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Analysis and dimensioning of battery switching system for electric vehicles

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Abstract

Electric vehicles (EV) have become increasingly popular, responding to the global environmental protection concept of reducing carbon dioxide emissions and providing users with a new technological experience. Nowadays, the market share of electric vehicles is growing, and their infrastructure, such as charging stations, is constantly being upgraded. Charging stations also need to use more clean energy, aligning with the eco-friendly concept of electric vehicles. As a common model for EV charging, Battery Switching Station (BSS) looks a promising solution to enable a more feasible deployment of electric mobility.

In this thesis, a BSS simulation is used, where a user drives an EV that needs to be charged to a battery switching station, and the BSS provides a battery replacement service. The BSS uses three types of energy, one from the smart grid, for which a fee is charged, one from solar power, and one from wind power. When the user arrives, the BSS provides the EV with a battery change if there is a fully charged battery available, if not, the user enters a waiting queue, and if the waiting time is too long, the user is lost. Lost implies that user needs to search for an alternative BSS. This thesis discusses how to improve the BSS system performance so that the user loss probability is acceptable and the electricity cost is minimized.

This thesis discusses the improvement of the BSS system by exploring the use of different charging scheduling strategies for different seasons and under varying electricity price, along with the addition of wind energy to the original system, which integrates only solar energy besides the traditional power grid.

The proposed strategies envisions that the charging of a battery can be conveniently postponed up to a maximum amount of time, depending on the renewable energy availability and the electricity prices. Modulating the maximum time by which a battery charge can be postponed over the four seasons (optimal 475 minutes in spring, 500 minutes in summer, 325 minutes in fall and 225 minutes in winter) allows battery switching station (BSS) operators to pay lower electricity bills to the grid, while still ensuring that the grid provides an acceptable Quality of Service to the users. By reducing the charging postpone time under low electricity prices (50 minutes if lower than 12.8 euro/MWh) and increasing it under high electricity prices (1000 minutes if higher than 24.3 euro/MWh), the electricity bill can be reduced. At the same time, the introduction of wind energy results in a cleaner renewable energy source, with multiple benefits for EV users, BSS operators, and the planet as a whole.

Keywords:

Electric veichels (EV); Battery Switching Station (BSS); Renewable Energy; Solar energy; Wind energy

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Chapter 1

Introduction

1.1 Motivations

As human beings in the progression of moving forward, preserving our planet and safeguarding the natural environment are also very important. A pressing issue the earth faces today is global warming, and one of the most important reasons is anthropogenic greenhouse gas emissions [1]. With the increase of global environmental awareness, electric vehicles have received more and more attention as a kind of environmentally friendly transportation. For example, the Dutch government has set a goal aimed at reducing CO2 emissions in 2020, and a related initiative of the Dutch Ministry of Transportation is to deploy one million electric vehicles by 2020[2] .

In addition to the problems associated with greenhouse gas emissions to the earth, the depletion of fossil fuels has become another important issue [3]. Wind and solar energy, as important renewable resources, will be used in electric vehicle systems, and hybrid electric vehicles are a good way to reduce the environmental impact of the transportation sector [4]. Since wind and solar power generation is intermittent, they cannot produce constant amount of electricity. Therefore, flexible backup power plants are needed to generate electricity when the renewable energy generation is low and energy storage is needed when there is excess generation [5].

Charging infrastructure is the backbone of the EV industry [6], and the EV industry is in full swing, so the design and creation of infrastructure has a promising future. However, in spite of the positive data, stakeholders are still concerned about the profitability of new ideas, and therefore they would like to simulate their plans before going into production [[7],[8],[9]]. EV battery switching system (BSS) , which replaces an uncharged battery with a fully charged one, is the most suitable solution for the current market, solving the problems of limited battery capacity, long charging time, limited driving range and inconvenient use of electric vehicles, Tesla has been engaged in this work for more than 6 years, and it takes less than 2 minutes to replace a battery, which is faster than refueling the combustion engine [10].

1.2 Objectives

This thesis is based on an electric vehicle battery switching system (BSS) simulation system, conducting deep analysis and exploration. One objective is to reduce the electricity costs with the premise of acceptable EV user losses. Another objective is to reach the green goal of sustainability.

For the first objective, exploration focuses on seasonal changes in data, aiming to reduce the costs season by season. Exploration also focuses on the electricity price data, designing rules to utilize more low price data and less high price data.

For the second objective, exploring the introduction of wind energy as clean energy, together with solar energy supplying the BSS system with electricity.

1.3 Structures

In order to achieve objectives, it is divided into several steps. The first step is to analyze the BSS system, then finding the relevant parameters and optimal settings for each season via observing data. After implementing the new electricity prices for 365 days, wind energy is also added to the system. Then a new rule for the new electricity prices is also applied to the system.

There are six chapters in this thesis. The first chapter is introduction. The second chapter is introduction of BSS, solar energy and wind energy. The third chapter is the details of the BSS system. The fourth chapter introduces the methodology of all explorations.

The fifth chapter focus on seasonal factors, exploring seasonal variations in system parameters to explore the potential of reducing system electricity costs.The sixth chapter uses new electricity price in BSS system, and adds wind energy into the system. The seventh chapter designs a new rule of utilizing electricity prices, focusing on the best options for cost reduction. The eighth chapter is conclusion.

The big-picture structure of this thesis is progressive. the first three chapters stand in the perspective of analysis, analyzing the BSS system from shallow to deep. Firstly clarifying the current and prospective market of the BSS system, highlighting the important position of renewable green energy in the market, then exploring the specific structure and detailed design of BSS system. The last five chapters stand in the perspective of inquiry, exploring the improvement of the system, aiming at reducing the system's electricity costs while considering an acceptable level of user loss. The first step of improvement is based on the analysis of the original system, since the costs show a clear seasonal variation, system parameters are adjusted seasonally. The second step focuses on the use of a new renewable green energy source, the wind power, in combination with the existing solar energy of the system, collectively aimed at reducing system costs. The third step focuses on improving the electricity pricing rules to see if there are more optimal rules to further decrease system costs.

Chapter 2

Overview of Battery Switching Station

2.1 Battery Switching Station (BSS)

Battery Switching Station (BSS) is an electric vehicle (EV) charging infrastructure that utilizes battery switching technology to quickly replace the batteries of EVs.The main principle of BSS is to use automated equipment to replace the low battery of an EV with a fully charged battery. In this system, when the user arrives at the charging station, if there is already a fully-charged battery, it is replaced directly; if not, the user has to wait for the next fully-charged battery, or if the waiting time is too long, the user will leave.

One of the advantages of BSS is that the battery replacement time is often comparable to the refueling time of a combustion engine vehicle, EV drivers don't need to wait for hours, allowing them to experience a driving experience more similar to that of internal combustion engine vehicles, this aligns with the goal of encouraging people to purchase electric vehicles.

The BSS simulation has 5 main components. The first is the user's EV that needs to have its battery swapped out. The second is Switch Platform, where a robotic arm removes the dead battery and swaps in a fully charged one, which is all automatic and without human assistance. The third is Charging Hub, where the removed battery is plugged into a dedicated socket and charged in the hub. The fourth is Battery Stock, a limited-capacity warehouse designed for storing rechargeable batteries. The fifth is Renewable Energy Source(RES), the BSS is equipped with a set of solar panels and a wind turbine.

There is a real-world example of the practical application of Battery Switching Stations (BSS). NIO’s power battery switching station has been gradually put into the market and started to use in 2018[11]. Nowadays, NIO's power battery switching station owns more than 1,400 patents, and there is a charging experience specially created for NIO users, which takes only one song to start with a full charge. Every time user switch to a new battery, a three-electricity self-test is performed to ensure that the vehicle and battery are always in optimal condition[12]. Figure 2.1.1-2.1.5 show the BSS of NIO in Shanghai, China.

Figure 2.1.1 NIO BSS

Figure 2.1.2 EV in NIO BSS

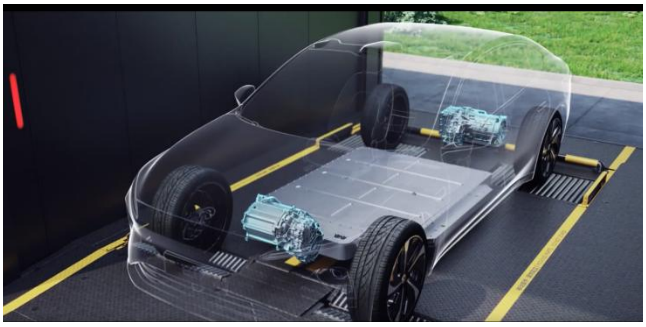

Figure 2.1.3 NIO BSS

Figure 2.1.4 NIO BSS

Figure 2.1.5 NIO BSS

2.2 Solar energy resource

Solar energy is one of the most promising renewable energy sources, which have emerged as alternative power systems to power electric vehicles. The use of solar energy is essential to eliminate dependence on conventional energy sources, which are non-renewable and polluting[13] .

There is a charging station model with solar energy for EVs. The principle of PV operation is shown in Figure 2.2.1 [14]. The source of electricity is solar panels on the roof. If there is not enough solar energy, it is taken from the smart grid. If the PV provide excess energy, it can be fed back to the smart grid.

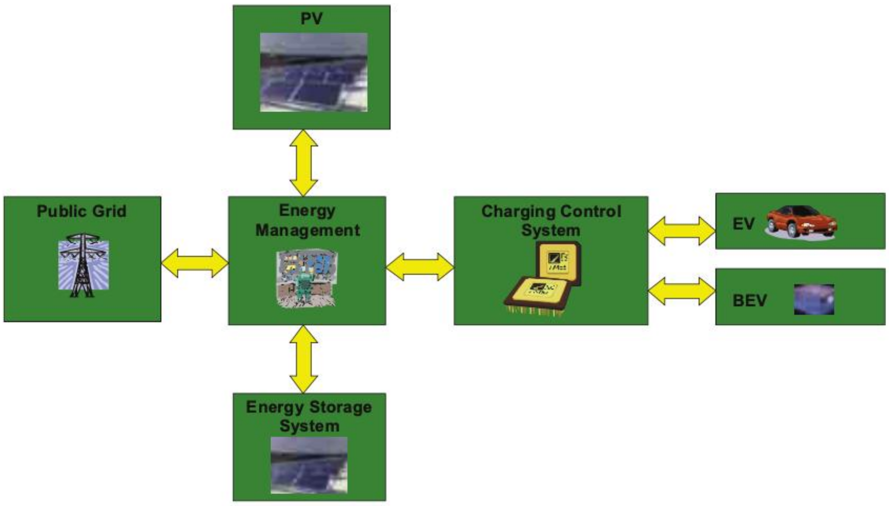

Figure 2.2.1 Structure of charging station

The use of solar panels on top of charging stations (similar to roof) to store electricity and combine it with grid power to charge electric vehicles has been widely applied in China. Figure 2.2.2 shows the completed PV-integrated charging stations.

