Tampere University

Shaiful Alam

MARKET BASED INTELLIGENT CHARGING SYSTEM FOR ELECTRIC VEHICLES

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ABSTRACT

Shaiful Alam: Market based intelligent charging system for electric vehicles
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The existing electrical infrastructure is very unlikely to expand overnight. Therefore, a smart solution is certainly needed to integrate the additional load which electric vehicles (EV) bring to the network. The aim of the thesis is to study the electricity market, different intelligences related to electric vehicle charging and establish an algorithm that produces an optimized charging schedule for electric vehicles. The algorithm ensures a cost profit for user and takes part in demand response by shifting the timing of charging loads based on energy prices.

The core intelligences integrated to the EV charging system in the thesis are cost optimization, peak shaving and load shifting. The algorithm follows the hourly unit cost related to the energy consumption and distribution fee in order to find the cheapest time slot for charging operation. It allocates as high charging power as possible to the cheapest time slots and then start selecting the expensive time slots until the battery is charged to desired state of charge. Along this process, the algorithm continuously calculates the maximum charging power available after other household usage. The Elspot area price of Finland for 2018 added with 0.3 cents/kWh margin and 24% VAT are used as energy prices. Distribution unit prices include time-of-use pricing for day and nighttime energy use in addition to the fixed fuse-based fee. By following these unit prices, the algorithm shifts the load from high demand to low demand hours in order to minimize the total costs.

The algorithm is implemented in MATLAB and tested through a case study on different type of Finnish detached houses. Detached houses with different load profile data are used as input for charging a 75 kWh EV with a 10 kW and 7.5 kW charger in different cases, where the other inputs remain same for all the test cases. The Elspot area price of Finland for 2018 added with 0.3 cents/kWh margin and 24% VAT are used as energy prices. Different day and night-time distribution prices are applied depending on the consumption. The simulation results are compared to regular EV charging, where the charging operation starts right after the EV is plugged in and finishes charging within shortest time.

The results from the simulation are investigated from user's and grid's point of view. From user's perspective, all the charging events with intelligent charging have costs savings over regular charging. The monetary profit is higher for higher charger rating (10 kW). In cases where the household usage is low, the proportional profit is high. From grid point of view, over 99% of the load gets shifted to night-time for 10 kW charger cases. For the 7.5kW charger, the amount of shifted load is over 97%, which is a little lower than 10 kW charger cases because of longer charging time. The findings of the case study validate the use of smart charging algorithm in order to ensure cost savings for the user.

Keywords: Charging of electric vehicle, smart charging, Intelligent charging, Market based EV charging

PREFACE

Master's thesis reflects on student's maturity and growth achieved on the way to graduation. After a long and remarkable time spent here in Finland, I am grateful to Finnish education system for such opportunity of being part of this society. I admire the positive energy everyone put into one another's life here every day.

I express my gratitude to all the friends, mentors and other people I met along this journey in Tampere University. I would like to thank you Pertti and Antti for your kind supervision for the thesis. Along this journey whenever I lost my way, I got my confidence back from you. I also want to thank Antti Mutanen for providing the data for simulation.

And last, but not least I am grateful to my parents for everything they have done for me.

Tampere, 2 November 2019

Shaiful Alam

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LIST OF SYMBOLS AND ABBREVIATIONS

AC	Alternating Current
BEV	Battery Electric Vehicle
BMS	Battery Management System
BRP	Balancing Responsible Party
CD	Charge Depleting
CET	Central European Time
CS	Charge Sustaining
DC	Direct Current
DoD	Depth of Charge
DR	Demand Response
DSO	Distribution System Operator
EV	Electric Vehicle
EVSE	Electric Vehicle Service Equipment
FCEV	Fuel-Cell Electric Vehicle
GRD	Greedy Based Scheduling
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
IC-CPD	In-Cable Current Protection Device
IEC	International Electrotechnical Commission
LBR	Load Balance Responsible
Li-ion	Lithium ion
PBR	Production Balance Responsible
PHEV	Plug-in Hybrid Electric Vehicle
POS	Price Oriented Scheduling
RCD	Residual Current Device
SoC	State of Charge
SoH	State of Health
TOU	Time Of Use
TSO	Transmission System Operator
V2G	Vehicle-to-Grid

1. INTRODUCTION

The modern era has made energy a basic need for human race. With the limited stored energy in different form like oil, coal etc. the efficiency of using the energy has become ”the talk of the time” in recent years. On top of that, the way of using the energy has been creating a lot of environmental challenges like increased carbon level in air, greenhouse effect etc. Burning of the fossil fuels are the main source of this increased carbon, more specifically carbon dioxide (CO_2). It comes in process of converting the chemical energy to directly usable form like electrical, thermal or mechanical energy.

Internal combustion engines (ICE) use fossil fuel, which is one of the biggest sources of CO_2 emission in today’s world. Introduction to renewable energy as solar power, wind power etc. opened a new opportunity to produce the energy in a “greener” way. This reason drove us to electrification of one of the biggest sectors of energy use, transportation.

Electricity usage in transportation is a century old concept. But due to the convenience of other options like ICE engines, it did not last for long. But at the end of 20th century, the environmental and other issues started forcing us to adopt the use of green energy for transportation. Renewable energy integration into electricity consumption has made the choice easier to choose the electric energy in this case. This process included adding the hybrid cars to the road. It was an effort to reduce the use of fossil fuels for driving wheels. But it was just a start of a new beginning. The success of hybrid cars inspired to bring the plug-in hybrid cars and eventually the (battery) electric cars take their part in today’s road. [21]

In the year 2005, number of EVs running in the roads used to be counted in hundreds. But by 2018, there were 5.1 million plug-in hybrid cars and EVs were in action [25]. This steep rise in the curve of EV usage refers to the future scenario of the road.

The biggest challenge electric transportation brings is the congestion of power demand to the current electrical distribution infrastructure. This extra load comes up with challenge of electrical infrastructure as well as power supply and demand congestion. To minimize this economic effect, load shifting throughout the day can be a feasible solution.

Regular charging time of EVs is more associated to the driving pattern and vehicle feature. As most of the vehicles sit idle at home during major time after work hours, it has a big flexibility with charging hours.

The purpose of this thesis is to study the electricity market and EV charging infrastructure and apply the possible intelligences in order make the operation profitable for user at the same time.

The objective of this thesis is to develop an intelligent charging EV algorithm for a detached single house scenario. The hourly energy pricing by retailer and distribution costs related to the energy consumed is considered for cost optimization in this study. The load profile distribution of the house itself during the day shapes the power consumption of EV charging.

This thesis is divided into seven chapters. Chapter 2 describes the Nordic energy market and its actors. Chapter 3 gives an introduction to electric vehicles, used battery technology, related definitions and EV charging mechanism. Chapter 4 describes different intelligences used in EV charging, algorithms and methods of their use in previous studies. Chapter 5 introduces the intelligent charging algorithm developed in this thesis, describes different parts of it and discusses the constrains. Chapter 6 carries out a case study with real time data set from 2018 for different type of detached houses. Chapter 7 describes the conclusion of the study and possibilities of related future work.

2. NORDIC ENERGY MARKET

Power is an important element of our daily life at home and outdoor. The increasing demand and supply have created dynamic power markets around the world. This chapter explains the structure of Nordic electricity market and digs deeper into the economic system to explain the method for price formation for end users.

Nordic countries have deregulated their own energy's market and integrated together to make a common Nordic power market in early 1990 [10]. That means the power market is not run only by the states anymore as it becomes an international power market. Later during 2010-2013, countries like Estonia, Latvia and Lithuania also joined Nordic market by deregulating their own energy markets. And now as the electricity sharing capacity is established between the Nordic, Baltic and the European continent, this power markets covers a big part of Europe [10].

Supply and demand usually determine the price of electricity. As high the demand is related to supply, higher the price is. This is the way how supply and demand get balanced in power market through price. The supply and demand balance system depend a lot on market players and different mechanism as demand response (DR) etc.

2.1 Market actors

Nordpool has a dynamic electricity trading pattern involving different market players. Small end users usually buy electricity from local retailer companies (retailer market). Large end users can buy the power directly from the wholesale market (like the power exchange run by Nordpool). Different market players and their role is covered in this chapter. For some actors like producers, retailers, end users etc. the market is open. Some part of the market, actors like TSO and DSOs are regulated monopolies.

2.1.1 Transmission system operators (TSOs)

Transmission system operator (TSO) is an organization that is neutral and totally independent from commercial players of the energy market. TSOs are the entities who ensures the stability and security of electric grid for a specific region. In other words, TSO ensures the frequency to be kept 50Hz and electricity is arriving to DSO end or in some cases some big customers.

TSO manages the regulating market in order to obtain the frequency stability of transmission grid. When the generation is higher than the consumption, the frequency rises and can go above 50 Hz. In this case, TSO ensures one or more electricity producers to reduce their electricity production. It is called as TSO procuring “down regulation”. In contrary, the consumption can be too high than electricity production. In this case, frequency can fall below 50 Hz. Then TSO ensures the extra supply by one or more producers generating more electricity or some consumers to temporarily decrease consumption. In this case TSO buys more power from a producer or consumer. It is called TSO procuring “up regulation”. This traded electricity is called regulating power.

TSOs in Norway (Statnett), Denmark (energinet.dk), Estonia (Elering), Lithuania (Litgrid) and Sweden (Kraftnät) are state-owned and ‘Fingrid’ the Finnish TSO is partly owned by Finnish public organizations and financial and insurance institutions.

2.1.2 Producers

The main task of producers is to produce electrical power. Producers bid-in on Nordpool spot market with their projected power generation for every hour of the next day. Balancing the real production with the projected plan is the main responsibility of Production balance responsible (PBR).

For power production there are 370 companies working in Baltic and Nordic regions [10]. Hydro power plants are the biggest source for power production in Nordic countries. According to Nordpool website, they produce half of the yearly demand with a normal expected amount of rain and snowfall.

Norway is almost fully dependent on hydropower as Sweden and Finland have mixture of hydro, steam driven thermal and nuclear power. Day by day renewable power is penetrating more in these power markets. That allows to reduce the use of expensive sources like oil, gas etc. As an example, thermal power was predominant in Denmark, Estonia and Lithuania, but wind power is becoming more important increasingly in Denmark.

Hydro is the cheapest power source among all [10]. Production cost goes high with the employment of more expensive power sources. During the dry years, Nordic power market become more dependent on the power import from nearby countries like Russia, Netherlands, Estonia, Germany and Poland.

2.1.3 Distribution system operators (DSOs)

Distributors ensures that the power generated by producers reaches the end users. DSO maintains the local grid. The number of distribution companies working in Nordic and

Baltic countries are around 500. The networks that is operated by the DSOs connects the private homes and other buildings to the grid.

In some countries, DSOs are obliged to ensure the meters are installed and read at the end users point. Like TSOs, DSOs are legally independent from the commercial players like producers, suppliers etc.

Figure 1 shows the relation between different market actors in Nordic electricity market.

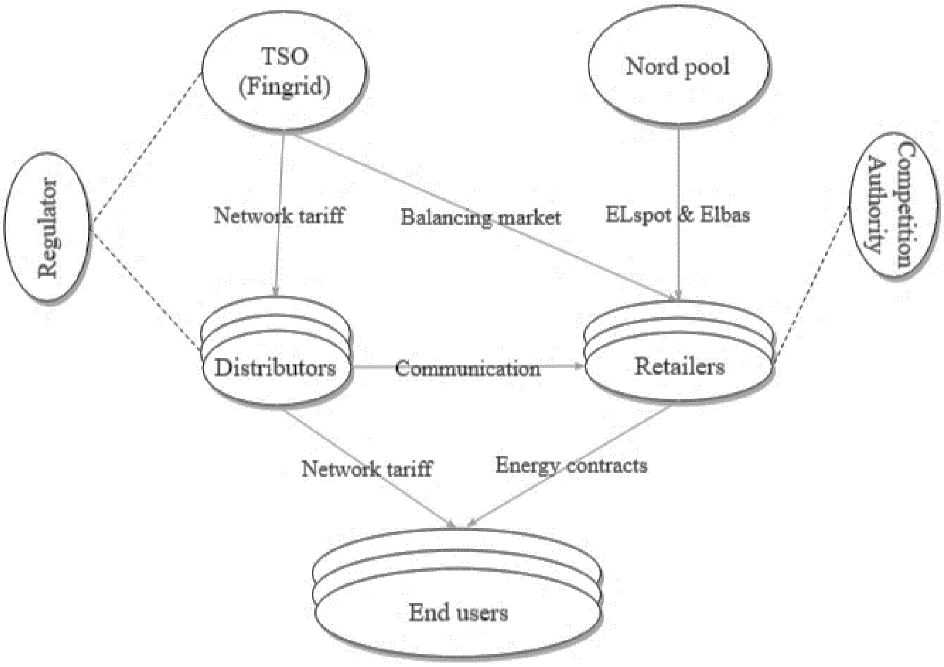


Figure 1. *Nordic market actors. Adopted and modified from [12].*

2.1.4 Retailers

Retailers or suppliers are ones who sell the power to end users (e.g. medium or small companies and households) Retailer buys the power directly from the producer or through Nord Pool. Retailers are the association that works between the end user and power market. There are usually different retailers operating within a country. End users have the freedom to choose one of them and one of the several contracts offered by that retailer. The different contracts a supplier can offer are for example fixed price and market price. [10]

Load balance responsible (LBR) is the entity that makes the plan of the generation and related consumption for the next day. Some retailers can take the role of LBR and in some cases LBR is a different entity. Several different retailers follow this common LBR. If there is an imbalance between planned generation and consumption, LBR must pay to TSO for the imbalances. LBR can take an active part in power market regulation by submitting bids subject to down and up-regulation.

2.1.5 Traders

Traders are usually representing the player of the market who owns the power. Power can be sold in many routes in power market from producers to the end users. Traders are the entity who buys the power from producer and sells it to retailer. Or they can buy it from one retailer and sell it to another. Traders do not own the power but acts as agents/intermediary for retailers and producers. [10]

2.1.6 End users

End user can be either a company or a household. End user pays for the power in three portions to three entities. End user pays to supplier for the power consumed, to DSO for power transmission and taxes to government. Every geographical area has its own assigned DSO. End users have the only option for a DSO in the area. [10]

2.2 Market models

The electricity price is set up in a way that includes both buyer and seller in the process. The models working in this process are Day-ahead market, Intraday market etc.

2.2.1 Day-ahead market (Elspot)

Day-ahead market, as well known as Elspot market, is the place where the majority power trading happens in Nord pool. Buyer and seller make the power trading bids here for the following day. According to Nord pool website, there are more than 300 traders in Nord pool's day-ahead market. Majority of these traders are active daily.

Day-ahead market is mainly driven by customer demand planning. Buyers (usually a retailer) assess the electricity demand for the following day and the price they are willing to pay for the volume. The seller (e.g. power plant owner, other traders) calculates and declares how much power it can deliver at what price. This demand prediction and offered price are calculated for every different hour from both buyer and seller side.

Figure 2 shows the relation between sets of selling bids and buying bids for price formation.

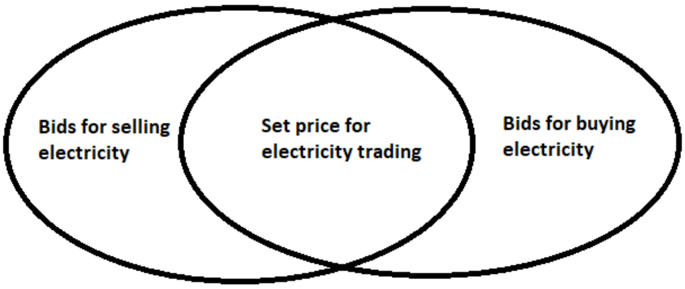


Figure 2. *Price formation.*

The time of bidding for following day power trading ends at 12:00 CET. Then these information goes through the calculations with an advanced algorithm to set up the price. Basically, the price is decided as the point of the curve where the selling and buying prices meet.

Figure 3 shows the supply and demand curve. The intersection point of these two curves is used for setting optimum price of electricity.

Figure 3. *Setting the optimum price depending on supply and demand side bidding [10].*

The main role of the power market is to establish the equilibrium between power production and demand. The inability to store energy makes it more important. Price formation of energy market related to demand and supply is more complex because the generated power needs to be delivered at very precise moment. The day ahead market helps to establish this equilibrium through forward planning, but the final balancing process takes place in real time balancing market through some adjustments. The price for electricity is set in a way so that the production cost of electricity for every individual hour of the day is set as lowest as possible.

The calculated prices for hours are declared at 12:42 CET or later. The traders are settled once the price is calculated. The power is delivered hour by hour as per contract from 00:00 CET the next day.

For electricity market the generation cost varies vastly over different source and installation. There are some installations that need intensive capital like hydro power, nuclear etc. These plants can run for years with very efficient costing. On the other hand, there are other expensive options like combined heating power or gas turbines. These resources are used in a way, so the fuel-efficient sources are used to cover maximum demand. The most expensive sources are used only during high demand with higher price of electricity.

The power trade is also dependent on the transmission constraints. When the demand is high and supply is set high to meet it, the transmission congestion might come in. Different area transmission prices are introduced to relieve this congestion. Thus, the transmission cost is set high to lower the demand in affected area.

2.2.2 Intra-day market (Elbas)

Intra-day market works as a back-up for the day ahead market to balance the supply to existing demand. Most of the electricity trade happens in day-ahead market, but Intra-day market gives the opportunity to tune the balance in case any challenges come up.

The day ahead market closes at noon CET. If anything happens between the closing of day ahead market and deliver next day, there need to be a backup plan. For example, a source like nuclear power plant can go off by this time. Then there will be some arrangement needed to meet this lagging demand next day. Here comes the intra-day market in action. Intra-day market gives the opportunity for buyers and sellers to trade the missing volume close to the real time and bring the balance back to market.

