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Smart Recharging of Electrical Vehicles with Battery Switching Technology

Supervisor:

Prof. Michela Meo
Dott. Daniela Renga

Candidate:

Gianmarco Centonze

Abstract

In recent years the climate crisis gained growing attention thanks to the work of the activists. The increased sensitivity towards the environment did not always translate into efficient actions actuated by the governments and this fight lacks a global effort.
However, some sectors are changing. Transports, which are among the main cause of pollution and greenhouse gases emission, has started a process of abandoning combustion engines to move to 100% electric powertrain. Indeed, the fleet of electric vehicles (EV) is getting more and more numerous and the rate of EV adoption is expected to increase.
Although the high penetration of EVs is good news for air quality and the environment, it brings issues that need to be addressed. Firstly, the effort of reduced pollution could be nullified if EVs are not combined with a renewable energy source. The batteries of the cars required a large amount of energy to be charged and this could cause an extreme load on the grid.
This thesis investigated a scenario in which EVs are widely used and the gas stations have been substituted by the battery switching stations, i.e. platforms that can swap the flat battery of a vehicle with a fully charged one. These stations are equipped with an array of photovoltaic panels that produces energy for the batteries and host charging and fully charged batteries. Hence, they provide flexibility to the grid and could prevent or even solve congestions, serving as energy storage stations and becoming agents of the smart grid.
This thesis aims to assess the feasibility of the battery switching stations. To

do that a discrete-event simulator has been built to study the system so that it is possible to evaluate how the station reacts with a certain traffic pattern with certain parameters.

By dimensioning the capacity of the batteries and the number of solar panels, this study observes that to compensate for a large amount of energy demanded by the vehicles a large number of panels is required, and adopting some charging strategies it is possible to reduce the costs.

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Chapter 1

Introduction

1.1 Motivations

Cars and transport have a big, negative impact on the planet, that starts before the car makes it to the road, since cars are made of materials with a major carbon footprint as steel, rubber, paints. However, 80-90% of the environmental impact is due to fuel consumption and emissions of air pollution and greenhouse gases that climate scientists say are driving global warming.[1] Fuel-powered vehicles not only contribute negatively to the climate emergency, but they release smog, carbon monoxide, and other toxins at street level, directly compromising our health. In the U.S. Greenhouse gas (GHG) emissions from burning fuel for transportation cause one-third of the total air pollution.[2] In Figure 1.1, the pie chart represents the global GHG emissions sector by sector. Data show that if we could electrify the whole road transport sector, and complete the transition to a fully decarbonized electricity mix, we could feasibly reduce global emissions by about 12%.[3]
Thanks to supportive regulatory frameworks, that aim at reducing CO_2 emissions, and additional incentives to safeguard Electric Vehicles (EVs) sales from the economic downturn caused by the COVID-19 pandemic, the EV market

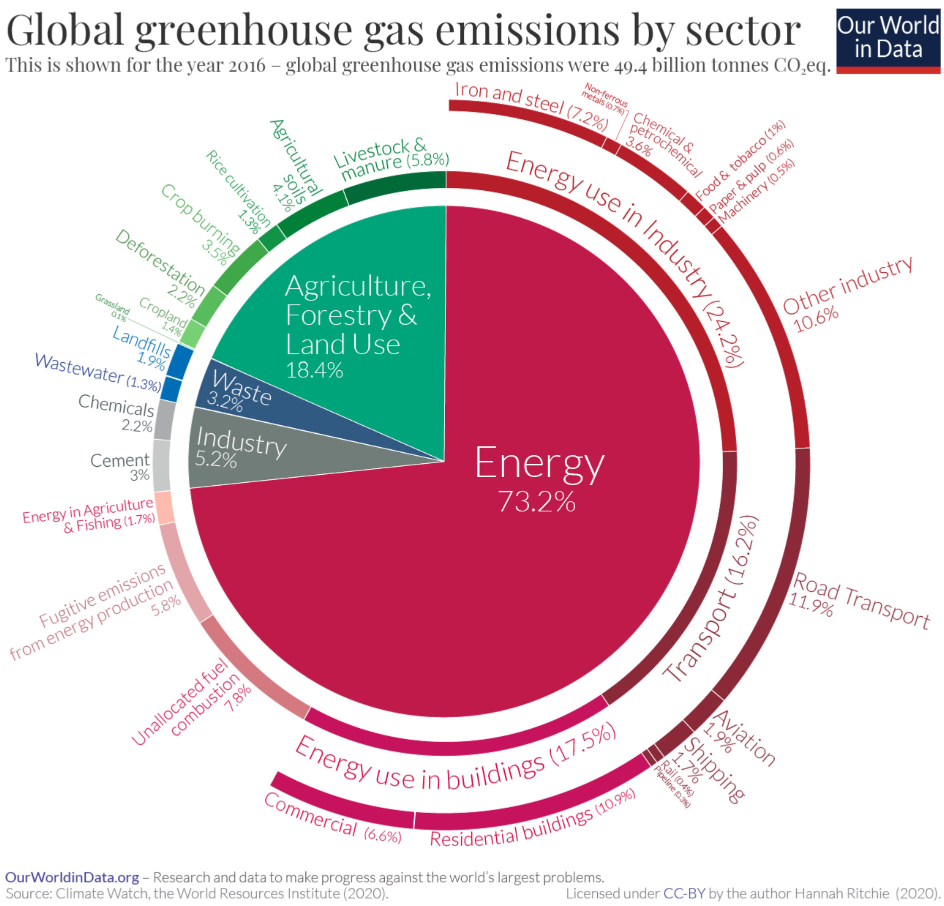


Figure 1.1: Global GHG emissions by sector.

has been growing fast: in 2020 the global electric car stock hit the 10 million units. Battery electric vehicles accounted for two-thirds of new electric car registrations and two-thirds of the stock in 2020. China, with 4.5 million electric cars, has the largest fleet, yet Europe had the largest annual increase to reach 3.2 million.[4]

The intent of this thesis is to investigate a scenario of battery switching stations, i.e. platforms that deploy a robotic arm to swap the flat battery of a vehicle with a full charged one, that could speed up the adoption of electric vehicles and, broadly speaking, to contribute to the global effort to increase the pace of the transition from fossil fuel energy to eco-friendly energy sources to fight the climate emergency.

1.2 Objectives

This thesis aims at dimensioning a battery switching station (BSS), analysing the behavior with different parameters and the quality of the service received by the customers.
A BSS can be compared to a gas station, in the sense that an electric vehicle (EV) is *refueled* with an operation that lasts for few minutes, whereas plug-in EVs charge process may last for longer amount of time (hours) that depends on the type of charger.
BSSs are equipped with a robotic arm that autonomously removes the battery from the vehicle and installed a full one. Subsequently, the flat battery will be charged by the station and it will be used to serve another customer.
A BSS can be represented as a client-server model, in which the server/station has a limited amount of resources (fully charged batteries) that depends on the size of the dock and the parameters of the charge process. If we consider negligible the time required by the battery swap, the queue is due only to the time for charging the batteries in the dock, whereas the loss is due to an impatient client/vehicle, that leaves the BSS without waiting for a battery becoming available.
Before a company could invest in the BSSs, it is necessary to verify the feasibility of the system in a real scenario, i.e. analyse the average service time, the loss probability, the average availability.

1.3 Structure

The thesis is composed by four chapters. The first one gives an overview of the electric vehicle technologies. Since the term EV may be confusing, it starts with a dictionary of the current EV types. Generally, the term electric vehicle refers to vehicles in which power is provided by batteries that needs to be charged by an external source. This thesis follows this trend. Then, it reports the characteristics of the modern electric vehicles on the market and it explains the components of the powertrain focusing on the battery.

The second chapter introduces the battery switching station and explains how it is structured. Afterwards, it reviews a model of integration between renewable energy sources and EVs, it assesses the pros and cons of the BSS and it cites some case studies.

The third chapter presents the simulator, the tools used to build it, the parameters, and the architecture. It explains the operation it performs and the strategies that implement smart charging.

The last chapter presents the results showing the most significant graphs and derives the final conclusions.

Chapter 2

EV Overview

The last years recorded a growing interest in EV technologies by the vehicle manufacturers and the policymakers, because EV models are attractive options to help environment and health issues, because they can reduce the dependency on fossil fuel energy reducing GHG emissions and with zero emissions they don't contribute to air pollution.

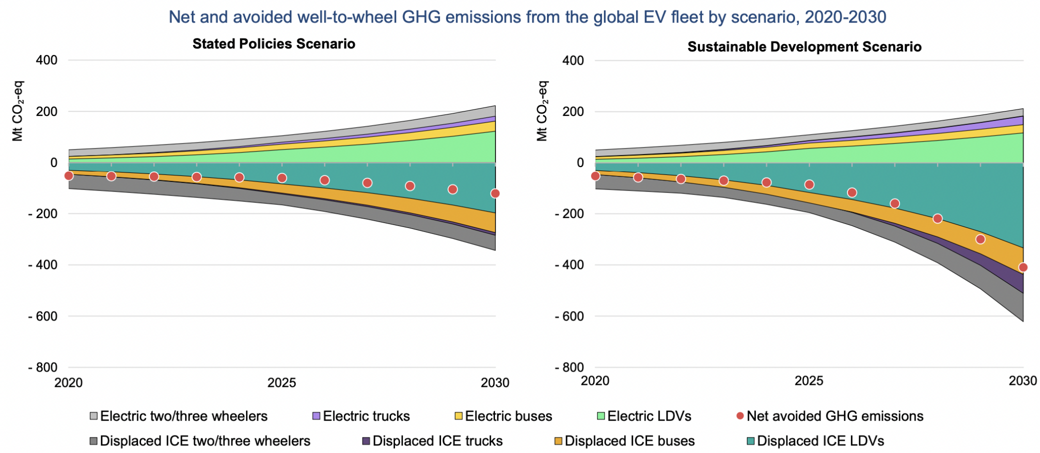


Figure 2.1: Net GHG reduction compared with increasing EVs adoption.[4]

In 2020, EVs saved more than 50 Mt CO_2-eq (million tonnes of carbon-dioxide equivalent) of GHG emissions globally, equivalent to the entire energy sector

emissions in Hungary in 2019.[4]
The projections for the decade expect that as the EV fleet will expand we will assist in a net reduction of GHG emissions (Figure 2.1), yet EV deployment needs to be accompanied by decarbonization of electricity generation. Indeed, the increasing number of EVs will cause an additional demand for energy, that has to be produced by renewable sources, otherwise the benefits on the environment will be nullified.[5]

2.1 Taxonomy

Since the term, Electric Vehicle is actually very vague and it includes different technologies, this section provides a dictionary of the existing EV types.[6][7]
EVs can be categorized as follow:

- **Battery Electric Vehicle** (**BEV**): power is provided only by the batteries. It does not produce any greenhouse gas (GHG), does not make any noise and therefore beneficial to the environment.

- **Hybrid Electric Vehicle** (**HEV**): power is provided by a combination of an Internal Combustion Engine (ICE) and an electrical power train. This combination can come in different forms. It uses the electric propulsion system when the power demand is low, i.e. low-speed conditions like urban areas; it also reduces the fuel consumption as the engine stays totally off during idling periods like traffic jams. This feature also reduces the GHG emission. When higher speed is needed, the HEV switches to the ICE. The ICE can charge up the batteries, HEVs can also retrieve energy by means of regenerative braking.