In China, PV-integrated charging stations are expected to be in place by 2023, and the use of solar energy for charging electric vehicles is already underway in large-scale applications[15]. Figure 2.2.2-2.2.4 shows the PV-integrated charging stations.

Figure 2.2.2 PV-integrated charging station

Figure 2.2.3 PV-integrated charging station

Figure 2.2.4 PV-integrated charging station

In order to promote the high-quality development of the new energy vehicle charging facilities industry, and to promote new technology, new products, new materials, new techniques and new equipment for charging stations and power exchange, China will hold the 2nd China (Qingdao) International Charging Station and Power Exchange Station Technology and Equipment Exhibition (CEVSE) on 26-28 September 2024 in Qingdao, showing the idea of innovation, co-ordination and green, promoting new technologies, products and services by using clean energy, that contribute to the achievement of China's 30.60 dual-carbon target.

2.3 Wind energy resource

Wind energy can already replace fossil fuels to provide clean and sustainable electricity, making it one of the most promising sources of renewable energy. By 2019, global wind energy generation will account for approximately 19% of total installed renewable energy capacity[16]. Wind energy is on the rise globally as countries aim to cut carbon emissions and shift towards a low-carbon economy. Battery energy storage has received significant attention in recent years due to rapid advances in battery technology and growing demand for electric vehicles. Battery energy storage systems are capable of storing electricity generated by wind turbines in large batteries, which are then discharged when needed to meet demand. This technology has high storage efficiency, fast response time and long storage time compared to other energy storage technologies. Figures 2.3.1 and 2.3.2 show the proportion of electricity generated from wind and solar power in different countries in 2016, varying geographically from country to country, e.g. in Denmark and the Netherlands almost all renewable electricity is generated from wind power[17]. Therefore, the application of wind energy as a clean fuel is promising, and so is the research on the application of introducing wind energy into the system.

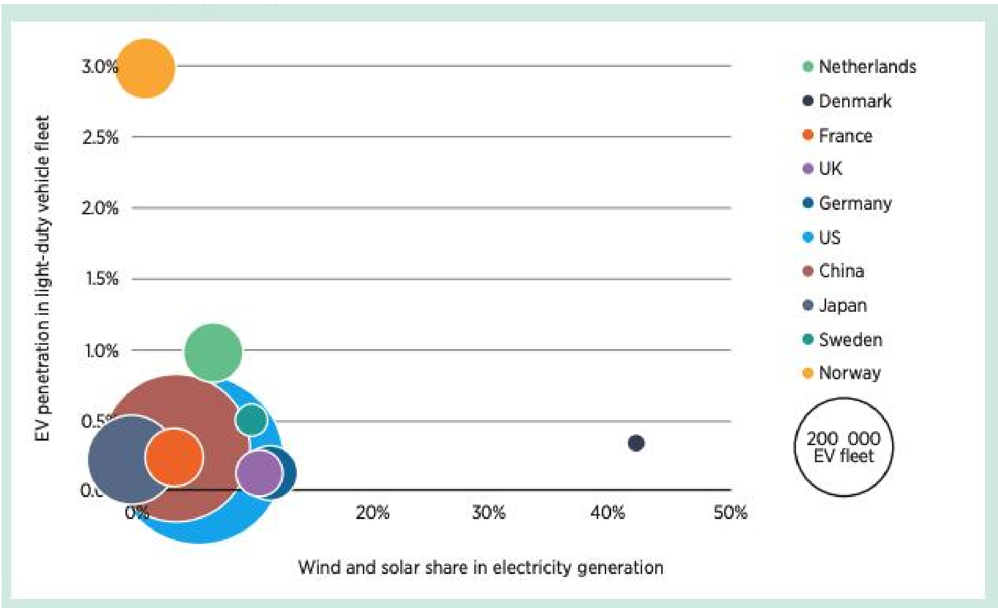

Figure 2.3.1 Wind and solar in electricity generation

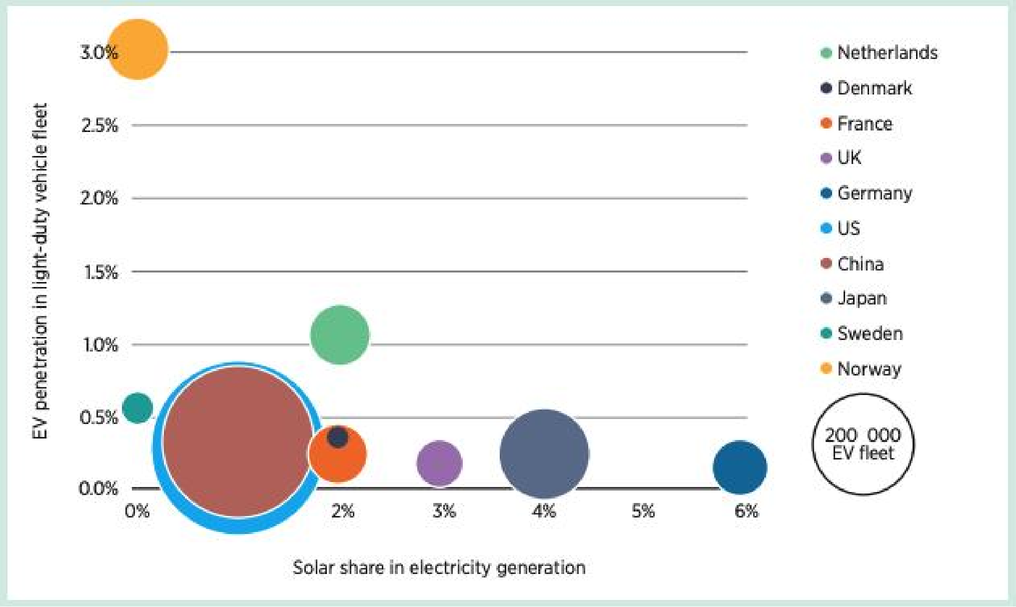

Figure 2.3.2 Solar share in electricity generation

First wind-powered electric car charging station in Barcelona in 2011. UGE and General Electric (GE) (figure 2.3.4) have partnered to install the world's first wind-powered electric vehicle charging station, Sanya Skypump, in Barcelona, Spain, to provide clean, renewable electricity. If the wind is not blowing and the car owner needs to recharge, the Skypump will charge the car with power from the grid[18].

Figure 2.3.4 Sanya Skypump

2.4 Controversies about BSS systems - market feedback

Any technology will face problems after it is introduced to the market. Metro BSS model has the following limitations since its introduction to the market[19]:

First, the profit is poor. It is cost US$500,000 (RMB 3.45 million) to build a power exchange station. Plus operating costs, land lease, and service personnel, the total cost is too high in the early stage of business. Consequently, the price for a single power exchange is high, the EV users will pay more. If the number of EV users decrease, the station utilization rate is low, the return on investment cycle is long.

Second, the technical standard is not unified. There are 145 kinds of battery model in GB/T 34013-2017 "electric vehicle power storage battery product specification size" standard, and different car companies have different module structures.

Third, uncertainty of technology. If technological breakthroughs are achieved in battery energy density, the mass production of solid-state batteries, the popularity of 800V electrical architecture and super-charging technology, the switching station may face obsolescence.

Now competing with BSS system is Supercharging Technology. Supercharging Technology is a kind of high-speed charging technology, this technology uses advanced charging equipment and systems, can in a shorter period of time for the electric car full of power, effectively shorten the charging time. Tesla abandoned the BSS system after a failed attempt to focus on the supercharging business. Xiaopeng Motor abandoned BSS to adopt supercharging technology.

NIO still insists on the BSS technology, but at the same time, it has also stepped up the development of super-charging technology and built new super-charging station, striving to form a sound intelligent energy service system to survive in the fierce market. Figure 2.4.1 shows the NIO swap stations and charging stations map in europe.

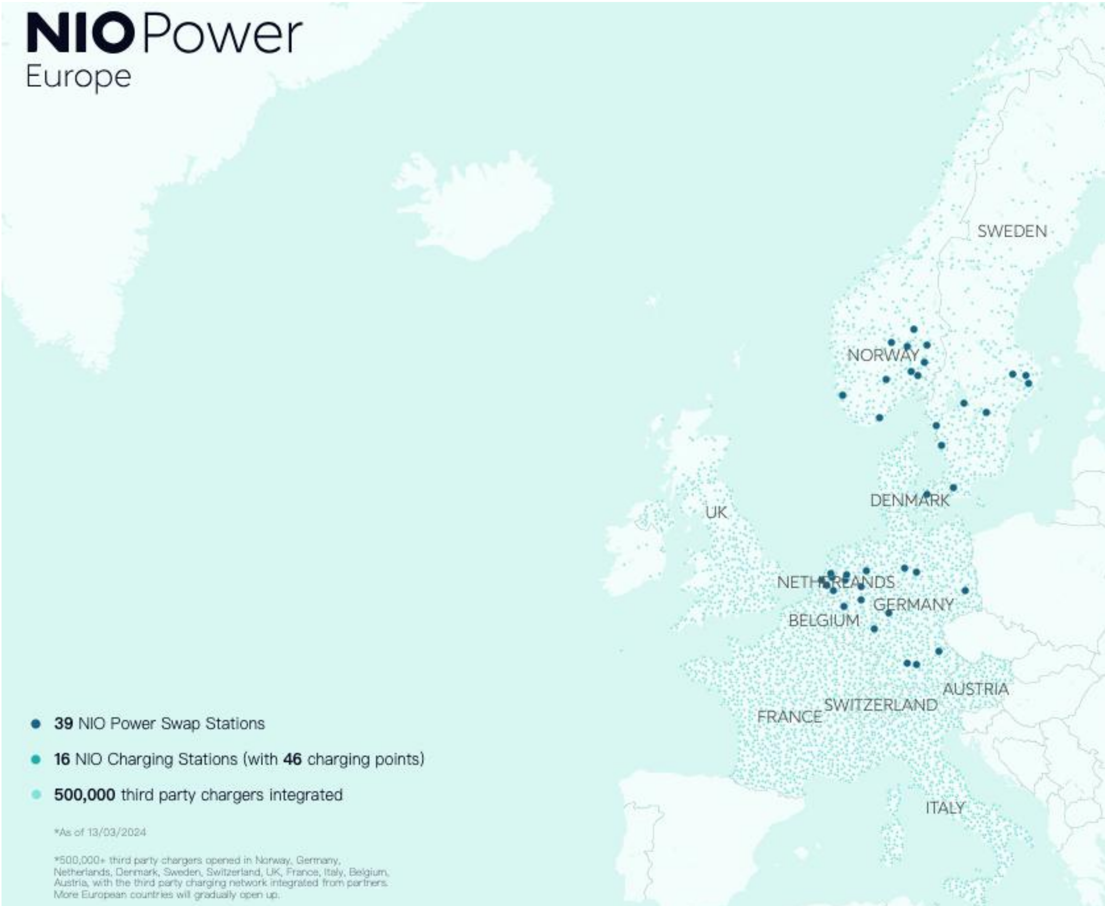

Figure 2.4.1 NIO EV stations map in Europe

Chapter 3

Dataset and Structure of BSS

3.1 Dataset

There are four databases used in this thesis, and the data are stored in the Data Manager module. The first one is the original electricity price. The data for the electricity price is taken from the Electric Vehicle Database [8], which collects all the data of electric vehicle EVs, and the data are used to eliminate the overlap between the surrounding EVs and to ensure the smooth flow of traffic in the long term.

