Signature

II Abstract

Nowadays, the increasing use of automobiles, together with environmental concerns and the development of intelligent systems, encourages the research in the field of electric vehicles. Therefore, the electric vehicle industry has grown enormously during the last recent years, posing new problems to society.

This work aims to develop an algorithm based on dynamic pricing for charging electric vehicles at public charging stations. It attempts to alleviate the high demand at peak hours, benefiting both the consumer's economy as well as the charging operators' profit.
The structure of this project is divided into several sections. Firstly, an introduction of the technical basis for this project is given. Secondly, the methodology carried out for the algorithm model is defined, pointing out the inputs, the objective function and the possible algorithms linked to artificial intelligence that can help to solve it.
Finally, using a block diagram model with the MATLAB Simulink tool, a simulation has been carried out implementing the algorithm, through which its effectiveness has been analyzed, reaching certain conclusions from the results obtained and future lines of work related to this field have been proposed.

Key words: Electric vehicles, dynamic pricing, machine learning, state of the grid

III Table of Contents

IV List of figures

V List of tables

VI List of acronyms

AC	Alternative Current
AI	Artificial Inteligence
CMS	Charging Management System
CPO	Charging Point Operator
DOD	Death of discharge
EV	Electric Vehicule
EVCC	Electric Vehicle Comunication Controller
FC	Fast Charge
HLC	High Level Communication
HVDC	High Voltage Direct Current
MLP	Multilayer Perceptron
OCPP	Open Charging Point Protocol
RBF	Radial Basis Function
SC	Slow Charge
SECC	Supply Equipment Communication Controller
SOC	State of charge of the battery
SVM	Support Vector Machine
ToU	Time of Use
V2G	Vehicule to grid

1 Introduction

In recent decades, the concepts of sustainable development and sustainability have been high on the public and political agenda as an approach to address climate change and its impacts. To this end, new legislation and policies worldwide are guiding companies and citizens towards sustainability. In particular, large multinational companies operating in highly polluting industries have a major impact on climate change. One example of these industries is the automotive industry.

The automotive industry has become one of the most important industries worldwide, not only economically but also in terms of research and development efforts. On the one hand, the number of vehicles on the road has increased over time, simplifying the transportation of people, and making it more comfortable and faster. On the other hand, this has caused a large increase in air pollution levels due to the emission of gases such as carbon dioxide ($\mathrm{CO_2}$), nitrogen oxides (NO_x), carbon monoxide (CO) or unburned hydrocarbons (HC).

Moreover, according to an European Union report, the transport sector generates almost 27% of carbon dioxide emissions (EPA, 2022), 70% of which come from road transport resulting in 682 million tons of $\mathrm{CO_2}$ (Bundesamt, 2020).

As a result, authorities in most countries are vigorously promoting the use of electric vehicles (EVs) with significant investments and incentives to avoid the concentration of $\mathrm{CO_2}$ pollutants, thus making EVs a key element of the energy transition. This will lead to changes in energy distribution, reducing demand for fossil energy sources such as diesel or natural gas, while creating greater pressure on the energy distribution grid.

To put this in perspective, during 2021 the total annual electricity consumption was 536,5 million kWh, assuming an average of 6,451 kWh per capita. It is observed how 87,5% of the energy is used in the country itself, exporting more than 78 MM kWh to neighbouring countries. In 2021, renewable energies accounted for about 52% of total real consumption in Germany (Statista Research, 2022).

As well, the electric vehicle industry has grown tremendously, especially in recent years, starting in 2010, when the German government proposed a target of reaching 1 million electric vehicles on German roads by 2020.

Thanks to this action, the number of pure electric vehicles driven in Germany reached its peak in 2021, registering more than 300.000 electric vehicles. The increase in the proportion of newly registered plug-in electric vehicles is surprising, given the huge demand for diesel and gasoline vehicles in Germany. Of the 52.275.833 vehicles on the road, approximately 13.5% of the vehicles sold in 2020 were plug-in electrics (Statista Research, 2022).

The federal government is taking the necessary steps to create a regulatory environment in which electric vehicles can thrive and has been offering incentives to boost demand for electric vehicles for years.
In late August 2014, the federal government announced some plans to introduce non-monetary incentives through new legislation that came into effect in early 2015. The measures include certain privileges for electric vehicles, such as allowing these vehicles to drive on bus lanes or have free and reserved parking spaces where charging points are available.
In 2015 the Bundestag passed the Electric Vehicle Act, mandated by the local government in March, to grant these non-monetary incentives. In it, it also registered the issuance of identification plates to prevent abuse of such privileges.
Also, the Bundesrat approved on May 12, 2017, a regulation amending the Federal Ministry of Economic Affairs and Climate Action's charging station ordinance II. The new regulations provide for not having to participate in the internal billing system of the electricity supplier, with the EV user being able to pay for electricity at charging stations with a common payment system.

The Federal Ministry of Economic Affairs and Climate Action has long advocated several measures to accelerate the development of the EV market, focusing primarily on three.
Firstly, the federal government is backing the purchase of EVs. It has thus earmarked up to 600 million euros to support the purchase of at least 300,000 EVs by 2019, with manufacturers contributing the same amount. On the other hand, a bonus of 4,000 EUR was established for the purchase of a new all-electric car and 3,000 EUR for plug-in hybrid vehicles. In addition, work is underway to expand the charging infrastructure, as the federal government has earmarked 300 million euros to facilitate the deployment of standard and fast charging points (Action, 2022).
Finally, the public sector is committed to electric vehicles, including the purchase of electric vehicles in its fleet, and intended to increase the number of EVs to at least 20 percent by 2019. To this purpose, the government allocated 100 million euros.

Despite all these improvement measures for the integration of electric vehicles in our daily lives, there are still different problems that create rejection towards innovation in this sector.

1.1 Problem

The challenges posed by climate change and the quest for sustainability are prompting the development of alternative technologies with low carbon emissions. The use of renewable energies for power generation has positioned electrification as one of the measures to reduce pollution.
In terms of mobility, the development of electric vehicles is growing exponentially despite being considerably more expensive, compared to the same model powered by fossil fuels.
Therefore, another important point that does not allow the customer to make up his mind is the vehicle's battery. It does not provide sufficient autonomy, being the market average 250 km, while a conventional vehicle can reach 1000 km. To this problem is added its difficult recycling, since lithium batteries are not harmless to the planet, creating an ecological problem.
Electric vehicles are expected to become widespread in the near future, with a great impact on the recharging infrastructure for electric vehicles. Today there are 45,000 chargers available, but soon will be insufficient for the large volume of cars.
Currently, another visible improvement environment is that charging stations use static prices that vary according to the energy supply, leaving aside many other variables such as demand, charging time, type of charging or vehicle idle time.
Therefore, in this work we will develop an algorithm for the dynamization of the charging prices of electric vehicle chargers in order to optimize the energy of the network so that there is no energy waste by adjusting the prices at the charging stations according to the actual circumstances, allowing the customer to reduce their costs as well as the operator of the electric charger to increase its profit depending on the circumstances.

For this purpose, different algorithms already in use today will be studied and compared with each other. Thus, after their analysis, an efficient charging pricing algorithm will be developed.

1.2 Objective

Firstly, the general objective is to develop an optimization model to standardize a pricing model for charging electric vehicles, by means of optimization tools and simulation models. MATLAB and Simulink tools will be used for its implementation.

With the achievement of the general objective, we want to solve the following specific objectives. First, it is intended to solve the problem of block of electric vehicle charging stations according to their location, in order to redistribute the vehicles throughout the geographical area. Moreover, it is also intended to solve management problems of electric vehicles, in order to reduce the coincidence in hours of high demand. Finally, it is set as a specific objective to develop a dynamic pricing algorithm to provide an answer to all the previously mentioned objectives.

1.3 Approach

Due to the fact that this project is an academic one and with a significant time limitation for its development, factors such as, for example, the update of the energy demand or the real-time market price will not be taken into account, leaving an open and extensive field in which to continue the development and improvement of the algorithm.

The approach of this project is briefly described below, indicating the points contained in this report:

- Technical overview necessary for the work: lists the different parts considered in the charging of an electric vehicle, methods of payment and operation of the electrical network.
- Design, using modelling and simulation software (MATLAB®/Simulink), of the dynamic EV charging algorithm.
- Results and discussion based on the data obtained from the previous model.

2 Basis

Several electric vehicles charging planning models have been proposed in the literature in recent years, finding very detailed works such as (Bernal, Olivares, Negrete-Pincetic, & Lorca, 2020) on current optimization methods for EV charging infrastructures.

In relation to the centralized charging strategy, the planning decisions are carried out by a control system in a centralized way looking for the optimal solution. In this way, despite the driver decides the time to connect the vehicle to the charger, the system will be responsible for deciding the start and end time of charging, seeking mutual benefit for the customer and the distribution company (Wang Q. Z., 2015).
Regarding to the literature review, previous works have different objectives and points of view. In the case of (Wang Q. Z., 2015) it is prioritized to minimize the cost first, while in other cases they look for maximizing the owners' satisfaction (Bernal, Olivares, Negrete-Pincetic, & Lorca, 2020) or the parking operator's profit (M. J Mirzaer, 2014). Another interesting objective is to minimize the difference between the energy purchased in the market and the energy consumed by the EVs.
Focusing on what is related to this work, (Joskow & Wolfram, 2012) uses a demand-side management mechanism through dynamic pricing to shift the load from peak to off-peak periods and thus minimize the purchase of electricity.
To work with dynamic pricing, we find several different schemes. The most common is time-of-use (ToU) (Yang, Dong, Wan, & Ng, 2013), where the price of electricity varies depending on whether the current time zone is on-peak or off-peak. Another example of a different scheme would be, by hourly variations (Wang Q. Z., 2015).

In general, electricity pricing systems are evolving towards real-time pricing, which is more economically efficient as it directly reflects supply and demand.

2.1 Technical basics standards

It is important to identify the different components, their functions, and characteristics, involved in our model for a correct adjustment to reality. In Figure 1 it is appreciated a very simplified scheme of the elements involved in the charging of an EV car. The energy coming from the grid, which can sometimes be supported by additional local sources as in type 2, travels to the charging terminals. There, there are specific charging infrastructures, which, thanks to artificial intelligence, can solve the problem of charging

EVs in the most efficient way. In the following, the mentioned parts will be described one by one.