- **Plug-In Hybrid Electric Vehicle** (**PHEV**): it uses a combination of ICE and electrical power train like HEV, but the main driving force is the electrical propulsion. The ICE is used to provide a boost or to charge up the battery pack to extend the range. PHEVs can charge their batteries directly from the grid. The carbon footprint is smaller than HEVs.

- **Fuel Cell Electric Vehicle** (**FCEV**): they use chemical reactions to produce electricity. They carry hydrogen in special high-pressure tanks. Electricity generated from the fuel cells goes to an electric motor that drives the wheels. Excess energy is stored in storage systems like batteries or supercapacitors.

- **Extended-range EV** (ER-EV): similar to the BEVs category, however, the ER-EVs are also provided with a supplementary combustion engine, which charges the batteries of the vehicle if needed. This type of engine, unlike PHEVs and HEVs, is only used for charging, so that it is not connected to the wheels of the vehicle.

The BSS is designed to substitute the battery of BEVs, which will be called EVs for simplicity.

2.2 EV Benchmarks

This section reports average benchmarks to give an idea of the capabilities of the current electric vehicles.
The data have been taken from the Electric Vehicle Database[8], which collects all data regarding EVs to make this information easily available to accelerate the adoption of sustainable transport by solving misunderstandings and myths surrounding the electric vehicle.
The main concern of customers is the autonomy of a vehicle, i.e. how far can I go once with full batteries/tank, and how much does it take to *refuel* the car. The range of EVs obviously depends on the capacity of the batteries, but also speed, style of driving, weather, and route conditions. Table 2.1 presents battery and range values for some purchasable vehicles and the mean values

Model	Capacity [kWh]	Usable [kWh]	Range [km]
Renault Twingo Electric	23	21.3	130
Mini Cooper SE	32.6	28.9	185
Citroen e-C4	50	45	250
BMW iX3	80	74	385
Tesla Model 3 Performance	82	76	470
Average	60	59.9	315

Table 2.1: Battery and range values from [8]. The range is an estimated mean of the range under different conditions.

of all the 180 car model contained in the dataset.
The charging time instead mainly depends on the charging infrastructure that can be categorized in three levels. These levels are summarized in Table 2.2.

Charging lvl	Typical power	Typical use	Time to Charge[1]
Level 1	2 kW	Home	4-11 hours
Level 2	20 kW	Public	1-4 hours
Level 3	100 kW	DC Fast	30 minutes

Table 2.2: Charging Power Levels [9]

2.3 Powertrain Components

This section focuses on the elements that compose a (B)EV powertrain. The parameters and their typical values have been taken from this study of the literature [10].

[1]Time to raise EV 60 kWh battery from 10% to 80%

2.3.1 Traction Battery

It is the most important and the most expensive component. Currently, the most advanced technology is the lithium-ion battery (LIB), that consists of interconnected cells, clustered in packs, whose dimensions (length, width, and height) and shape (pouch, prismatic, and cylindrical) depend on the manufacturer.
The primary parameters are:

- Gravimetric energy density [Wh/kg] at cell and pack level
- Volumetric energy density [Wh/L] at cell and pack level
- Battery C-rate [h^{-1}]
- Number of battery cycles
- Cost [€/kWh]

The energy density is the amount of energy stored in a given system or region of space per unit volume (volumetric) or mass (gravimetric). Both have been steadily increasing in recent years. Nowadays it has more than doubled the values of 2012, when it was almost 100 Wh/kg. Some researchers claim that the limit of the lithium-ion technology is around 350-370 Wh/kg and that it will be reached by 2030. Then new cell chemistry and technology will be needed to make further progress in gravimetric energy density.
The energy density at the pack level is always lower than at the cell level, because the battery also contains other components, e.g. cooling, wires.

The C-rate describes the maximum charge or discharge current in relation to the energy of the battery. A C-rate of 1 means that the battery can be completely discharged in one hour. Because of internal resistance loss and the chemical processes inside the cells, a value between 2 and 5 hours is considered realistic.

The number of battery cycles is the maximum number of cycles that the battery can withstand before its useable energy drops to 80% of its initial value. The literature considers this number to be realistically in a range between 1000 and 3000.

Nowadays the cost is around 150 €/kWh and it is expected to decrease in the next years.

Battery Ageing

LIBs are subjected to deterioration over time, which consists of capacity degradation and a resistance increase. Battery degradation is the result of several simultaneous physicochemical processes and it depends on the cell chemistries, time, (ambient) temperature, current load, voltage, accumulated ampere-hour throughput, and mechanical stress[11].
The conditions of a battery are described mainly by two parameters: state-of-charge and state-of-health.
The state-of-charge (SOC) is the ratio between the currently available capacity ($Q(t) = \alpha \cdot \beta \cdot Q_N$) and the total capacity at the previous full charge [12]:

$$SOC = Q/Q_0 = \alpha \tag{2.1}$$

The state-of-health (SOH) is the ratio between the remaining capacity in aged batteries Q_0 and the initial, nominal capacity Q_N [12]:

$$SOH = Q_0/Q_N = \beta \tag{2.2}$$

The capacity degradation was used to describe the aging behavior of a battery, but in recent years, changes in internal resistance have received more attention

as an aging characteristic as well. Indeed, as the resistance increases, the ohmic heat generation increases, and the available energy is reduced as power is lost to ohmic heating[11].
The battery ageing mechanism can be decoupled in:

- **calendar aging**: it is due to the consequences of battery storage; several studies showed the impact of high temperature, which facilitates corrosion and lithium loss, and high SOC, which represent the ions proportion present on electrodes that promote chemical reactions[13].

- **cycle aging**: it happens when the battery is either in charge or discharge and it is the direct consequence of the level, the utilization mode, the temperature conditions, and the current solicitations of the battery. The higher ΔSOC (i.e. the state of charge variation during a cycle) is, the higher is the loss of battery power[13].

Many studies show that to preserve the battery life, the SOC should be maintained between 20% and 80%.[14]

2.3.2 Electric Machine and Gearbox

The electric machine converts electrical energy into mechanical energy and it is coupled with the gearbox that transmits the machine torque to the wheels. It is described by: gravimetric power density [kW/kg], machine overload factor, maximum rotational speed [min^{-1}], costs [€/kW].
Due to the high variety of the losses caused by the gearbox, the exact modeling of its efficiency is very complicated, therefore researchers use a fixed value, typically between 92-97%.

2.3.3 Power Electronics

Power electronics control the power from the battery to the motor. The efficiency of the power electronics varies according to its operation conditions, however, a realistic range is between 85% and 95%.

2.4 Cost Assessment

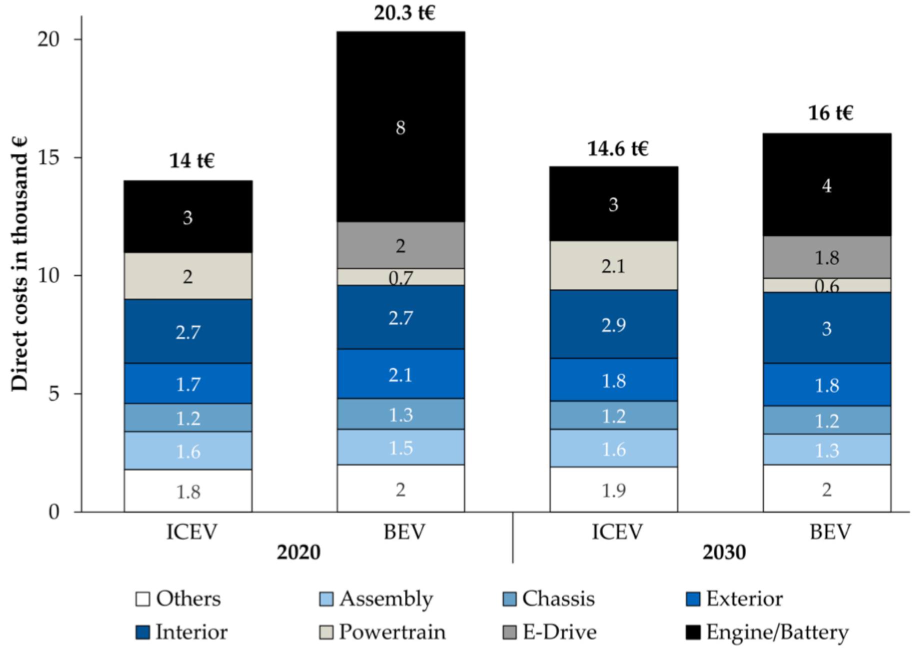


Figure 2.2: Current and future cost of the structure of BEVs / ICEVs.

Figure 2.2 compares the costs of an ICE vehicle with those of an EV with a 50 kWh battery. As we can see, ICEVs are remarkably cheaper than EVs, yet, according to the projections, the price difference is going to decrease due to the battery prices falling. The battery indeed is the most expensive car component for EVs and it constitutes more than one-third of the total cost. Figure 2.3 shows the projection, derived from the literature, of the battery pack costs in the next years. The researchers estimate that as current battery pack costs are already at the lower end of the reviewed range (minimum values), the costs by 2030 will be in the lower range too.

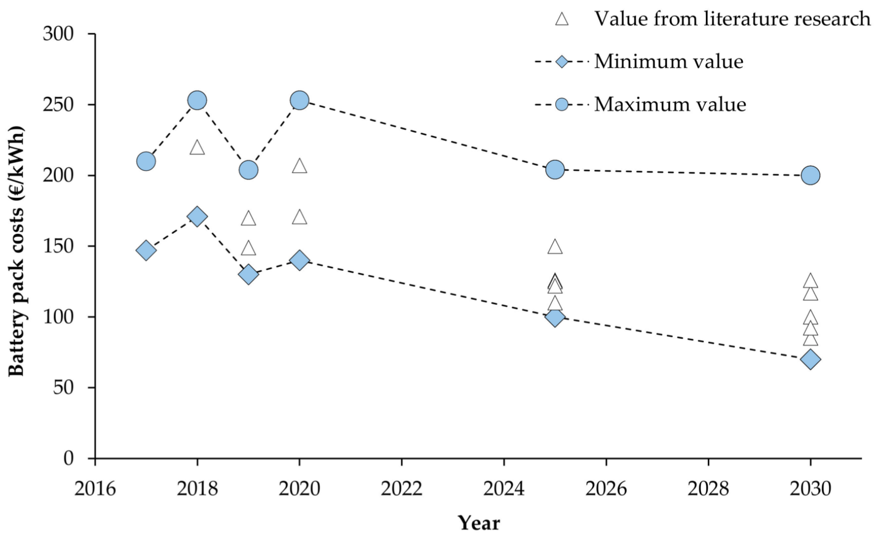


Figure 2.3: Development of battery pack costs.

Chapter 3

The Battery Switching Station

A Battery Switching (or Swapping) Station (BSS) is similar to a traditional gas station, where a compatible EV replaces its flat battery with a fully charged one.
The main advantage of the BSS is that the time of the switching process is comparable with the refueling of ICE vehicles. This system would eliminate any driving range limit that plug-in EVs are subjected to. Imagine the case of a driver that needs to drive for 1000 km, a distance larger than any EV range. With a traditional plug-in vehicle, the driver has to stop likely two-three times to charge the car and it would probably take hours since the most common charge is level 2 (Table 2.2). With a BSS instead the stop could last few minutes.
The deployment of BSSs could encourage the purchase of EVs instead of ICE cars, making the driving experience more similar.
The BSS is also an actor of the smart grid, because the surplus of energy stored in the batteries or the surplus of energy produced by the renewable energy source could be sold to the grid.