The range of an electric vehicle obviously depends on the battery capacity, but also on the speed, driving style, weather and route conditions. Charging times are largely dependent on the charging infrastructure and can be categorized into three levels. Table 3.1.1 summarizes these levels.

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

Table 3.1.1 three charging levels of EV

The electricity price data is in csv format, divided into four seasons, each hour corresponds to a electricity price, the price at each hour is the average value of that season. An example of the format is shown in the table3.1.2 below:

Hour	Season	Cost (euro/MWh)
0	SPRING	43.79152174

1	SUMMER	52.35195652
2	WINTER	44.01511111
3	FALL	60.21571429

Table 3.1.2 dataset sample of electricity price

The second database is the output power in watts per hour of a PV panel with a nominal capacity of 1 kWp during a year. The source of the data is based on the real irradiation data for a Typical Meteorological Year in the city of Turin, Italy[20]. The format of the dataset is csv, converted to json for reading when used in the simulation system, and the database records the power generated in each hour of each day of the year, as exemplified in the following table3.1.3:

Month	Day	Hour	Output power (W)
1	1	10	172.659

Table 3.1.3 dataset sample of solar energy

The third database is the electric price, it is necessary to use more accurate and updated electricity price, so that the simulation can draw conclusions closer to the current situation. The data are the hourly electricity price for the Northern Italy Physical national zone for each day from January 1 to December 31, 2022, in csv format, as shown in the following table3.1.4.

Month	Day	Hour	Price(euro/MWh)
1	1	5	10.465086

Table 3.1.4 dataset sample of electricity price

The fourth database is the electricity generated by wind energy, in csv format, converted to json for reading when used in the simulation system, and derived from energy production data provided by the Open Power System Data (OPSD) project (Data, 2020)[21]. The dataset contains data for 37 European countries from 2012 to 2017. The dataset was created by downloading relevant data from sources such as

Transmission System Operators (TSOs) in different countries, resampling them and merging them into one large CSV file. In this system, data from Belgium, Switzerland, Germany and Denmark from January 1, 2015 to December 31, 2015 were used and all variables are expressed in hours. Actual onshore wind energy production was considered, and each production data was normalized by the corresponding monitored capacity in order to calculate the amount of wind energy generation (in watts), which was generated by turbines with a capacity of 1 MW/watt each. Examples of the data used are as follows (table3.1.5):

Month	Day	Hour	Output power (W)
1	1	5	0.282846033

table 3.1.5 dataset sample of wind energy

3.2 BSS parameters:

Postponable batteries (F): The parameter is the maximum number of batteries that can be postponed for charging.

Postpone time (Tmax): The parameter is the maximum time by which a battery charge can be suspended befor resuming.

Waiting tolerance (Wmax): The parameter is the maximum amount of waiting time that EV users accept to wait in queue, in case no battery is currently fully charged, hence ready for swapping, at the BSS. It’s set to 15 minutes.

Battery capacity (C): The parameter is the battery capacity of electric vehicles, it is set that all EVs have a 20kWh battery.

Number of sockets (Nbss): The parameter is the number of chargers installed at the BSS and it corresponds to the maximum number of batteries that can be charged simultaneously.

Number of PV panels (Spv): The parameter is the number of PV panels featuring 1kWp capacity installed in BSS.

3.3 Performance indicators:

The section list the indicators that measure the performance of BSS simulation. These indicators include:

Losses: The indicator is the number of EV users lost each day of the year. A lost EV user is a user that cannot be served by the BSS and leaves, the queue due to exceeding the waiting time Wmax.

Cost: The indicator is the daily cost of electricity provided by smart grid for charging batteries.

Waiting time: The indicator is the time that EV users spend waiting in the queue to receive service.

Average ready batteries: The indicator is the average number of batteries that are ready for battery swap upon EV arrival.

Savings: The indicator is the daily vaule of extra amount of solar energy that is not used to charge the batteries at the BSS and is hence sold back to the smart grid at half the selling electricity price.

3.4 Structure of the BSS

The core of BSS simulation is a python code that reproduces the behavior of the BSS, modifying the parameters to obtain statistics and (as in chapter 3.3) performance indicators, such as customer loss ratio, to analyze the response. The simulation can continuously charge the batteries with energy from the grid, as well as with PV panels and turbines. In addition to meeting Quality of Service (QoS) constraints, BSS uses a number of rules to make battery charging cheaper or more environmentally friendly. BSS is a discrete event simulator using python 3.+ and macOS, using the following libraries: matplotlib, numpy, random, pandas.

The BSS simulation is running in sequence.

As long as an instance of EV is created, the BSS simulation starts running, the function that related to EV arrival deal with the event, there are there scenarios, EV will get the fully charged battery swap service, EV will wait in the line to get service and EV will leave when the wait time is too long. Each new EV triggers the next one.

There are two ways that batteries can be charged, one is from the smart grid company, which will pay for the electricity according to the hourly electricity prices provided by the grid company. Another is through the renewable energy, solar energy and wind energy.

The waiting line is after the EV arrives, when the charged battery is not ready, EV needs to wait to get service. There is a maximum waiting time that simulates the EV user waits in BSS, when the time is exceeded, the EV will leave, BSS will lose a customer. The postpone time is associated with waiting time, postpone time is allocated for batteries to utilize more renewable energy or benefit from lower electricity prices, which is good for the cost of BSS and EV users, and also good for the environment.

Overall, the BSS system is running triggered by the EVs, and finding the balance among providing battery swap service for EVs, ensuring service qualities and controlling the time and cost of battery charging.

3.4.1 BSS architecture

Figure 3.4.1.1 below shows the BSS simulation of object-oriented design, with the various parts interconnected.

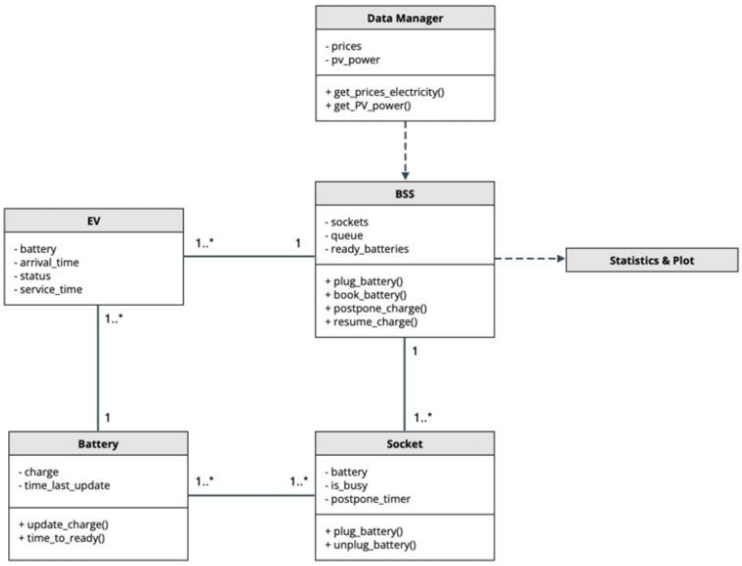

Figure 3.4.1.1 structure of BSS simulation

The simulation creates an EV instance at each arrival interval. The EV instance creates a battery instance and requests the swap service from the BSS module. The battery module keeps track of the battery's charge level, follows each event refresh, and provides the time it takes to fully charge the battery.

The core of the architecture is the BSS module. If a fully charged battery is available, it replaces the battery directly with an arriving EV, if no battery is available, it puts the EV in a queue and waits until the battery is fully charged before providing service.

The BSS can charge the batteries in the queue directly from the grid, as well as using solar and wind power to charge the batteries.

The data manager module is used to store and retrieve all the data needed to calculate prices and to update the solar and wind power levels. This data is then used to create graphs and charts.

3.4.2 BSS main functions

This section lists the main functions that the BSS simulation serves for EV users.

update_all_batteries()

This function is used to update the charge of all batteries, and is called every hour and before every event. After updating the battery charge, BSS will check if it is necessary to restore the batteries that have been delayed in charging.

arrival()

This function is used for each user arrival. First the function calls update_all_batteries() to update the charge of all batteries, immediately after generating a new EV instance, and sets its inter-arrival time with an exponential function, which depends on the simulator's current hour. arrival() is divided into three cases:

1) there are fully charged available batteries, then the BSS swaps the batteries and plugs the dead ones into the free sockets; 2) there are no available fully charged batteries, the BSS checks when the next battery will be ready, and puts the EV into the queue to wait if the time required is less than Wmax; 3) there are no ready batteries, the time for the next battery to be ready is greater than Wmax, or all rechargeable batteries are booked by other vehicles, the EV cannot be serviced and the user is lost.

serve queue()

This function performs a full charge battery swap for the EVswap in the wait queue. This event occurs after the arrive() function, when the battery reserved for the vehicle is fully charged, the BSS removes the EV from the FIFO queue and performs the swap.

battery available()

This function is used when the battery has finished charging. The BSS pulls it out of the socket and places it on the docking station with the other fully charged batteries.

set_price_Tmax()

This function is used to set optimal postpone time and thresholds for electricity prices.

locate_season()

This function is used to set optimal postpone time and optimal number of postponed batteries for each season.