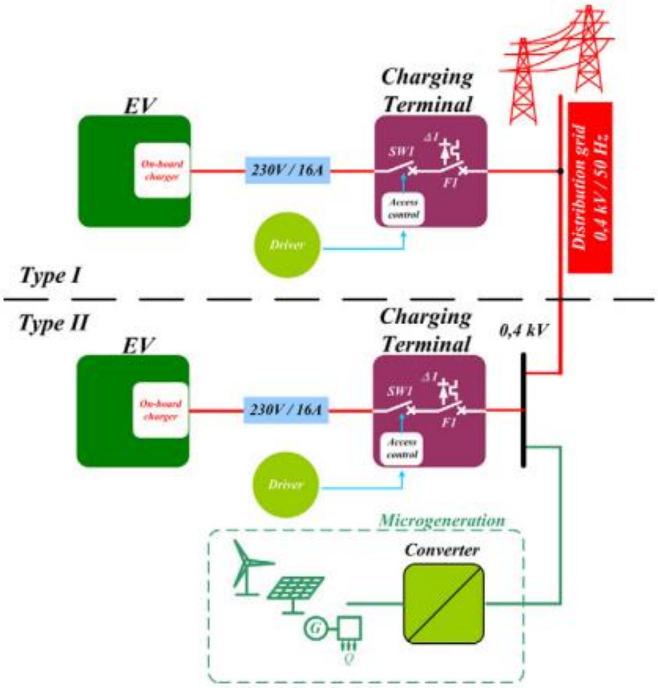

Figure 1 Energy structure of an EV charging system (Benysek, 2012).

- Electrical grid

The city's electricity grid, which provides power for EV batteries, gets its energy in different ways. According to a 2020 study in Europe, it is estimated that 38% of the electricity comes from renewable energies, followed by fossil energies with 37% and finally nuclear with 25% (Pita, 2021).

- Charging infraestructure

This electric transport system, like any other transport system, requires an infrastructure that allows access to the recharging service or access to a source that powers its engine. In this case it is electricity, this is a challenge for the insertion of electric vehicles due to the need to have a reliable, accessible and convenient service for the end user (Ministry of Industry & IDAE, 2012). Currently there are three different types of charging, slow, semi-fast and fast, the first one being mostly located in homes and the second two for public charging. This parameter will be of important relevance when setting prices (Armijos, 2021).

Table 1 Distint charging modes and their characteristics (Adil Amin, 2020)

Charging Mode	Charging Characteristics						Advantages	Disadvantages
	Charging Outlets	Voltage Rating (V)	Current Rating (A)	Power Rating (kW)	Supply Connection	Charging Period (Hour)		
Mode 1	Domestic	120 V_{AC}	12–16	1.4–1.9	Single phase	6–10	Low installation cost Less impact on utility	Slow charging rate Long charging period
Mode 2	Domestic, Public	240 V_{AC}	80	19.2	Single/Three phase	1–3	Fast charging time Energy efficient	High installation cost Impact on the utility
Mode 3	Public	480 V_{DC}	80–200	20–120	Three phase	0.5	Very fast charging time High energy efficient	High installation cost High impact on the utility

- Artificial intelligence

Artificial intelligence is used to optimize resources and make the most of renewable energies. In this way, electricity can be distributed efficiently through the available infrastructures. The design of vehicles also requires greater driving autonomy, faster recharging, and durability, and this is where artificial intelligence comes in, allowing drastic reductions in development and research times.

- Electric Vehicle

The EV is the main component of the chain, as it is the consumer of the energy coming from the grid. The following is a brief definition of the three main components of an electric vehicle as shown in Figure 2. They will be the electric motor, responsible for converting the electrical energy into mechanical energy which will be transferred to the vehicle's transmission and will turn the wheels. Another element to consider is the vehicle control unit or controller, which is responsible for controlling the starting, running, forward and reverse rotation, speed and stopping of the vehicle components. Finally, the main component of an electric car is its battery, which receives and stores energy from the charger. It is currently a decisive element in the decision to choose an electric vehicle.

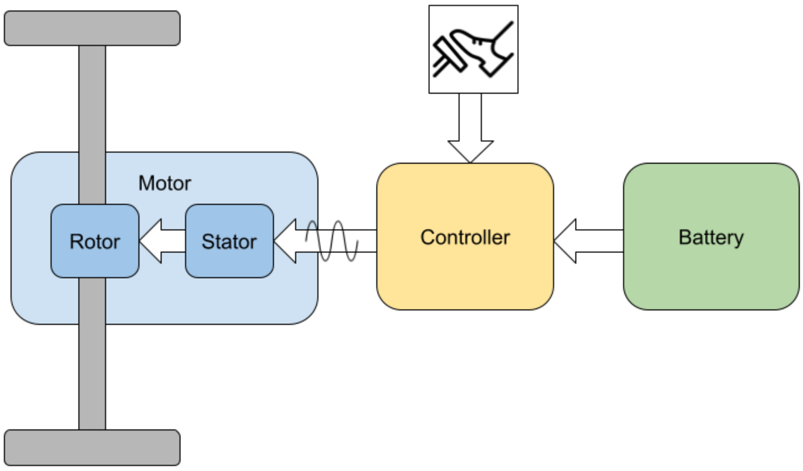

Figure 2 Electric vehicle components (Cavagnis, 2021)

2.2 Software and standards

Once the necessary elements for charging an electric car have been analyzed, the connections between all of them will be specified.
ISO 15118 Road vehicles -Vehicle to grid communication interface is an international standard that specifies the communication between an electric car and its charging point. The standard defines aspects that influence the identification, association, control, and optimization of charging or discharging, payment, load levelling, cybersecurity and privacy for high-level communication (HLC) conductive and wireless communication between the electric vehicle communication controller (EVCC) and the supply equipment communication controller (SECC).This is not only limited to message encryption and user authentication, but also allows energy data to be transferred between EVs and the charging station. In this way, better charging management decisions can be made (Ampcontrol, 2021).

In this case, the car would send the battery state of charge to the charging station, transmitting the actual amount of energy requested and specifying the intelligent charging output. With this improvement, we avoid problems such as charging the EV with an insufficient amount of energy, inefficient optimization of inter-vehicle charging or complicated solutions requiring too many time resources to do so.
Once the vehicle energy data has been sent to the charging station, this data must be transmitted by the CPO to the central charging management system (CMS) via the Open Charging Point Protocol (OCPP). The protocol is responsible for communicating the EV

charging station and a central management system, it describes the messages that the charging stations and the IT backend send to each other to authenticate new EV users, track energy meter values or give charging orders.
With ISO 15118 and OCPP 2.0, the vehicle sends the requested amount of energy to the charging point, and the charging point forwards this information to the backend system, so that vehicle charging can be planned as optimally as possible.

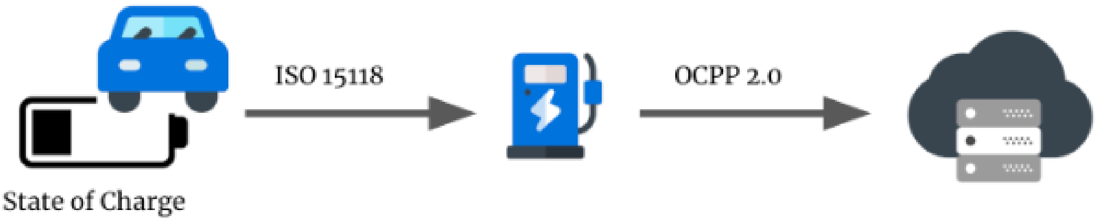

Figure 3 Connection via ISO 15118 and OCPP 2.0 (Ampcontrol, 2021)

2.3 Payment concepts

Nowadays the payment method has evolved drastically, being able to pay with our phone or even with a watch. The billing model for charging an electric vehicle can follow several different formats. There are some charging stations that can be used free of charge, but this is less occasional. In general, a small initial connection fee is usually charged to initiate charging of the electric car. Subsequently, it can be billed either by time in minutes or by consumption in kWh.
The payment model may vary depending on the supplier and can be made with a credit card or on the basis of a subscription model in which the account is billed.
Regardless of the billing method used, payments are usually processed in a similar way using a physical credit or debit card terminal. It is necessary to take into account the qualities that it must have, since the environments in which they will be available are usually outdoors and the customer will want to make the transaction as quickly as possible.
In order to go deeper into the subject, different concepts related to the payment method will be defined below:

- Payment gateway: Allows acceptance of credit cards and other alternative payment methods. This authorizes the transfer of funds between the customer and the electrical load provider. This gateway can be created through a web portal, mobile application, or contactless point-of-sale devices.

- Card payment: Carrying cash is becoming less and less popular, so PIN terminals or contactless technology is being implemented to make it quicker and easier for drivers to refuel.

- E-Commerce: In this case drivers can go to their brand's website or app and pay for a charge when needed, so secure online transfers can be made with the credit card.

2.4 Grid parameters

Power distribution networks are made up of three main components, the generating plants that produce electricity from fossil or renewable fuels, the transmission lines that carry the electricity from the generating plants to the demand centres, and the transformers that reduce the voltage so that the distribution lines can deliver power to the end consumer.
Generally, power distribution networks employ electrical circuits that operate with AC alternating current, which means that both the voltage and the current of the circuit vary sinusoidally in time, with a given angular frequency. The nominal frequency in Germany of the distribution system is set at 50Hz. This level should be kept as constant as possible, allowing a tolerance of 0.050 Hertz.
When there is a potential difference between two points across a conductor, a flow of electrons occurs. The charge from the point with the higher potential is transferred to the lower one until its electric potential is equalized, thus creating an electric current. This parameter gives us the information in which direction the electricity flows. In this way we can know if the energy is being required by the network or on the contrary demanded by the consumer. This can be high voltage, medium voltage or low voltage.
First of all, high voltage installations are used to transport energy over long distances. For this purpose, it is necessary to raise the voltage in order to reduce the current flowing through the line and thus avoid energy losses due to heating of the conductor cables and electromagnetic phenomena. This group includes installations that exceed a voltage of 36Kv.
Next, once the energy is at its destination, it passes through an electrical substation to be transformed into medium voltage energy, with voltages between 1 and 36kW. And finally there is the low voltage when the electricity finally reaches the consumer being the least dangerous, below 1 kW.
If a lot of electricity feeds the grid in relation to the amount consumed, the electrical frequency increases, exceeding 50Hz. Since power plants are designed to operate with a

certain frequency range, there is a risk that they will disconnect from the grid after a period.