3.1 Components

This section describes the essential components of a BSS. It does not look into the mechanical aspects, but it shows the system from a logistic point of view.

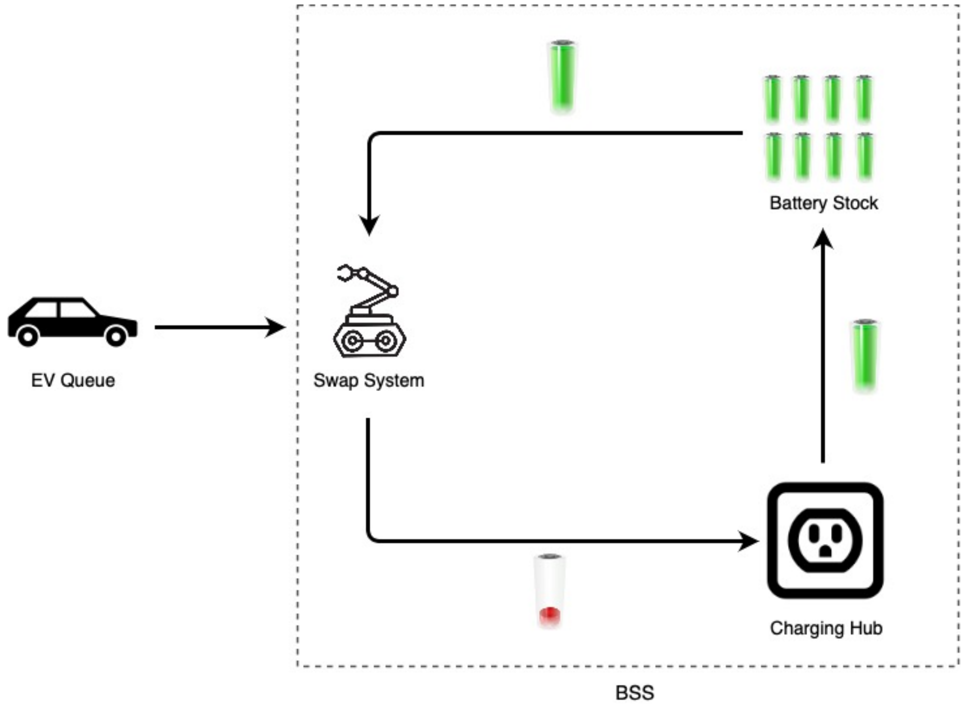


Figure 3.1: BSS Model

- **EVs**: the clients of the BSS arrive at the station when the battery is almost flat and the vehicle has a few kilometers of autonomy left. They eventually wait in a FIFO (First In First Out) queue if either the station is serving another vehicle or there aren't batteries in the stock.
- **Switch Platform**: it deploys a robotic arm to remove the flat battery and install a fully charged one. It can serve one vehicle at a time and it doesn't need human assistance.
- **Charging Hub**: the flat battery after being removed is plugged in a special socket and charged in the hub. The process takes a time that

depends on the battery capacity and the charging rate (*Time = (Full Capacity [kWh] - SOC)/ Charging Rate [kW]*).

- **Battery Stock**: it stores the batteries that are charged. Its capacity is limited.

- **Renewable Energy Source (RES)**: the BSS is provided with a set of photovoltaic panels or a wind turbine. The interaction of the BSS with RES is described in the next section.

3.2 Interaction with RESs

EVs have a key role to achieve air purification goals, since they emit no CO_2 and other pollutants, yet lower emissions of GHG determined by a substantial increase of EVs could cause higher emissions by the electricity generation when it is based on fossil fuel combustion.
The widening of the EV fleet will drastically increase the electricity demand. It's hard to tell precisely how much energy will be required, but it is estimated that the consumption of an 80% share of EVs will differ between 3 and 25% of total electricity demand across EU member states.[5]
The integration of RESs with EVs could lead to a decarbonization effect and an improvement of resource efficiency, however, several investments by nations are required. Nations should also implement management strategies depending on the types of renewable energy they produce. States with high solar energy production, for example, may prefer charging peak to be during the day and they may adopt different strategies with respect to states that produce wind energy or a combination of both.
Furthermore, the uncoordinated charge of a fleet of EVs could cause a large electric load resulting in higher power systems peak-load and distribution grid congestion issues.
EV technology should cooperate with renewable energy production to fix its

drawbacks: in particular, it should achieve a synergy with photovoltaic generation (PV) to provide individual and systemic benefits, by decreasing both technology costs and ecological footprints and even stimulate the development of each technology.[15]

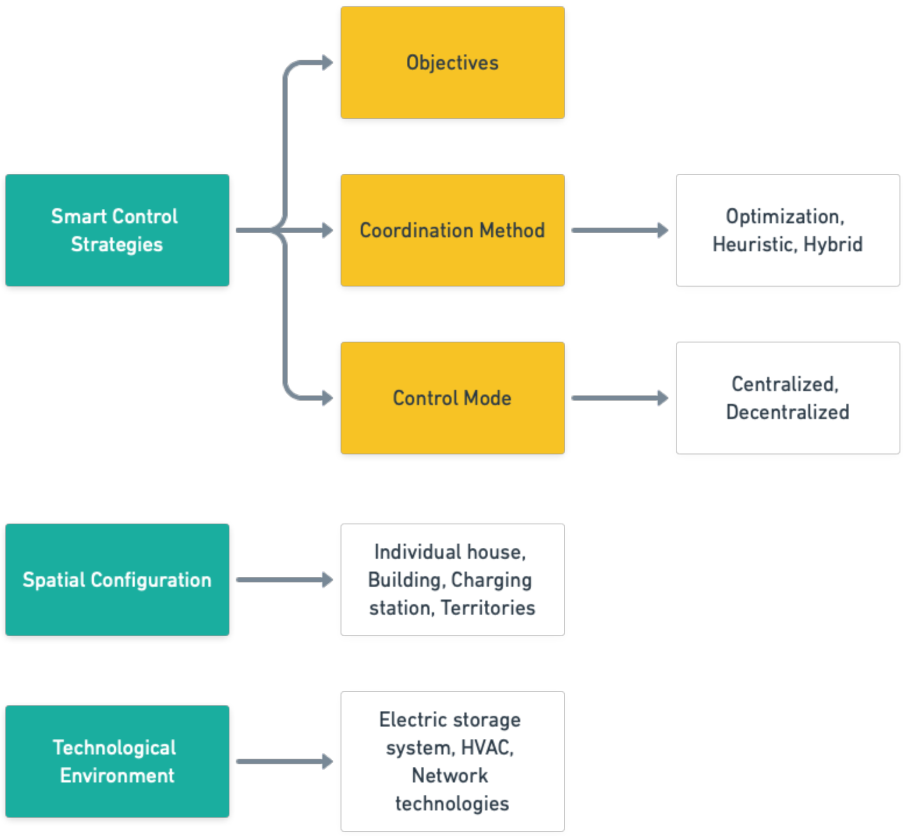


Figure 3.2: Interaction with RES

In [15], the researchers have identified the technical aspects of the EV/PV synergy that is depicted in Figure 3.2.

The main component is the smart control strategies. A key element of the strategies is the ability of the EVs to use bidirectional flow (vehicle-to-grid, V2G), i.e. to drain and deliver energy to the system.

A strategy has an objective to achieve. In this case, it can be a monetary

objective, e.g. increasing the revenue of a charging station or decreasing the electricity cost, or a physical objective, e.g. increasing energy efficiency and decreasing the ecological footprint.
The control mode coordinates the charges of the EVs. If it is centralized, a special agent, called aggregator, manages the schedule of the EV fleet charges. This provides good results, but it requires exchanging a very large amount of data. If it is decentralized, EV drivers respond to the incentives of an aggregator. This requires a less complex communication infrastructure, but the gains are lower since we don't know how drivers react to incentives.
The coordination method is the mathematical formulation of the control strategy, e.g. an objective function (based on cost, energy efficiency, or ecological footprint) to be optimized.
The control strategies are tailored for a specific spatial configuration that brings specific constraints.

3.3 Pros and Cons

The deployment of the BSS can bring advantages to the EV drivers and, as an actor of the smart grid, to the community.
Firstly, a widespread network of BSS would solve range anxiety, i.e. the fear that a vehicle has insufficient range to reach the destination. The term, which is primarily used in reference to BEVs, is considered to be one of the major obstacles to the large-scale adoption of all-electric cars.[16] Moreover, the swap is comparable to refueling an ICE vehicle in terms of duration.
The second benefit is that the drivers wouldn't be the owners of the batteries of their vehicles, since the batteries would belong to the BSS owners or to a company that has an agreement with the BSS owners. Therefore, the price of the EV should considerably decrease, because the battery is the most expensive component. The company owning the battery could offer a subscription to the users to lease the battery, it would charge the driver to access to the swap

service and it would offer to substitute if the capacity decrease due to age problem or any other damage maintaining the costs reasonable.
The main drawback is that all the vehicles should be compatible with the switching process. It is necessary to create a universal standard for batteries in order to make them switchable, hence different electric automakers should produce EV models with a not embedded battery that can be dismounted easily.
The BSS brings another advantage: it can be an actor of the smart grid. The schedule of batteries charge can be indeed flexible, e.g. it can postpone the charge to less busy hours preventing peak-loads of electricity, acting like an aggregator, or it can discharge the battery to sell the energy to the grid.
Moreover, the BSS doesn't need to *call* the EVs to plan to charge/discharge; it neither needs to use incentives, because it already holds the batteries in the stock, as opposed to the plug-in charge station scenario.

3.4 Case Studies

This section brings up three case studies of real existing companies that in recent years have deployed, or still deploy, a fully operative network of BSS.

3.4.1 Tesla

Tesla is an electric vehicle and clean energy company based in Palo Alto, California. It began production of its first car model, the Roadster, in 2009. In 2017, Tesla started production of Model 3, the all-time best-selling plug-in electric car worldwide, which, in June 2021, became the first electric car to sell 1 million units globally.
In 2013, Tesla showed off a 90 seconds battery swapping technology, but later the company changed its plans and decided to invest in Superchargers.[17]
As of February 18, 2021, Tesla operates over 23,277 Superchargers in over

2,564 stations worldwide.