3.4.3 Postpone rules

Each time a user arrives and the battery charging is completed, the BSS checks to determine if the charging of some batteries can be deferred to save electricity, thus finding a balance between quality of service and cost. F is the maximum number of batteries that can be deferred.

Algorithm 1: The BSS first checks for clean energy, (the original system checks if the available solar energy is equal to zero), the improved algorithm checks if the sum of solar and wind energy is less than 0.15 (Chapter 6.2.1) (algorithm 1). If not, there are two convenience algorithms:

Algorithm 2: Defer charging to a time when grid electricity is cheaper. With the Wmax, BSS will search a electricity price cheaper than current electric.

Algorithm 3: Defer charging until the next wind or solar energy production. If the energy from solar panels and wind turbine is zero, the postpone time will be set as Tmax.

Algorithm 1 Postpone charge

```
i←0
if pv < 0.15 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
```

Figure 3.4.3.1 Postpone algorithm 1

Algorithm 2 Check convenience (cheapest price)

```
i←0
timer ← 0
while i < Tmax 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
```

Figure 3.4.3.2 Postpone algorithm 2

Algorithm 3 Check convenience (solar power)

```
timer ← 0
pv next ← get pv power(month, day, hour + Tmax)
if pv next > 0 then
    return Tmax
else
    pv now2 ← get pv power(month, day, hour + 1)
    pv next2 ← get pv power(month, day, hour + Tmax + 1)
    if pv now2 ≤ pv next + pv next2 then
        return Tmax
    end if
end if
```

Figure 3.4.3.3 Postpone algorithm 3

Chapter 4

This chapter is describing the methodology of the attempts, the results and details will be expanded in following chapters.

4.1 seasonal exploration

The original BSS system is using the same parameter settings throughout the year, but system components like solar energy is obviously varying in seasons, so observing the BSS data of cost of grid electricity and EV lost is needed.

The daily electricity cost of the original system in a year is shown in Figure 4.1.1.1, and the daily customer loss value is shown in Figure 4.1.1.2. The four colored dotted lines represent the seasons, which enables more intuitive data observing. Orange is the last day of winter, green is the last day of spring, blue is the last day of summer, and purple is the last day of autumn. So the days between orange line and green line represent spring, the days between green line and blue line represent summer, the days between blue line and purple line represent autumn, the remaining days represent winter.

From the two figures, it can be seen that the EV users loss rate is very low in spring and summer, and the solar energy is very abundant in spring and summer. So the parameter TMAX can be largely increased in spring and summer, and a optimal TMAX can be found in winter and autumn. Increasing TMAX means EV users will wait more time to get ready batteries, which may cause increasing loss rate, but using more solar energy will reduce the cost of BSS. The increasing scope is controlled by the premise that the average EV users loss rate is less than 1.5. The parameter F may also be contributed, so it is also set experiment to find the optimal maximum number of batteries can be postponed.

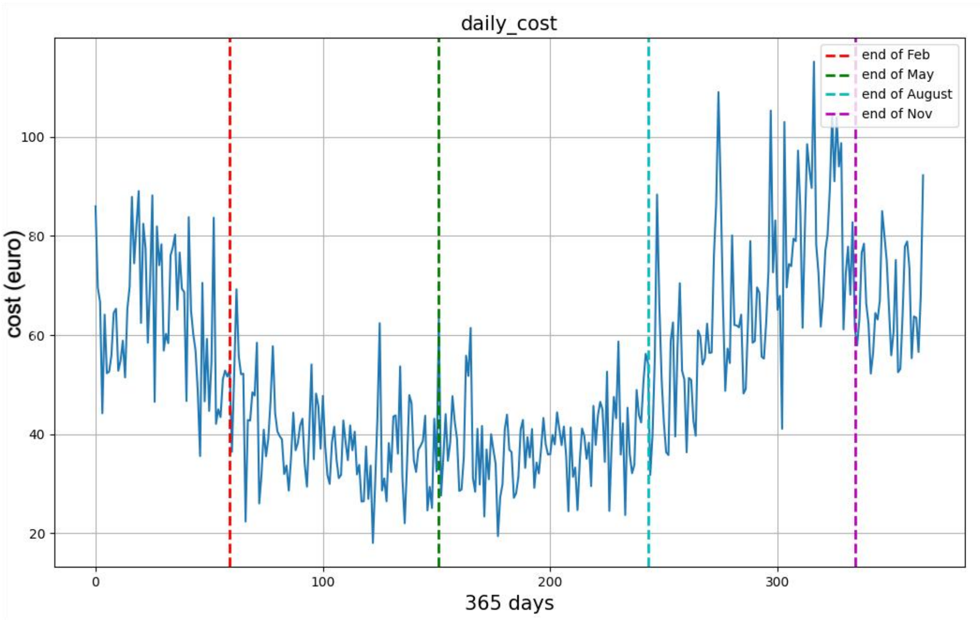

Figure 4.1.1.1 daily electricity cost in the year

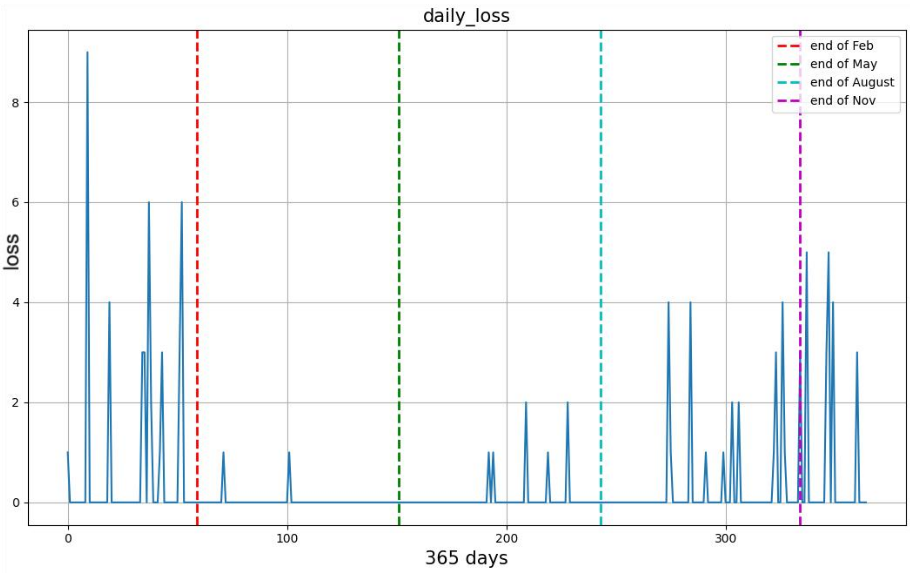

Figure 4.1.1.2 daily user lost in the year

The detailed trying of find optimal TMAX and F are showed in chapter 5.

4.2 wind energy

Before introducing the wind energy into BSS system, a new electricity price data is implemented. The new electricity price data is updated dates, and the hourly prices are more accurate and closer to reality.

After using the new electricity price data, the optimal TMAX and F will be checked

again.
Wind energy align with the solar energy as clean energy is providing electricity energy for charging batteries. The introduce of wind energy, with the modified postponed algorithm, can efficiently reduce the cost of the system.
The details of using wind energy is shown in chapter 6.

4.3 new price rule exploration

Average daily customer losses and average electricity costs in the system before implementing the new price rule are shown in Table 4.3.1:

lost	cost (euro)
1.18082	23.33109

Table 4.3.1 average cost and lost of the year without new price rule

After observing the new electricity price data, the prices are varying time to time, like the price is high when it's the peak, and the price is low when it's the valley. In order to explore the probability of reducing BSS cost, a new price rule is implemented, aiming at using more low prices and avoiding using high prices.
The first important step is to set the optimal TMAX for high price and low price separately.
The second important step is to set the low price threshold and high price threshold, which means the prices data can be divided into three parts, first part is low prices, second part is high prices, third part is medium prices. Medium prices can also be called unaffected prices, due to those prices will use optimal postpone time (TMAX) in chapter 4.1, and will not be affected by the new postpone time in this rule.
After sorting and observing the 8761 rows of price data, the thresholds of prices are according the number of prices that regard as low price and high price, like if approximate 200 is the number of prices affected by this rule, so the last 100 prices are low prices, the 100^{th} price from the bottom is the threshold of low prices,

samilarly, the top prices are high prices, the 100th price is the threshold of high prices. The excel macro will help with it.

Under this new price rule, the unaffected electricity prices, that prices between high prices threshold and low price threshold, will obey the seasonal optimal TMAX, which discussed in chapter 5, the prices under low price threshold will obey optimal low price TMAX and the prices over high price threshold will obey optimal high price TMAX.

The details of the new price rule is showed in chapter 7.

Chapter 5

Seasonal Exploration

5.1 Seasonal evaluation

5.1.1 TMAX

In this section, the main focus is to test whether the cost of electricity can be reduced, with the acceptable lost, by using different TMAX values during the four seasons of the year. Tmax is expressed in minutes.

Keeping the TMAX in winter and fall as the original system default value of 120 minutes, and bringing the TMAX in spring and summer into [200, 400, 600, 1000], the results are shown in Figure 5.1.1.3. As mentioned in chapter 4.1, in the figure, the days between orange line and green line represent spring, the days between green line and blue line represent summer.

From the figure, it can be seen that increasing the TMAX value can indeed get less electricity cost, but at the same time, the customer loss rate will also increase, and when the TMAX is around 600 minutes, it can get a good cost-lost equilibrium. Therefore, a new round of TMAX test is conducted in spring and summer to find the optimal solution.