On the other hand, if we supply too little power to cope with the demand, the frequency drops. From 49 Hz, automatic load shedding plan is activated to avoid power outages. This is because, if the frequency drops too much, the voltage plants are shut down one after the other, until there is a complete collapse of the grid, which is known as power blackout.

In the case of Germany, 45% of grid energy consumption was obtained through renewable sources, mainly from biomass plants and volatile sources such as wind and solar PV during the 2020 period. As a result, it is undergoing a major transformation, causing a disruption in the traditional electricity supply chain.

Currently, Germany has a total transmission grid length of about 35,000 kilometers, transmitting power with maximum voltages between 220 and 380kV, usually through alternating current. Although it is true that the new lines between northern and southern Germany, which are expected to be completed in 2025, will be more efficient using high voltage direct current (HVDC) technology. (Russell, 2021).

3 Methodology

An algorithm is a set of instructions that specify the sequence of operations to be followed to solve a problem. It is independent of both the programming language in which it is expressed and the computer on which it is executed. (Rodriguez, 2002). As a condition, an algorithm must be generally precise and easy to understand when indicating the steps to be performed. In addition, it must be predictable when starting from the same initial conditions since the same results must be obtained. The algorithm must be finite it must end up in a fine without ending in a loop (Nuñez Camacho, 2017).

In this paper, a rule-based algorithm for EV charging price estimation is developed for simulations in MATLAB. The algorithm uses input parameters such as wind, solar and biomass energy production, charger occupancy, energy consumption and grid status. With this information the model calculates and assigns a certain price per kWh.It has been decided to use MATLAB mathematical software because of its simple and easy to use environment. The software has its own programming language, M-Code, which allows working with matrices, functions, algorithm development or even communicating with other programming languages such as Java or C++.
The main program also has many extensions with a wide variety of ToolBoxes, such as Modbus Explorer, PID Tuner or Simulink, which is the extension used for the simulation of our model.
Simulink is a graphical programming environment mostly used for modeling, simulation, and analysis of dynamic systems. The platform allows us to implement many different blocks within its library. In it we can simulate both continuous and discrete systems, being able to have a large number of applications, especially in the fields of automatic control and signal processing. In addition, like MATLAB, BlockSets can be added, which are different extensions to larger ones.

In this section the steps followed for the design of the model will be developed. First, the inputs of our model (3.1) are explained, followed by the constant parameters necessary for its development. Next, the objective function (3.2), in which our algorithm is promoted with its relevant constraints, is presented. Finally, different machine learning related algorithms are proposed (3.3).

3.1 Inputs

All algorithms are composed of three main sections: the inputs, where the data are entered, the process, which is the set of operations to be performed to provide a solution to the problem, and the output, where we obtain the final result after the process.

Below is a summary of the inputs and outputs of the algorithm. In this case the inputs are given as xls files created in Excel. We will now analyze the different fields to be studied according to the variables.

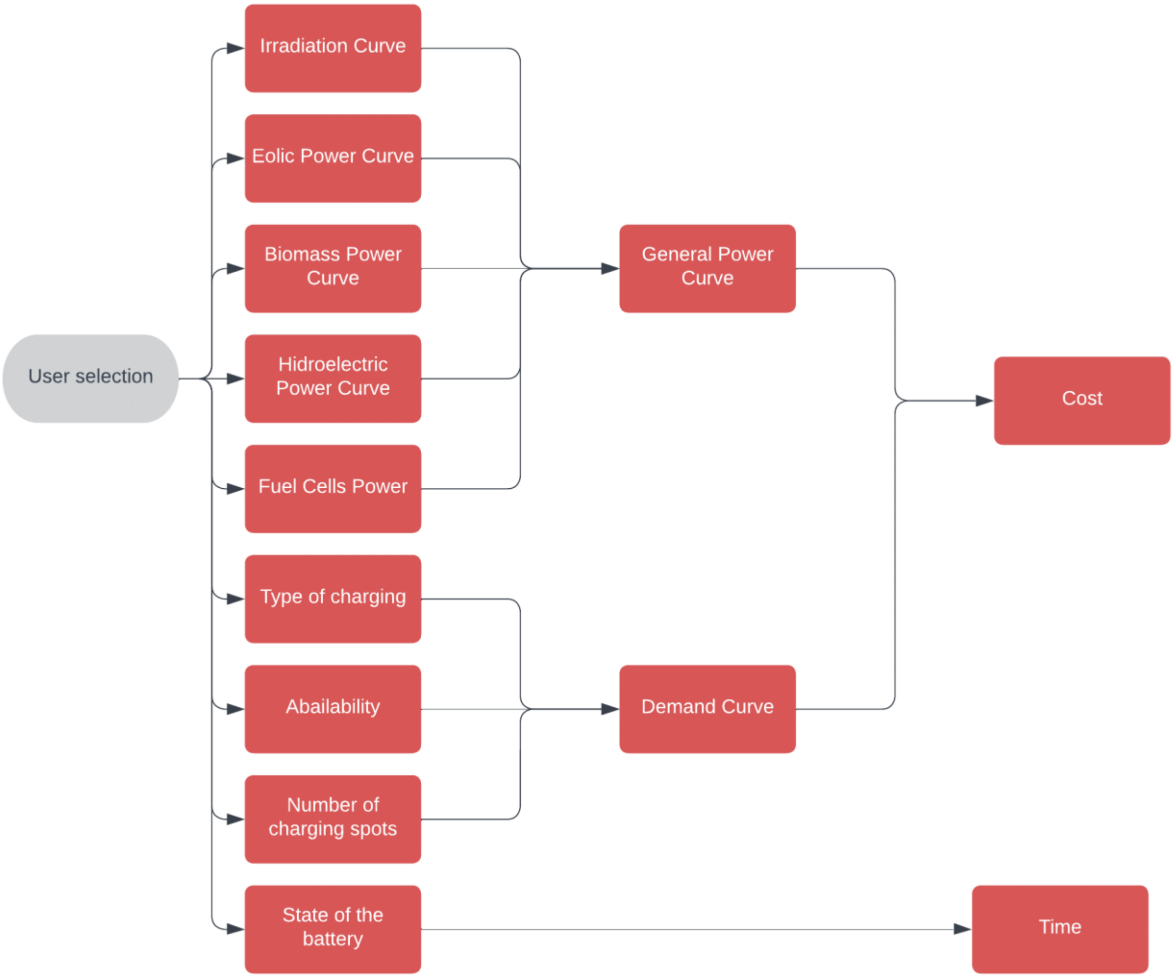

Figure 4 Algorithm inputs

- **Radiation**

The energy supply comes from different sources. Among them we find solar energy.

Photovoltaic systems generate energy that converts light into electricity using semiconductor materials. The photons contained in the sun's rays strike the photovoltaic cell, exciting the electrons in the cell due to charge separation in the absorber material. The movement of the electrons creates a small voltage producing direct current, which is stored in batteries and through a voltage inverter can be converted into alternating current.

To analyze it, we must study the amount of solar irradiation and according to this the energy obtained depending on the location and the period of the year at that time.

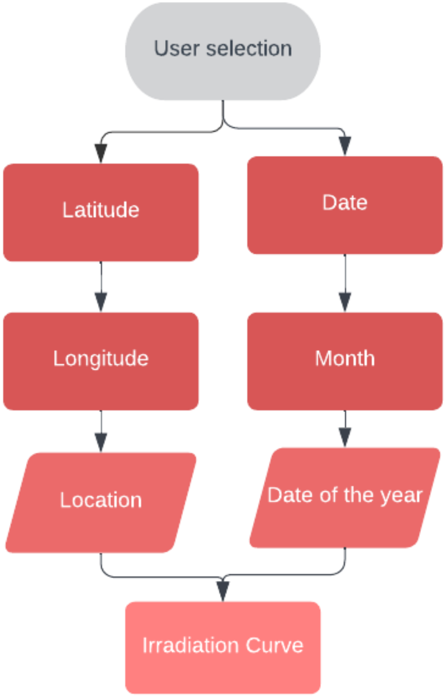

Figure 5 Necessary parameters for irradiation curve

The user must choose the latitude and longitude of the location to perform the study, to obtain the location and be able to download the irradiance data in that area (Trujillo, 2015). Subsequently, the user must choose the day and month to continue with the study. With the data, a date is obtained, from which an average is made of the same date in previous years for which there is a record. In this way we manage to homogenize the data.

The result of this block is an irradiance curve (W/m2) throughout the day. A bell shape is observed due to the hours of daylight presence during the day.

For its analysis we will start from the data collected in 2009, measured in W/m2, with a total of more than 35,000 data in total, with a difference of 15 minutes between each measurement. The solar irradiance for each month during 2009 is illustrated above.