After declaring the hourly prices for day ahead market, the capacities that are accessible for Nord pool’s following intraday market is published at 14:00 CET. In Intra-day market trades happen continuously, and the market gets closed for a specific hour one hour before the real supply time. Prices are set based on first-come first-served principle in cases the bids are same.

With the injection of more unpredictable renewable energy sources, the importance of intraday market is increasing day by day. Different renewable energy sources like wind power forecast includes high uncertainty in nature. It causes an offset in day ahead traded volume and produced volume, and Intra-day market helps to ensure the supply to bring back the equilibrium. [10]

2.2.3 Balancing market

Balancing market maintains the balance between demand and supply in real time. Balancing market is usually managed by TSO. The bids at day-ahead market and intra-day market are made before the actual consumption. These predictions can go wrong sometimes and that results there are either higher supply than demand or vice versa [9].

TSO upholds the dynamic balance between demand and supply in real time through introducing automatic frequency control and by accumulating balance power available in balance market [8]. Market players that have the capacity that can be regulated, submit their available regulating volume to this market. TSO buys power from this balance market and sells it to the balancing responsible party (BRP) that have the extra demand [2]. BRP is the entity that balances the equivalent ‘injection’ and ‘subtraction’ from the grid. [3]

2.3 Demand response (DR)

Demand response is a broad idea in general. It can be described as the change of actions by consumers in order to balance the supply and demand management of electricity. These actions are enabled through different feedback (e.g. price) from the service providers in market. [1]

When the power consumption goes high, the market responds to it in several ways. One way is to maintain this balance most of the power market uses is to shift the load from peak hour to off-peak hours. Hours that have high demand are referred as ‘peak hour’ and hours with low demand are ‘off-peak’ here. The way the market responds to this extra load from existing generation and changes the end user’s usage from their normal usage pattern is known as demand response [1]. This whole load shifting is done in most of the market by introducing incentive for the user. That means end users get electricity for lower price when the demand is low. US energy department has defined the demand response as “changes in electricity consumption by customers due to electricity price difference in different time or by some other incentive provided by the market to change the electricity usage pattern when there is a possibility of system reliability going low” [11].

DR can be used to increase the efficiency of the system by using minimum resource possible. It enables improvement of the distribution system planning and usage leading to lower electricity prices in short and long term.

3. CHARGING OF ELECTRIC VEHICLES

This chapter describes the mechanism of different electric vehicles, different battery technology used for electric vehicles, their charging mechanism, related terminology and standards for EV charging.

3.1 Electric vehicle (EV)

The term 'EV' is used for a broad meaning in related industry. Total number of EVs in today's world can be described in four categories depending on the design of electric train. These are-

- Battery electric vehicles (BEV)
- Plug-in hybrid electric vehicles (PHEV)
- Hybrid electric vehicles (HEV)
- Fuel-cell electric vehicles (FCEV)

Battery electric vehicles (BEV) can be described as full electric vehicles, where a set of battery installed in the car is charged mainly from power grid and partially by regenerative braking. Wheels are driven by the electric motor that is powered by the battery pack. Battery EVs have a simple design powertrain compared to ICE engines as there is no clutch involved also in some cases not a gearbox. Here traction power flows in a simple path from battery to wheels through motor drives, motor, mechanical coupling, and transmission (if available).

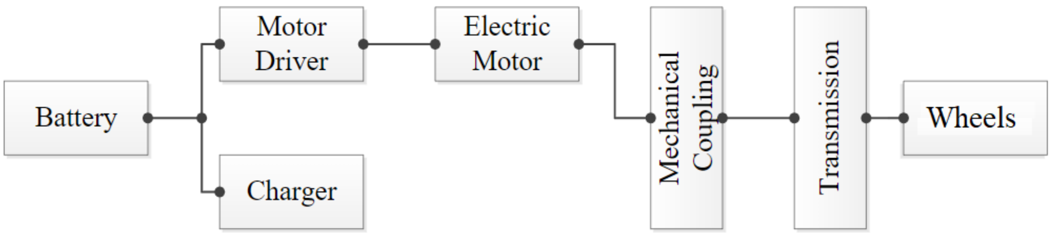
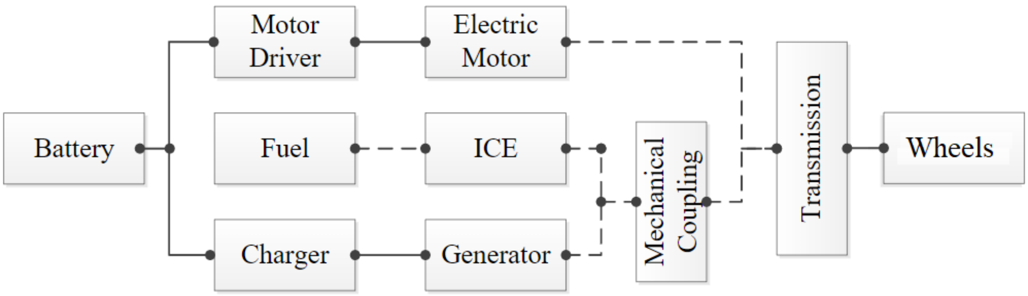


Figure 4. *Battery EV architecture [21].*

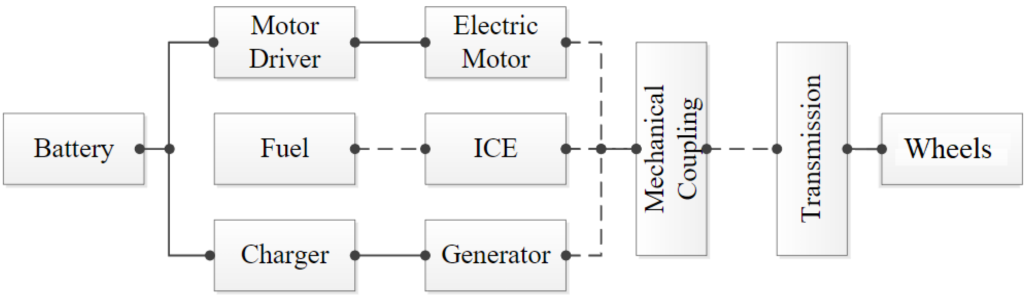
Plug-in hybrid electric vehicles (PHEV) engage both electric motor and internal combustion engine (ICE) to power the wheels. Typically, PHEVs have smaller size battery banks than BEVs that gives comparatively lower battery range. PHEV's driving range is mostly reinforced by the IC engine. Therefore, the combined driving range of battery bank and IC engine helps the user to get rid of range anxiety.

This combined hybrid system in PHEV uses both battery and fuel in two different mode known as charge sustaining (CS) and charge depleting (CD) mode [6]. In charge sustaining mode, fossil fuel is burned through IC engine to generate the power needed for the operation and charge depleting mode uses the battery as primary source for energy. PHEV reduces the gasoline usage while operating in CD mode [4].

Including both IC engine and battery driven motor makes the PHEV architecture a bit complex. There are two powertrain architecture available for PHEVs. Series and series-parallel architectures. In series powertrain, the traction power of wheels generates only from electricity. Power from both battery and IC engine combines as DC power flow that powers the electric motor. Therefore, IC engine does not take part in driving the wheels directly as conventional IC vehicles. On the other hand, series-parallel powertrain design allows both electric motor and IC engine to get directly coupled with wheels. That means wheels get driven by engine and motor while using fuel and battery as power source respectively.



(a) PHEV series architecture.



(b) PHEV series-parallel architecture.

Figure 5. *PHEV architectures [21].*

Electrical energy is used for both PHEV and BEV to drive electric motor to create the propulsion force for the automobile. This electricity is provided by a battery on board.

This battery can be charged by power grid in both case of BEV and PHEVs. For EVs on-board motors also works as charger when regenerative braking is enabled [6].

Hybrid electric vehicles (HEV) uses traditional fuel source such as gasoline or diesel to drive the wheel through internal combustion engine. These vehicles also include a smaller battery bank that cannot be charged from an external energy source. The battery packs are charged by mostly regenerative breaking and/or the ICE and are used to improve overall fuel efficiency of the car.

Fuel-cell electric vehicles (FCEV) also consist of battery bank to store the energy and, uses an electric motor to drive the wheel, but unlike other EVs, it uses fuel cells, typically hydrogen as power source to drive the vehicle and charge the battery pack. One of the main differences between FCEV and ICE vehicles is the propulsion system. FCEVs have more efficient propulsion system than conventional ICE vehicles. The battery bank in FCEVs is very small in size compared to other EVs. But it cannot be charged from external power sources. This technology is still in its beginning stages.

Electric vehicle (EV) is defined in this thesis as the road vehicle that includes an electrical powertrain and an electrical energy storage that can be charged from an external energy source.

3.2 Electric vehicle battery technology

Battery technology is the key technology for EV industry as this is the most influencing factor for desired range, performance and reliability of EV. Today, small-scale batteries represent quite mature technology that serves most of the daily chores we use. These cannot be considered as suitable for EV purposes because of capacity limitations. In contrast, large-scale batteries are mostly developed for stationary uses in power grid as renewable energy integration or emergency power backup. These batteries usually come with lower specific energy (Wh/kg). Batteries for EV usage are subject to more robust usage. Size and weight constrain of large-scale batteries brings challenges in matter of acceleration, braking distance and driving range of EV. For electric vehicles usage larger specific energy is needed for the battery as it allows higher energy stored with less weight involved.

Table 1 shows the list of some top-rated recent electric car models and their battery technology with driving range.

Table 1. Recent top-rated electric cars (BEV and PHEV) and their used battery.

Car	Battery technology	Driving range (electric) up to
Mitsubishi i-MIEV	Li-ion	160 km
Tesla Model 3	Li-ion	386 km
Tesla Model X	Li-ion	523 km
Chevrolet Spark EV	Li-ion	132 km
Tesla Model S	Li-ion	600 km
Ford Focus Electric	Li-ion	122 km
Chevrolet Bolt EV	Li-ion	415 km

As shown in Table 1, Li-ion is the most used battery technology at current market. Li-ion batteries, when discharged, convert chemical energy to electrical energy. This electrochemical conversion takes place mostly by oxidation-reduction reactions. Basic components of a Li-ion battery are anode (negative electrode), cathode (positive electrode), electrolyte, membrane and container.

In the process, anode gives electron to the outer circuit that acts as load and gets oxidized. In return, cathode receives the electron from outer circuit. Inside the cell electrolyte mediates ion transfer between anode and cathode in the process. Membrane keeps anode and cathode separated, so they do not get short circuited. Container holds all the components and serves the safety purpose. Typical anode is made of graphite. Different cobalt oxide-based materials (NCA, NMC) are mostly used as cathode material for passenger car EVs. Li-ion moves from cathode towards anode through the electrolyte during the charging process while charging. Vice versa happens during the discharging. [21]

There has been a growing attention towards development of new technology that can offer more advanced energy density and lower cost. Recent research shows that for example lithium-sulfur batteries could someday be a good alternative that can promise higher electric range for EVs [26]. This technology is still in early development phase.

To quantify and characterize the battery performance in EV applications, there are certain definitions used widely. Most of them are used in this thesis. These are described in the following.

Pack, module and cells are the basic components of an EV battery. Multiple modules located and used as a whole, makes a *battery pack*. Similarly, multiple cells connected in series and maybe also in parallel delivers as a *module*. *Cell* is the smallest possible unit of the battery pack that contains the electrodes, electrolyte and separator. Typically, output voltage of a cell varies from 2 to 4 volts depending on the design.

State of charge (SoC) represents the percentage of energy available compared to total usable energy of a battery. Due to technical limitations perfect gauging for SoC is always hard for battery management systems. A simple formula for calculating SoC [21] is,

$$SoC = \frac{\text{Amount of charge available}}{\text{Total usable amount of charge}}\% \tag{3.1}$$

Depth of charge (DoD) is represented as the percentage that got discharged from the total usable amount of charge [21].

$$DoD = \frac{Amount\ of\ charge\ discharged}{Total\ usable\ amount\ of\ charge}\ \% = 1\text{-}\ SoC \tag{3.2}$$

State of health (SoH) is the term used to present the maximum charging capacity compared to the ideal capacity of the battery. It is very closely related to performance deprivation and remaining lifetime.

The number of charging-discharging cycles that a battery can perform, until it is running with a minimum performance is called a *cycle-life* of a battery. Usually cycle-life of a battery is calculated for charging and discharging in nominal conditions. However, due to different challenges such as high temperature, battery does not get charged or discharged in nominal condition in real life. Therefore, the actual life of a battery can be higher or lower than the rated cycle-life depending on the individual cell properties.

The capacity of EV battery can be measured in different metrics. The amount of charge that is transferred in one hour with a one ampere flow is one *Ah*. *E-rate* represents the amount of power need to drain the battery in one hour. Another popular term used to measure the battery capacity is *watt-hour capacity*. Apparently, it is the product of battery voltage and Ah rating. A higher capacity battery needs added time to charge and outwardly provides longer driving range for EV.

Specific energy is the ratio of rated battery capacity in Wh and total physical weight of the battery in kg. In short, specific energy is how much power a battery can deliver per unit mass. As related to packaging and battery weight, specific energy indicates how much additional weight this battery is going to add to the EV. That affects the performance of EV regarding the driving range, breaking etc. Specific energy [21] is computed as

$$\text{Specific energy} = \frac{\text{Rated capacity in Ah} \times \text{Battery voltage}}{\text{Battery mass in Kg}} \tag{3.3}$$

Specific power is referred to the peak available power (in watt) of the battery per unit weight (kg). It is related to different performance degree of EV like acceleration, regenerative braking etc. Gravimetric power density is another name of specific power. Specific power is computed [21] as,

$$\text{Specific power} = \frac{\text{Rated maximum power}}{\text{Battery mass in Kg}} \tag{3.4}$$

Energy density and *power density* of a battery is known as nominal energy (Wh/L) and nominal power (W/L) of unit volume respectively. These are related to the physical space needed to achieve a specific performance goal for EV.

The acceleration and top speed of EV is determined from the electric motor specification and *maximum discharge current (continuous)* of the battery. This maximum discharge continuous current rating means the maximum current that can be drained from the battery continuously. It is set by manufacturers to protect the battery life. Another discharge current rating called *maximum 30-sec discharge pulse current* affects the acceleration performance of EV that is set by battery design. It is the peak current that battery can drain in pulse up to 30 second.

To prevent shorter battery life, the battery is taken out of use after a minimum permissible voltage. It is called the *cut-off voltage*. It is considered as the charge empty state of battery while using. The equivalent resistance of the battery is called *internal resistance*. It is different for charging and discharging.

Battery management system (BMS) works as a link between the vehicle and battery in order to maximize the performance and protect battery health. It also minimizes total power consumption. In order to do so, BMS continuously monitors different property of battery and maintains the control by communicating with battery. Different BMS functions are,

- Under and over voltage protection
- Cell balancing
- Control of battery charging and discharging
- Short circuit protection
- Thermal protection
- Determine battery SoC and SoH
- Safety protection.

Figure 6 shows a block diagram of a battery management system and the dynamics of its major functions. The sensing unit consist of temperature, voltage, current and SoC monitoring systems. These sensing units continuously collects data in order to determine different actions needed by balancing and protection unit to maintain safe operation of battery. SoC level determining is a challenging job since factors like manufacturing conditions, battery age, SoH etc. comes into consideration [21].

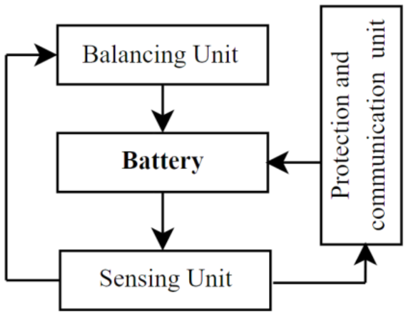


Figure 6. *Battery management system (BMS) block diagram[21].*

Typically, multiple cells are connected in series inside a module/pack to obtain the higher voltage requirements. Because of chemical offsets, these cells have different properties. That leads to different voltage level for different cells. This phenomenon can harm the battery life as well as lead to other threatening incidents. Balancing unit of BMS continuously collects voltage readings and balances the voltage level of different cells of the battery pack. In this process, widely used techniques are buck-boost shunting, multi winding transformers, dissipative resistors and switched capacitors.

3.3 Electric vehicle charging

To prevent the premature life of batteries of EV, its charging mechanism is very important. Improper charging of batteries can damage them very easily. That is why, EV needs to be charged through a proper charging mechanism (Figure 7). The setup needed to charge an electric vehicle is known as electric vehicle service equipment (EVSE). The physical EVSE usually consists of power cords/cable, vehicle connector/socket outlet and in some cases 'in cable protection device'. [21]

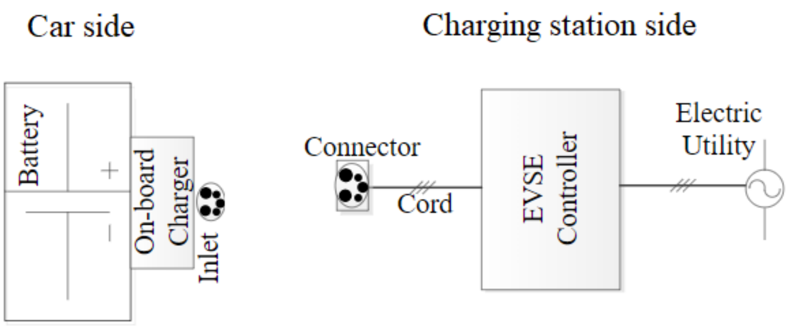


Figure 7. *EV charging setup outline [21].*

AC charging and DC charging are the two types of charging available for EVs. For AC charging system the on-board charger placed inside the vehicle that rectifies the AC power to DC power. In DC charging system AC to DC power transformation is done outside the vehicle in the charging station. The on-board charger gets bypassed while charging from a DC source. Due to high-quality power requirements the car always needs to be charged through an authorized charging station [6]. There are different charging solutions used around the globe and those are described in the following section.