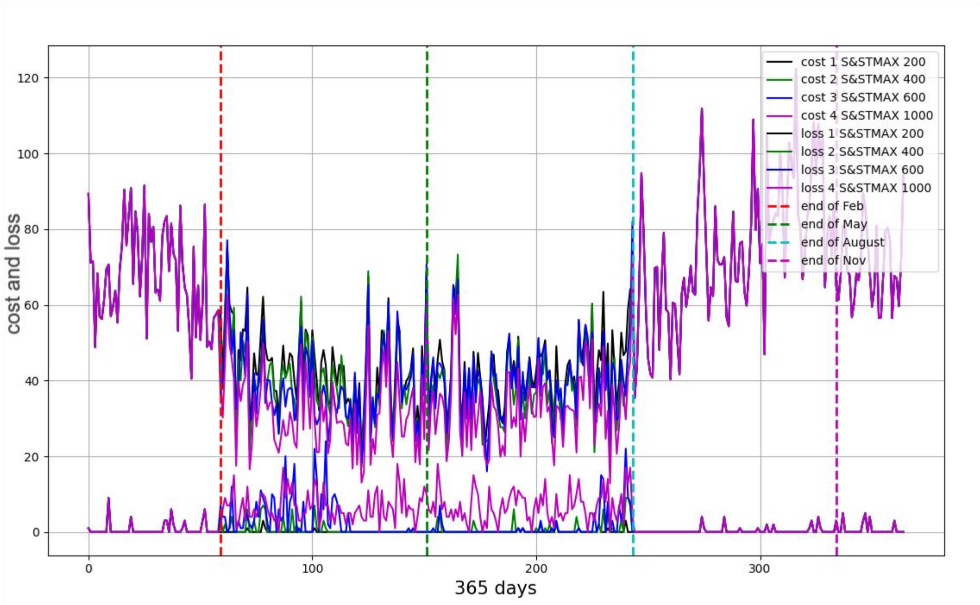

Figure 5.1.1.3 daily cost and loss in the year with Tmax[200, 400, 600, 1000]

For Spring, TMAX are brought into [200, 400, 500, 600] to get Figure 5.1.1.4, and it is found that the optimal solution may exist in the range of 400-500 minutes, and then the values of TMAX are brought into [425, 450, 475, 500] to get Figure 5.1.1.5, and it is found that the optimal solution of TMAX may be 475 minutes, and then the values of TMAX are brought into [400, 425, 450, 475, 500, 525, 550] to get Figure 5.1.1.6, and thus the optimal solution is indeed 475 minutes (about 8 hours).

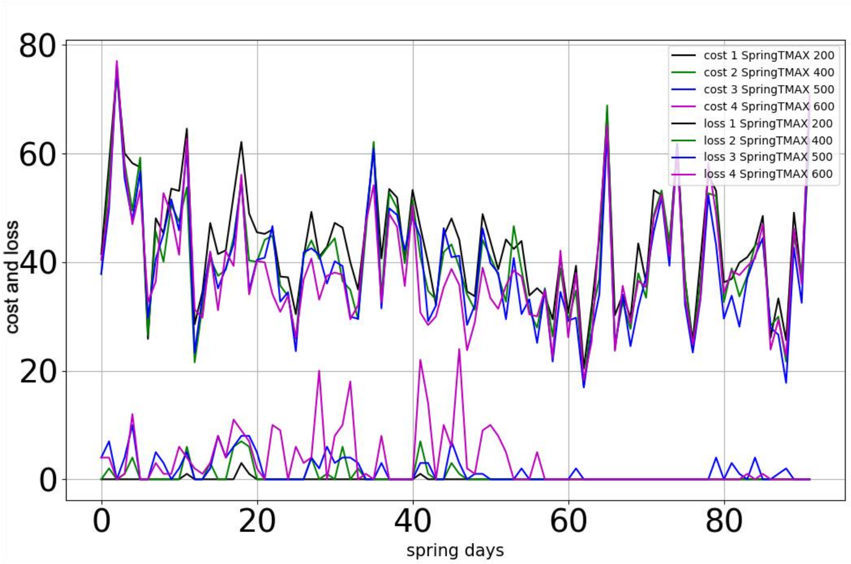

Figure 5.1.1.4 daily cost and loss in spring with Tmax[200, 400, 500, 600]

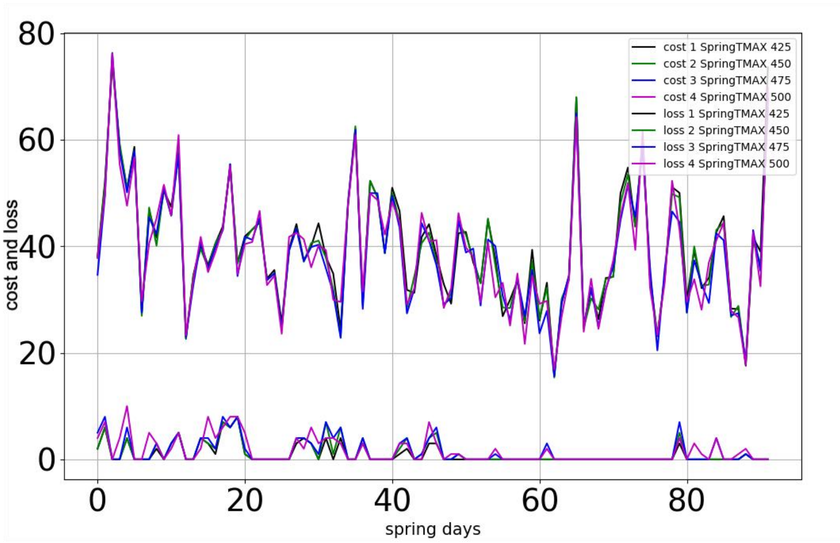

Figure 5.1.1.5 daily cost and loss in spring with Tmax[425, 450, 475, 500]

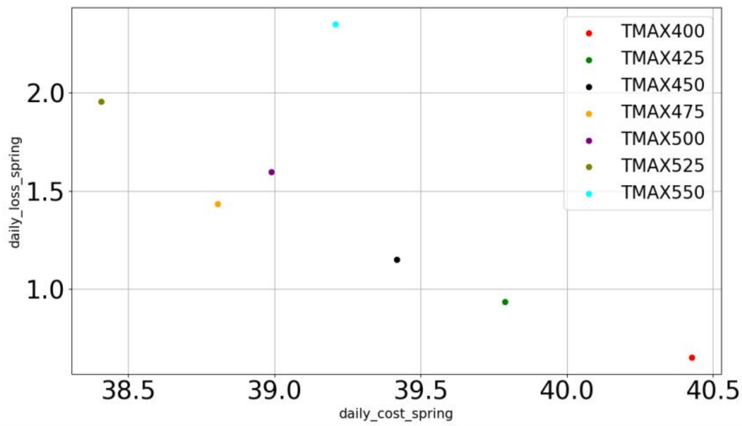

Figure 5.1.1.6 average lost in spring with Tmax[400, 425, 450, 475, 500, 525, 550]

Similarly, for summer, TMAX are brought into [200, 500, 600, 1000] to get Figure 5.1.1.7, and it is found that the optimal solution may exist in the range of 500-600 minutes, and then the values of TMAX are brought into [475, 500, 525, 550] to get Figure 5.1.1.8, and it is found that the optimal solution of TMAX may be 500 minutes, and then the values of TMAX are brought into [450, 475, 500, 525, 550, 575, 600] to get Figure 5.1.1.9, and it is found that the optimal solution is indeed 500 minutes.

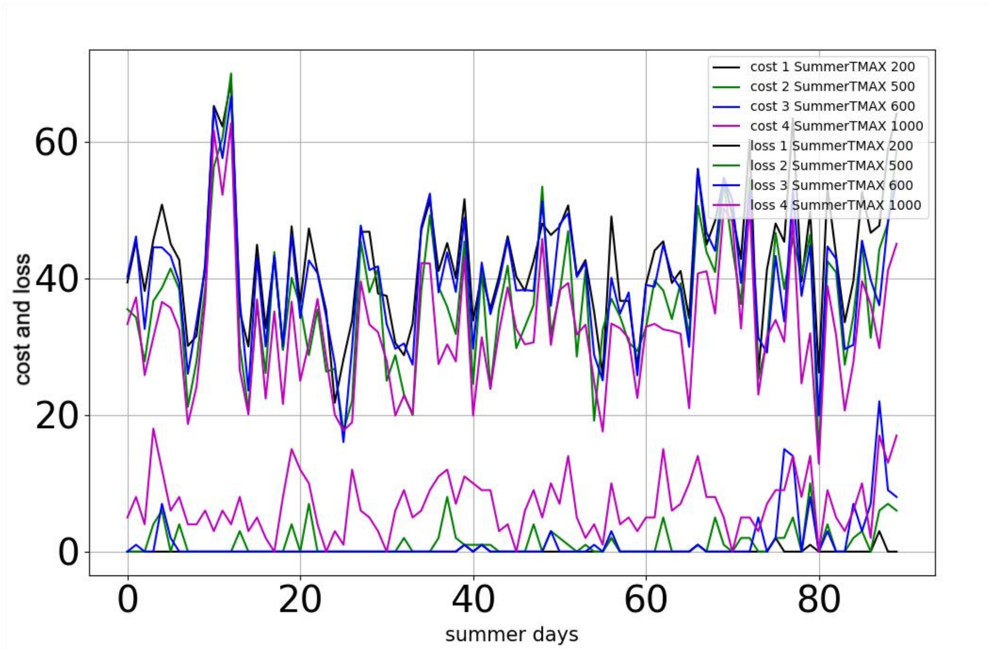

Figure 5.1.1.7 daily cost and loss in summer with Tmax [200, 500, 600, 1000]

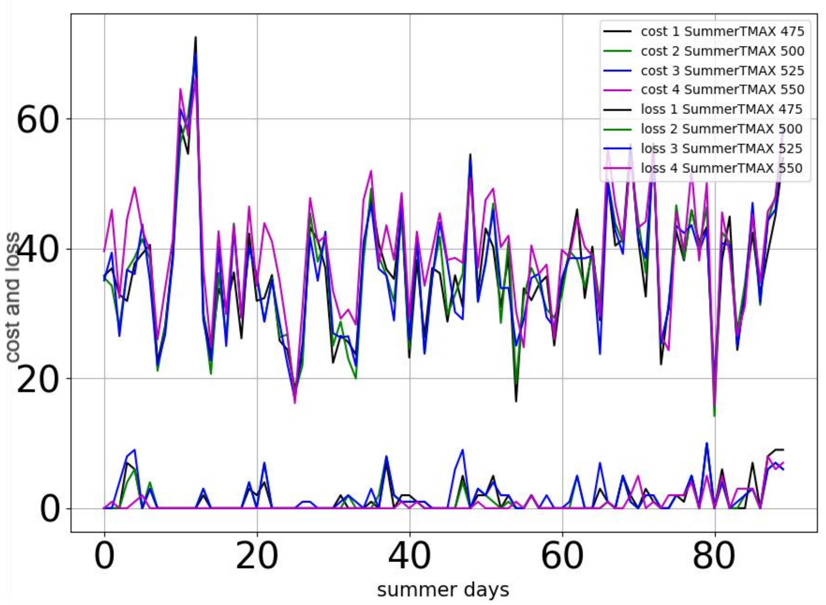

Figure 5.1.1.8 daily cost and loss in summer with Tmax [475, 500, 525, 550]