Figure 3.3: Tesla Supercharger

3.4.2 Nio

Nio is a Chinese electric vehicle manufacturer that is betting on battery swapping to compete against Tesla. The company was founded in 2014 and has sold around 120,000 EVs. Nio has so far built around 300 battery-switching stations and it plans to add at least 3700 BSS by the end of 2025.[18]
In August 2020, the automaker launched Battery-as-a-Service, whereby customers buy the car but lease the battery. In this way, buyers can keep up-to-date with battery technology as it improves.
In May 2021, Nio announced a Norway expansion plan, saying it would begin delivering cars to Norway by September 2021.[19]

3.4.3 Ample

Ample, a San Francisco-based developer of switchable electric vehicle (EV) batteries, has raised $160 million in a new funding round. The company has

Figure 3.4: Nio Working BSS

developed a battery for EVs and an automated process for quickly swapping out flat batteries for newly charged ones.[20]
Ample aims to make its batteries and swapping process more widely available to different brands.
The industry's response to shortening the charging time has been to develop technology like DC fast chargers, which have managed to shave it down to only 20 or 30 minutes. But Ample co-founder John de Souza said that improvements in charging time don't get rid of fundamental problems: "[Fast charging] generates a lot of heat; the grid doesn't support it".[21]

3.5 Summary

We have seen that to move towards a zero-emissions future we have to combine EV technology with renewable energy sources that produce power to charge

Figure 3.5: Ample BSS

the vehicles. Plug-in models don't address this issue, since they drain power from the grid, and delegate the decarbonization to the political establishment. Furthermore, they don't address yet the peak load that could be caused by a large fleet of EVs in need of a charge.
Since the EV fleet is expanding constantly, it is necessary to face these problems: battery switching stations would deploy photovoltaic panels on the rooftop to produce clean energy to power the batteries and, if energy from the grid is needed, they could schedule the charges to avoid peak loads.
This scenario doesn't require a massive communication infrastructure for coordinating the charge of vehicles and drivers don't have to be involved.
For example, a peak load can be avoided by postponing the charge of some batteries or by exclusively using the power from the solar panels. These decisions are up to the BSSs, but they can be stimulated by the smart grid increasing the electricity price when it is under stress and decreasing the price in the other periods. BSSs could even decide to discharge some batteries and sell the

energy to the grid to prevent congestions.

The investigated scenario

We want to assess a scenario in which a BSS serves a car-sharing firm, whose vehicles are equipped with a 20 kWh battery. This capacity, according to the Electric Vehicle Database, should provide (on average) a driving range slightly longer than 100 km. Since car-sharing works only in the cities, the range could be even longer because the speed must be mild and the car could retrieve energy from frequent regenerative braking.
Figure 3.6 presents how the battery switching station should look like. The concept reveals that the number of photovoltaic panels is expected to be high, because their efficiency is usually not so elevated and it puts a constraint on the capacity of the batteries, i.e., given the number of sockets that depends on the number of arrivals, a trade-off between the battery capacity and the number of panels should be found, otherwise the solar energy would not be sufficient. The next section will deepen the dimensioning of the batteries and the panels.

Figure 3.6: BSS with PV panels installed on the roof.

Chapter 4

The BSS Simulation

As already mentioned in section 1.2, the main contribution of this thesis is the calibration of the parameters of all the actors involved in the BSS system (the station, the batteries, the vehicles, the photovoltaic panels) and assessment of the feasibility of the system with respect to the grid and the customers.
The core of the work consists of a computer simulation that reproduces the BSS behavior and, by simply changing the value of certain parameters (e.g. the number of batteries that the station can hold), it is possible to analyze the response, since it provides statistics and performance metrics, such as the loss rate or the average time that a client (i.e. an EV driver) waits in the queue.
The analysis of the statistics allows tailoring the BSS for a specific traffic pattern. The goal of the station is to serve an EV at any time with the lowest waiting time possible.
The first step was building a baseline model of the BSS able to serve an adequate number of customers. The modality of the arrivals is described in Section 5.1. The volume of traffic has been set to a reasonable value, i.e. 100 vehicles per day, each vehicle with a 20 kWh battery. This phase consisted in calibrating the parameters to have an acceptable loss rate. Losses are due to impatient drivers: when an EV comes to the station and all the batteries are still charging, the driver waits for some minutes and then it goes away, so

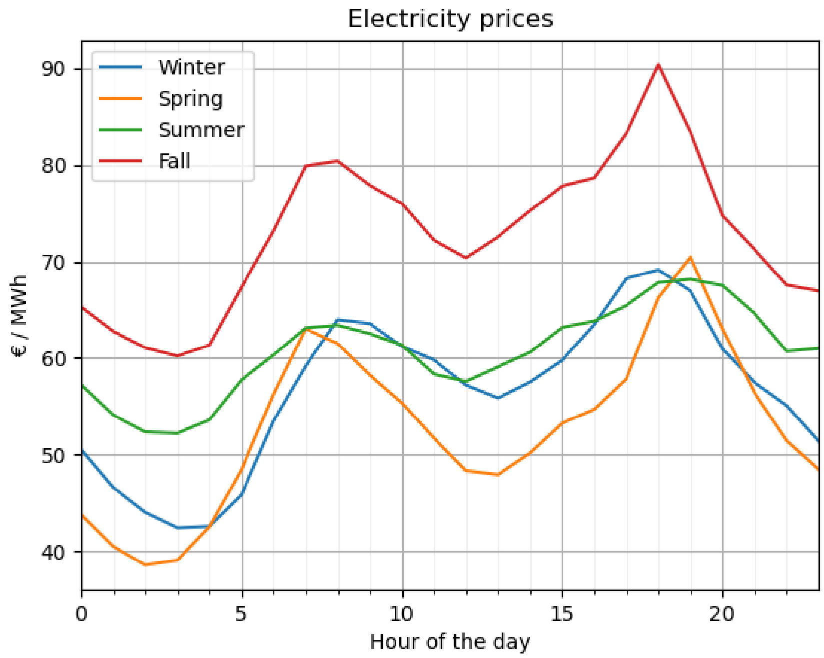


Figure 4.1: Electricity cost reported by the Italian energy market.[22]

the BSS missed a customer. So far the BSS was set to charge the batteries continuously using exclusively energy from the grid.

Afterward, the PV panels were implemented, so that they can contribute to the grid to charge the batteries. Besides satisfying Quality of Service (QoS) constraints, the BSS implements some strategies to make the charge of the batteries cheaper or more environmentally friendly. To do that, an algorithm can postpone the charge in a time slot in which the energy price is expected to be cheaper (usually during night hours and the midday, as we can see in Figure 4.1), or when the PV panels installed on the roof of the station produce electricity. Obviously, this happens during daylights hours. Figure 4.2 shows the average output power for each hour and season, that is double in summer and spring with respect to winter and fall.

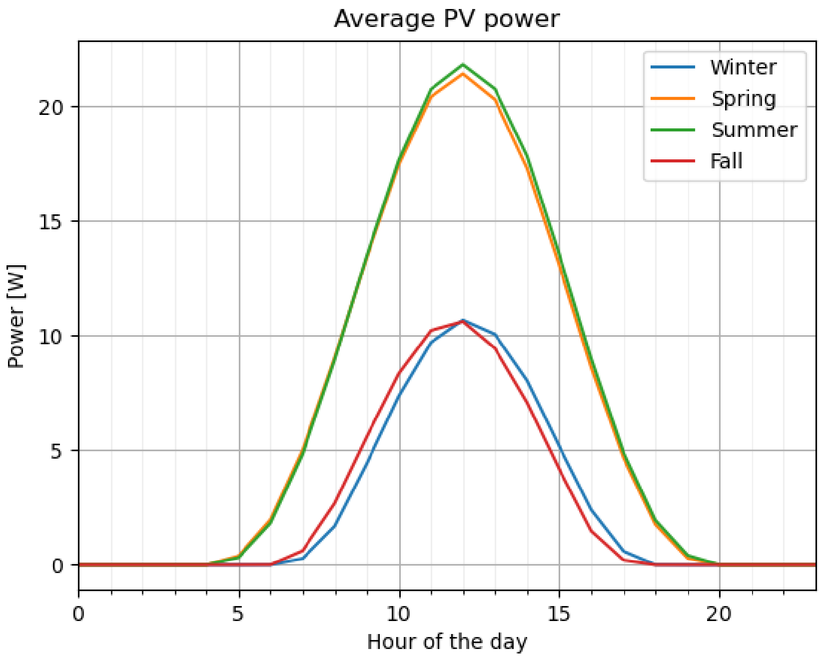


Figure 4.2: Output power by hour of a solar panel with nominal capacity of 1 kWp for a period of 1 year.

4.1 Simulation Tools

A discrete-event simulator was designed to reproduce the behavior of the battery switching station, because mathematical modeling did not seem to be a practicable approach due to the high number of parameters. The simulation has been built using Python 3.8.5, in PyCharm 2021.2.2 installed on a macOS 11.6 device.

Moreover, these libraries have been used: `matplotlib`, to generate the plots to analyze the statistics and visualize the results; `numpy`, to compute the statistics; `random`, that was used to draw the inter-arrival time between the EVs coming at the station using a Poisson distribution; `pandas` to operate over the datasets.

4.2 Datasets

The first dataset contains the output power, for each hour of the day, of a PV panel with a nominal capacity of 1 kWp for 1 year, expressed in Watts. The data are derived considering real irradiation data during the Typical Meteorological Year in the city of Turin, Italy. Figure 4.3 shows the amount of power produced by one panel for each day of the year.

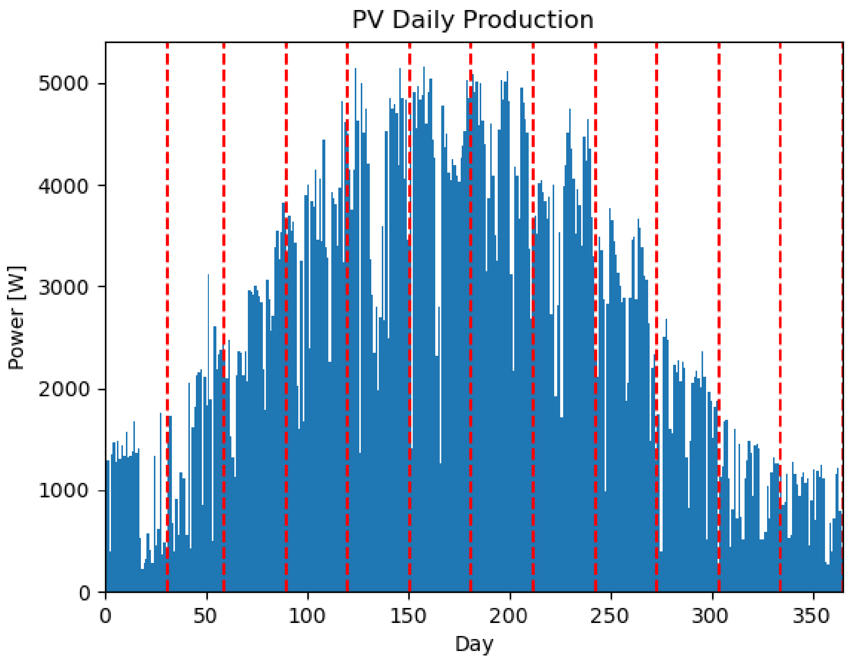


Figure 4.3: Amount of power produced each day.

The second dataset contains the the average daily electricity prices per season, expressed in €/MWh, reported with a time granularity of 1 hour (Figure 4.1).

4.3 BSS Parameters

This section explains the parameters of the BSS that defines its behaviour and its performances. Some values are taken from the literature, for others reasonable values have been picked.

- **Number of sockets ($\mathbf{N}_{bss}$)**: it is the number of batteries that the BSS can charge simultaneously. If all the sockets are busy, the station rejects a new client.

- **Battery capacity (C)**: in this scenario all the vehicles have a **20 kWh** battery. The bigger are the batteries, the larger is the impact on the grid.