Four kind of charging modes are defined in the international standard IEC 61851-1: mode 1, mode 2, mode 3 and mode 4. Three of them are AC charging methods and one is DC.

Mode 1 is a low current AC charging method that is used mostly for very light vehicles. In practice mode 2-4 are the widely used methods for charging passenger cars [1].

Mode 2 charging is a slow AC charging method that comes with an in-cable control and protection device (IC-CPD). Mode 2 is a widely used charging method. Most of the EV sold is provided with a mode 2 charging cable. These devices include safety features like residual current device (RCD). For safety purposes, the protection device IC-CPD usually restricts the charging current to 8–10 A. Like many European countries, Schuko single phase sockets could be used in Finland for mode 2 slow charging, as those are available in different households for engine preheating during winter. Low current capacity of those sockets can be a challenge in that case. 3-phase IEC-60309 plugs and sockets or 1-phase high current camper plugs and socket could be a good option. In that case, an additional costing for setting up the charging point appears as these two kinds of supplies are not available in most of the households.

Different regulative organizations and EV related industries recommended mode 3 charging solution for EV charging in regular use. Mode 3 comes with higher current charging possibilities compared to mode 1 and 2. For this kind of charging solution, dedicated charging sockets for EVs are used. The standard for mode 3 socket is defined as ’type 2’ in IEC 62196-2 in most of the European countries. And this ‘type 2’ socket was declared as mandatory for all public fast charging stations by EU directive 2014/94/EU [1].

The only DC charging mode is available is mode 4. It introduces the possibility for fast charging with high power supply, because in this case the charging station is situated totally outside the vehicle. That gives the opportunity to include bigger setup for AC to DC power transformation. Typically, these charging stations have up to 50 kW nominal power [1], but 150 kW and 20 kW commercial stations also available. Mode 4 chargers can charge the car very fast. These charging stations also comes with advanced safety features.

Table 2 summarizes the properties of all the wired charging modes.

Table 2. *Different EV charger modes [1].*

Charging mode	Description
Mode 1	• AC charging method. • Used mostly for charging light vehicles. • These are used with low charging current and short periods. • Maximum AC current flow allowed: 16 A. • There must be an RCD included with the feeding socket. • Available in 1- or 3-phase charging.
Mode 2	• AC charging method. • Known as slow charger for electric cars and most available system in present. • Cable includes a protective device (IC-CPD) that can restrict the current flow through the cable after certain extent. • RCD is included into the IC-CPD protective device. • Includes continuous earth conductor continuity checking. • Includes a protection system so there is no AC voltage available on the delivering side of the cable until the cable is properly connected to the vehicle. • Maximum AC current flow allowed: 32 A. • Available in 1- or 3-phase charging.
Mode 3	• AC charging method • Available in 1- or 3-phase charging. • Allows high current charging up to 70A for 1-phase and 63 A ×3 for 3-phase • Includes continuous earth conductor continuity checking. • Includes a protection system so there is no AC voltage available on the delivering side of the cable until the cable is properly connected to the vehicle. • This charging method has possibility to control the charging current taken from the charging station . • This mode is planned for the basic EV charging.
Mode 4	• DC charging method • The continuous communication between the charging station and vehicle is used to control the charging process in this mode. • This mode has theoretical maximum charging power of 120-170kW according to IEC 62196-3. Practical products typically have lower nominal power. • The charging cable is fixed with the charging station.

Wireless charging technology is an emerging technology as it allows the vehicles to charge in a contactless way. Inductive power transfer enables the possibility to charge the vehicle even during driving. Therefore, the electric range can be extended without subjecting the vehicle to additional time for charging services. On top of that, it creates the opportunity to reduce the size of required battery [22] that can help to improve the EV performance in a lot of way. But there are certain safety concerns like change of exposing human body to a high frequency magnetic field that is required in between transmission and receiving coil for wireless charging. In addition, the high price plays a negative role behind deploying the technology.

3.4 EV as electrical load

The electricity consumption of an electric vehicle can be different depending on the size, technology used and producer. Considering the small-medium electric vehicles during 2013-2018, it has been estimated that the average consumption of electricity is 130-140 Wh/km of drive for a study [19]. This estimation was mostly based on contemporary theoretical calculation depending on the electric motor, battery and charger efficiencies available. In Nordic countries, the energy usage of EV is also depends widely on ambient temperature, road surface condition etc. Another study shows that, the estimated range for different EVs varies widely depending on the driving speed, usage of heater etc. in practice. As example, a 55 kWh Tesla have the highest range of 280 km driven in average 50 kmph in −20 °C ambient temperature. And a 24 kWh Nissan Leaf have the mileage of 105 km with the same conditions. That makes the average consumption 180-220 W/km for wintertime [28].

A traditional personal vehicle runs 16600 km a year in average [20]. Assuming the consumption as 170 Wh/km, the annual consumption of an electric vehicle would be 3780 kWh. Due to the limited range of electric vehicles, the regular driven km can be lower for EV. Therefore, EVs can have a yearly consumption of less than 2240 kWh. To make a comparison, a typical Finnish detached house that does not include electricity for heating, consumes 5000 kWh [29] [30] electricity per year. It means that adding an EV to household consumption can increase the electricity demand up to 75.6%.

The consumption of the EV is different than other household electricity usage. Unlike most of the heavy household electric chores, the consumption (charging) takes place during a different time than its usage(driving). Depending on the driving pattern, charging installation etc. most of the EVs need 2-8 h of charging for a full battery. Subject to the time of charging taking place, it can be represented as a huge opportunity (storing the energy for later use) or a serious challenge for electricity service providers to expand the capacity for additional usage.

Fluctuation in demand is the most undesirable property an electric power system seeks for. If a significant sum of EV owner starts charging their EV right after arriving home from office, this will surge the demand of electricity during a time of the day that is already typically a peak time.

That leads the demand side strategies for electric power system to take different measures like load shifting etc. to obtain a flatter demand curve. Load shifting is a strategy that enables the shifting of certain quantity of electrical load from a busy hour to the time period that have lower expected demand. In this case, if a big enough portion of the EV users delay the event of charging till the evening or early morning, the EVs would still be charged fully for the next day. In this case, the charging would take place during the off-peak hours.

Another market actor ‘fleet operator’ comes to consideration when discussing electric vehicles (EV) as load. Fleets operator acts as the middleman between the electrical network and EV but does not necessarily own the EVs. EV owners have contractual agreements with fleet operators in terms of charging, payment, level of control etc. The main task of fleet operators is to manage EV charging. An individual operator or the retailer himself can be acting as fleet operator.

4. INTELLIGENT EV CHARGING METHODS

In this chapter, different intelligences used in developing a smart charging algorithm is discussed. Problems related to EV charging have been studied and can be divided into three different perspectives. Customer oriented study, grid-oriented study and aggregator-oriented study [13].

4.1 Intelligent charging vs. regular charging

Regular charging of an EV is referred in this thesis as direct 'plug and go' charging. That means the power transfer starts right after it is plugged in to charger and charges the EV battery to full capacity continuously or until it is plugged off.

Introduction of different intelligence like load shifting, load balancing, load shaving etc. adds new dimension to performance, safety and reliability to EV charging and its integration to grid usage. Load shifting means using the hours of low demand or low price to support the electricity grid and utility and gain some monetary profit for the user. A toy example is described here to explain the effect of intelligences like load shifting, peak shaving etc. applied to EV charging.

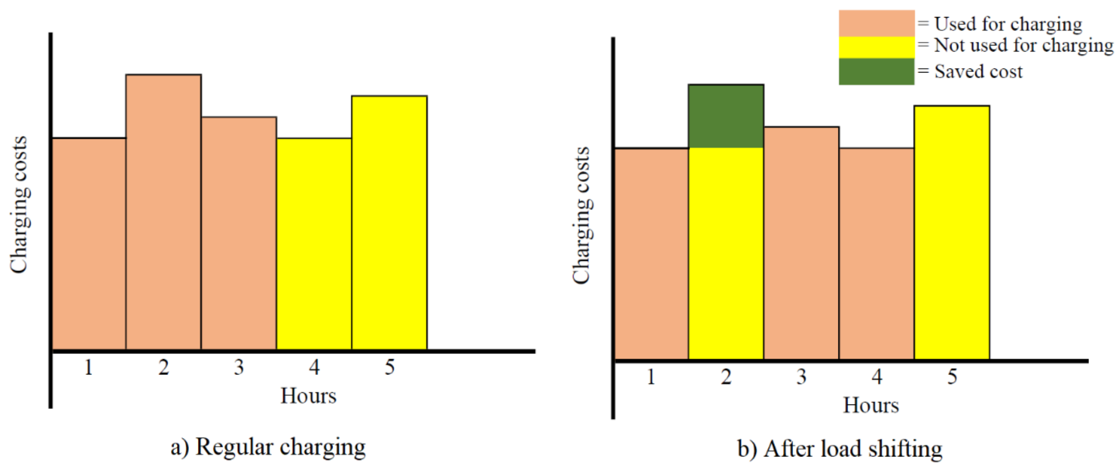


Figure 8. *Load shifting.*

Assuming a vehicle arriving and plugged in at the starting of hour 1 (shown in Figure 8 a). It has five hours to charge full battery, but it needs only three hours of charging to reach the full battery while charging with rated charging power. Hours no. 1, 3 and 4 have the lower electricity price depending on the grid demand compared to hour 2 and 5. Assuming the rated charging power is available for the whole charging time, regular plug in charger would use hour number 1,2 and 3 for the charging event, but an optimized intelligent charger will shift the charging load from high price hour 2 to low price hour 4. In this case, customer saves the extra costs of hour 2 (shown in Figure 8 b).

Introducing similar scenario to a user charging the vehicle in a detached house that have limited power capacity can be used to explain peak shaving. Due to other household uses, power available for charging EV is limited in detached houses. The summation of power rating of EV charger and total household usage cannot be set over the fuse power rating of the house. In this case, for a regular charger user needs to set the EV charger power rating as the remaining capacity of house fuse rating when the household power usage is at the maximum level. Therefore, some power capacity of house will remain unused when the household's electrical appliances are not in full use (Figure 9 a). With this limited power, capacity EVs will need more time to charge.

An intelligent charging system with peak shaving optimization in this case would use the full available power after the other household usage for charging. In this case, The EV charging with intelligent power system (Figure 9 b) leaves with higher SoC than that of a regular charger(Figure 9 a).

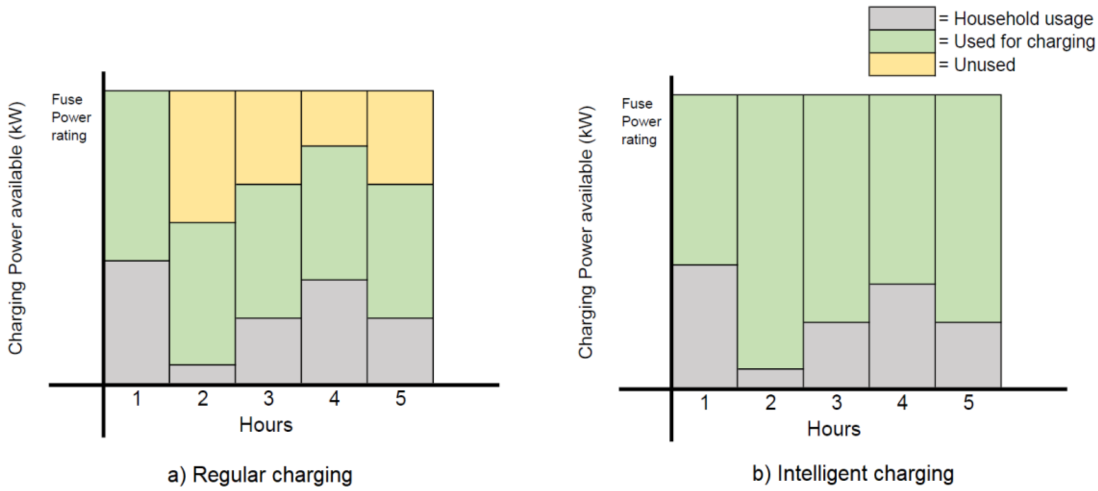


Figure 9. *Peak shaving.*

4.2 Admission control mechanism

An aggregator oriented study in scheduling electric vehicles in a workplace station conducted by *Zhe Wei et al.* considering the service quality under time of use pricing shows that it is 30% more profitable than the state of art solution [15]. This model incorporates an admission control algorithm, so all the vehicles arrived at the charging station gets proper power supply to get fully charged before it leaves. The model is shown in Figure 10.

To ensure the good quality of service, each admitted EV needs to be charged to full battery before it leaves facility. That is the main motive of admission control mechanism.

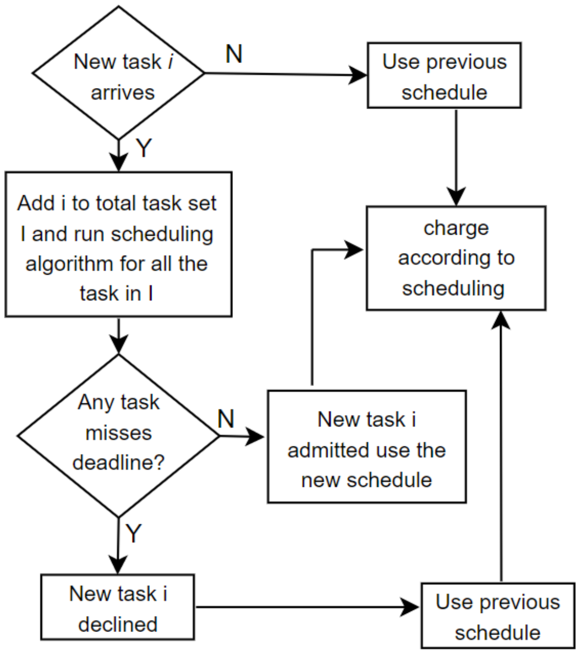


Figure 10. *Admission control mechanism [18].*

Admission control mechanism can be described as virtually planned scheduling procedure in other words. When a new EV arrives to the charging facility, it is added as a new task as *i* to total scheduling task set, *I*. *I* consist of more tasks related to the admitted EVs that arrived the facility before. Each admission much fulfill desired goal to achieve target SoC. Therefore, algorithm checks if all the EV gets to full battery by desired time if task *i* is added to the existing schedule. If it fulfills, a task is added to *I* and the facility continues its charging schedule according to the new schedule, but if not, the newly arrived vehicle is declined, and it continues the previous charging schedule. The figure above illustrates the admission control algorithm [18].

4.3 Time of use price-based systems

The hours of the day are divided in TOU price system with different electricity energy prices depending on the demand and supply of the grid. Usually the hours are divided into three load schemes. Peak load, off-peak load and mid-load [14]. Peak load time consists higher electricity price. Off-peak load time has the lowest prices considering e.g. that the demand is low compared to the supply. Table 3 shows a typical TOU pricing model according to season, load and voltage in Jeju, South Korea [14]. TOU price-based systems aim for the lowest price hours to use for charging to minimize the costing.

Table 3. *TOU price model of energy price for different seasons [14].*

Class	Time period	Charging season		
		Summer (jeon/kWh)	fall/spring (jeon/kWh)	Winter (jeon/kWh)
Low voltage	off peak hour	57.6	58.7	80.7
	mid-load hour	145.3	70.6	128.2
	peak hour	232.5	75.4	190.8
High voltage	off peak hour	52.5	53.5	69.9
	mid-load hour	110.7	64.3	101
	peak hour	163.7	68.2	138.8

The hour circulation can be different depending on the season. Figure 11 shows the hour distributions for peak, off-peak and mid-load hour in different seasons Ontario, Canada [16].

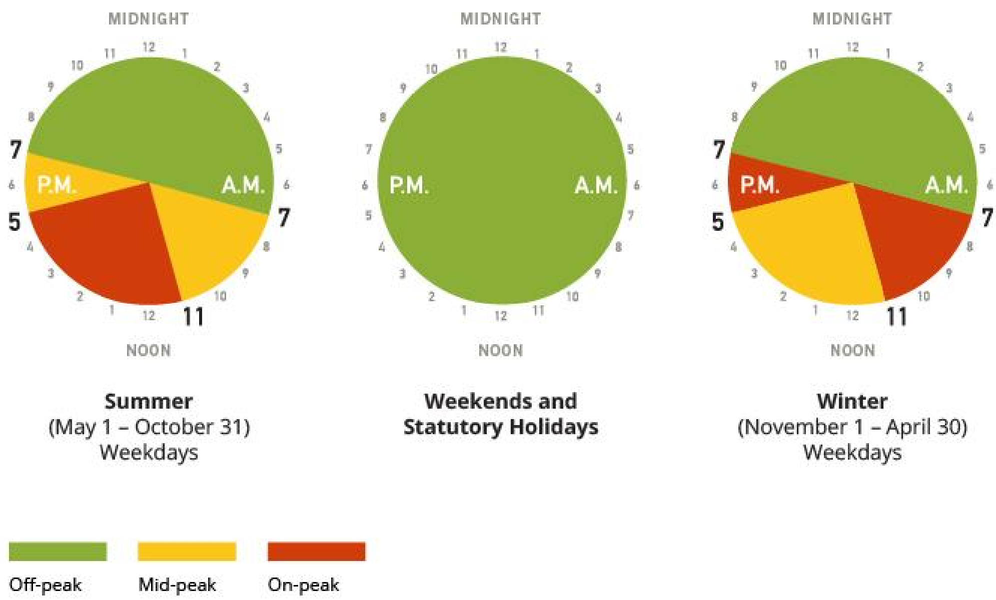


Figure 11. *Typical time of use rate periods [16].*

While scheduling the charging hours for admitted vehicles to the system, the charging priority is dependent on the urgency of the task. The objective is to find the best allocation for charging vehicles in a way, the lowest price hours serves most of the charging to minimize the total cost. As the arrival of vehicles are not prescheduled, this optimal allocation is hard to be guaranteed.