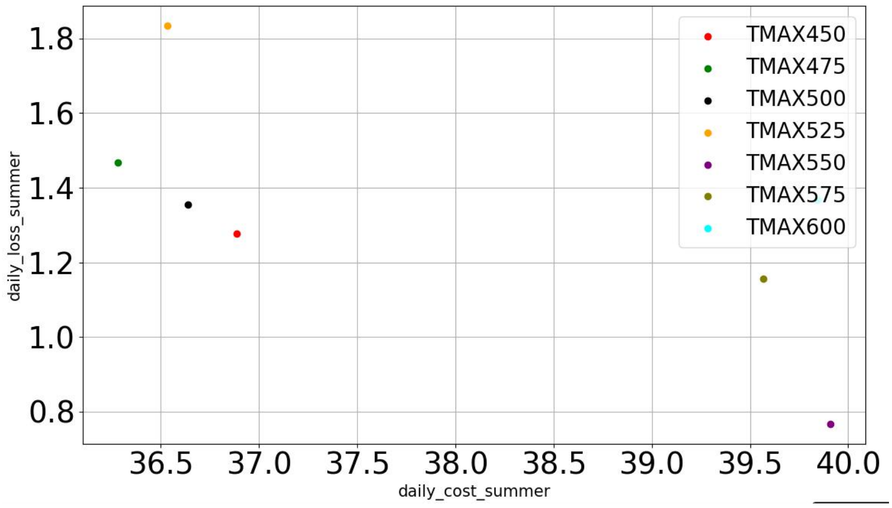

Figure 5.1.1.9 average cost and loss in summer with Tmax[450, 475, 500, 525, 550, 575, 600]

Although solar energy is not as abundant in the fall and winter as it is in the spring and summer, there is still room for improvement, so the same approach is used for fall and winter.

For fall, bring in the values of TMAX [150, 200, 250, 300, 325, 350, 375] to obtain Figure 5.1.1.10, with an optimal solution of 325 minutes. For winter, bring in the values of TMAX [125, 150, 175, 200, 225, 250, 275] to obtain Figure 5.1.1.11, with an optimal solution of 225 minutes.

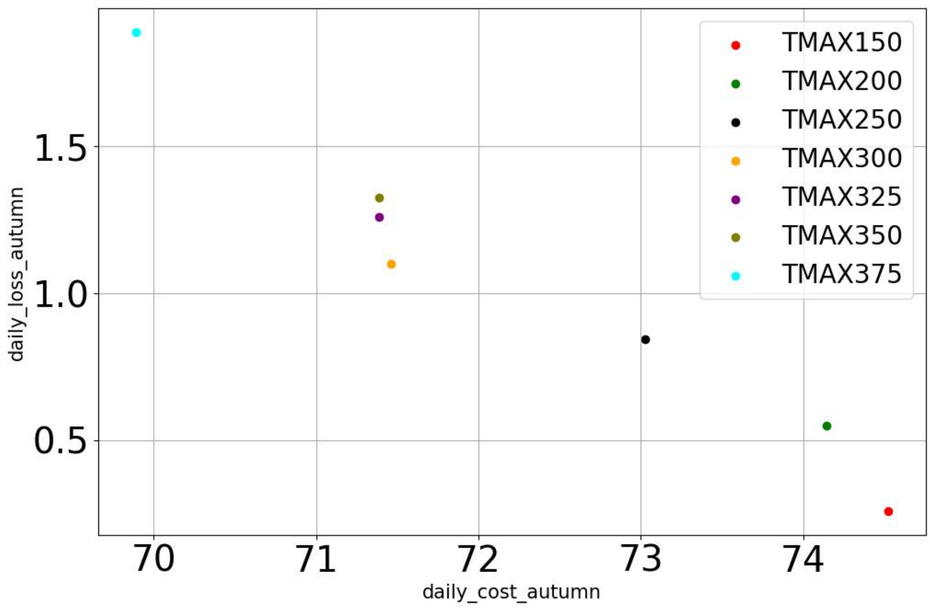

Figure 5.1.1.10 average cost and lost in autumn with Tmax[150, 200, 250, 300, 325, 350, 375]

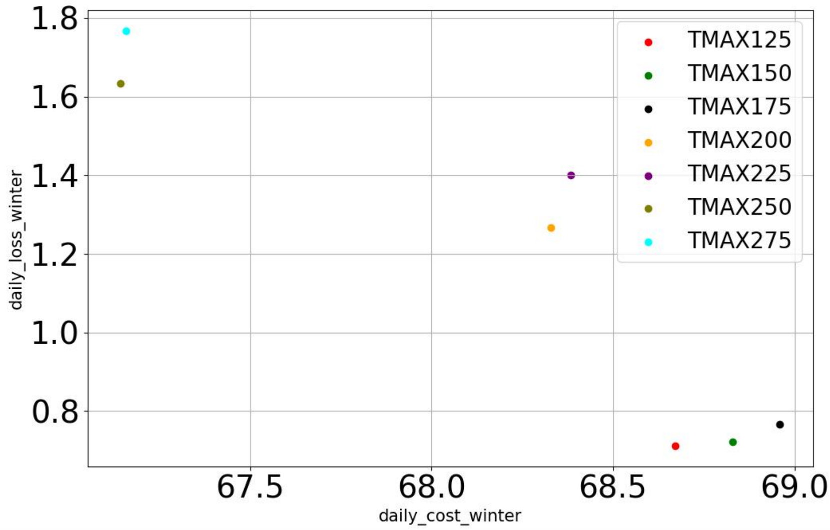

Figure 5.1.1.11 average cost and lost in winter with Tmax[125, 150, 175, 200, 225, 250, 275]

Therefore, the use of different TMAX values for the four seasons can effectively reduce the electricity cost. And the optimal TMAX for spring, summer, fall and winter is 475 minutes, 500 minutes, 325 minutes and 225 minutes separately. It can be seen that, there is plenty sunshine in spring and summer, so the TMAX can be set longer (approximately 8 hours) to use more solar energy. In fall and winter, the system is more dependent on the smart grid.

5.1.2 F value

In this section, the main focus is to explore whether the cost of electricity can be reduced by using different values of F during the four seasons of the year.

The F-value is the maximum number of batteries that can be recharged at a later date. Increasing the F-value increases the likelihood of customer churn, but allows for greater use of solar energy.

In testing different F-values, different optimal TMAX values for the four seasons derived in the previous section are applied.

Bringing in the F-values [0, 11, 15, 17, 19, 20, 22], we obtain the cost-lost in spring as in Fig. 5.1.2.1, in summer as in Fig. 5.1.2.2, in fall as in Fig. 5.1.2.3, and in winter as in Fig. 5.1.2.4.

It is clear from the graph that the larger the F-value, the lower the cost and the more the lost. The optimal solution for F value in spring, summer, fall and winter is 17.

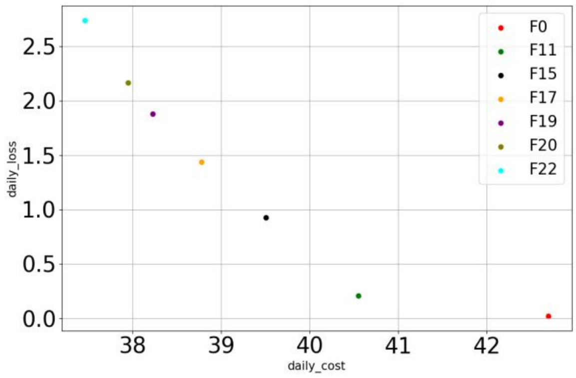

Figure 5.1.2.1 average cost and loss in spring with F [0, 11, 15, 17, 19, 20, 22]

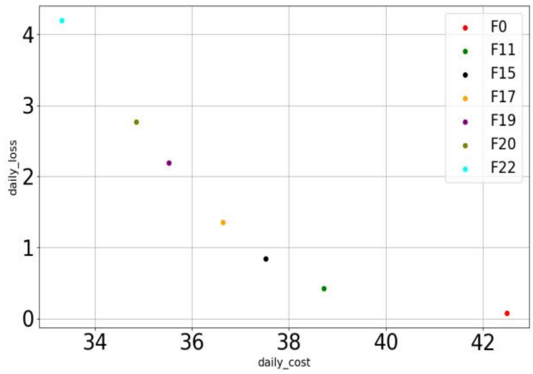

Figure 5.1.2.2 average cost and loss in summer with F [0, 11, 15, 17, 19, 20, 22]

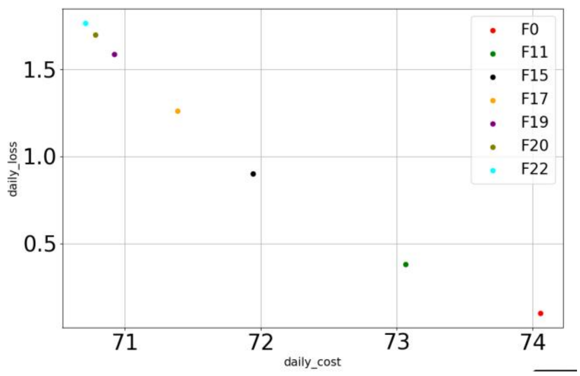

Figure 5.1.2.3 average cost and loss in autumn with F [0, 11, 15, 17, 19, 20, 22]

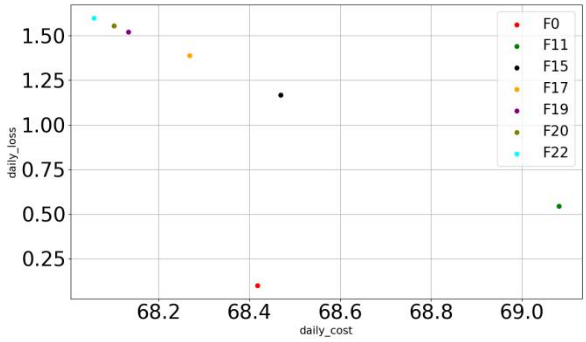

Figure 5.1.2.4 average cost and loss in winter with F [0, 11, 15, 17, 19, 20, 22]

It can be seen that, the lost is almost positively correlated with F in each season, and the cost is almost negatively correlated with F in each season. Which means increasing the maximum number of batteries that can be postponed, the EV users will leave due to waiting for too long time, but using more solar energy, the cost will decrease. So the TMAX and F are both influencing the solar energy utilization rate, the different solar energy utilization result in different cost and lost.