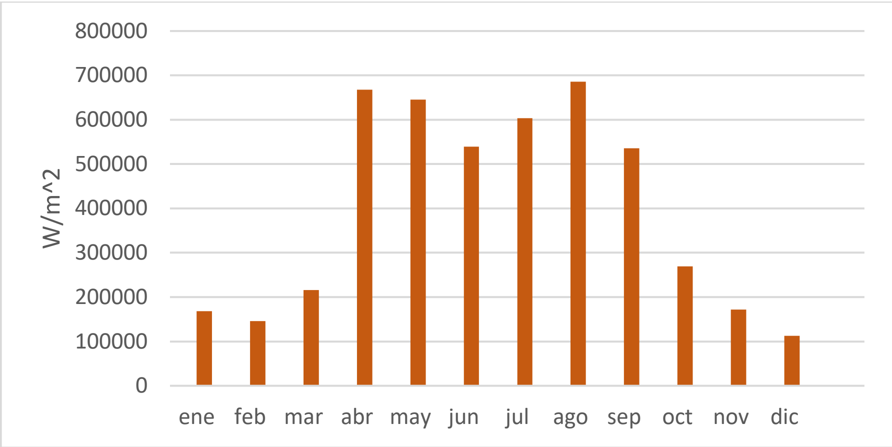

Figure 6 Chart of solar energy by month

- ## Wind

In case of wind energy, the analysis will be similar to the solar irradiation one, since being the kinetic energy of the wind, the data will depend both on the location and the period of the year in which the study is to be carried out. In this way we can obtain the average wind speed according to these parameters (Faiella & Gesino, 2002).

$$P_{wind=}\frac{1}{2}*p*v^3*\pi*r^2$$

This expression indicates that the maximum wind power available from the wind is proportional to the density of the air, the area exposed perpendicularly to the wind flow and the cube of the wind speed (Francisco Eraso-Checa, 2018).

In reality, not all kinetic energy can be converted into useful energy. The Betz limit, aerodynamic and mechanical frictions, electric generator efficiency, etc. will only allow us in practice, in the best case, to obtain 40% of the available wind power.

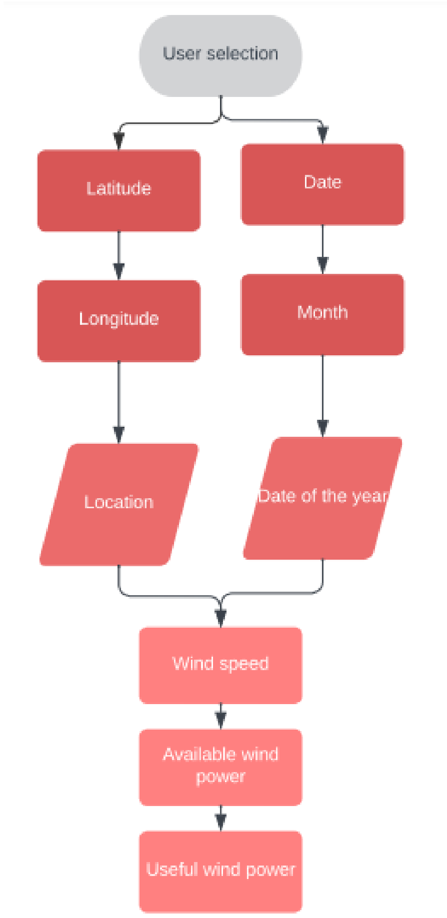

Figure 7 Necessary parameters for wind curve

- **Biomass**

By origin and properties, biomass includes a heterogeneous group of organic materials. In terms of energy, the term biomass is used to refer to renewable energy based on the use of organic matter formed biologically in the near past or derived from it.

Biomass is characterized as a renewable energy source, and its energy content ultimately comes from solar energy fixed by plants during photosynthesis. During the combustion or gasification process, the bonds of organic compounds are broken, releasing energy and producing carbon dioxide and water (Fernandez, 2003).

After prior sorting of the waste, it is fed to the boilers for combustion. The boiler water is then converted into steam, which is preheated in the feed tank by heat exchange with the combustion gases from the boiler itself.

As in other conventional thermal power plants, the steam obtained in the boiler passes through the steam turbine connected to the electric generator where the electrical energy is produced. Power outputs of up to 50 MW can be obtained.

For this project it is not important the amount of waste materials available, but rather the number of biomass plants available and their performance.

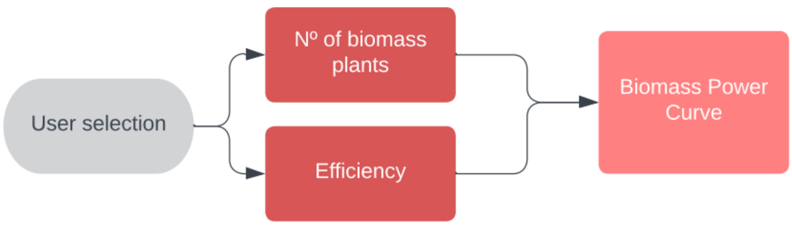

Figure 8 Necessary parameters for biomass power curve

- **Demand curve**

It is necessary to know the demand for vehicles requiring electric recharging points, as a random variable for the study. In this case, to find the demand we have used a collection of data on the power consumed.

In many cases, demand is affected by different factors. Some of the issues that affect demand are location, as the volume of vehicles that a charger in a shopping mall receives is not the same as one on the outskirts of the city.

It is also affected by the availability of free places to charge the car and in turn by the number of chargers in the same place, since if the customer knows that there are several, the probability that one is free is higher.

Finally, demand is also affected by the type of vehicle charging, since if a charging center does not have fast or moderate charging, it would be reducing its customer base.

- **State of the battery**

Below, the calculation of charging time for each vehicle is analyzed. In order to do this, it is necessary to know the SOC (state of charge of the battery) both at the beginning and at the end of the recharge and, in turn, the capacity of the vehicle's battery.

These data allow to calculate the charging time as the capacity to be charged divided by the power of the charger. The capacity will be the difference between the final capacity minus the initial, which in turn, is calculated as the corresponding SOC, by the capacity of the battery.

It must be considered that for a correct use of the battery and to take advantage of its maximum useful life and charge cycles, the batteries must not be completely discharged, but according to the manufacturer they must respect the DOD, minimum depth of discharge. For lithium-ion batteries, which are the most common, this value is around 80%. (Masoum AS, 2011).

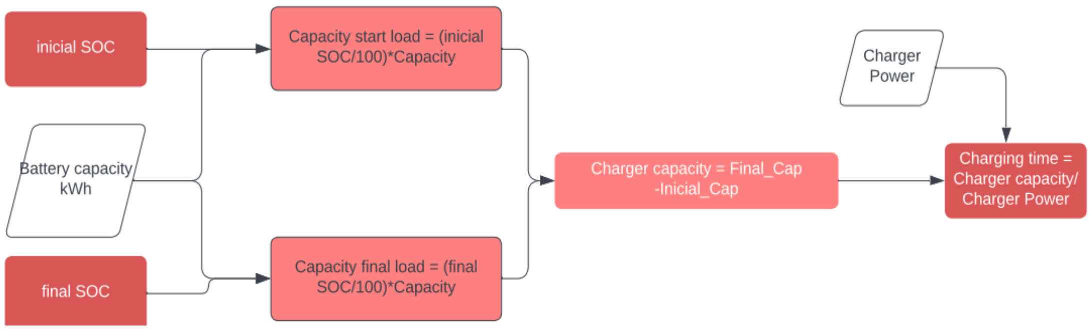

Figure 9 Flow chart to obtain the loading time

3.2 Aim

Globally, the intention to reduce carbon (CO2) emissions has motivated the extensive practice of EVs. However, uncoordinated charging and uncontrolled integration of EVs into the distribution grid deteriorates system performance in terms of power quality issues.

Furthermore, it is difficult to store large amounts of electrical energy. Consequently, the consumption of electrical energy should be equal to the production at any time. This requires an accurate forecast of the consumption so that the planned production corresponds to the actual subsequent consumption as much as possible**.**

The purpose of this work is to optimize the energy grid, both in terms of price, maximizing the profit while using dynamic pricing, and time. To achieve this, energy demand and supply must be in balance, thus avoiding moments of overproduction or energy shortage. For stability, the power generated must be equal to the power consumed. For this, the network must be able to respond to the volatility of voltage and frequency disturbances. This requires adjustments to balance frequency disturbances and power outages. An example may be the use of batteries to overcome these problems.
Mathematically, the power potencial can be represented as the sum of all power generation sources minus the demanded power as a function of frequency, according to the following equation. The sum in the power flow must be equal to zero for each hour i (Rodríguez, 2020).
In my theoretical case I have designed a microgrid where energy is obtained from different sources. First, solar energy is obtained from a field of solar panels. There are also electric windmills to obtain wind energy as well as a biomass plant and a hydraulic press and several fuel cells, where energy is obtained. On the other hand, in a real case such as a mini-city, the energy required will depend on the inhabitants of the city, through the expenditure in their daily lives in their homes, industries, the recharging of electric cars at public service stations and the relevant expenditure of the city's electrical lighting network. In our theoretical model, only the energy demanded through the charging of electric vehicles per hour in the microgrid has been taken into account, in order to simplify the subsequent calculations.

$$\Delta f\left(P_i^{Grd}\right) = f(P_i^{Rad}) + f(P_i^{Eo}) + f(P_i^{Bio}) + f(P_i^{\boldsymbol{Pm}}) + f(P_i^{Fu}) - f(P_i^{De}) = f(P_i^{Ne}) - f(P_i^{De}) = 0\ Hz$$

P_i^{Grd} refers to the grid power , which is the sum of the energy obtained from solar radiation P_i^{Rad}, wind sources P_i^{Eo}, biomass P_i^{Bio}, pumped-storage power **s**tation $P_i^{\boldsymbol{Pm}}$, fuel cells P_i^{Fu} and subtracting the power demanded P_i^{De}.

To check the state of the grid, we will look at the frequency as this depends on the power. The frequency of the grid will vary around the nominal frequency, so if the frequency is increasing and accelerating, it will indicate that the load is light, and decreasing when the grid is heavily loaded. As the price in turn depends on the state of the grid, this can help us predict whether the cost of charging an EV will be higher or not.

On the other hand, the values of the parameters that will be kept constant throughout the model must be defined. For this example, we have assumed:

- Number of chargers available: 5
- Maximum price kWh: 0.4204 €/kWh
- Minimum price kWh: 0.2264 €/kWh
- SOCf: 100%
- SOCi; 20%
- Market energy price: 0.3234 €/kWh

• Objective Functions

From the total energy needed, we can calculate the function of the total daily cost as a function of power for a charging service provider.