4.3.1 Greedy based scheduling (GRD) mechanism

When there are several charging tasks in que, selecting the right time slot for right task is a challenge. Considering the charging demand and time constrains, the highest priority of charging should be given to a task that have higher urgency.

For this purpose, a metric called flexibility were introduced that indicates the urgency of each task. Flexibility of a task is defined by “the difference between amount of remaining time to complete a task and remaining unfinished charging requirement” [23].

To solve the problem greedy based scheduling suggests, higher the flexibility of task, higher its deferability. That means if a task is not flexible (flexibility=0), then it has the highest urgency [18]. This task should be served immediately to ensure that it ends before the deadline.

Apparently, GRD scheduling mechanism has higher resource utilization ratio and its performance regarding admission performance is outstanding, but it does not consider the variation of price depending on the hour of the day. Therefore, it does not ensure the utilization of lower price hours to maximize the monetary profit.

The simulation was compared to the results to ‘real time scheduling’ [17] that is treated as the benchmark comparison algorithm. The result shows that, during high traffic hours this algorithm achieve higher profit than real time scheduling algorithm. During the low traffic, the profit gain over real time scheduling goes up to 30% that is quite high in comparison [15].

4.3.2 Price oriented scheduling (POS) mechanism

To lessen price insensibility of GRD scheduling, a price-oriented scheduling (POS) mechanism was developed to ensure the monetary profit. The aim of POS is to employ more charging task to high profit or low-price hours. That means the task with higher amount of energy is allocated to high profit periods until the high profit period reaches its capacity limits. Then it keeps doing the same for lesser profitable periods and finally ends at the most expensive period if the charging service is still needed.

Although POS scheduling mechanism mostly concentrates on profit maximization, it does not ensure the lowest task declining probability for different tasks arriving at different time, as example in case of a parking garage situation. That becomes a performance issue in case of a service provider ensuring best resource allocation for its charging services.

In addition to that study, the authors *Zhe Wei et al.* proposed an advanced approach that incorporates practical battery charging characteristics in another paper [18]. On top of admission control and scheduling algorithm, an *adaptive utility-oriented scheduling algorithm* is adopted in the study to optimize the charging operator utility. The aim is to lower the utility cost, lower the task declining probability and higher the profit margin for charging operator.

4.3.3 Charging model considering TOU price and SoC curve

A study by *Yijia Cao et al.* included one of the battery characteristics into consideration while developing a charging schedule for EV charging depending on TOU price. [27]

The charging power vs SoC curve is not entirely linear in nature for charging of EV batteries. The study develops a charging algorithm for a single EV. Considering the time constrain from a user as the user needs the vehicle to be charged within specific time, this algorithm works towards these goals:

- Finish charging within specific time
- Charge to full battery or higher with maximum charging power available within the user specified time
- Use the lowest price hours for most power usage

Considering an EV performs the charging operation within charging time available, user pays, total cost = $\sum charged\ power \times corresponding\ unit\ price$. Charging power for the EV is selected as the minimum value among maximum rated power for charger, maximum charging power rating of battery and maximum power rating set by user.

Figure 12 shows the overall process of charging system developed by *Yijia Cao et al.* [27]

The system creates a charging schedule without any optimization in the beginning. Then it calculates the charging power for next cheapest hour and shifts the charging load to that hour if it is within charging time available. And it continues the process for all the hours till the SoC is full.

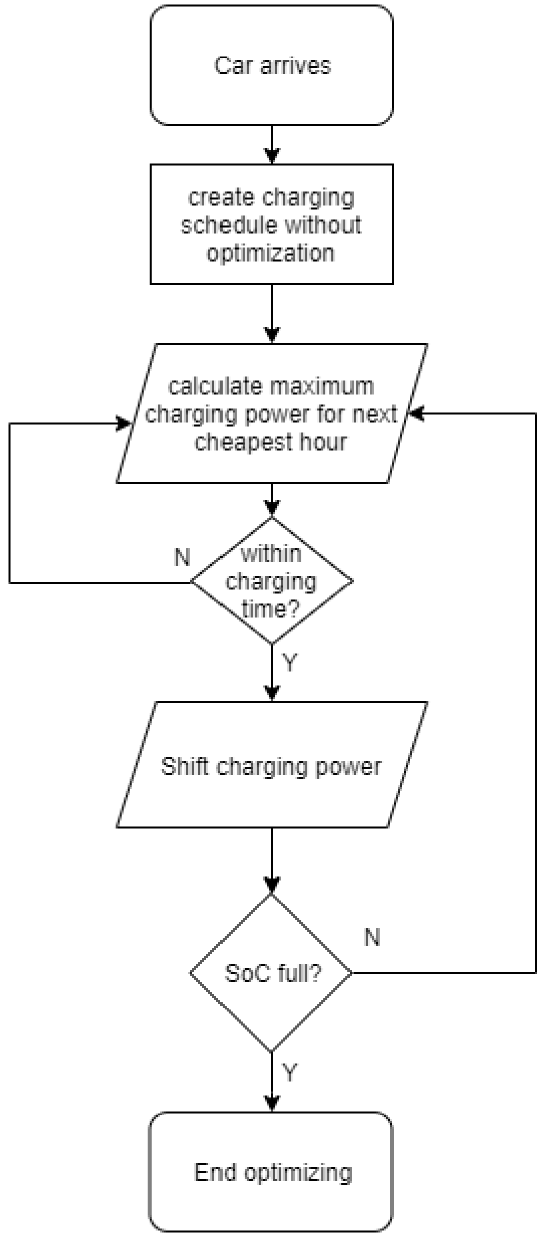


Figure 12. *Optimizing of charging schedule by TOU price [27].*

5. DEVELOPED MARKET BASED INTELLIGENT EV CHARGING ALGORITHM

In this chapter, development of a market based EV charging scheduling is described. An energy price list is set by retailer that states the energy price for every hour of the day. These hourly prices reflect the demand and supply in the electricity market. Additionally, a cost based on TOU (two-time) distribution tariff is applied. In addition, a fixed monthly distribution cost is set depending on the fuse size of the house. The distribution costs related to energy consumed is also designed in a way that it reflects power congestion of network. This developed algorithm calculates and schedules the EV charging in lowest possible costs within a given time to charge the vehicle to a certain state of charge. By following the low-price hours, the algorithm shifts the electric load of charging toward low price period of the day.

5.1 Intelligences applied

The main task of the algorithm is to create a charging schedule that can offer the minimum possible costs for a charging session and shift the charging load to low price hours. There are different related terms and intelligences that comes into consideration while planning for achieving such goal. The intelligences applied to the developed algorithm for the thesis can be summarized as below.

- **Finding lowest possible costs**: The algorithm finds the lowest possible costs for one charging event. Following the hourly energy costs and distribution costs, the algorithm finds the total costs per unit energy for all the hours of the day. It then assigns highest possible power transmission to the hours that have lowest total (energy and distribution) cost. A related toy example is presented in detail in section 4.1 as description of *load shifting*.
- **Peak shaving**: EV charging power consumption can increase the power demand up to maximum power capacity available for the facility. Maximum capacity available is dependent on variable loads of the charging facility like other household usage. In these cases, user needs to be careful about switching loads ON without tripping the main fuse/protection device off while charging the vehicle with maximum charging power. Intelligence like peak shaving prevents this. For creating the charging sched-

ule, this algorithm calculates the possible maximum power available for charging during an hour from historical data of other household usage. Then it calculates the total energy transferred for that period.

The maximum charging power is restricted by charging power available from facility or grid (P_{grid}) and the rating of onboard charger, P_{user}.

$$P_{max} = min(P_{grid}, P_{user}) \quad (5.1)$$

Therefore, the possible maximum charging power for EV as expressed in (5.1). That makes the optimum costing more challenging specially in a case when maximum power limit of P_{grid} or P_{user} is less than optimum during the lowest price hours. Another toy example is described for peak shaping in section 4.1 for detailed explanation.

- **Optimize within limited charging time**: EV is going to be plugged-in at the charging facility for a certain time. That leads to the challenge of optimizing the charging operation to be finished within given time.

5.2 Suggested topology

A feasible topology of the system is important for proper data handling within the system. Topology is referred here as the body of the charging system where the intelligence algorithm is implemented. For implementing the proper intelligences, algorithm needs to collect, process and deliver certain set of data within different parts of the system. That makes the right implementation of algorithm crucial. According to study of different components of the system, the topology and information flow mechanism suggested for developed system is shown in Figure 13.

Stakeholders that share different information in this system are electricity market actors, user, electric vehicle, charging station, hysterical power consumption record and facility power usage data monitor. Electricity market actors provide the price information for the electricity. Algorithm gets the hysterical power usage data from the record. User inputs own priorities (e.g. target SoC, time of vehicle leaving the facility etc.) through mobile application or input devices installed in charging station. In case user does not give any new input for target SOC or time of next trip, it follows the setting of most previous operation.

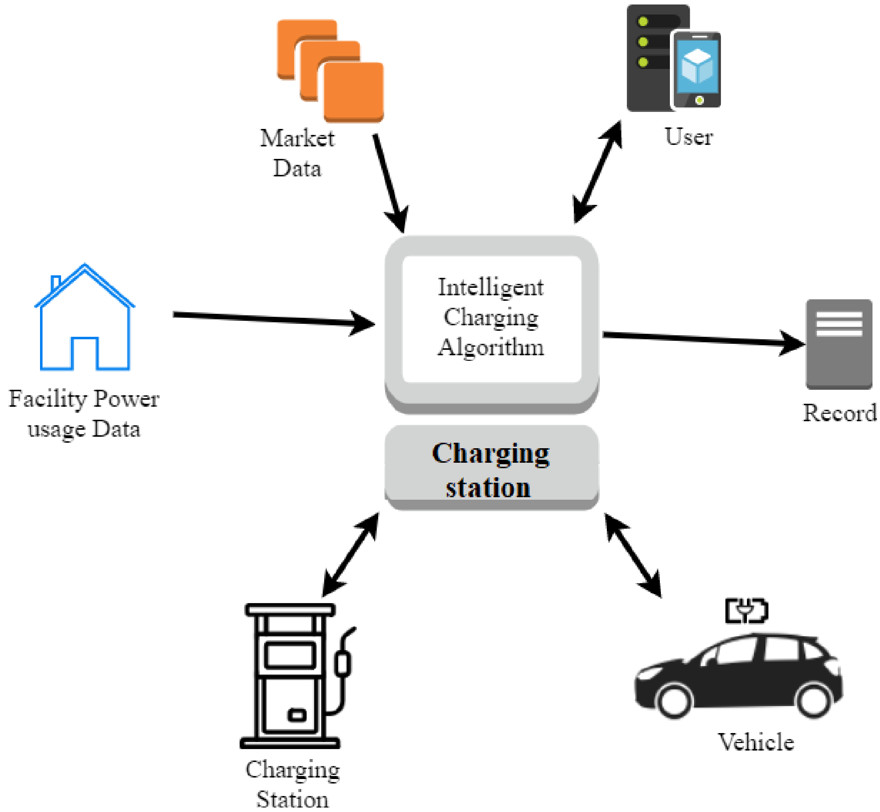


Figure 13. *Suggested System Topology.*

While EV is connected to charging station, it continuously exchanges the information like battery SoC, battery capacity etc. with charging system. Charging stations share the information about maximum allowable charging power. All the power information from different parts of the system is used to calculate the maximum charging power available. In the whole system, the charging station is the best possible position for the implementation of the algorithm. Although the vehicle onboard charger can be an alternative position for the algorithm's implementation, continuous data handling required for calculating maximum power available requires extra attention. External charging station is already connected to the facility and connectivity solution with other stakeholders like market data, vehicle etc. is easier for the communication system.

5.3 Model for optimized intelligent charging

5.3.1 Problem description

An EV arrives at household (charging station) at a certain time and will be leaving the facility after certain period. After arrival a charging schedule need to be developed considering the hourly energy price and distribution cost related to the amount of power drawn from network at specific time. Assumed, EV arrives the charging station and plugged-in at t_1 and leaves at t_2. It needs to be charged up to desired SoC by t_2. The total time available for charging, T= $t_2 - t_1$.The available power for charging is P_c and battery has fixed charging efficiency as η_c.

5.3.2 Objective function derivation

The actual power the battery stores is shown in (1)

$$P(t) = P_c(t)/\eta_c \qquad (1)$$

η_c is the efficiency of charger and $P_c(t)$ is the power delivered from facility (electric grid). In this thesis, the value of η_c is approximated to be 1. As the energy has different hourly price, the price per unit energy is a function of time M(t). Cost for energy consumed can be expressed as shown in (2).

$$C^{energy}(t) = M(t)P(t) \qquad (2)$$

An hourly unit distribution charge that is also different for different hour of the day, D(t) is added to the cost related to the consumption. Distribution costs can be expressed as shown in (3).

$$C^{distribution}(t) = D(t)P(t) \qquad (3)$$

The total costs related to every charging event starting from t_1 and ending at $(t_1 + T)$, can be expressed as shown in (4). Here, T is the total time available for charging.

$$C^{total} = \int_{t_1}^{(t_1+T)} \{M(t)P(t) + D(t)P(t)\}\, dt \qquad (4)$$

The expression shows that both the cost is dependent on the power consumed at a certain time. That indicates that to achieve the lowest total charging cost, the charging should be made during the hours with the lowest sums of the energy and distribution prices.

For a convenient calculation, the total charging time is divided into very small events. N is the total number of events and each event period length is Δt. With that information equation (4) can be expressed as,

$$C^{total} = \sum_{i=1}^{N} \{M(t_i) + D(t_i)\}\, \Delta t \,.\, P(t_i) \qquad (5)$$

The time between t_1 and t_2 can be divided into K slots where every slot has period length of Δt. $Charging_{slot}$ is the set of total slots that have duration of Δt available for charging. Here, Δt is the unit time for charging. As an example, Δt can be as small as fraction of second or a full second. It is seen from (5) that, total cost for charging can be minimized if the slots that have lowest $\{M(t) + D(t)\}$ and belongs to $Charging_{slot}$, can be used for charging.

5.4 Developed algorithm

The whole process of car charging can be divided into two parts, then 'main algorithm' and the 'optimizing algorithm'.

5.4.1 Main algorithm

The main algorithm shows all the events happening between the car arriving (plugged in) and car leaving (plugged off) (Figure 14).

The steps are described below,

- Step 1. Car arrives the charging facility and gets plugged in.
- Step 2. The algorithm collects all the data necessary from different parts of connected system. It collects the price information from market and finds the total hourly cost per unit energy for next 24 h. Current state of charge (SoC) and battery capacity data is taken from the vehicle. Average power consumption for 24 h is collected from the historical data. That does not confirm to take the real time power consumption into consideration while checking for available charging power, but it gives more realistic calculations for the charging power. User defines the end time for charging and target SoC at the end of charging event. The data about total power available from the facility is collected from charging facility (e.g. detached house charger box). Current time is collected from the vehicle in case it does not match the system time. Otherwise different vehicle system time can lead to a wrong result.
- Step 3. Define the charging slots available between the starting time and end time in distance of Δt, and then store the charging slot info into a data set $Charging_{slot}$.
- Step 4. Analyze the possibility of charging for all the hours starting from the cheapest to expensive hours. Then store the possible charging hour information to the charging table. The next subchapter named 'Optimizing algorithm' explains this step in more detail.
- Step 5. Using the optimized charging table created from step 4, EV is charged until the end of charging schedule.
- Step 6. Check if the target SoC is reached. If the desired SoC has not been achieved yet, go back to step 4. If the target SoC is achieved, go to step 7.

- Step 7. Store the record and finish charging.

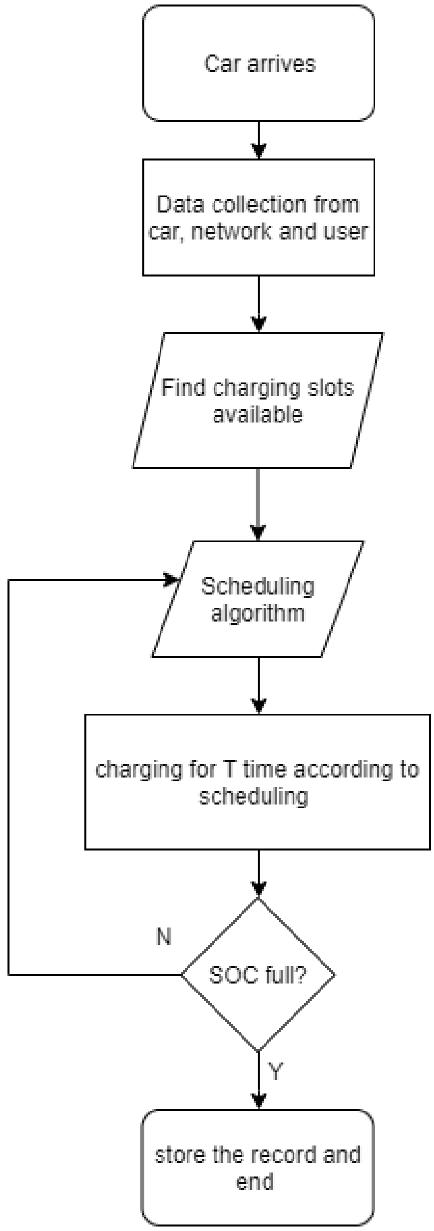


Figure 14. *Developed algorithm.*

5.4.2 Optimizing algorithm

Optimizing algorithm checks all the hours starting from cheapest electricity price (energy cost + distribution cost) for the possibility of energy transfer. This is the main part of algorithm that minimizes the costs and implements other intelligences to achieve the desired charging schedule.