Comparing the figure 5.1.2.1 and figure 5.1.2.2 with figure 5.1.2.3 and figure 5.1.2.4, it can be found that, when increasing the F, the lost in spring and summer are much higher than winter and fall, it is due to the TMAX in spring and summer are set very large, the BSS system is already postponed more time for charging batteries to use more solar energy, so increasing F will lead to large losses in spring and summer.

Chapter 6

Wind Exploration

6.1 New price data

The optimal TMAX and F in chapter 5 are implemented in the BSS system.

As time goes by, it is necessary to use in the system new data on electricity price, the new data are hourly electricity price from January 1st to December 31st, 2022 for the Northern Italy region, which comes from the Italian Energy Market Operator "Gestore Mercati Energetici ".

An example of the data is shown in the following table 6.1.1:

Year	Month	Day	Hour	Price(euro/MWh)
2022	1	2	17	15.041168

Table 6.1.1 sample of new electricity price data

The table shows the electricity price is 15.041168 euro/hour for January 2, 2022 from 17:00 to 17:59 .

The following figures show that the system validates the optimal TMAX and F values obtained in Chapter 5 with the new electricity price. Figure 6.1.1 and Table 6.1.2 show the electricity (cost) and customer loss (lost) per day in a year when the system uses the new price, but use the original TMAX with F (not optimal TMAX with F). Figure 6.1.2 and Table 6.1.3 show the electricity (cost) and customer loss (lost) per day in a year when the system uses the new price with the optimal TMAX and F values.

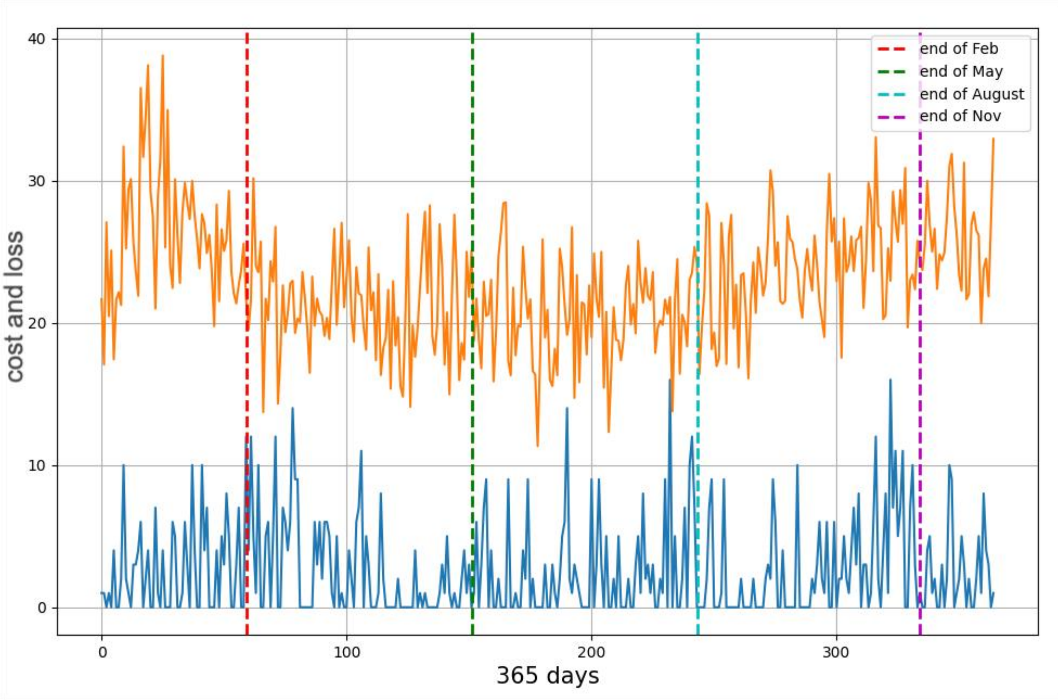

Figure 6.1.1 daily cost and lost of the year with new price without optimal Tmax & F

Daily_loss	Daily_cost (euro)
2.60548	22.91037

Table 6.1.2 average cost and lost of the year with new price without optimal Tmax&F

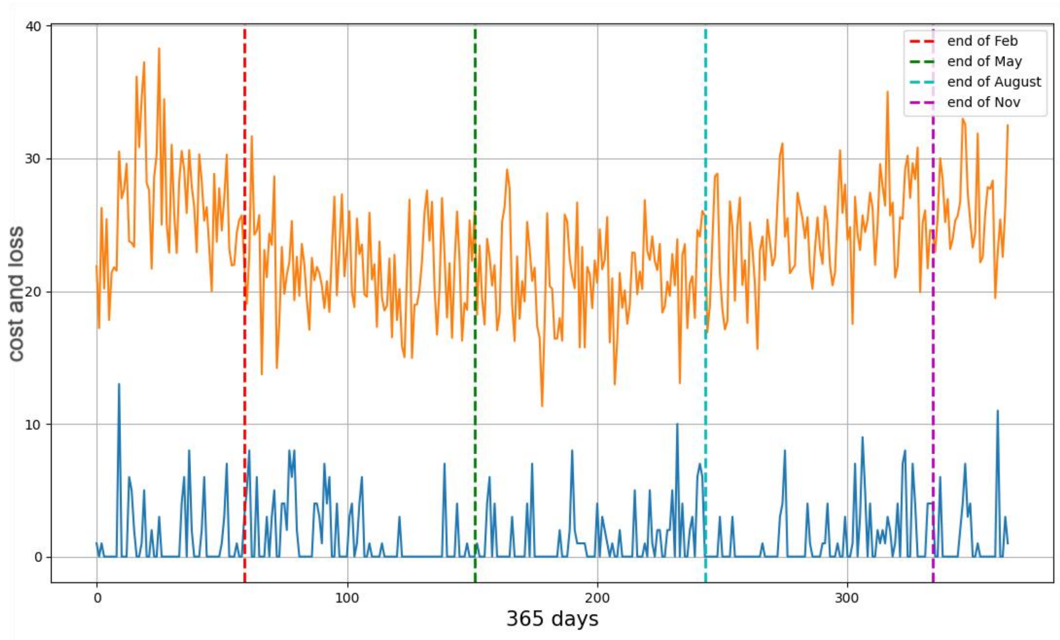

Figure 6.1.2 daily cost and lost of the year with new price and optimal Tmax & F

Daily_loss	Daily_cost (euro)
1.36712	23.25345

Table 6.1.3 average cost and lost of the year with new price and optimal Tmax & F

From Fig. 6.1.2 and Table 6.1.3, it can be seen that the lost is effectively reduced within the range of 1.5, but there is a slight increase in the cost. In order to verify that the optimal TMAX and F are still valid, the method in Chapter 5 is repeated when the system is using the new price, and after tens of repetitions of trying other different values, this TMAX and F value is still the optimal one.

It can be concluded that all the conclusions in Chapter 5 still hold after the system updates the electricity price.

6.2 Wind energy

Wind energy is a widely used new energy source, so wind energy is added to this system. The wind energy data was collected from wind turbines installed in Belgium in 2015 and applied to the original system, the graphs(6.2.1-6.2.4) and tables(6.2.1) obtained are as follows:

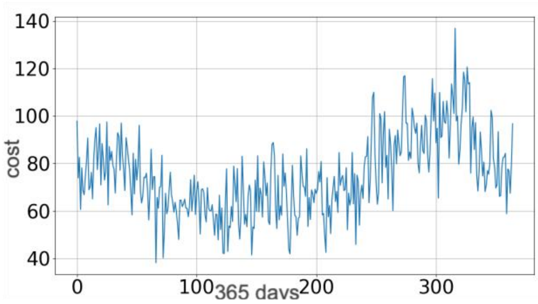

Figure 6.2.1 daily cost of the year only with solar energy

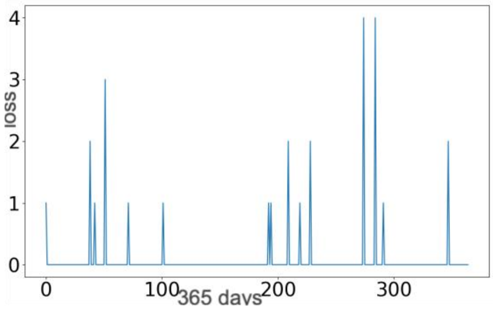

Figure 6.2.2 daily lost of the year only with solar energy

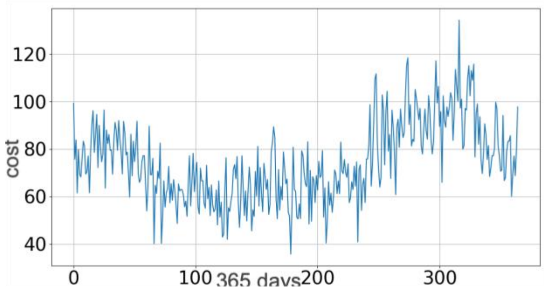

Figure 6.2.3 daily cost of the year with wind and solar energy

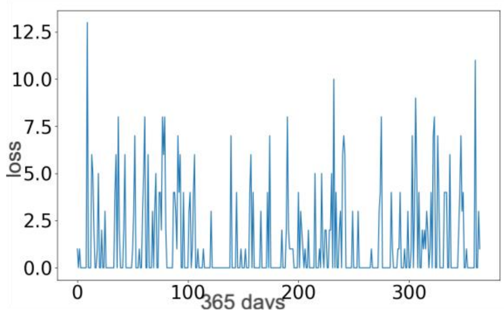

Figure 6.2.4 daily lost of the year with wind and solar energy

Cost(solar only)	Lost(solar only)	Cost(solar and wind)	Lost(solar and wind)
74.54558	1.36712	75.19756	0.07397

Table 6.2.1 average cost and lost of the year

Figure 6.2.1 shows the daily cost of using only solar energy, figure 6.2.2 shows the daily lost of using only solar energy. Figure 6.2.3 shows the daily cost of using solar and wind energy toghter, Figure 6.2.3 shows the daily lost of using solar and wind energy toghter,

Table 6.2.1 shows the year average of electricity cost and user lost in solar energy only and in solar and wind energy separately.

From the figures and the table, it can be concluded that after adding wind energy, the probability of customer loss is greatly reduced, but the value of cost increases. The analysis suggests that the rise in cost is attributed to the postpone rule of batteries charging.