In the case of our theoretical microgrid we will consider an hourly rate of λ_i, using time periods i equivalent to one hour unit, which will allow us to query the daily cost of energy F_d, multiplying the electricity used by its price at that instant of time. We will use the following expression:

$$F_d = \sum_{i=0}^{24} \lambda_i * \Delta T(i) * P_i^{Net} = \lambda_i * \Delta T(i) * (P_i^{Rad} + P_i^{Eo} + P_i^{Bio} + P_i^{Pm} + P_i^{Fu})$$

$$F_d = \sum_{i \in D}^{24} \sum_{n \in N}^{24} \Delta T(i) * \lambda_i * P_{EV,n}^{Ne} * S_{i,n}$$

From now on we will use the following nomenclature to refer to the parameters:

D	set of time i ∈ $\{i_0, \ldots, i_j\}$;
N	set of all EV n ∈ $\{n_0, \ldots, n_j\}$;
λ_i	forecast electricity market price at time step by *i* ;
α_i	forecast electricity sales price at time step by *i* ;
ΔT	length of a time step;

$P_{EV,n}^{Net}$ rated charging power of the EV;

$S_{i,n}$ charging schedule of the nth EV at time step *i;*

R_n revenued obtaines from n;

F_n cost of charging n;

q quick charge;

s slow charge;

P_i^{max} maximum charging rate of vehicle *n;*

$Av(t)$ availability of EV in time *i*;

α_i selling price of energy in time *i*;

$\alpha_{i_{min}}$ minimum selling price of energy in time *i*;

$\alpha_{i_{max}}$ maximum selling price of energy in time *i*;

SOC_n(i) battery state of charge of EV *n* in time *i*;

$e_n^+(i)$ charged energy to vehicle *n* in time *i*;

μ^+ charging efficiency of vehicle *i*;

x_i binary parameter to know the status of the loader in time *i*;

The minimization of this objective function leads to a flattening of the load profile, which is favourable for system planners and operators, since most of the load is carried out in profitable time slots, reducing the electricity bill (Esmaili & Goldoust, 2015).
To fully optimize the benefits of charging station operators, in addition to minimizing costs, the revenue from charging the various vehicles must be taken into account to optimize the profit.

The objective function to be maximized is shown below, where the profit of the charging station operators is reflected. It first considers the revenue obtained from charging electric cars (Rn) minus the cost of energy purchased from the grid.

$$\text{Max} \qquad \sum_{n \in N} R_n - \sum_{i \in D} F_i$$

The income obtained will depend on the amount of energy demanded and in turn on the price we wish to set for electricity. In this case we are working with dynamic prices, so this will depend on different factors such as availability, the state of the grid or demand, among others.

The revenue per vehicle load is calculated as the energy times the load price for each type of load. In this paper we will differentiate only between fast charge (FC) q and slow charge (SC) s.

$$R_i = \sum_{i=0}^{24} \alpha_{i,q} P_{EV,n,q}^{Net} + \sum_{i=0}^{24} \alpha_{i,s} P_{EV,n,s}^{Net}$$

To work as optimally as possible, as mentioned in equation 1, the power flow in the grid should be zero, being the demand equal to the electricity supply.

Finally, the following function is available to calculate the dynamic price

$$\alpha_i = P_{market} * X_{abailability} * X_{st.of\ the\ grid} * X_{charging\ type} * X_{location}$$

It should be noted that the last two parameters mentioned have not been taken into account for the simulation of this model.

For the description of the model, it is necessary to define a series of restrictions. In order to analyze them correctly, they have been separated into blocks according to their subject matter.

- Market constraints
  - Set a maximum power that can be supplied at the same time.

    $$Av(t) * P^{max} = P_{av}^{max}(t) \qquad \forall \text{ i} \in \text{D}$$

  - Maximum price

    $$\alpha_{i_{min}} \leq \alpha_i \leq \alpha_{i_{max}} \qquad \forall \text{ i} \in \text{D}$$

  - Chargers in use

    $$x_i = \begin{cases} 1 \ Charger\ occupied \\ 0 \ \ Free\ charger \end{cases}$$

- Battery constraints

- How energy is stored in the battery (3[a])

$$SOC_n(i+1) = SOC_n(i) + e_n^+(i) * \mu^+ \qquad \forall\ \mathrm{i} \in \mathrm{D};\ n \in \mathrm{N}$$

- Battery charge limits (max, min)

$$SOC_{oi} = SOC_i(t_0) \qquad \forall\ \mathrm{i} \in \mathrm{I}$$

$$SOC_{fi} \leq SOC_i(t_f) \qquad \forall\ \mathrm{i} \in \mathrm{I}$$

3.3 Search Algorithm

The complex task of determining the right prices requires that a company know not only its own operating costs and availability of supply but also how much the customer values the product, what the future demand would be, where the energy comes from and several other variables. It is needed a wealth of information of its customers, of demand and supply, as well as of the weather for adjusting the prices at minimal cost. This has led to increased adoption of dynamic pricing and to increased interest in dynamic pricing research (Jaehyun Lee, 2020).

Different AI-based models have been proposed for the algorithm developed in this work in order to obtain the optimal price and cost of electric car charging. In our case, it is necessary to quickly process large amounts of data using algorithms that change over time and improve in what they are intended to do, which is why we will now analyze different algorithms that would allow us to solve our model based on machine learning.

Machine learning is an application of AI that allows systems to learn and improve automatically from experience without be expressly programmed to do so. This is a very important ability to make predictions, through the identification of patterns in a series of data.

Machine learning models can be classified according to the way they establish patterns and rules, i.e., according to their learning process. We divide them into unsupervised supervised and hybrid models. (Hush & Horne, 1993).

- Supervised: This type of algorithm uses already classified training samples. In this way, rules and patterns will be established based on the distribution of features to categorize the observation. This block includes SVM algorithms, MLP and Näive Bayes neural networks (Antón, 2014).

Within this group we can make a further subclassification.
On the one hand linear models, where a line of best fit is created to predict the data, giving as a solution a linear combination of features. Table 2 shows the most common algorithms of this group, with their different applications, advantages and disadvantages.

Table 2 Examples of lineal models of supervised algorithms

ALGORITHM	DESCRIPTION	APPLICATION	ADVANTAGES	DISADVANTAGES
Linear Regression	Simple algorithm modeling linear relationship between inputs and a continuous numerical output variable	-Prediction of stock or housing prices.	-Easy to understand -Interpretable results by output coefficient	-Assumes linearity between inputs and outputs. -Sensitive to outliers.
Logistic Regression	Similar to the previous one but a categorical output is obtained.	-Customer churn prediction.	-Easy to understand - Useful for multi-class predictions	-Assumes linearity between inputs and outputs -Can be over-fit with small or large data
Ridge Regression	Penalizes features with low predictive scores	-For classification or regression. -Predictive maintenance of vehicles.	-Less prone to overfitting -Good fit to data with multicollinearity	- Predictors are retained in the final model. - Does not perform feature selection
Lasso Regression	Same performance as ridge regression	-Predicting housing prices. -Prediction of clinical data.	-Less prone to overfitting -Can handle high dimensional data	-It can maintain highly correlated variables.

On the other hand, there are models based on decision trees, where "if-then" rules are used.

Table 3 Examples of decision tree models of supervised algorithms

Table 3 shows the most common algorithms of this group, with their different applications, advantages, and disadvantages.

Table 3 Examples of decision tree models of supervised algorithms

ALGORITHM	DESCRIPTION	APPLICATION	ADVANTAGES	DISADVANTAGES
DECISION TREE	They produce preconditions through decision rules on features.	-For classification or regression. - Credit score modeling	-Understandable -Can handle missing values	-Prone to over-adjustment -Sensitive to outliers
RANDOM FORESTS	Combines the output of different decision trees	-Predicting housing prices	-Reduced over-adjustment -Higher accuracy than other models	-High complexity of training -Not very interpretable
XGBoost	Efficient and flexible gradient boosting algorithm.	-For classification or regression -Insurance claims processing	-Accurate results -Capture non-linear relationships	-Adjustment of complex hyperparameters -Does not work well on sparse parameter set
Regresor LightGBM	Gradient bracing frame designed to optimize efficiency	-Airline flight time prediction -Cholesterol levels prediction	-Can handle large amounts of data -High computational training speed	-Can be over-adjusted -Hyperparameter adjustment can be complex

- Unsupervised: A priori in these models it is not known what the set of features represents. The purpose of this algorithm is to find similarities between the data that allow them to be grouped according to their similarity. This block includes clustering algorithms such as k-means. Two subgroups can also be distinguished here. On the one hand clustering models that allow you to categorize records into a certain number of clusters and in this way be able to indentify natural groups in the data. In this group we find algorithms such as K-means, hierarchical clustering or Gaussian mixture models. On the other hand, we find the a priori association algorithms, based on rules that identify the most frequent set of elements in a data set.

- Hybrids: The benefits of both supervised and unsupervised algorithms are combined. This is the case of radial basis function (RBF) neural networks.

After the analysis of all the different algorithms included in the machine learning discipline, it has been concluded that to solve the algorithm of this work the most recommendable are the Linear Regression or Lasse Regression, since both offer us predictions on the numerical variable that is the price in a fast way and with great volume of data.

4 Results

Although our model has both time and cost as outputs, in the practical part of this work we have only worked with cost for the simulation.

In order to perform the algorithm, the market price of energy has been obtained first. For this purpose, a minimum and maximum price has been established according to the maximum power points found in the network. Then, the rest of the energy values have been interpolated to give an estimation of the market price.
To obtain the values of the minimum and maximum kWh price when charging the car, the average price per kWh in Germany in December 2021 has been taken as a reference which is 0.3234 €/kWh.