The optimizing algorithm is shown in Figure 15.

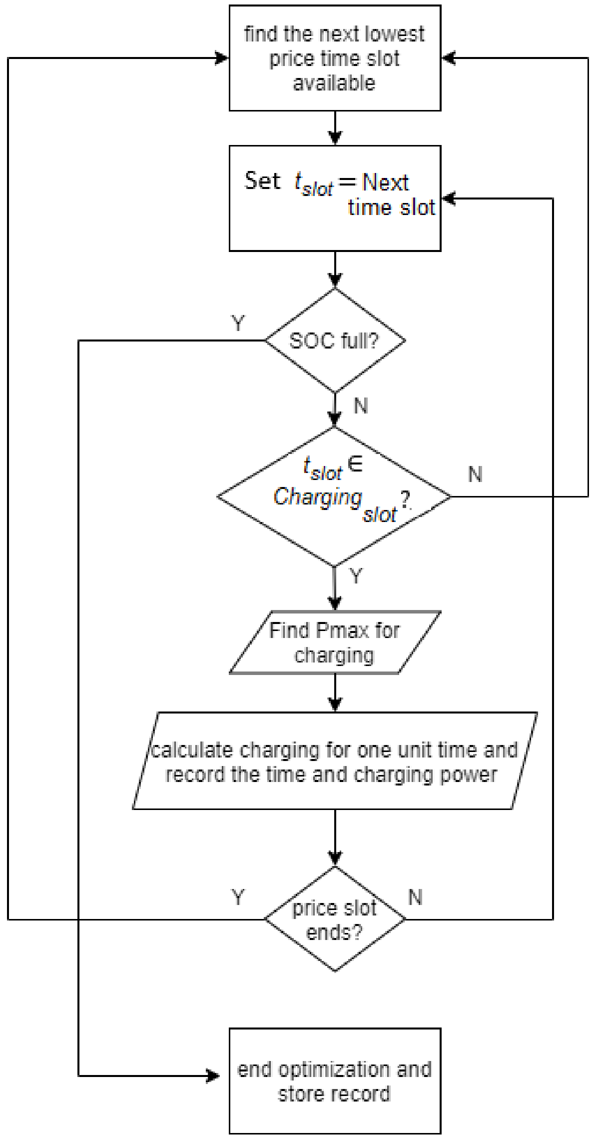


Figure 15. *Optimizing algorithm.*

The steps of algorithm are described below,

- Step 1. Find the cheapest available time slot (hour of the day) from price list. Set the first time slot as starting point of the charging event
- Step 2. Set the next number of Δt (e.g. number of second, depends on the unit time Δt) as current slot, t_{slot} .
- Step 3. Checks if the SoC is full or reached to desired SoC. If yes, go to Step 8. Otherwise go to step 4.
- Step 4. Checks if t_{slot} is a member of $Charging_{slot}$. If yes, go to step 5. Otherwise, go back to Step 1.

- Step 5. Find maximum power available for charging by calculating $P_{charger}$. $P_{charger}$ is calculated from the Maximum power available in the facility, P_{fuse} and power usage in other sections from the same facility, $P_{other\_utility}$.

$$P_{charger} = P_{fuse} - P_{other\_utility}$$

- Step 6. Calculate the parameters for charging for unit time (Δt) from, t_{slot} and record the data for this action.
- Step 7. Check if the same price hour ends. If yes, go to step 1. Otherwise, go to step 2.
- Step 8. End the optimization process, build total charging schedule and store the record.

5.5 Constraints

The developed algorithm comes with certain constraints.

- **Battery charging efficiency**: In this thesis, it is assumed that the charging efficiency, η_c is constant through the whole charging process, but practically, η_c is a variable dependent on temperature, current [5] and state of health (SOH) [7]. As it is given that proper measures are taken to keep the temperature constant throughout the charging process, still the charging current and SOH changing is present. But the effect of changing charging current and SOH is ignored in this thesis.
- **Total charging time:** Charging time needed for car cannot be more than 24 h for this model. If the car is plugged in for more than 24 h and still not charged to target SoC, a new charging event introduces the next day.

6. CASE STUDY

The developed algorithm was analyzed through a case study by simulating EV charging in some detached houses of Finland. This chapter describes the simulation process including parameters for initial settings, expectations, results and reasoning behind different characteristics of algorithm through the simulation.

Different detached houses are divided into four types depending on the consumption profile. These are the following.

- Type-4: Detached houses that do not have electric heating.
- Type-5: Energy efficient detached houses with electric heating.
- Type-6: Detached houses with direct electric heating and timed domestic water heater.
- Type-7: Detached houses with domestic electric storage heater.

All the houses should pay the bill for energy consumption and a distributor tariff bill related to the amount of energy consumption. The energy and distribution cost vary during the day depending on the hour of use. On top of that a fixed distribution charge depending on the fuse size is added on monthly basis. The fuse rating of all the houses are 3x25A.

The developed algorithm was implemented in a MATLAB program for simulation with real time data. The simulation was run for the whole year 2018 except the last day. The following sub-chapter describes the initial settings and value selection for the simulation work.

6.1 Setting simulation

The initial data and settings that the algorithm needs to start the simulation are described below.

Household power usage data: Load profiles for the four types for detached house customers were taken from a study made for Finnish Energy Authority in 2018 [29][30]. These profiles describe average electricity consumption in Finnish detached houses. That means these consumption models do not model the exact energy consumption of a detached house. In real life, hourly power or energy consumption varies a lot depending on the size of the house, number and habits of the users and other variables. The following graphs in Figure 16 show average hourly consumptions for different type detached houses during 2018.

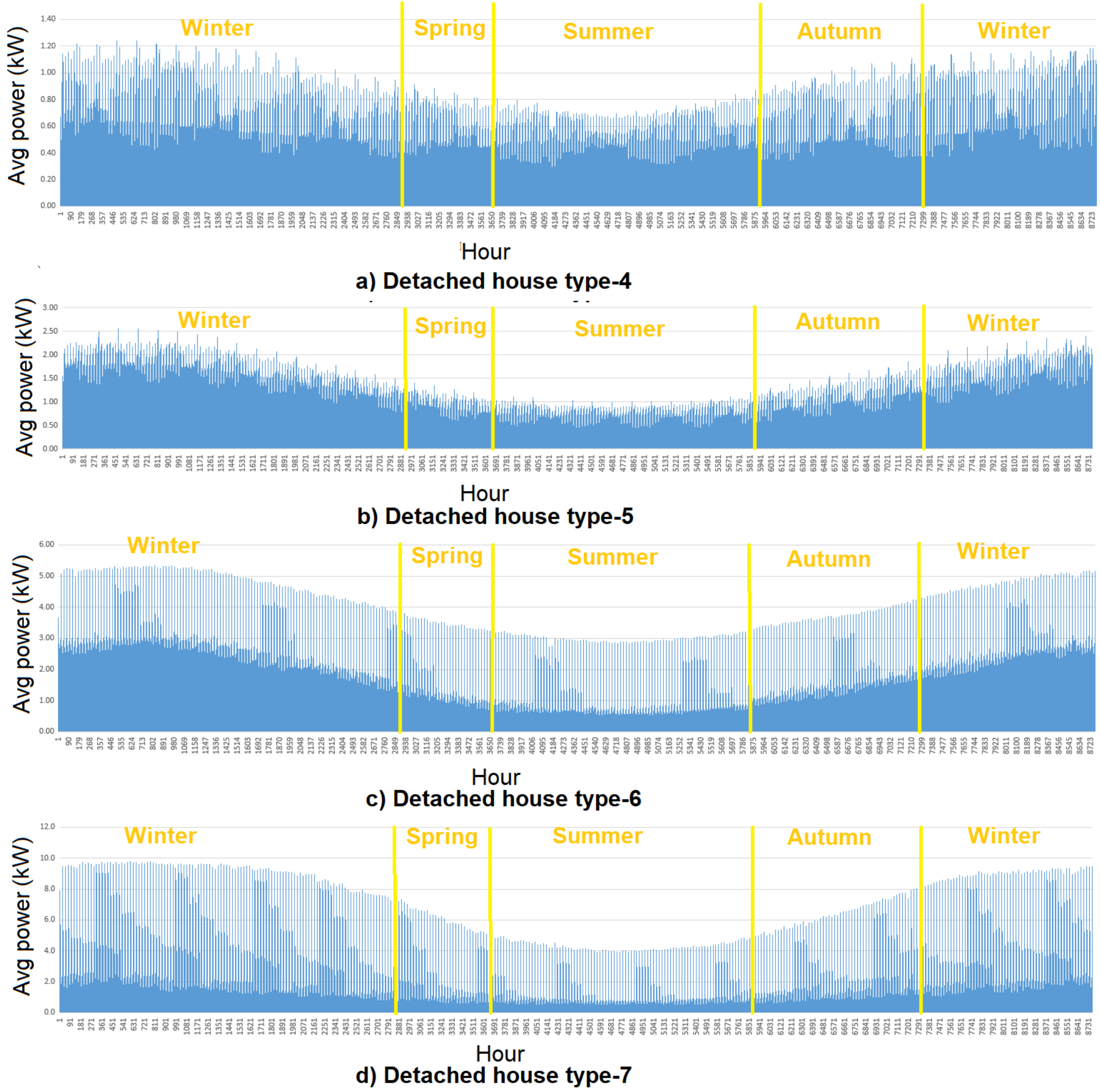


Figure 16. *Average hourly power consumptions of different detached houses during 2018.*

For this study, these average consumptions are used as consumption for a single detached house.

Hourly energy price: Hourly energy prices are not very common in Finland yet. In this study, spot prices from Nordpool for 2018 were used as hourly prices. A value added tax of 24% and 0.3 cents/kW margin were added on top of the spot price. That gives more realistic customer end electricity prices for different hours of 2018. Figure 17 shows hourly price distributions in cents/kWh for different month.

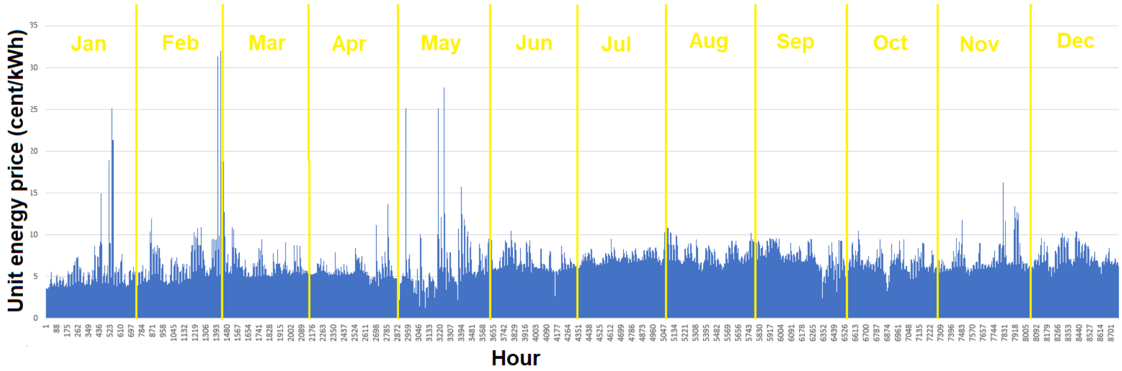


Figure 17. Customer end hourly energy prices per unit for 2018 [10].

Hourly distribution price: Distribution price component that is dependent on the energy consumption have two face values. A lower price for off-peak and a higher price for peak hours of the day. On top of that there is a monthly fixed cost of 31.09 €.

In this study, the fixed price component is considered during comparing monthly bill differences only. In rest of the cases, this component is ignored. Figure 18 shows the distribution cost for different hours of the day. The same list is used for all the days of the year for simulation.

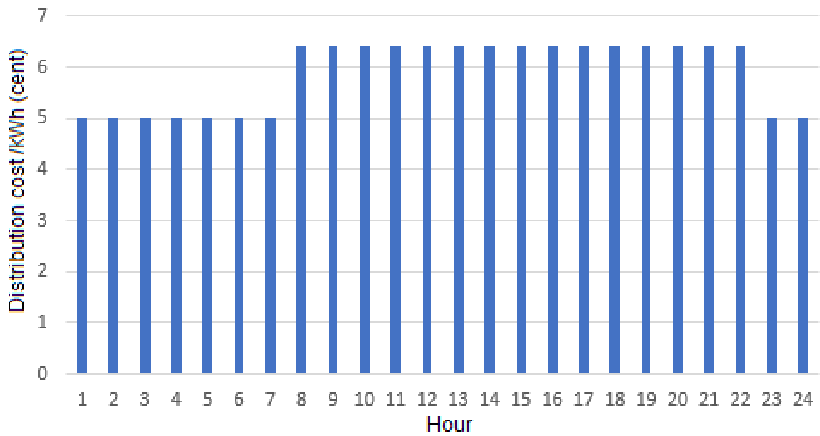


Figure 18. Distribution unit prices in different hours of the day

EV arrival time: It is assumed that EV gets connected to the charging facility right after arriving. Although real time EV arrival time depends on the driving behavior and lifestyle of the user. EV arrival time is set as 17:00:00 (time in 24h format hh:mm:ss) for all the simulation events for this study.

EV departure time: Assumed that EV leaves the facility at 8:00:00 (time in 24h format hh:mm:ss) in the morning. That gives a total available window of 15 hours to charge the EV to target SoC.

Initial SoC: For all the simulation events the initial SoC for EV is assumed as 10%.

Target SoC: For all the simulation events EV is expected to charge till the battery is full (SoC = 100%).

EV and its battery capacity: An EV with a battery capacity of 75 kWh is chosen for this study. Depending on the manufacturer and model a 75 kWh EV can have different driving ranges. For example, one of the bestselling EV is Tesla 3. It has a 75-kWh model that have a driving range of 400km+ [24].

Rated fuse power of house: It is assumed that all the houses have the same fuse rating as 3x25A. The nature of protection device installed in the houses allows 80% of the fuse capacity to be used for total electricity usage of the house. Therefore, total power that can be used for total electricity usages = 0.8 x 3 x 230 x 25 W = 13800 W = 13.8 kW. Additionally, the house type has three-phase network connections with different number of loads connected to different phase. If there is no phase-wise charging current control is installed, the most loaded phase is a restricting factor for three-phase EV charging operation.

Rated charging power for charger: As described in chapter 3.3, charger power can vary from 3.5-22+ kW depending on the type of charger. For this study a 10-kW charger is chosen. With a 75-kWh battery, this charger would require 7.5 hours to charge the battery from zero to full if the rated maximum power is available.

The value of smallest unit time (Δt): Setting the value for Δt is important for the precision of the cost optimization. For this simulation work all the calculations were made by setting the smallest unit time as (Δt=) 1 second.

Peak and off-peak hours: The typical peak hours (high demand) are assumed as 7:00 – 22:00 and rest of the hours are considered as nighttime off-peak (low demand) hours.

6.2 Results and analysis

The simulation over the whole year 2018 gives long list of schedules that include a huge amount of data regarding time, power usage, cost and state of charge. Looking from both user and grid point of view, the total simulation results brings different perspectives into observation. From customer point of view, the most important utility is optimizing price. From grid point of view, proper load distribution during day is the main parameter to assess the success of optimizing algorithm.

In this chapter, the results are taken into discussion according to different customer type and season of the year. Finland is a country of four seasons with clear differences between each other. Due to a big range of change in temperature (roughly from -30˚C to

+30 ° C) in different seasons (Figure 16), energy usage for heating changes a lot during the year. The segments of simulations from different seasons of the year are analyzed to study the effect of optimized algorithm over EV charging process. Four different months, January, May, July and October are taken into brief investigation as example of wintertime, springtime, summertime and autumntime, respectively.

Grid has the highest electricity demand during winter among the seasons (Figure 16). Winter season starts in Finland from the end of the year (November) and lasts until April. More demand in household means less power available for EV charging. That makes the charging time for EV higher. Therefore, there is less possibility for the algorithm to shift the charging event from peak hour to off peak hour, and that affects the total cost savings through using costly hours.

None of the calculated charging costs for an individual event during this simulation include the fixed distribution cost component.

6.2.1 Type-4 detached house

Type-4 detached houses currently have average annual consumption of around 5 MWh. That consumption is distributed throughout the year. Because there is no electric heating, the load profile does not vary a lot during the year as shown in Figure 16 (a). Still there is a small decrease in consumption at the middle of the year during summertime. The simulation results from different seasons are presented below.

Winter

Analyzing the load distribution for charging with the algorithm (smart charging) and without any intelligence (regular charging) shows a clear picture of load shifting. Figure 19 shows the load distribution for individual charging events during different day types of the week. Simulated data from dates 1st January (a public holiday), 6-8 January (typical winter weekend and weekday) 2018 is taken for this chart. All the charging hour lies on the peak demand hours of the day after plugging the vehicle in without optimization, but after optimization all the power usage hours are shifted to off peak hours.