- **Charging rate ($\mathbf{C}_r$)**: to preserve a good battery lifespan, the charging rate should preferably not exceed half the capacity of the battery per hour, so it is set to $C/2 =$ **10 kW**, that means that a flat battery is fully charged in 2 hours.

- **Threshold capacity ($\mathbf{B}_{th}$)**: in periods of high demand, the BSS can deliver a battery even if it is not fully recharged, as long as it has achieved a minimum charge level, i.e. B_{th}. The threshold is set to **80%** of the full capacity.

- **Number of PV panels ($\mathbf{S}_{PV}$)**: the number of photovoltaic panels installed on the roof of the station. Assuming a PV panel efficiency of 19%, a 5 m^2 panel has a nominal power of 1 kWp, i.e. in optimal conditions, it will produce 1 kW.

- **Waiting tolerance ($\mathbf{W}_{max}$)**: it is the amount of time that drivers can wait for a battery in case the charge of the next available battery is completed shortly. It is set to **15** minutes.

- ***Postponable* batteries (F)**: it is the number of batteries whose charge can be postponed to exploit solar power or to use cheaper energy from the grid.

- **Postpone time ($\mathbf{T}_{max}$)**: it is the maximum time, always expressed in minutes, that the charge of a battery can wait before starting.

4.4 Architecture

Figure 4.4 shows the object-oriented design of the battery switching station simulator. Each element of the real station corresponds to a module that interacts with the others providing and demanding services.

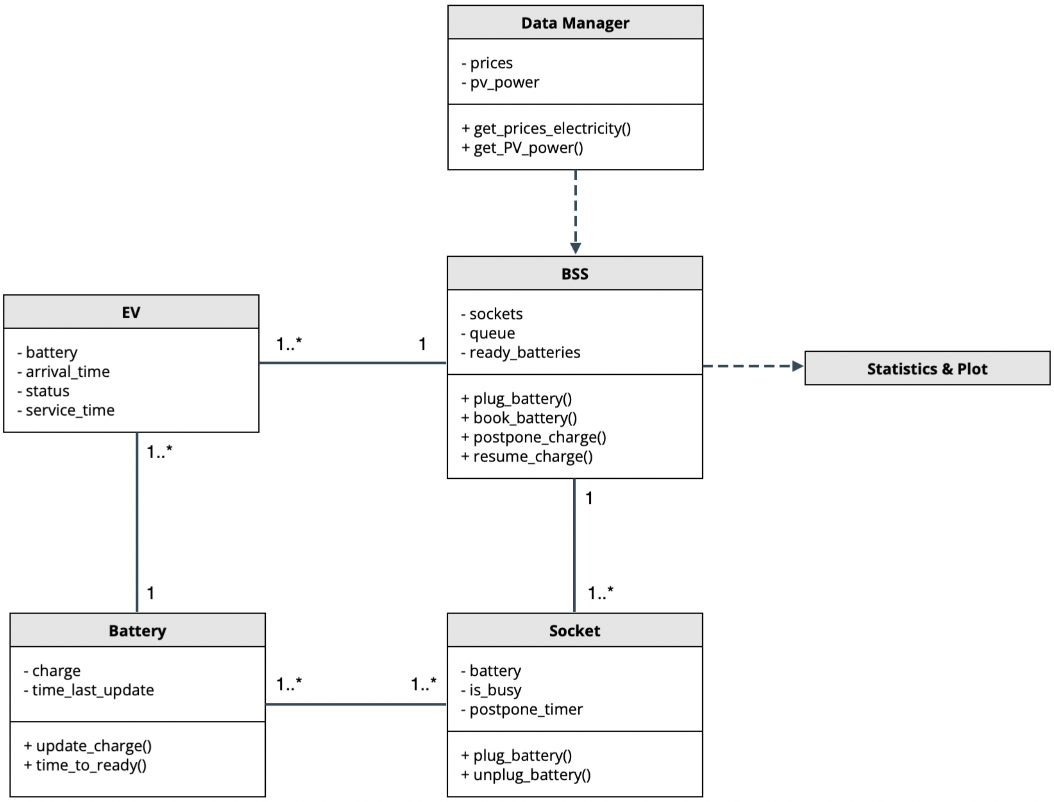


Figure 4.4: Class Diagram of the BSS Simulator.

The simulation creates an instance of EV every inter-arrival time. The EV instance creates the instance of Battery and requests a swap service at the BSS module. The Battery module keeps track of the level of the charge, updates it at every event, and can provide the time to the full charging.
The BSS module is the core of the architecture. It immediately serves an EV if a ready battery is available, otherwise, it holds the EV in a queue until a charging battery is full. It has multiple instances of Socket (depending on the capacity of the system) and each Socket holds a battery. The BSS can plug a battery in a Socket, reserve a charging battery for a vehicle that is waiting in the queue, decide to postpone or resume the charge by changing the status of a socket. When it comes to compute the cost of a charge or to update the battery level with solar power the BSS retrieves the data from the Data Manager module.
The Statistics module retrieves the data from the BSS and compute stats every hour or every day of the simulation and eventually plots the data.

4.4.1 Sequence of Operations

Before the simulation starts an instance of BSS and N_{bss} Sockets are created and each socket is associated with a flat battery. The simulation starts when an instance of an EV is created, then every new EV triggers the next one. This event is an *arrival* and is handled in the homonymous function.

arrival()

Firstly, this function calls *update_all_batteries()* to update the charge of the batteries plugged in the sockets. Subsequently, it generates a new EV and sets its inter-arrival time with an exponential function with a parameter that depends on the hour of the day.
Then, three cases are possible:

1) a fully charged battery is available, therefore the BSS swaps the batteries and plugs the flat one in a free socket;

2) there is no ready battery, the BSS checks when the next battery will be ready and if it takes less than W_{max} time the EV is put in the queue and it waits;

3) there is no ready battery, the next one takes too long to be ready or all the charging batteries are booked for another vehicle: the EV can't be served and the client is lost.

serve_queue()

This event happens after case 2 of *arrival()*. When the battery that has been reserved for a vehicle is fully charged, the BSS pops the EV out of the FIFO queue and executes the swap.

battery_available()

This event is triggered by a battery that has completed its charge. The BSS unplugs it from the socket and puts it on the dock with the other full batteries (in the simulation the ready_batteries variable is incremented).

update_all_batteries()

This function is called every hour and before every event, because of the price of the electricity and the solar power production change with hourly granularity. After updating the battery levels, the BSS checks if it has to resume the charge of a battery that has been postponed (see Section 4.4.3) because the postpone timer has expired.

4.4.2 Performance indicators

This section explains the performance indicators that have been used to evaluate the behavior of the system. The indicators are the following:

- **losses**: the BSS is not able to provide a battery to a client in W_{max} time, so the client goes away; it is the absolute number of clients lost on average each day during the year;
- **waiting time**: average delay of the station in serving the clients, due to EVs that waits for the next ready battery;
- **cost**: the average of daily costs of the energy bought from the grid to charge the batteries;
- **cost per service**: it is how much the station spent to charge a battery to serve a client: it is the daily cost divided by the number of arrivals minus the losses;
- **average ready batteries**: it is the average number of batteries that a vehicle finds when it arrives at the BSS;
- **savings**: if the solar panels produce a surplus of energy, the station sells it to the grid for half the price of the energy; it is the average daily value.

4.4.3 Postpone Strategies

At every arrival and every time a battery completes its charge, the BSS checks whether it can postpone the charge of some batteries to save money on energy, finding a trade-off between the quality of service and the costs. It always tries to put off the maximum number of batteries, specified by the F parameter. Hence, N_{bss} - F is the granted number of always active sockets.
Firstly, the station checks whether solar energy is being produced. If not,

it checks the convenience of the rescheduling (Algorithm 1). Two policies of convenience have been tested:

- postpone the charge in a time slot in which the electricity provided by the grid is cheaper. This method assumes that the station knows beforehand the energy price for every time slot.
  When the BSS has to put off a battery it checks whether the panels are producing energy to avoid wasting of it, then it looks for a time slot (all the slots that do not exceed the T_{max} constraint) in which the electricity is cheaper than the current one. If the charge of a battery requires more than an hour to be completed it also take into account the price of the subsequent hour and the residual charge (Algorithm 2).

- postpone the charge when the panels provide solar power. If the energy from the PV panels is 0, then the charge is postponed by T_{max} if the panels are expected to produce. The simulation uses certain data about the weather condition, recorded in 2018, whereas in a real scenario the BSS can't know with certainty the amount of power that will be produced and it should use weather forecast (Algorithm 3).

If the station considers postponing convenient, it sets a timer for the socket that is decreased at each hour and when it expires the socket resumes the charge.

Algorithm 1 Postpone charge

```
i ← 0
if pv == 0 then
    while postponed_batteries < F do
        if socket[i] is charging and socket[i].battery is not booked then
            timer ← check_convenience()
            if timer > 0 then
                socket[i].timer ← timer
                postponed_batteries + +
            end if
        end if
        i + +
    end while
end if
```

Algorithm 2 Check convenience (cheapest price)

```
i ← 0
timer ← 0
while i < T_max do
    prices.append(energy_prices(month, day, hour + i))
    i + +
end while
if charge < C/2 then
    timer, prices ← min(prices)
    return   timer
else
    delta_charge1, delta_charge2 ← charge.split()
    timer ← cheapest_hour(prices, delta_charge1, delta_charge2)
    return   timer
end if
```

Algorithm 3 Check convenience (solar power)

```
timer ← 0
pv_next ← get_pv_power(month, day, hour + T_max)
if pv_next > 0 then
    return  T_max
else
    pv_now2 ← get_pv_power(month, day, hour + 1)
    pv_next2 ← get_pv_power(month, day, hour + T_max + 1)
    if pv_now2 ≤ pv_next + pv_next2 then
        return  T_max
    end if
end if
```

Chapter 5

Results

This section presents the results of the simulation of the battery switching station. The simulation has been run several times to dimension the parameter and to test strategies for reducing the costs, so that this project could provide a feasible and profitable model to an actual BSS firm.