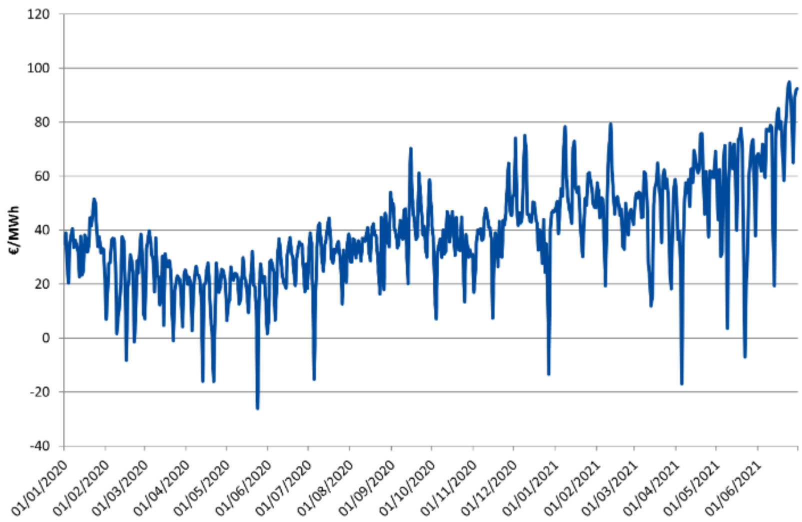

Figure 10 Daily price of the EPEX SPOT market in Germany (AleaSoft, 2021)

In Figure 10 we can observe the variation of prices throughout the first half of the year 2021. We have taken this period as they are recent data in time and similar to the current ones, but without being affected by the war crisis. After analyzing the data, it has been concluded that the price should have a tolerance of 30% from the average price. In this way, the most significant data will remain relevant, but we will limit the outlier prices that are not beneficial to the study. The price limits have been calculated multiplying 0.3234 €/kWh by 1.3 resulting in 0.4204 €/kWh for the maximum price and multiplying 0.3234 €/kWh by 0.7 resulting in 0.2264 €/kWh for the minimum price. Figure 11 shows how the price variation would be between the stipulated limits.

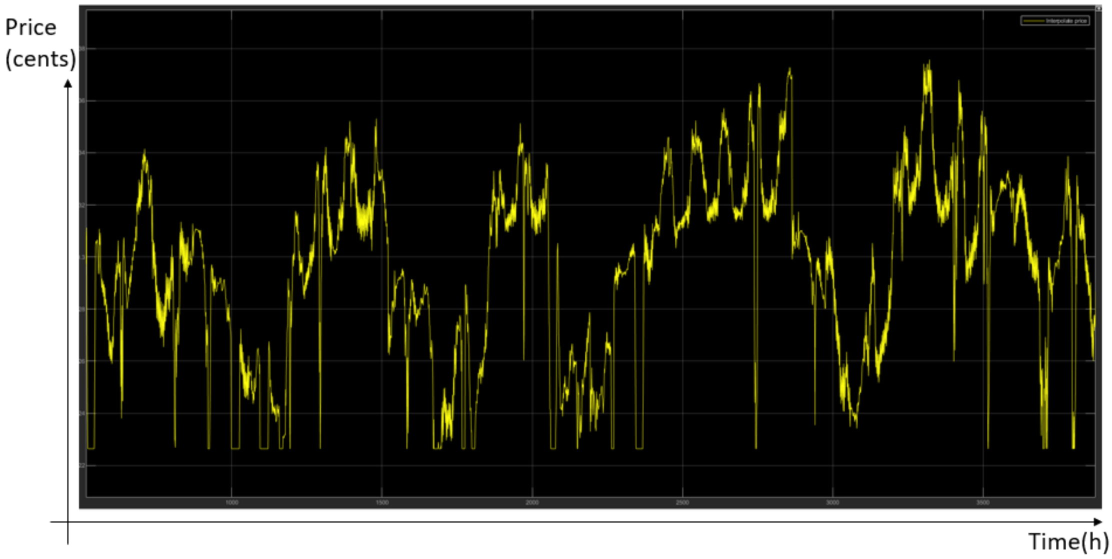

Figure 11 Graph of the weighted price from the state of the grid

The next parameter to take into account is the availability of space to charge the car. We assume that the total number of chargers available is 5. For this purpose, we have created a uniform random variable whose output data are numbers between 0 and 5. Based on this, it has been decided to increase the price by 3% if more than three loaders are being used and the same discount if less than three are being used.

¡Error! No se encuentra el origen de la referencia. shows a comparison of the price change after being altered:

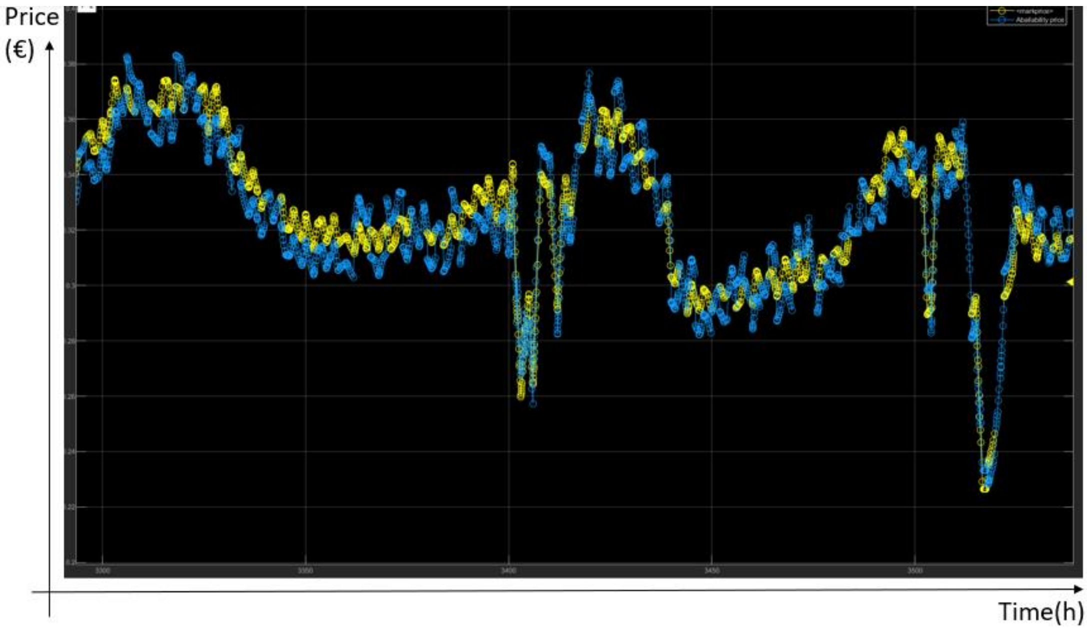

Figure 12 Graph comparing the market (yellow) and availability (blue) price.

Subsequently, another parameter to be taken into account was the state of the power grid. In this case, if the grid suffered overproduction, it was decided to discount the price by 5% with respect to the market price. On the other hand, if there is an energy deficit in the grid, the price will increase by 5%.

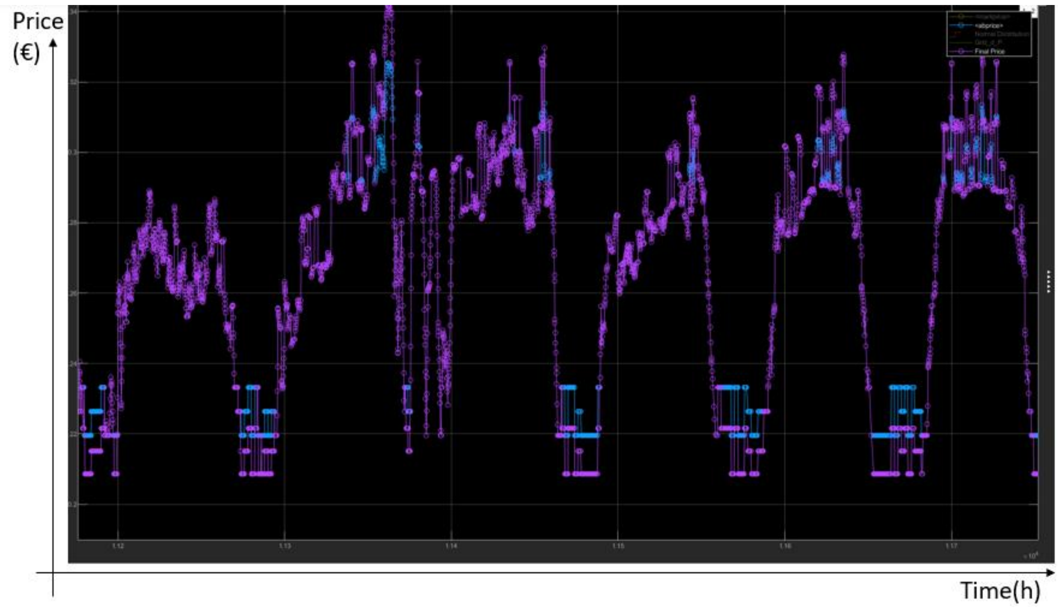

Figure 13 Graph comparing the availability (blue) and final dynamic prices (purple).

It is interesting to compare how the price varies from the beginning. In yellow colour we find the market price, on the other hand in blue the price after suffering the availability variations and the last one in purple after suffering variations due to the state of the network.

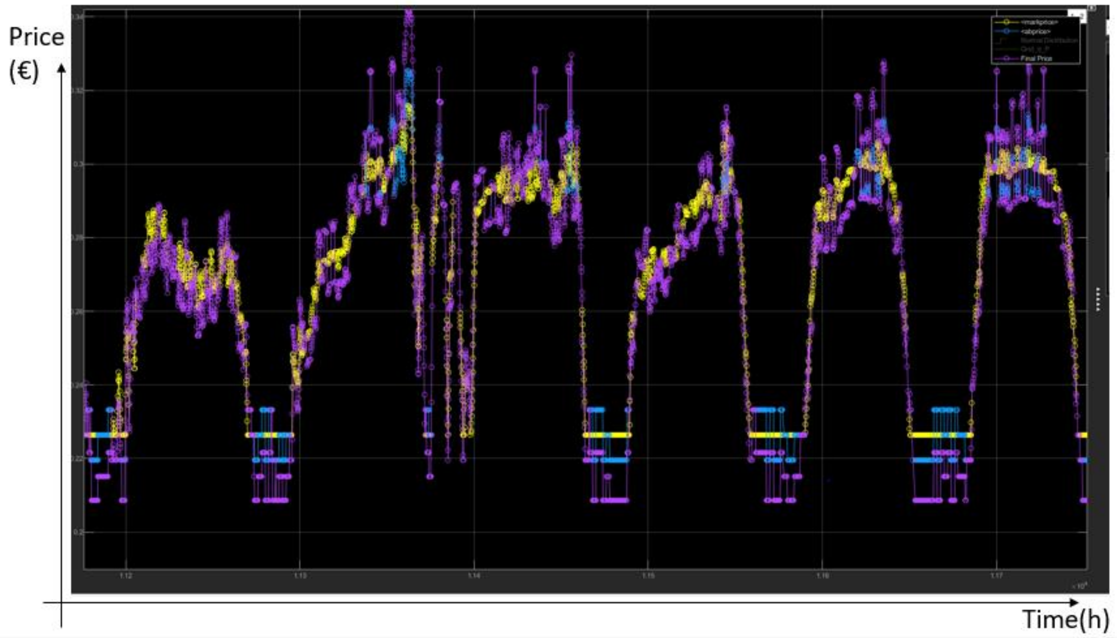

Figure 14 Overall comparison of the prices obtained in this work

Finally, once the new price has been calculated, it has been decided to see how this affects demand. In this case we observe how the demand increases when prices are lower or how it increase when it reaches the 2740 seconds, due to a drop in prices.