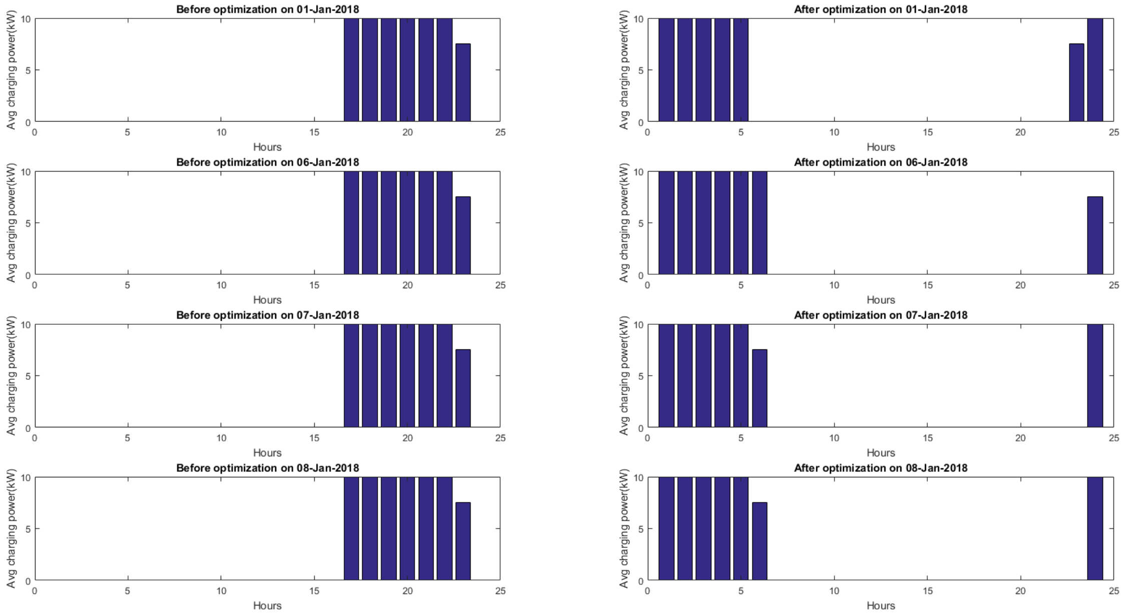


Figure 19. *Typical load profiles with and without optimization during different days of the week in winter.*

From the household load profile in Figure 16 (a) it is noted that the peak power is quite low (~1.3 kW) in contrast to the available maximum power of the house (13.8 kW). Therefore, a charger rated 10 kW can use its maximum rated power to charge the EV. That is the reason behind the household load profile have no effect in the charging power profile for type-4 houses.

According to the simulation results for January-April and November-December 2018, 100% of the charging load gets shifted to the off-peak hours from peak hours during winter.

Table 4 shows the monetary profit for all the events of January 2018 as an example of charging events happening during winter. There are some days of the month like day 19 or 23 that have comparatively higher profit percentage. This is because of high electricity price hours during the peak hours that lead to high charging costs for regular method (without optimization). After the optimization, these loads are shifted to the low-price (off-peak) hours, which reduces the charging cost exceptionally.

Table 4. Profit by optimizing algorithm in January 2018 (winter season) for Type-4 detached houses.

Day	Cost without Optimization (Euro)	Cost with Optimization (Euro)	Profit (Euro)	Profit Percentage %
1	6.60	5.73	0.87	13
2	7.28	5.88	1.40	19
3	6.87	5.88	0.99	14
4	7.17	5.91	1.26	18
5	7.13	6.04	1.09	15
6	7.12	5.88	1.24	17
7	6.87	5.79	1.09	16
8	7.13	5.88	1.25	17
9	7.33	6.01	1.32	18
10	8.04	6.20	1.85	23
11	8.06	6.13	1.93	24
12	7.48	6.09	1.39	19
13	7.21	6.01	1.20	17
14	7.00	5.79	1.21	17
15	7.10	5.50	1.60	23
16	7.35	5.98	1.37	19
17	7.82	6.06	1.76	22
18	7.89	6.17	1.73	22
19	9.69	6.14	3.55	37
20	7.57	6.14	1.43	19
21	7.64	6.12	1.51	20
22	8.65	6.34	2.31	27
23	10.05	5.86	4.19	42
24	7.28	5.22	2.06	28
25	7.48	6.08	1.40	19
26	8.04	6.17	1.87	23
27	7.17	5.93	1.25	17
28	6.76	5.93	0.84	12
29	7.34	5.97	1.37	19
30	7.66	6.08	1.58	21
31	7.33	5.88	1.44	20

The average cost profit for the charging events during January-April 2018 is 17.81% for type-4 detached houses. This charging cost optimization is reflected to the monthly bill for the house.

Assuming the average load profile as actual load during the month, total monthly electricity bill (January 2018) for optimized and regular charging is compared in Figure 20. The bill (Figure 20 b) includes all the cost components for energy and distribution related to total energy consumption and the fixed distribution monthly cost. Looking from user's point of view, Figure 20 (a) gives a good example of intelligent algorithm influencing the monthly bill during winter for type-4 detached houses.

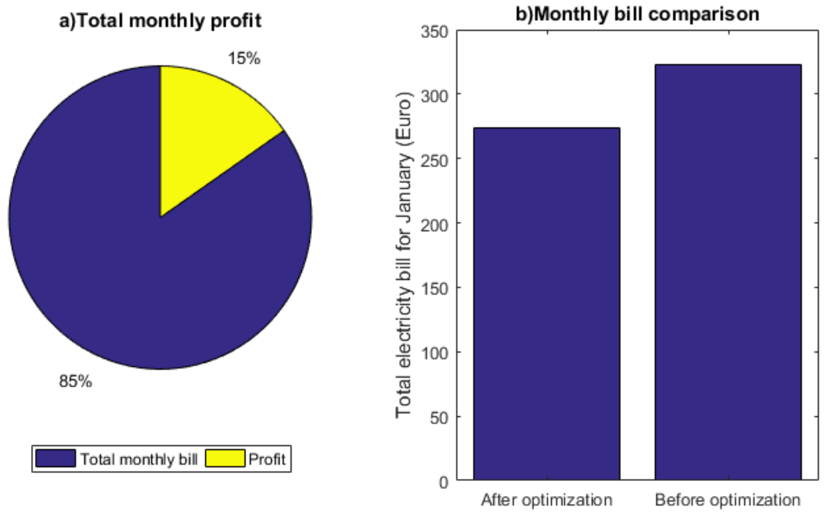


Figure 20. *Monthly bill comparison before and after charge optimization.*

Spring

During the spring, the average household consumption is like the winter for type-4 houses as the heating is not included into the electricity consumption, but there is a very abrupt change in energy hourly price during May (Figure 22). Figure 21 shows the optimization effect on charging load distribution on a public holiday, a typical weekday and weekends respectively during spring.

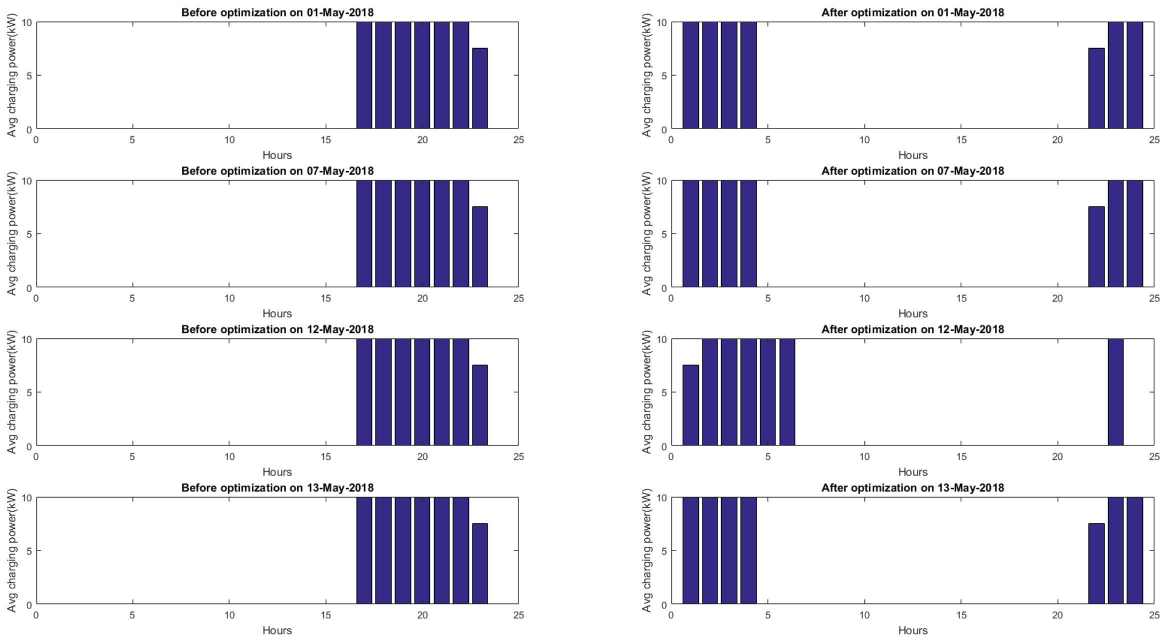


Figure 21. *Optimization effect on charging load distribution during spring for type-4 detached houses.*

During May, 100% of the peak loads are shifted to off-peak hours with intelligent charging for type-4 detached houses. All the charging loads are shifted to off-peak hour after optimization in most of the cases, but some of the load may remain in peak hour region in some cases. As the total load during the off-peak hours is not high enough to influence changing the peak charging power, the reason behind this is different. The hourly price during the charging event of one of the weekend days (12th may) is shown in the Figure 22. It shows that there are some cheaper hours during the peak hours (hour 15 and 16) that are cheaper than some of the off-peak hours.

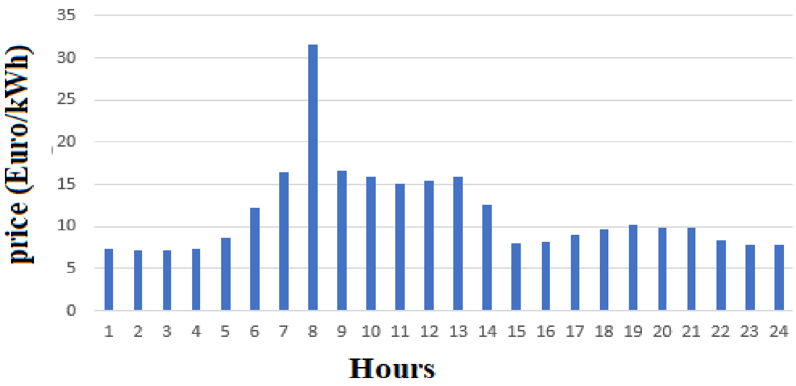


Figure 22. *Hourly sum of total distribution and energy price/kWh for 12th may*

That causes the algorithm choosing these peak hours before those off-peak hours for charging. Therefore, some of the charging loads may remain in the peak demand hours of the day in cases vehicle arrive before 15:00 h.

Figure 23 shows the daily charging cost comparison for week 19.

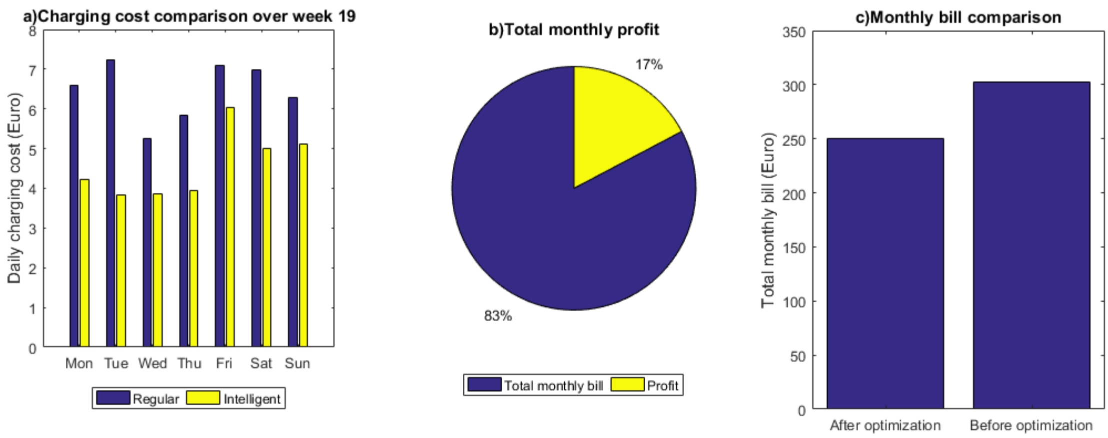


Figure 23. *Cost comparison of regular and intelligent charging during spring for type-4 detached houses.*

The effect of charging optimization is not very regular for different events during the week. Abrupt high-energy price hours cause this. The average cost profit for charging events during this month is 23.21%, but the values are distributed almost evenly between a wide range where the smallest value is 15.24% and the highest is 53.75%.

Total monthly cost saving over bill is 17% for May 2018 (Figure 23 b) after optimization.

Summer

Summer starts in June and the warm weather lasts until mid-September in Finland. Simulation data taken from starting of June until end of August are studied as summertime simulation. For type-4 detached houses 100% charging load gets shifted to the off-peak hours during June-August. Figure 24 shows the comparison between regular charging and intelligent charging load distribution for typical summer weekday and weekend.

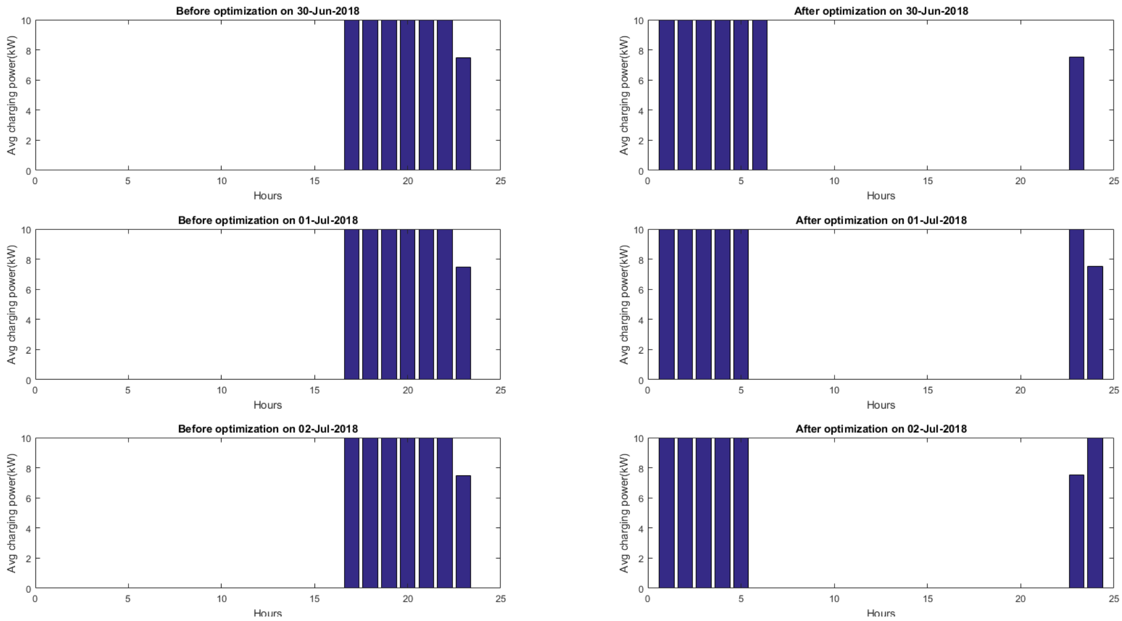


Figure 24. *Load distribution for EV charging of typical days of June-July 2018 for type-4 detached houses.*

The data plotted were taken from June 30th, 2018 and July 1-2, 2018 respectively. Like the previous result from winter, all the loads are shifted from peak-hour to off-peak hour. In this case, the load profile peaks are lower than that of winter load profiles. Therefore, like wintertime the household loads do not have any effect on available EV charging power or charging time.

Looking from customers point of view, simulated charging cost comparison over a week of July 2018 (Figure 25 a) gives better idea about cost profit for every charging event. The charging cost have an average profit margin of 17.36% over the regular charging during June-August.

In terms of monthly bill comparison (Figure 25 b), monthly profit is 11%. This is less than the profit of a wintertime month, January. The reason behind this is the comparative lower costs during peak hours in summer.

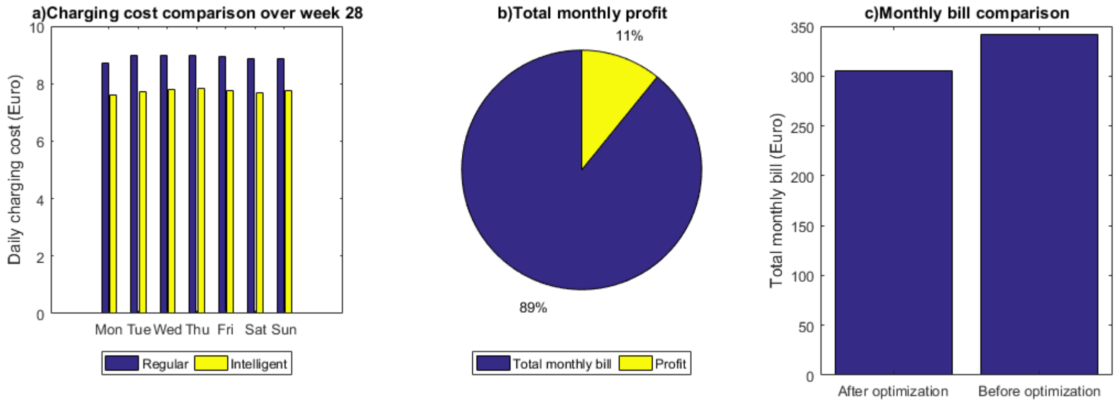


Figure 25. *Weekly and monthly cost and profit comparison of July 2018 for type-4 houses.*

Autumn

Autumn is very short period in Finland. Simulation for October is considered while studying the optimized results for autumn. 100% of the charging loads are shifted to the off-peak hours after optimization during October for type-4 detached houses. Figure 26 shows some typical day's load distribution effect of optimizing algorithm during autumn 2018.