6.2.1 Wind energy and Postpone rules

Postpone is used to determine whether a new uncharged battery enters the queue, waiting for charging, or loses this EV user. As the postpone algorithm introduced in chapter 3.4.3, the rules of postpone are represented in a flowchart as shown in Figure 6.2.1.1:

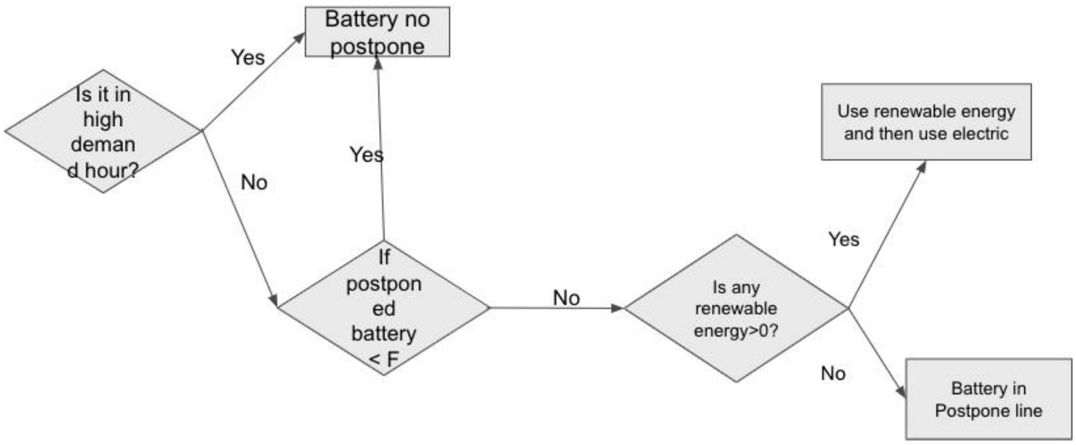

Figure 6.2.1.1 postpone flowchart

From Fig. 6.2.1.1, the original rule of the system is that as long as there is new energy in the system, there is no postpone and the battery starts charging directly. However, the new wind energy produces a very small amount of electricity per hour, and if the original rule is used, after using a very small amount of wind energy, the remaining electricity will need to be obtained from the smart grid, which adds a lot of cost, and therefore the original postpone rule needs to be changed.

The change of the postpone rule is based on the data of the new wind energy used by the system. When the wind and solar energy is less than the threshold value, new batteries are still allowed to enter the queue, part of the core attempts for the threshold value are as follows in Table 6.2.1.1:

Threshold	0.19	0.2	0.15	0.17	0.18
cost (euro)	23.273	23.261	23.337	23.305	23.281
lost	1.362	1.4	1.1480	1.252	1.329

Table 6.2.1.1 average cost and lost with different threshold

Table 6.2.1.1 records a small portion of the threshold attempts. The threshold row of table 6.2.1.1 is the new threshold that is substituted into the system, the cost row is the average year cost of electricity when the system is using this threshold, and the lost row is the average annual loss of users when the system is using this threshold. Therefore, the threshold is set at 0.15 to keep the loss within an acceptable range and minimize the cost.

The new Postpone rule is shown in Figure 6.2.1.2 (same as the algorithm 1 in chapter 3.4.3):

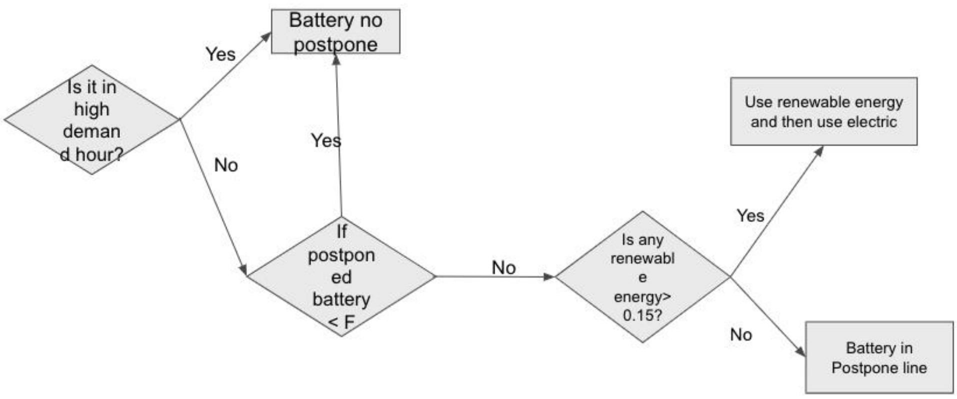

Figure 6.2.1.2 new postpone rule flowchat

Table 6.2.1.2 shows the average cost and lost of a year in BSS, with the new postpone rule.

Cost(solar and wind)	Lost(solar and wind)
23.337	1.1480

Table 6.2.1.2 average cost and lost with wind energy and new postpone rule

Chapter 7

New Rule Exploration

7.1 New Price rule

After applying the optimal TMAX value, the optimal F-value, the new electricity price of 2022, wind energy, and the new postpone rule, it is possible to reduce the cost within an acceptable lost value, and this chapter discusses this possibility.

Average daily customer losses and average electricity costs in the system before implementing the new price rule are shown in Table 7.1.1:

lost	cost (euro)
1.18082	23.33109

Table 7.1.1 average cost and lost of the year without new price rule

In the electricity price data, there are 8761 electricity data of different time in 2022, and the average value is 18.24830298 Euro/hour.

By using macro formulas in Excel, it is possible to obtain the number of electricity prices that are affected after the threshold has been set.

First presuming if the new price strategy will affect around 200 prices, through macro formulas, it can be found that there are 110 prices greater than 26, so maximum price threshold is 26. There are 109 electricity prices less than 11.3, so the minimum price threshold is 11.3.

The TMAX value is set to 800 when the maximum price threshold is exceeded, and TMAX set to 100 when it is smaller than the minimum price threshold. The obtained data are shown in Table 7.1.2:

lost	cost(euro)
1.19452	23.32659

Table 7.1.2 average cost and lost of the year with new price rule

It can be seen that the new pricing strategy results in a slight increase in lost and a slight decrease in cost, so the new pricing strategy is effective in reducing the cost within an acceptable value of lost. Then finding the lowest cost becomes the goal.

The system data when the TMAX value is 1000 when it is over the maximum price threshold and 50 when it is less than the maximum price threshold are shown in Table 7.1.3:

lost	cost (euro)
1.22192	23.32042

Table 7.1.3 average cost and lost of the year with new price rule

These two TMAX values (max1000 and min50) are within the reasonable range, and can cause a slight increase in lost and a slight decrease in cost, so these two values are used as the TMAX thresholds for the new price strategy.

Repeat the step above to find the thresholds of maximum price threshold and minimum price threshold, under the max TMAX thresholds 1000 and min TMAX thresholds 50.

Presuming if the new price strategy will affect around 700 prices, through macro formulas, it can be found that there are 396 prices greater than 25, so maximum price threshold is 25. There are 308 electricity prices less than 12, so the minimum price threshold is 12. The results are shown in Table 7.1.4:

lost	cost (euro)
1.25479	23.31174

Table 7.1.4 average cost and lost of the year with new price rule

Presuming if the new price strategy will affect around 1000 prices, through macro formulas, it can be found that there are 498 prices greater than 24.7, so maximum price threshold is 24.7. There are 497 electricity prices less than 12.5, so the minimum price threshold is 12.5. The results are shown in Table 7.1.5:

lost	cost (euro)
1.26301	23.31056

Table 7.1.5 average cost and lost of the year with new price rule

Presuming if the new price strategy will affect around 1200 prices, through macro formulas, it can be found that there are 636 prices greater than 24.3, so maximum price threshold is 24.3. There are 647 electricity prices less than 12.8, so the minimum price threshold is 12.8. The results are shown in Table 7.1.6:

lost	cost (euro)
1.25479	23.31171

Table 7.1.6 average cost and lost of the year with new price rule

These two thread values (max24.3 and min12.8) are within the reasonable range, and can cause a increase in lost (within 1.5) and a decrease in cost, so these two values are used as the electricity price thresholds for the new price strategy.

By comparing the data in table 7.1.6 and table 7.1.1, it shows that the new price strategy is effective, it can reduce the average cost with an acceptable average user loss rate, but the effect is very small, thus it is up to the BSS service provider who run the BSS to decide whether or not to apply this new pricing strategy, as compared to the inclusion of the optimal four-season TMAX value, which significantly improves the system's lost-cost, this new pricing strategy provides a limited improvement. But in some specific situation, if there is a sudden and dramatic increase in the cost of electricity in one of the future winters, such as the winter of 2023, the price of electricity rose sharply as a result of the war, it might be better to use the new pricing strategy.

Chapter 8

Conclusion

The thesis discusses the in-depth analyses of BSS(battery switch station) and explores the improvements of BSS.
Seasonal changes have been added into BSS, The best TMAX (Max pause time for charging) is 475 minutes in spring, 500 minutes in summer, 325 minutes in autumn, and 225 minutes in winter. The best F(Max postponed batteries for charging) is 17 for each of the four seasons.
A new clean energy source, wind energy, has been added to the BSS. By introducing wind energy, it is closer to achieving our goal of sustainability and environmental friendliness.
A new price rule has been added in to BSS, and the system is using the updated electricity prices. The optimal TMAX for high prices is 1000 minutes, the optimal TMAX for low prices is 50 minutes. The threshold for high price is 24.3 euro/MWh, the threshold for low price is 12.8 euro/MWh. If the electricity prices are more even, the cost reduction by the new price rule is not significant. so it is possible to choose whether or not to implement the new price rule, depending on the specific scenarios.

There are two points that can continue to be improved. First is the price rule, more price rules can be designed differently for different realities. As mentioned in chapter 7.1, the price rule will be more effective in the winter of 2023, which high electricity prices caused by war. Second is the battery switching operation time. In BSS, it is set to be few minutes, in commercial practice, the typical exchange time is 5 minutes. Therefore if the exchange demand is high, the operation time has to be planned.

The future of BSS technology has many improvement directions. First cloud computing and big data analysis can be implemtationed in data module and decision making module, thus BSS can have a new way to deal with data and have more flexible decisions. Second, solar energy data can be predicted. Real data such as temperature and humidity access to machine learning models, used to predict solar power generation in a more realistic way, so as to better regulate the scheduling of electricity [22]. Third, as mentioned in chapter 2.4, the drastic competition in market share is between BSS and BCS (battery charging station) [23], these two models generate four possible combinations single BSS, multiple BSS, integrated BSS and BCS, and multiple BSS and BCS [24]. Therefore, these four combinations are the way forward in future charging station design.

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