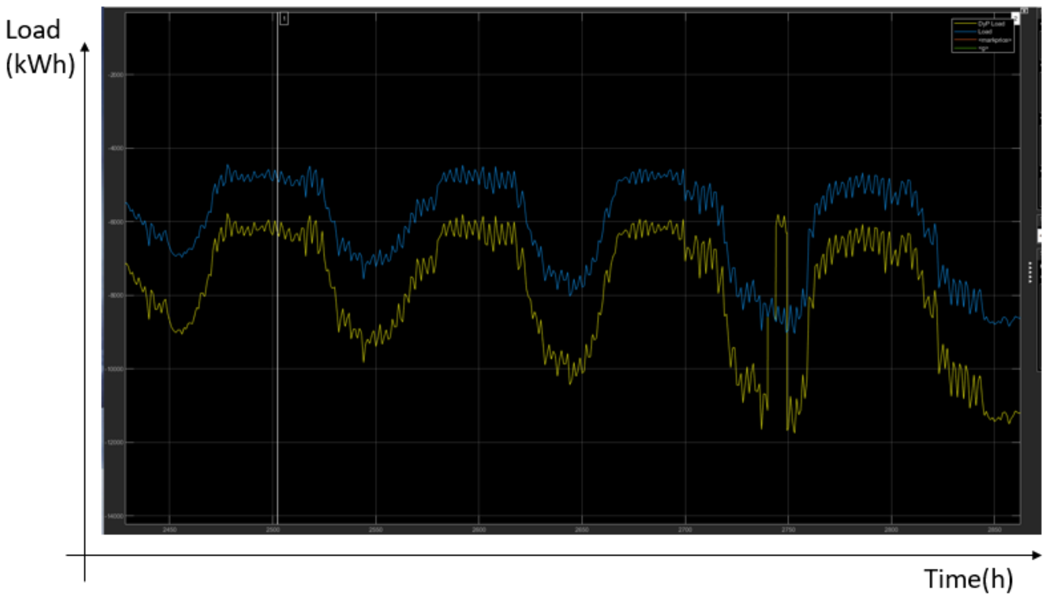

Figure 15 Graph comparing demand with static and dynamic prices

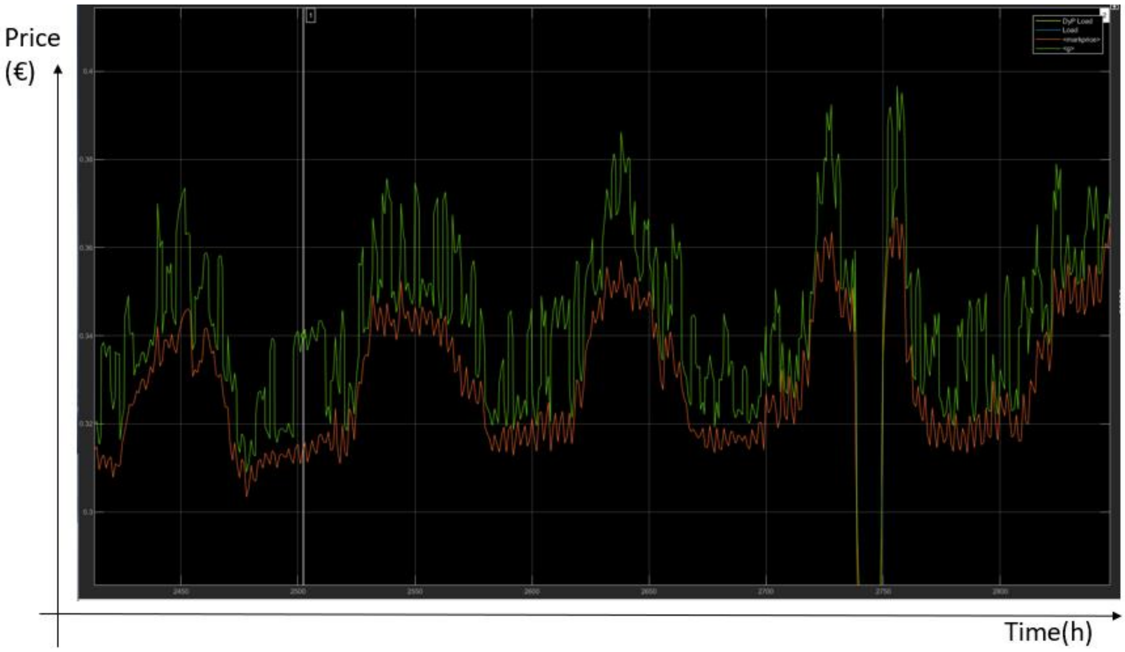

Figure 16 Graph comparing market and dynamic price according to the load

Next, we are going to study the different possible cases, depending on the state of the variables of our algorithm:

Table 4 Different results while implementing the dynamic pricing algorithm

RATE	Number of chargers	State of the grid	Market Price	Abailability Price	Final Price	Variation
Price increase	4	-6100GW	0.3608	0.3716	0.400	10.86%
Price dicrease	0	17.848 GW	0.2264	0.2196	0.2086	-8.53%
Equal price	3	1107GW	0.2545	0.2545	0.2545	0%
Price increases & decreases	5	11584GW	0.2264	0.2332	0.2215	-2.21%
Price decreases & increases	0	-2730GW	0.3110	0.3017	0.3168	4.11%

In the first example the price rises by a total of 10.86%. This is due to the fact that first of all, the charging station ports are mostly occupied, with only one free port. This first parameter increases the price by 2.99%. Next, the grid is in deficit of electricity, which causes the price to increase by 7.46%, compared to the previous price.

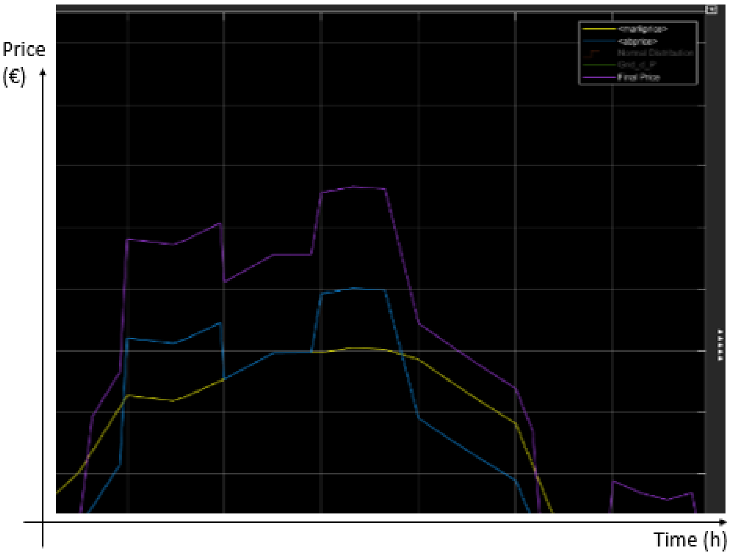

Figure 17 Price increase example

In the second example, both parameters benefit the consumer. It can be seen that out of the 5 loading ports, all of them are empty and there is a large overproduction in the network, which causes the price to decrease by 8.53%.

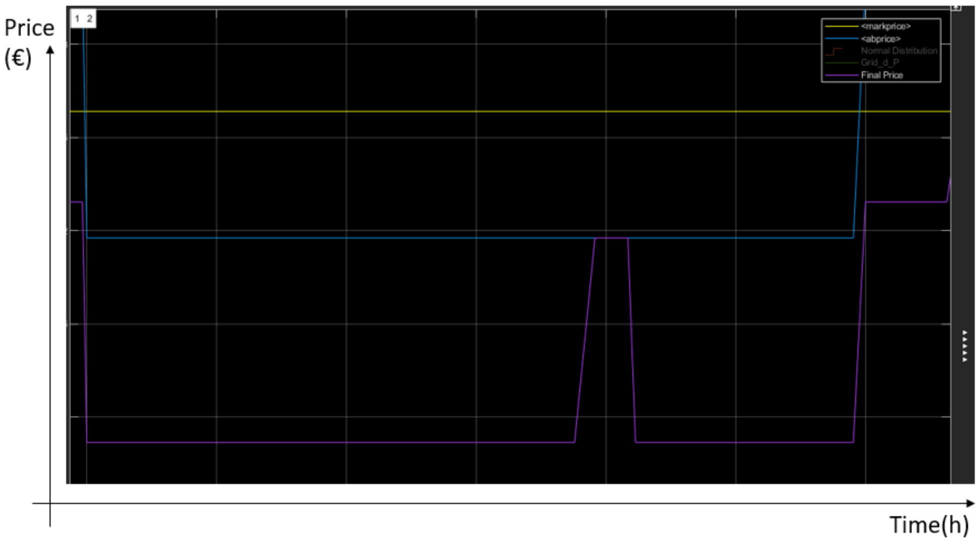

Figure 18 Price decrease example

For the third case, the price remains constant. This is because the standard parameter for charger availability has been set to 3. On the other hand, even though the grid state has 1107 GW of overproduction, this does not influence the final price, since a tolerance has been set in the grid ranging from -2000GW to 5000GW, where the price remains constant. In the next two examples, we see how the parameters influence the price in opposite ways. In the first case there are no chargers available, so when a free slot is found, the next user will have a cost overrun as vehicle charging is in high demand, which causes the price to increase by 3%. On the other hand, in turn there is an overproduction in the network which causes the price to decrease by 5.2%. Finally, it is observed that the price has decreased with respect to the price established by the market, due to the fact that according to our criteria the variable of the state of the network has a greater weight compared to the availability of load.