5.1 Baseline

Figure 5.1 presents the traffic pattern of the EVs/clients that arrive at the station, i.e. the absolute number of EVs that on average arrive for each hour of the day (for example: the BSS is expected to serve between 12:00 and 12:59 on average 10 clients). The inter-arrival time between two vehicles is drawn with an exponential function that receives as input a parameter that depends on the hour. The parameters are chosen in such a way that the pattern has three peaks during the day.
The program can simulate one year or more or a shorter period of time. Figure 5.2a shows the daily arrivals during a one-year simulation. The exact number of arrivals varies day by day, but is usually greater than 80 and smaller than 120. The average number of arrivals is around 100. Although, the arrivals are not constant, the losses are stable: the mean value is 0.02%, whereas the daily

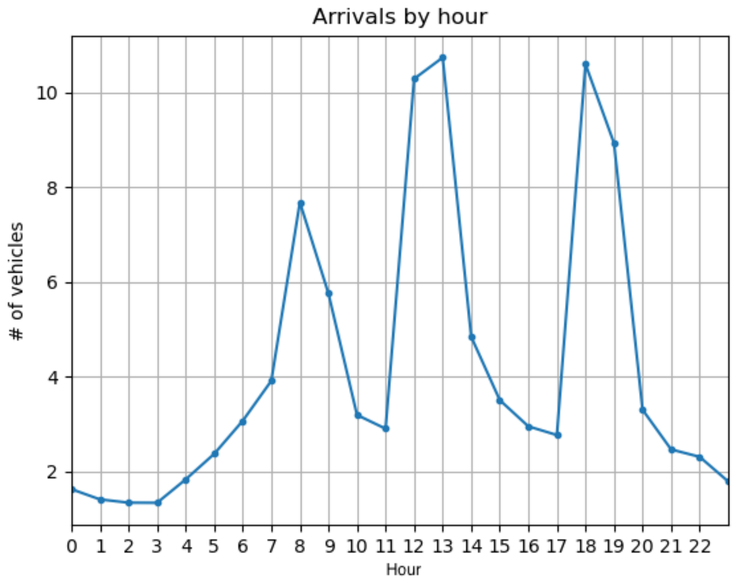
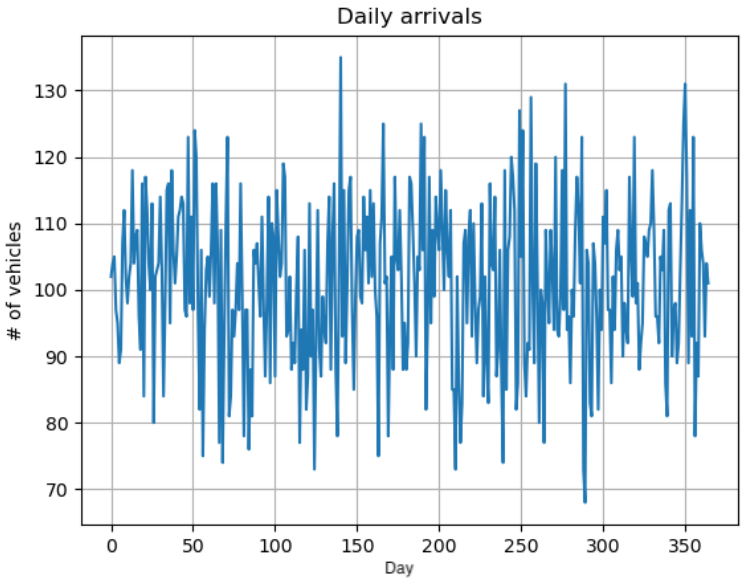


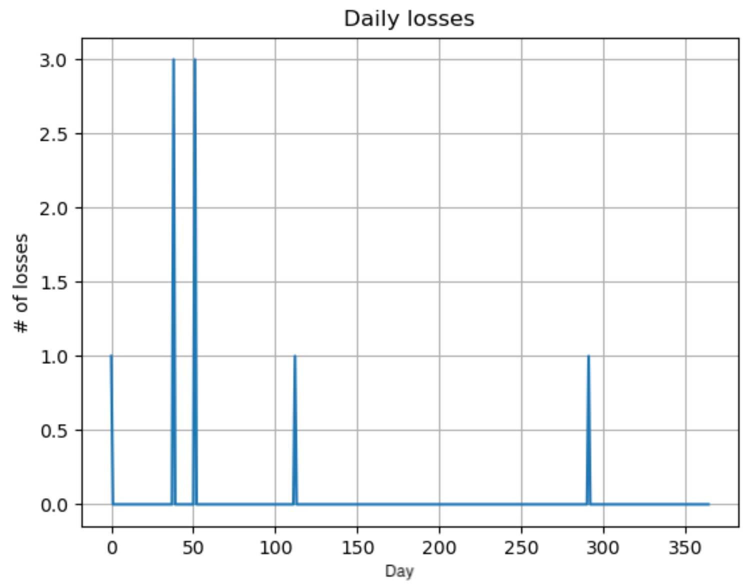
Figure 5.1: Daily arrivals by hour.

value never exceed 3 EVs per day (Figure 5.2b). The losses are low and stable because N_{bss} is set to 20 (this choice is justified subsequently in this section.). Moreover, during the three peaks of traffic, the station charges the batteries up to B_{th}, i.e. 90% of the full capacity. This choice is convenient to face the high demand and it is positive for the batteries lifespan.

In this phase, the system is not using either the PV panels or any strategy to handle the charges. Panels and strategies don't have any impact on the arrivals, since they are the input of the system and the number panels don't modify the losses, because if they are not able to guarantee the fixed charging rate, the grid occurs to make up the difference. Figures 5.3a and 5.3b represent the baseline costs and energy consumption of the BSS. The costs depend exclusively to the electricity price, indeed, during the fall (that goes from day 250 up to 320, circa) they are more expensive (Figure 4.1).

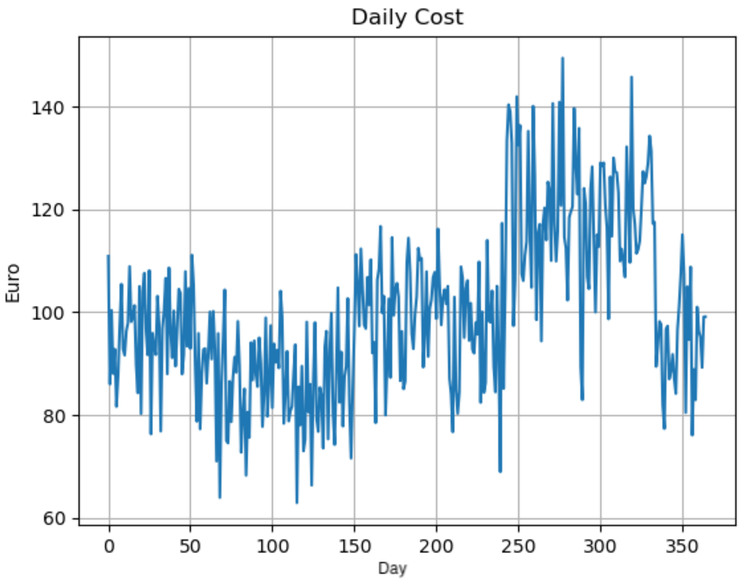


(a)

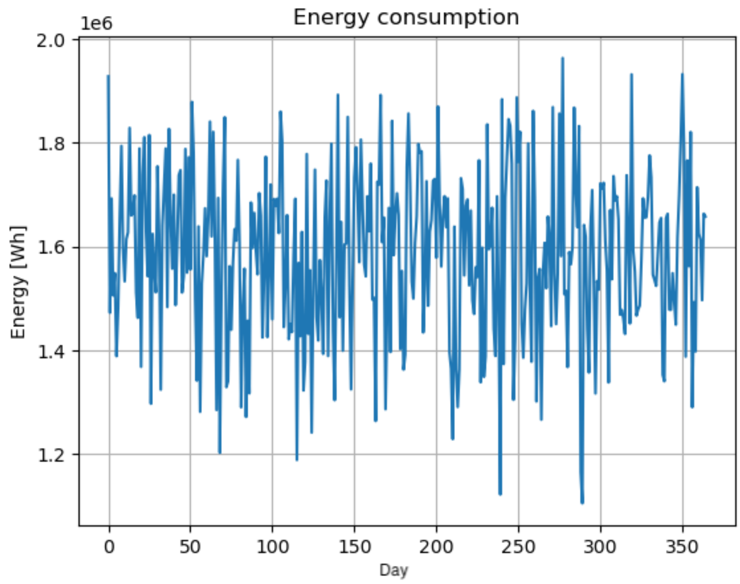


(b)

Figure 5.2: Daily number of arrivals (a) and daily losses (b).



(a)



(b)

Figure 5.3: Daily cost (a) and daily energy consumption (b) for a one year simulation.

5.2 PV panels implementation

After assessing the baseline behavior of the station, the photovoltaic panels were implemented. Several values of S_{PV} and N_{bss} were tested. The number of panels should be regulated concerning the number of sockets, given that each socket shares the power provided by the panels and the amount of energy should be significant enough to allow to adopt some strategy that helps the BSS to exploit a possible surplus of energy, that happens when the panels produce more energy than the one required to charge all the batteries plugged in the active sockets at C_r.

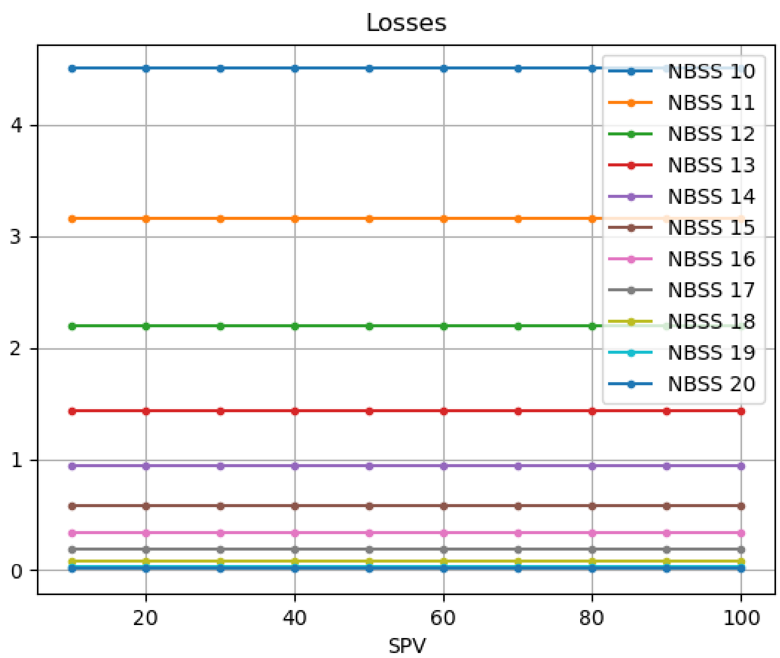


Figure 5.4: Losses by number of sockets and number of panels.

Figure 5.4 shows the losses during the simulation of one year with respect to the number of sockets, N_{bss}, and the number of panels, S_{PV}. As expected, as N_{bss} increases the loss rate decrease, whereas as S_{PV} increases the cost per service decreases (Figure 5.5), because it increases the ratio of free solar power with respect to the grid contribution.