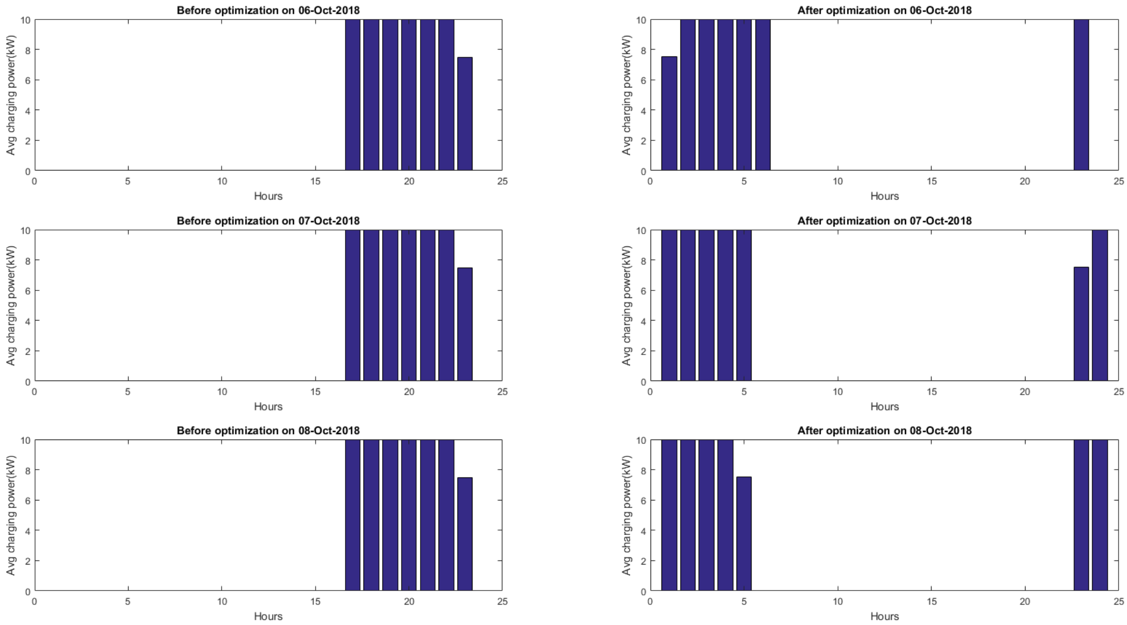


Figure 26. *Load distribution for EV charging of typical days of autumn 2018 for type-4 detached houses.*

Figure 27 (a) shows the cost comparison for different charging events during week 41. The average cost profit after optimization for all the charging events happening during October is 19.50%. The effect of optimized charging in monthly bill of October is 15%.

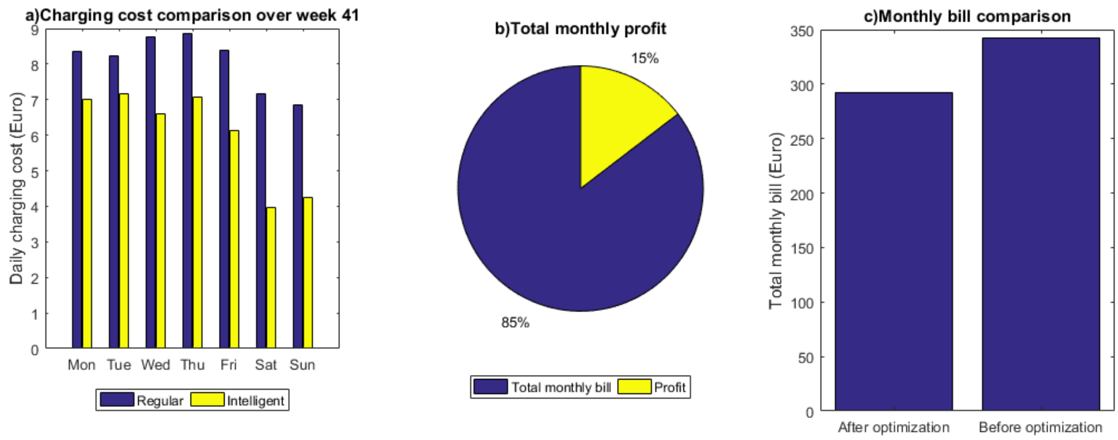


Figure 27. *Cost comparison after optimization during autumn for type-4 houses.*

The overall summary for the whole year 2018 for type-4 detached houses is as follows,

- 100% of the charging load gets shifted to off-peak hour zone during the whole year.
- Average costs for one optimized charging event is 6.86 € (not including the fixed distribution price component) and average profit is 1.49 € per event compared to regular charging.

6.2.2 Type-5 detached house

Type-5 detached houses have average yearly consumption of around 10 MWh with the fuse rating of 3x25 A. This type of houses includes electric heating into the electricity consumption. Therefore, the average daily power usage varies during the different seasons of the year. Optimized simulation results found from different seasons of the year is presented according to different seasons in this chapter.

Winter

Figure 28 shows the load distribution for individual charging events during different day types of the week. Simulated data (for type-5 houses) from dates 1st January (a public holiday), 6-8 January (typical winter weekend and weekday) 2018 is taken for this chart.

From the household load profile in Figure 16 (b) it is noted that the peak power is low (~2.5kW) compared to the available maximum power of the house (13.8kW). Therefore, a charger rated 10kW can use its maximum rated power to charge the EV even during the maximum household usage. Hence, the household load profile has no effect in the charging power distribution profile here.

As shown in the graph (Figure 28) all the electrical loads are shifted to the off-peak hours of the day after charging optimization.

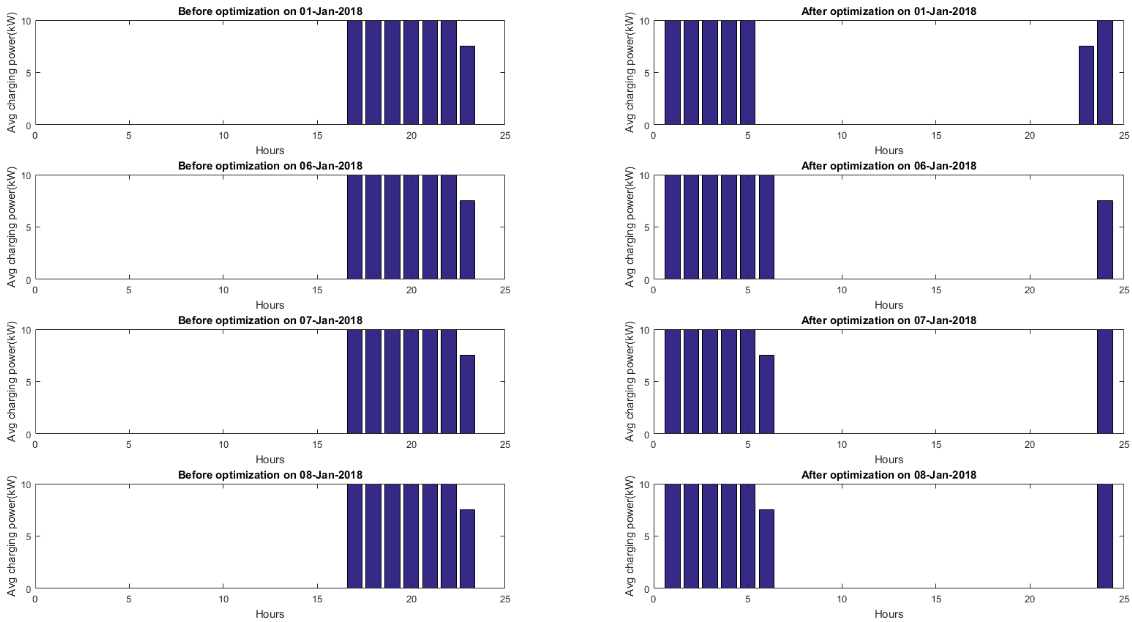


Figure 28. *Load distribution for EV charging of typical days of winter 2018 for type-5 detached houses.*

The simulation result for months January-April and November-December 2018 shows that 100% of the load is shifted to the off-peak hours for type-5 customers.

The average cost profit for the charging events during January-April 2018 is 17.81% for type-5 detached houses. Figure 29 (a) shows some typical charging event cost comparison over a week during this time. This data is taken from week 1 simulations.

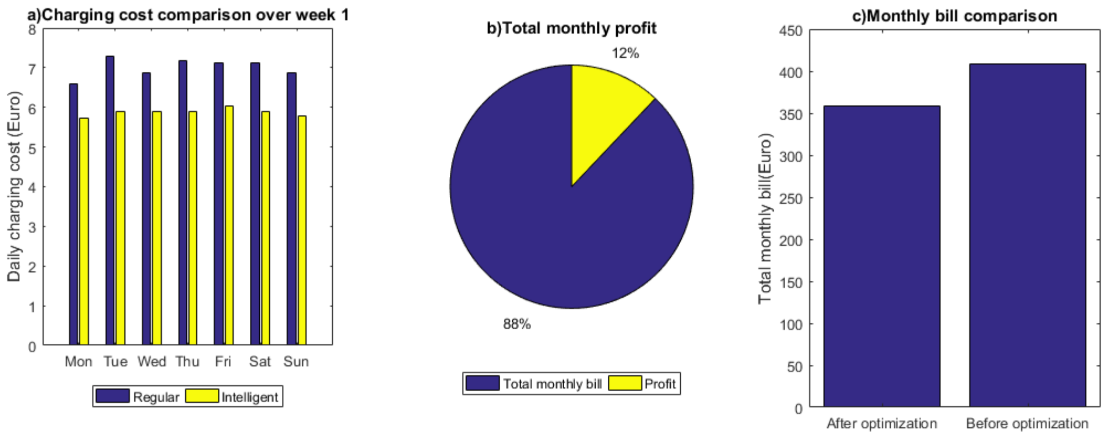


Figure 29. *Cost comparison after optimization during winter for type-5 houses*

The effect of optimization in average monthly bill is shown in Figure 29 (b and c). This bill is calculated for January including the average load profiles as the actual load data.

Spring

During the spring, the average electricity consumption reduces from the past days in winter for type-5 houses. Therefore, the load profile of the house does not have any effect on charging power of EV like in wintertime as shown in Figure 30.

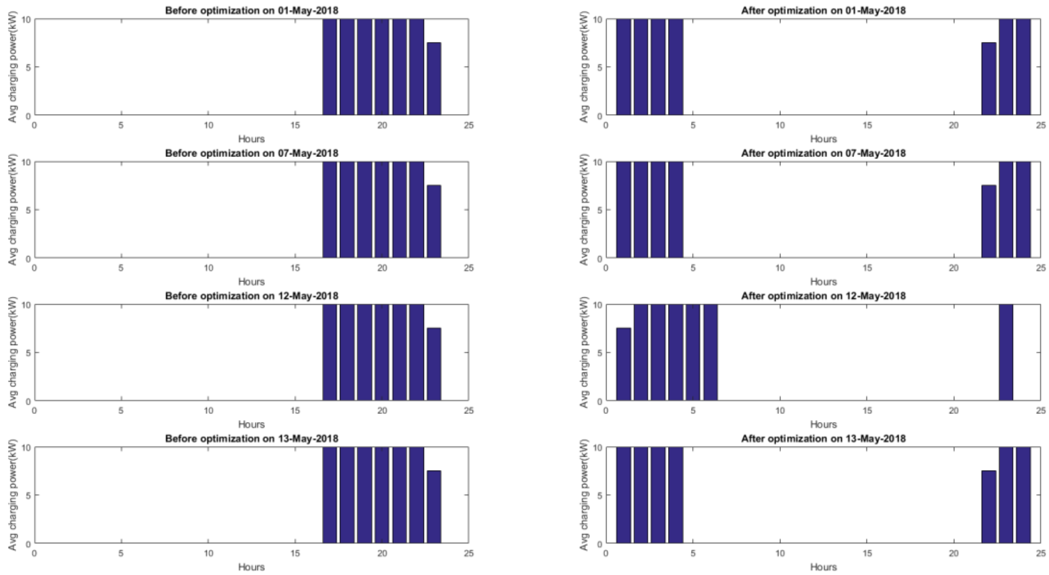


Figure 30. *Load distribution for EV charging of typical days of spring 2018 for type-5 detached houses.*

This data is taken for the same days of type-5 houses simulation as used for type-4 houses simulation (Figure 21). During May, about 100% of the peak loads are shifted to off-peak hours with intelligent charging.

Figure 31 (a) shows the cost differences of regular and intelligent charging during different days of the week. These values are taken from week 19 data for type-5 houses.

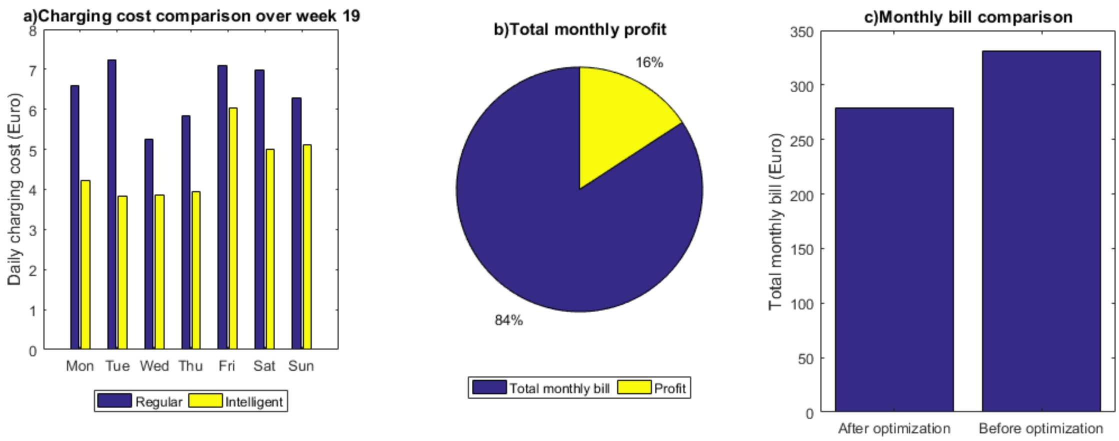


Figure 31. *Cost comparison after optimization during spring for type-5 houses*

The average charging cost profit for all the charging events happening in May for type-5 houses is 23.21%, but this value varies from the minimum value of 15.24% to maximum 53.75%.

Summer

Summertime has the lowest average power usages for the household among the seasons (Figure 16 b). Therefore, there is maximum power available for EV charging during the peak hours for house are higher than the past two seasons. Figure 32 shows the data from some typical weekend days and a weekday respectively from July 2018.

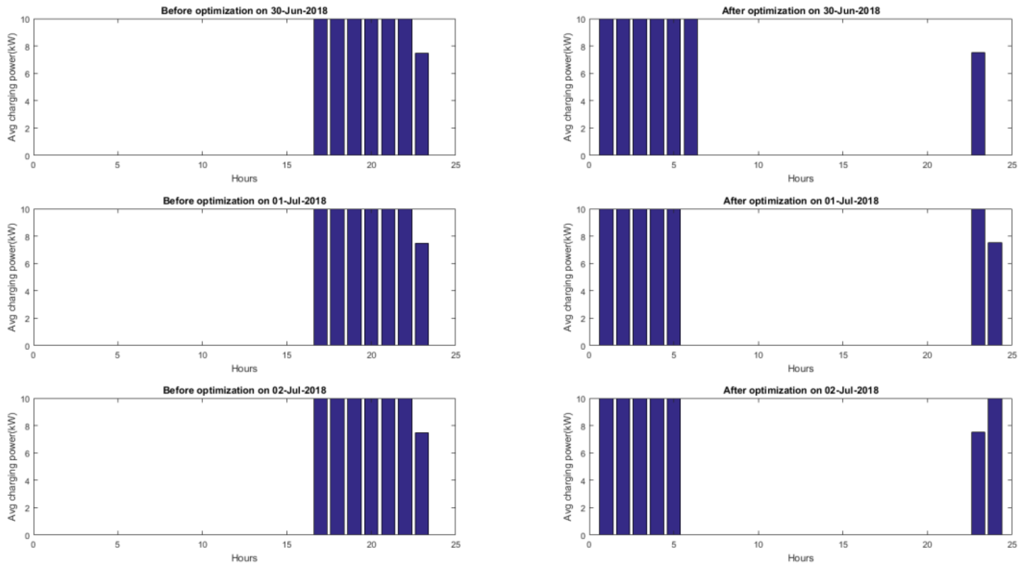


Figure 32. *Load distribution for EV charging of typical days of summer 2018 for type-5 detached houses.*

For type-5 detached houses 100% charging loads get shifted to the off-peak hours during June-August.

The charging costs have an average profit margin of 17.36% over the regular charging during June-August. The effect of this optimization in monthly bill is shown (for July) in Figure 33 (b and c).

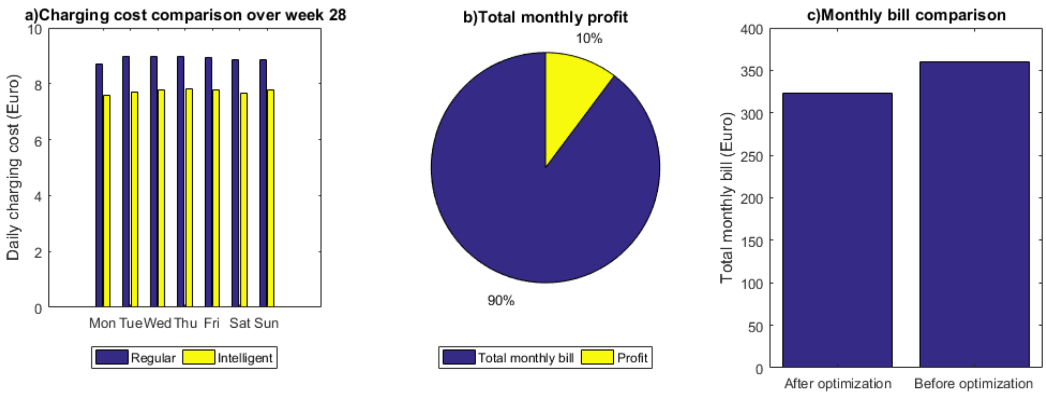


Figure 33. *Cost comparison after optimization during summer for type-5 houses*

Autumn

During the autumn, the average household consumption starts to rise with colder days approaching, but it does not go over the average wintertime daily consumptions for type-5 detached houses.