The second case is similar. It is observed that there are enough seats available, so a discount of 3.1% is made to the user. But on the other hand, there is a shortage of electricity in the network, which causes the final price to increase by 5%.

Signal Statistics

	Value	Time
Max	3.760e-01	28866.000
Min	2.264e-01	230.639
Peak to Peak	1.496e-01	
Mean	2.713e-01	
Median	2.729e-01	
RMS	2.733e-01	

Figure 19 Market price values

Signal Statistics

	Value	Time
Max	4.022e-01	3318.000
Min	2.086e-01	1010.000
Peak to Peak	1.935e-01	
Mean	2.696e-01	
Median	2.719e-01	
RMS	2.718e-01	

Figure 20 Final price values

From the signal statistics provided by MATLAB, we can draw different conclusions.

First, it is observed that both the maximum price and the minimum price have a greater margin between them in the final price. Thus, in the case where there is load availability and there is an overproduction in the grid, the dynamic pricing algorithm would benefit the consumer economy by reducing the price of energy. On the contrary, if there is a deficit in the energy network and there are no available slots in the chargers, it would benefit the profit of the charging station operators.

On the other hand, the difference between the maximum and minimum values is significantly higher in the second case, going from 1.496e-01 to 1.696e-01, since our algorithm works by increasing or decreasing the price depending on the conditions of the variables, creating a greater difference between the prices.

As is logical, the mean, median and RMS are very similar in both cases, since despite the variations, the values are still in the same price bracket. What we can observe is that, in general, the conditions are usually beneficial for giving discounts to customers, since the final price is usually somewhat lower than the market price, since the values of the mean, median and RMS are somewhat lower in Figure 20.

5 Discussion

In this section the assumptions and results are analysed and discussed.

The general hypothesis of the model was to establish an optimal price for charging electric cars. In this way, both the customer could reduce the cost of charging his car and the distribution companies could reduce the price risk, since the real market price would always be considered.

The general idea of the model is good, since it contemplates many variables that influence the price directly or indirectly.

In this case in the simulation, it was not possible to carry out the influence of the locations. Not taking into account whether there was a possibility to charge the car in the vicinity or on the contrary the customer had no other option to charge his vehicle than at the supply where it is located.

On the other hand, the market price has been estimated based on established maximum and minimum values. This may not be the best solution, because of the variability of the price of electricity today. The ideal solution would be to have real time data on the market price. From there, we could implement the designed algorithm, obtaining an optimized and much more objective price, considering the rest of the variables.

6 Summary and outlook

For the development of the algorithm for the charging of electric vehicles based on dynamic pricing, different variables such as the availability of the charger or the state of the network have been evaluated.
Through a simulation, it has been observed how the application of the developed dynamic pricing algorithm can reduce the charging price of an electric vehicle by reducing its minimum price by 0.0178 €/kWh, as well as increase the maximum profit of the charging operators by 0.0316 €/kWh.
In this way, it allows to calculate the optimal price for each circumstance, while using the state of the grid efficiently, trying to keep the power in it stable to avoid energy waste. Therefore, the effect of implementing the algorithm in dynamic pricing could have a positive impact on increasing the use of renewable energies, by using the resources we have more efficiently and reducing the amount of energy required.

The expected future increase of electric vehicles requires a developed recharging system, which is why the implementation of the dynamic pricing algorithm will allow us to deter the demand of vehicles, between different schedules, avoiding peak hours in order to obtain a more affordable price.
An idea for future studies continuing this line of work could be to insert the term vehicle-to-grid (V2G). This would take advantage of the ability of vehicles to provide energy and services to the grid by charging and discharging their batteries. It would require the implementation of software that allows bi-directional charging and discharging of the batteries, as well as a special power electronics interface.
This way, the efficiency of the distribution network can be improved by regulating the frequency, reactive power supply, balancing the load, reducing peak loads and creating revenue for both vehicle users and charging station operators according to their needs.
Therefore, the dynamic pricing algorithm must be further developed to include the real-time market price, in addition to other variables, such as location, which may affect the charging price. It is important to note that the results obtained highlight the advantages of using dynamic pricing for charging electric vehicles. Therefore, this should be studied further.

7 Bibliography

Action, F. M. (2022). *Electric mobility in Germany*. Von https://www.bmwk.de/Redaktion/EN/Dossier/electric-mobility.html#:~:text=Purchase%20grant%20(environmental%20bonus)%3A,a%20new%20all%2Delectric%20vehicle abgerufen

Antón, D. A. (2014). Desarrollo e implementación de un algoritmo.

Armijos, J. P. (2021). *Diseño y desarrollo de una solución informática para la gestión de puntos de carga para vehículos eléctricos en la ciudad de Cuenca.*

Bernal, R., Olivares, D., Negrete-Pincetic, M., & Lorca, Á. (2020). *Management of EV charging stations under advance reservations.*

Bernal, R., Olivares, D., Negrete-Pincetic, M., & Lorca, Á. (2020). *Management of EV charging stations under advance reservations.*

Casillas, R. V. (2018). EL VEHÍCULO ELÉCTRICO, UNA SOLUCIÓN MEDIOAMBIENTAL.

Esmaili, M., & Goldoust, A. (2015). Multi-objective optimal charging of plug-in electric vehicles in. *International Journal of Electrical Power & Energy Systems*.

Faiella, L. M., & Gesino, A. J. (2002). *Gestión de variables meteorológicas y mapeo eólico.*

Fernandez, J. (2003). *Energía de la Biomasa.*

Francisco Eraso-Checa, E. E.-R. (2018). *Metodología para la determinación de características del viento y evaluación del potencial de energía eólica en Túquerres.*

Hush & Horne, B. (1993). Progress in Supervised Neural Networks. *IEEE Signal*, 10(1):8-39.

Jaehyun Lee, E. L. (2020). Electric Vehicle Charging and Discharging Algorithm. *Energies, 13(8).*

Joskow, P., & Wolfram, C. (2012). Dynamic pricing of electricity. *Am. Econ. Rev.*, 102, 381–385.

M. J Mirzaer, A. K. (2014). Real-world based approach for optimal management of electric vehicles in an intelligent parking lot considering simultaneous satisfaction of vehicle owners and parking operator. *Energy*, 76:345-356.

Masoum AS, D. S.-S. (2011). Smart load management of plug-in electric vehicles in distribution and residential networks with charging stations for peak shaving and loss minimisation considering voltafe regulation. *IET Gener, Transm Ditrib*, 5(8):877-88.

Nuñez Camacho, D. (2017). *Algoritmo para generar alternativas de gestión de carga en un usuario no regulado para un programa de respuestas de la demanda.*

Pita, C. (04. December 2021). *Newtral Data*. Von Así se produce la energía eléctrica en los países de la UE: https://www.newtral.es/energia-por-paises-electricidad-europa-ue-espana/20211204/ abgerufen

Rodriguez, J. (2002). *INTRODUCCIÓN A LA PROGRAMACIÓN. TEORÍA Y.* España: Editorial Club Universitario.

Rodríguez, J. D. (2020). *Algoritmo de optimización para sistema de gestión eléctrica inteligente.*

Russell, K. A. (11. Junio 2021). *Set-up and challenges of Germany's power grid* . Von Cleanenergywire: https://www.cleanenergywire.org/factsheets/set-and-challenges-germanys-power-grid abgerufen

Statista Research, D. (24. June 2022). *Statista*. Von https://www.statista.com/statistics/646075/total-number-electric-cars-germany/#:~:text=Germany%3A%20number%20of%20all%2Delectric%20cars%20registered%202008%2D2021&text=About%2013.5%20percent%20of%20cars,were%20plug%2Din%20electric%20cars.&text=The%20auto% abgerufen

Trujillo, M. J. (2015). *Diseño e Implementación de un algoritmo para la gestión de la energía de un sistema híbrido móvil con fuentes renovables* . Mérida, Yucatán.

Wang, Q. Z. (2015). Review of real-time electricity markets for integrating distributed energy resources and demand response. S. 138,695-706.

Wang, Q. Z. (2015). Review of real-time electricity markets for integrating distributed energy resources and demand response. *Appl. Energy*, 138, 695–706.

Yang, L., Dong, C., Wan, C., & Ng, C. (2013). Electricity time-of-use tariff with consumer behavior consideration. *Int. J. Prod. Econ.*, 146, 402–410.

A Annex Function Code

Draw maximum and minimum power in the network:

```
plot(p1.time, p1.signals.values); %Obtain state of the grid graph on
screen

maxp1=max(p1.signals.values) %Obtain maximum power

minp1=min(p1.signals.values) %Obtain minimum power
```

Matlab function to interpolate prices as a function of power:

```
function markprice = interpolar(u, pmin, pmax)

   med=pmax-pmin/2; %Obtain average power

   per=(pmax-u)/med;

   cost=per*0.3234; %Convert to price

   if cost<0.2264 %Establish minimum limit

       cost=0.2264

   else if cost>0.4204 %Establish maximum limit

         cost=0.4204

   else

         cost

       end

   end

markprice = cost;
```

Price function according to availability variable:

```
function abprice = fcn(data, b)

if data<3 % 3 is established as the average value

    pa=b*0.97 %If it is lower, the price is reduced

elseif data>3
```

```
    pa=b*1.03 %If it is higher, the price increases
else
    pa=b
    end
abprice = pa;
```

Function for dynamic final price:

```
function g = fcn(s, data)
if s>5000 %Superior tolerance for over-production
    data=data*0.95
elseif s<-2000 %Lower tolerance for power deficit
    data=data*1.05
else
    data=data
    end
g = data;
```

Function for final load:

```
function y = fcn(cn, cv, load)
if cv>cn; %Comparation of previous price and dynamic price

    loadn=load*0.7;
elseif cv<cn;
    loadn=load*1.3;
else
    loadn=load;
end
y = loadn;
```