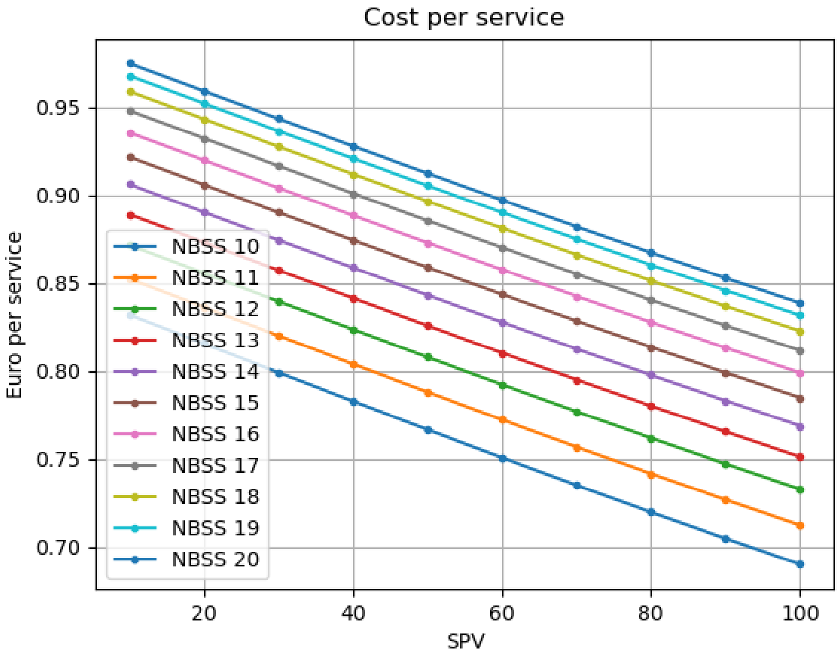
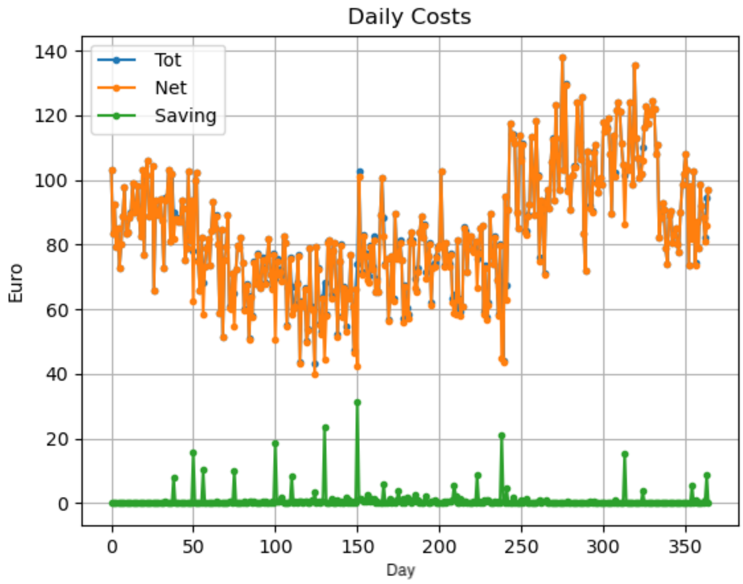


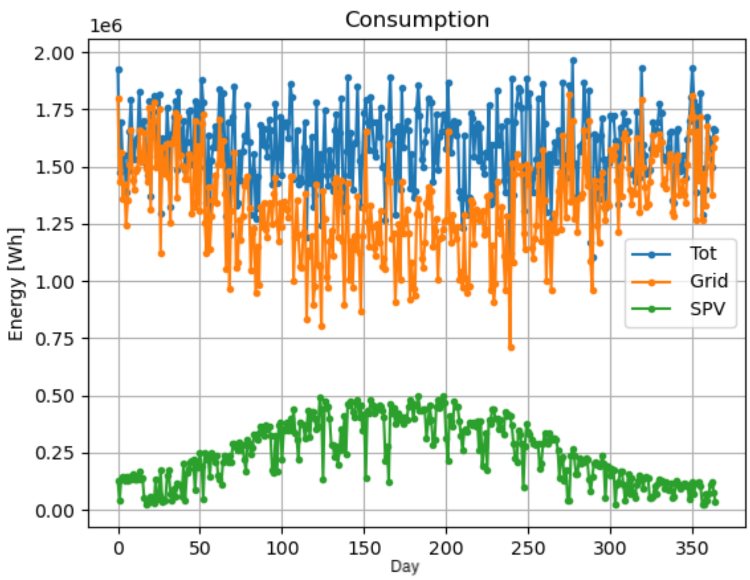
Figure 5.5: Cost per service by number of sockets and number of panels.

Since the next step foresees to apply strategies to postpone the charge to reduce the costs, i.e. reduce the contribution of the grid, N_{bss} was chosen, because it provides almost 0 losses. Indeed, we expect the average number of ready batteries to decrease and the loss rate to increase, therefore N_{bss}=20 is chosen to have more flexibility.

Figure 5.6a represents the total cost, that is the expenditure for the energy absorbed from the grid, and the savings, that is the extra energy produce by the panels that is sold to the grid for half the price of the electricity. Figure 5.6b shows instead the contribution of the grid and the panels.



(a)



(b)

Figure 5.6: Cost and energy consumption with 100 panels.

5.3 Postpone strategies application

A solar panel with a 1 kWp output, i.e. a maximum power output of 1 kW in optimal conditions, has an area of 5 m^2, which means that 100 panels occupy 500 m^2 of space. Although the occupied space is remarkable, the contribution to the charges is still modest with respect to the grid. Indeed, as we can see in Figure 5.6b, the amount of energy provided by the panels and used by the sockets never exceeds the one of the grid. Furthermore, Figure 5.7 demonstrates that the sockets are using almost all the solar energy produced and that there is no waste of it.

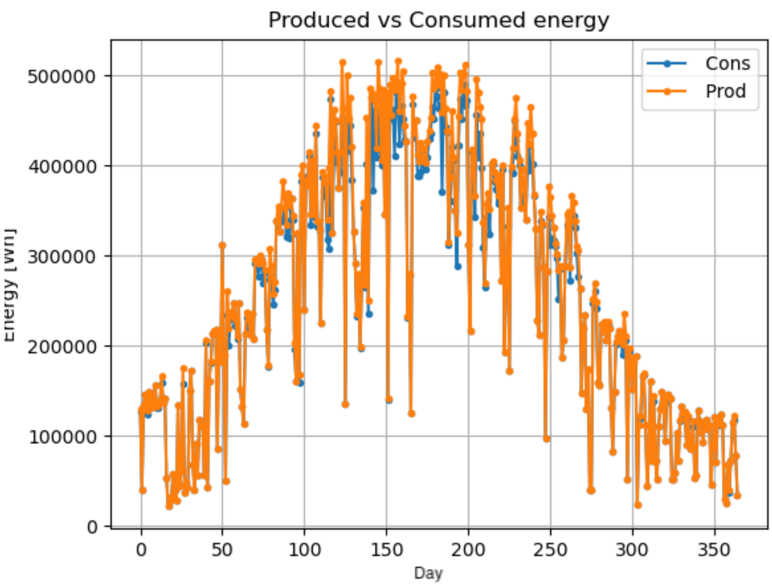
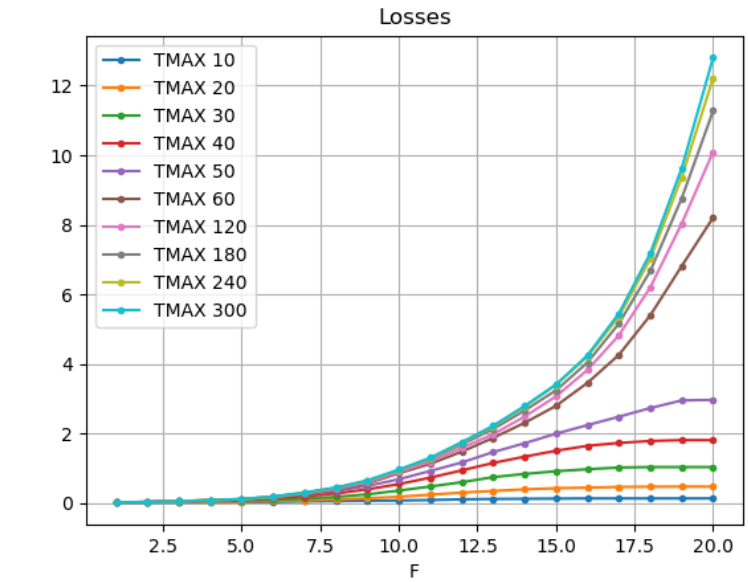


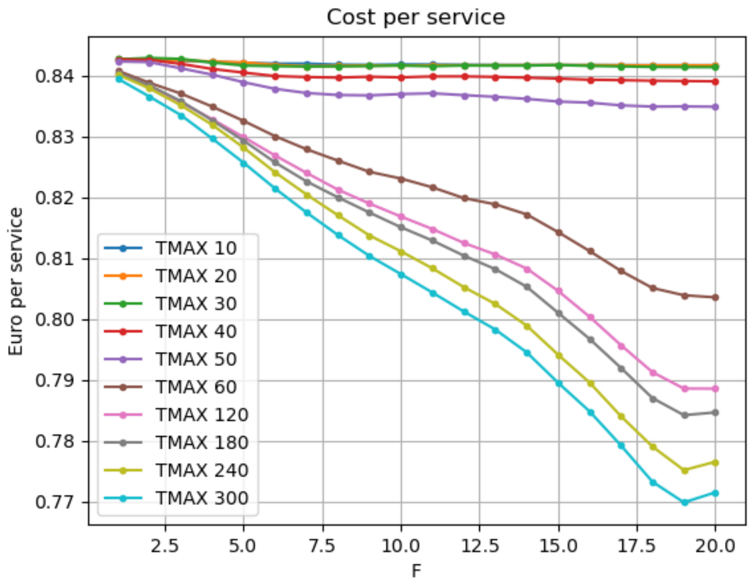
Figure 5.7: Daily produced and consumed solar energy with S_{pv}=100.

In this step, the postpone strategy depicted in Algorithm 1, 2 was deployed. This policy works on the electricity prices trying to put off the charges in an hour when the energy cost of the grid is cheaper. The algorithm doesn't postpone the battery if the PV panels are producing energy and moves the charge in the hour that does not exceed T_{max} with the cheapest electricity

cost.
Obviously, if postponing the charges impacts negatively the performance of the BSS in terms of waiting time and loss rate; hence a trade-off should be found.
Figure 5.8a illustrates how the loss rate dramatically increases for large values of F and T_{max}, that guarantee the lowest costs; whereas, small values of T_{max} (less than one hour), do not decrease the costs significantly.
Given 100 daily arrivals, a reasonable loss rate of the station should be <2%, i.e. less than two lost customers per day on average. If we compare the cost per service and the net cost (the total cost minus the savings) with F=11 and T_{max}=300 and with F=0 (no postponing), the BSS records a 4% reduction of the cost per service (respectively 0.804347 and 0.842503 euros per service) and a 6% reduction on the net cost (respectively 79.843471 and 84.893281 euros).
The main issue of this approach is that the mean value of the loss rate is acceptable, but if we look at the daily values of the losses we can see that during winter and fall they are too high, while they are almost zero during summer and spring. This happens because the batteries are not postponed if the solar panels are working, therefore the station rarely put them off during these seasons, but it only moves the charges of the batteries that arrive in the evening during the night when the electricity is cheaper and the traffic is less intense.
Hence, this algorithm performs well in sunny seasons, yet it performs poorly in the rest of the year. Moreover, it doesn't take into account the sustainability purpose of the station.
Figure 5.9a and 5.9b shows that if we deploy this algorithm, but we allow the BSS to *wake up* the postponed socket if it needs to serve a client, the loss rate consistently decrease but the reduction on the cost per service becomes negligible.

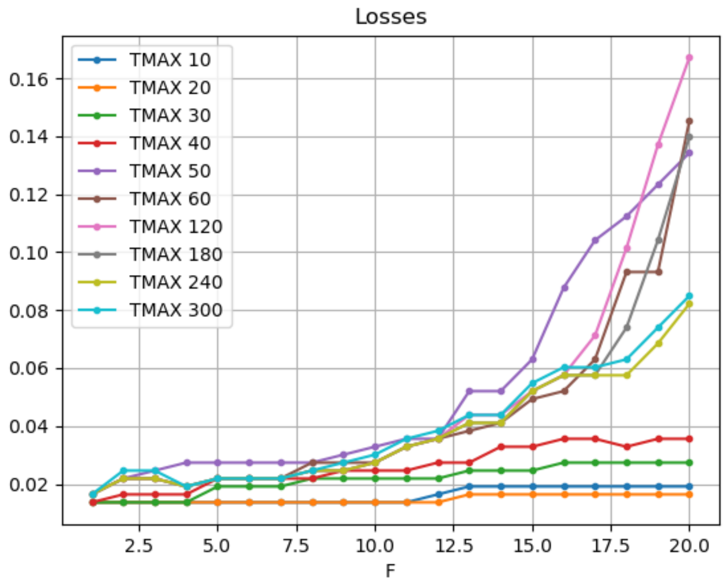


(a)

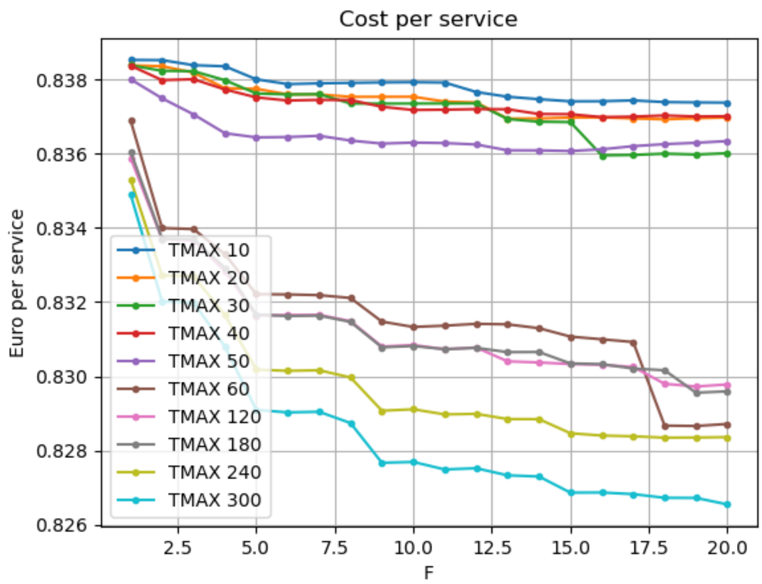


(b)

Figure 5.8: Losses (a) and cost per service (b) with postpone for cheaper electricity price strategy. S_{pv}=100; T_{max} is expressed in minutes.



(a)



(b)

Figure 5.9: Losses (a) and cost per service (b) with postpone for cheaper electricity price strategy. S_{pv}=100. BSS can anticipate wake up of batteries. T_{max} is expressed in minutes.

Maximising solar power usage

After trying to exploit cheaper hour slots, a different approach was tested. Since that 100 panels couldn't provide enough energy to apply any strategy (Figure 5.7), S_{pv} was set to 500, i.e. 500 photovoltaic panels installed on the battery switching station (Figure 5.10). This dimensioning slightly changes the scenario, because the BSS should be a big facility with 2500 m^2 of PV panels.

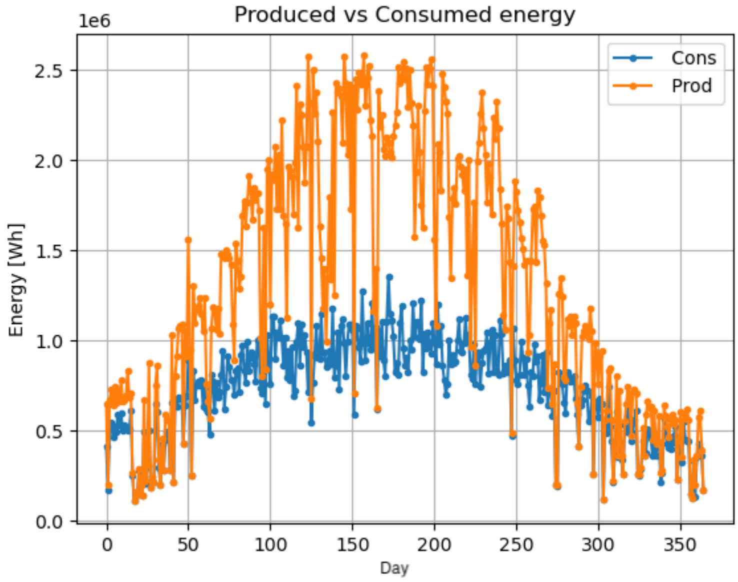


Figure 5.10: Daily produced and consumed solar energy with S_{pv}=500.

The algorithms implemented are the ones described in section 4.4.3 (Algorithm 1, 3). This algorithm tries to move the charges when the panels produce energy (in a real scenario the BSS would use weather forecast and mathematical model to estimate the production). This shift happens especially during the evening and the night to put off the batteries to the next morning, therefore the charges are postponed by exactly T_{max} minutes, because if we would resume the charge process as soon there is the sun, i.e. at sunrise, all the batteries would wake up together and they would share the energy provided at sunrise that is usually low. This wouldn't interfere with the system performances, but it would increase the consumption of the grid energy. A fixed T_{max} instead allows the BSS to resume the charges gradually, according to the order of arrival.

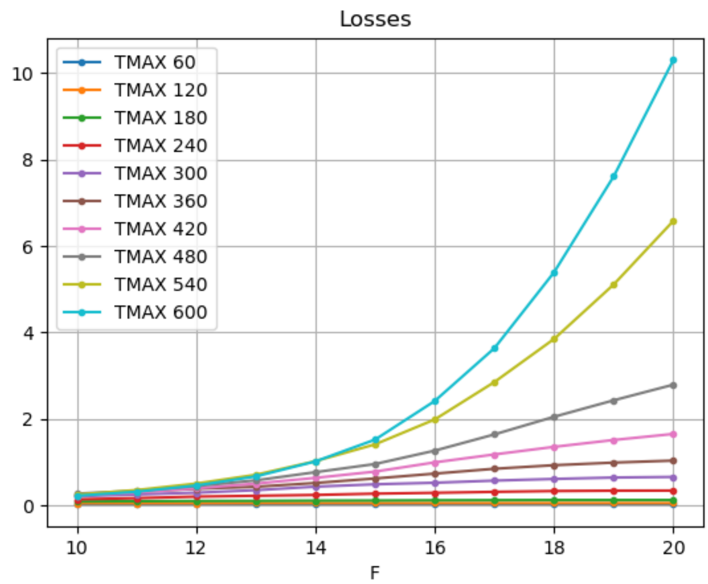


Figure 5.11: Losses with postpone for maximizing solar power usage. S_{pv}=500. T_{max} is expressed in minutes.

Figure 5.11 and 5.12 shows the values of the losses and the cost per service for different F and T_{max}. In this case, the simulation was run for an entire year and the optimal parameters were found. With F=17 and T_{max}=480 (8 hours) the average daily losses are 1.643836, which is less than the threshold (2 daily losses) that we used to assess the system acceptably. The cost per service (0.496740 euro) and the net costs (37.465598 euros) are 9.7% and 10% lower than the case with 500 panels but without postponing (0.550179, 41.637631 euros). The lines representing T_{max} >480 intersect the others because with these values the batteries are put off around midday when the traffic is more

intense and the PV production is shared between more sockets, thus the costs per service are higher.
This algorithm presented the same issue as the other one, i.e. even if the average loss rate is low, the daily losses may be occasionally high. Therefore, instead of picking two values simulating one year, the values could be selected running the simulation for each season, because each season presents similar weather conditions. Hence, for each season the same plots of Figure 5.12 were drawn and for each season a pair of F and T_{max} was sorted. T_{max}=480 was the optimal postpone delay for every season; the values of F, the maximum number of idle sockets, are: 13 (winter), 20 (spring and summer), 16 (fall). This settings slightly reduces the average loss rate and make the daily losses more homogeneous. The cost per service is slightly increased (0.500426 euro), but still 9% lower than the case without postponing and the net cost is still 10% lower.

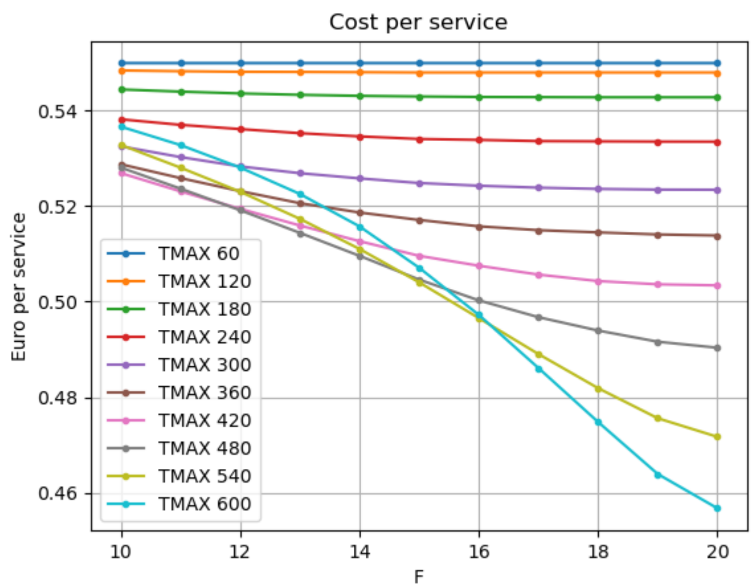


Figure 5.12: Cost per service with postpone for maximizing solar power usage. S_{pv}=500. T_{max} is expressed in minutes.

A 20 kWh capacity can work for vehicles employed for a car-sharing service, but the EVs sold nowadays are equipped with bigger batteries, thus, the algorithm has been tested with C=40kWh, providing a 6% reduction on both net cost and cost per service, and C=70kWh, providing 5% on net cost and 4.3% on cost per service.

5.4 Conclusions

Global warming requires the world to make radical changes in different industrial sectors and individual habits. These changes are already visible in some fields, such as transportation, where the climate emergency required the abandonment of fossil fuel to convert to clean energy and zero emissions. In the next future, all the ICE vehicles would be replaced with electric vehicles, that don't pollute the urban area since they don't emit GHG gases. Yet, to have no negative impact on the environment, they need to be charged with clean energy sources.

The battery switching station, not only incentives the adoption of EVs making the driving experience more similar to the one of ICEV allowing an instantaneous *refueling*, but it takes responsibility for the energy used to charge the batteries deploying a set of PV panels to generate that energy.

The BSS simulator was built to understand under which conditions the station is feasible and whether the solar panels could provide enough energy for the batteries.

The results were presented and discussed in Section 5 and they revealed that to manage on average 100 daily arrivals the station needs to host 20 sockets for the charge of the batteries. Given a capacity of 20 kWh for each vehicle, 500 panels are needed to cope with the energy demand and perform a smart control over the schedule of the charges. The algorithm implemented in the simulator provides a 9% reduction on the cost per service and 10% on the net costs providing a better usage of the power of the panel and diminishing the energy drained from the grid.

This work is meant to be a contribution to the sustainability challenge that current societies are facing. It exposed the potentiality of the battery switching stations and the flaws that have to be addressed. One future development could be a new smart charging algorithm that would both consider the PV panels production and the electricity prices at the same time with a more dynamic postponing.

In conclusion, the BSS is a great resource to face the issues that a bigger and bigger EV fleet could bring and it could play a key role in the future of the smart grid.

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