Figure 34 shows the load shifting after optimization for typical weekend and weekdays of autumn. 100% of the charging loads are shifted to the off-peak hours after optimization during October.

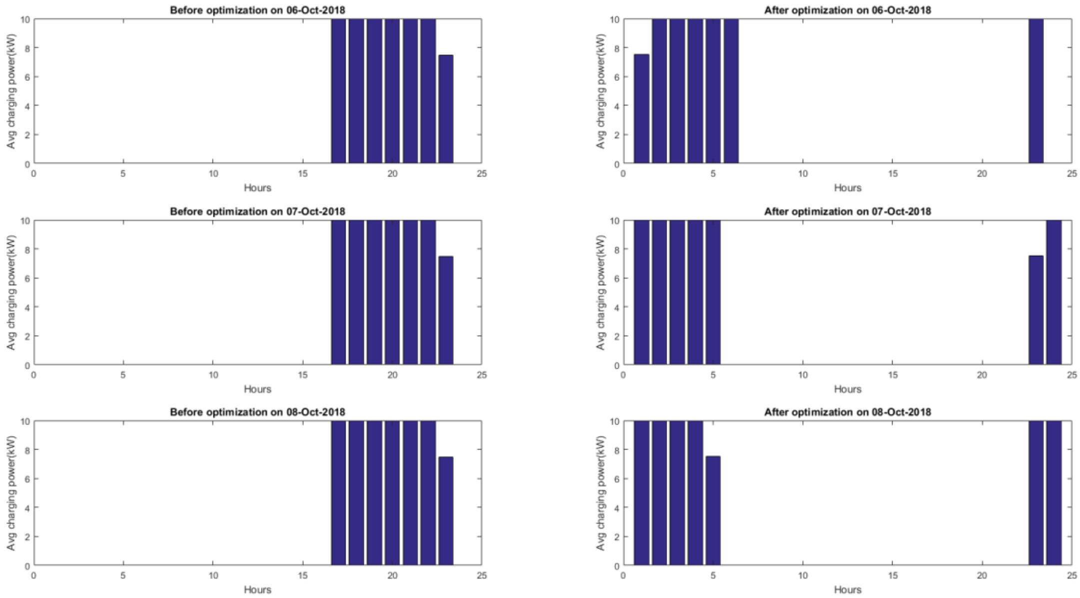


Figure 34. *Load distribution for EV charging of typical days of autumn 2018 for type-5 detached houses.*

Figure 35 (a) shows the cost comparison for different charging events during week 41. The average cost profit after optimization for all the charging events happening during October is 19.5% for type-5 houses.

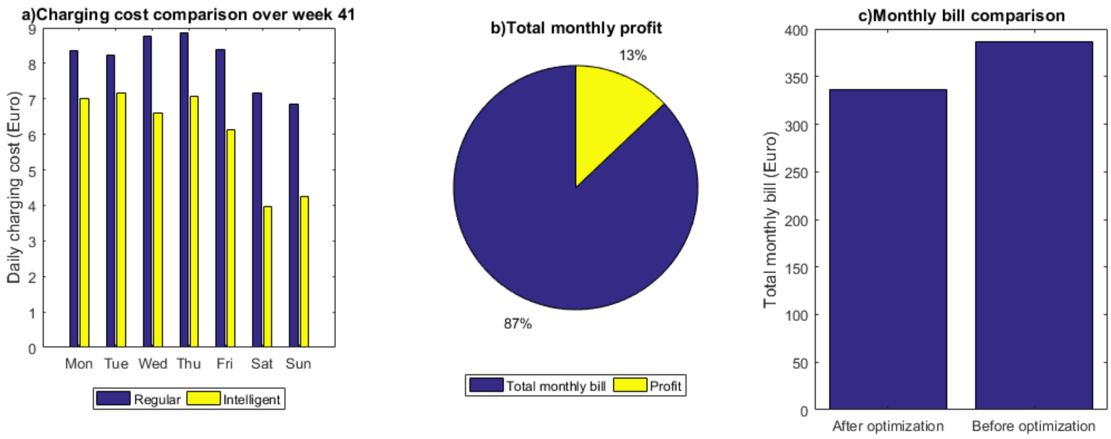


Figure 35. *Cost comparison after optimization during autumn for type-5 houses*

The overall summary for the whole year simulation for type-5 detached houses is as follows,

- 100% charging load gets shifted to off-peak hour zone during the whole year.
- Average cost for one optimized charging event is 6.86 € (not including the fixed distribution price component) and average profit is 1.49 € per event compared to regular charging.

6.2.3 Type-6 detached house

Type-6 detached houses have direct electric heating and timed domestic water heater. Yearly average energy consumption for this type of house is around 16 MWh/year. These house types have fuse rating of 3x25 A. Optimized data found from different seasons of the year for type-6 detached houses are presented according to different seasons below.

Winter

Analyzing the load distribution for charging with the algorithm and without any intelligence shows a clear picture of load shifting. Figure 36 shows the load distribution for individual charging events during different day types of the week. Simulated data from dates 1st January (a public holiday), 6-8 January (typical winter weekend and weekday) 2018 is taken for this graph. All the charging hours remain on the peak demand hours of the day after plugging the vehicle in without optimization. After the optimization all the power usage hours are allocated to off peak hours.

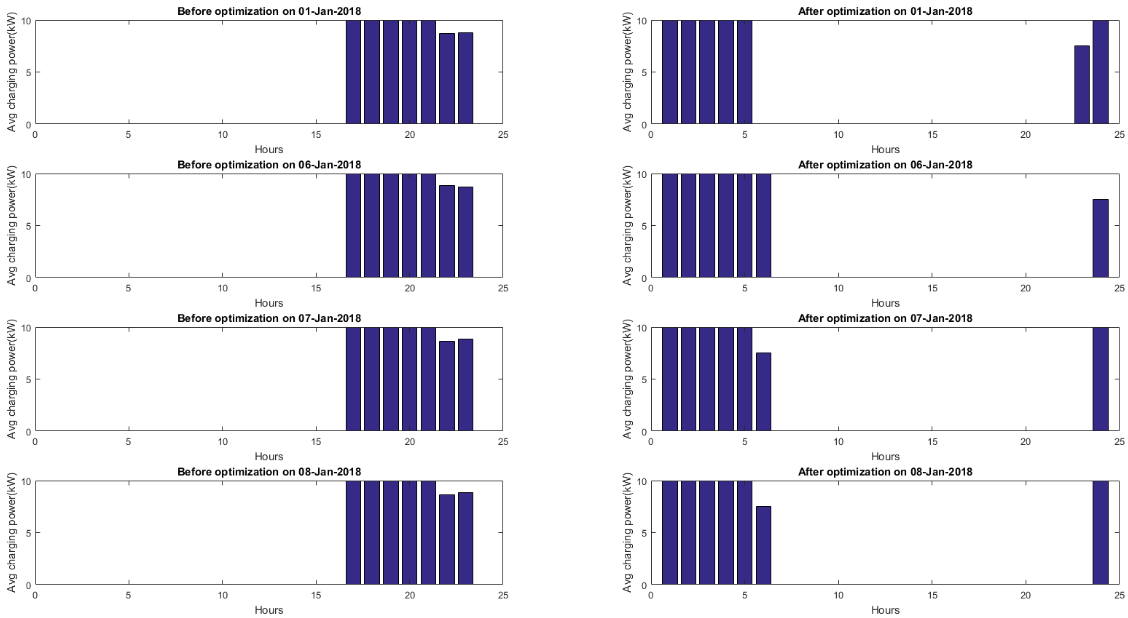


Figure 36. *Load distribution for EV charging of typical days of winter 2018 for type-6 detached houses.*

The simulation for January-April and November-December 2018 shows that 100% of the load is shifted to off peak hours after the optimization for type-6 detached houses.

Average cost profit for charging events happening during January-April 2018 is 17.81% for type-6 detached houses. Figure 37 (a) shows the comparison for some typical days from week 1.

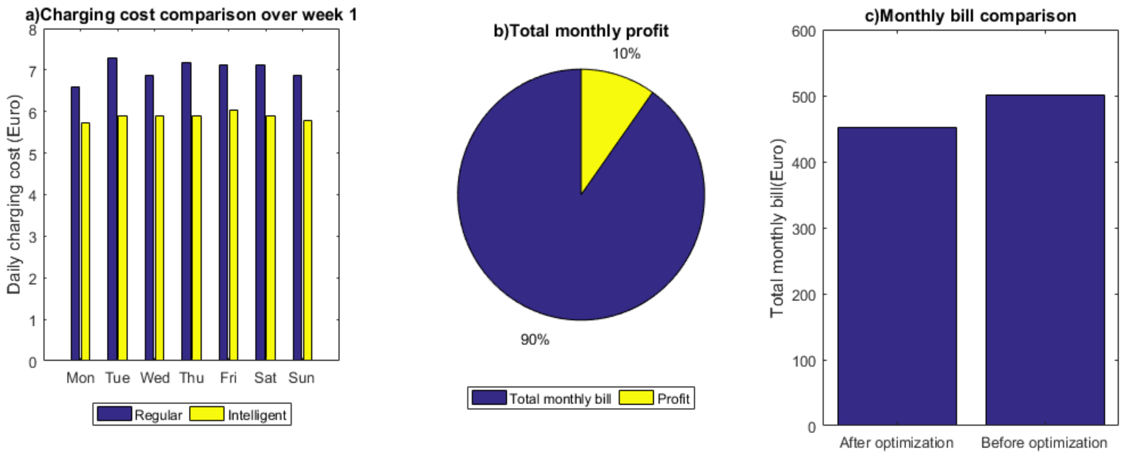


Figure 37. Cost comparison after optimization during winter for type-6 houses

The effect of cost optimization in monthly bill is shown in Figure 37 (b and c). The cost profit is 10% compared to the regular charging. This bill is calculated for January including the average load profiles as the actual load data.

Spring

During the spring, the average electricity consumption reduces from the past days in winter for type-6 houses. Therefore, the load profile of the house does not have big visible effect on charging power of EV like in wintertime as shown in Figure 38.

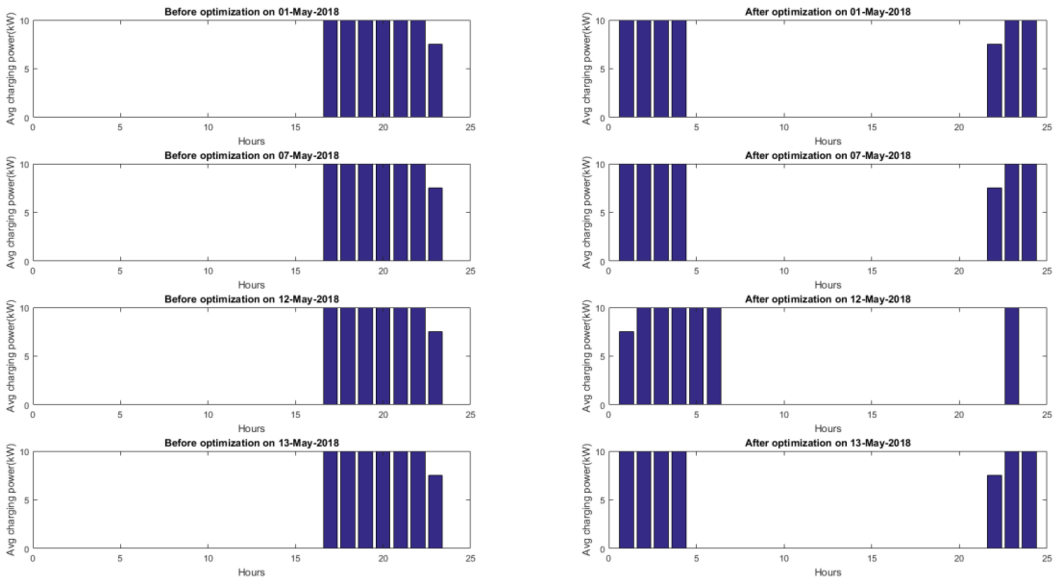


Figure 38. Load distribution for EV charging of typical days of spring (May) 2018 for type-6 detached houses.

Simulation results show that about 100% charging load gets shifted to off-peak hours after optimization during May 2018 for type-6 detached houses.

The cost optimizations are not very regular during different days of the week 19 (Figure 39 a). The average charging cost profit for all the charging events happening in May for type-6 houses is 23.21%. The effect of optimization in monthly bill is shown in Figure 39 (b and c).

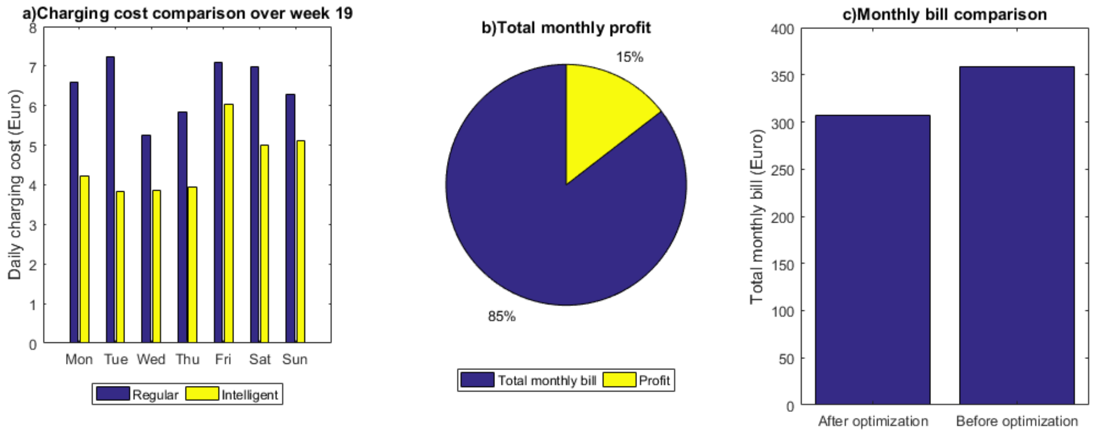


Figure 39. *Cost comparison after optimization during spring for type-6 houses*

Summer

Summertime has the lowest average power usages for the household uses compared to the other seasons (middle part of the graph Figure 16 c). Therefore, there is maximum power available for EV charging during the peak hours that are higher than in the past two seasons. Some typical days load shifting is shown in Figure 40 from June-July.

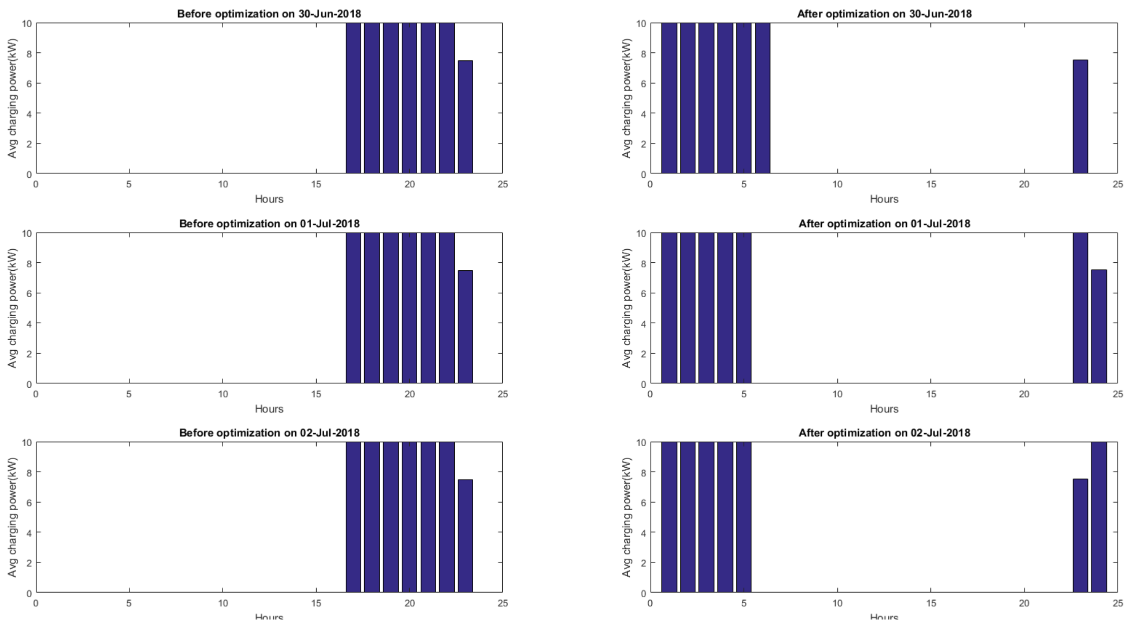


Figure 40. *Load distribution for EV charging of typical days of summer 2018 for type-6 detached houses.*

June-August 2018 simulation data shows that 100% charging load is shifted to off-peak hours.

Average cost profit for charging events during June-August 2018 is 17.36%. Some typical charging events comparison is shown in Figure 41 (a). The monthly bill has 10% profit compared to the month using regular charging.

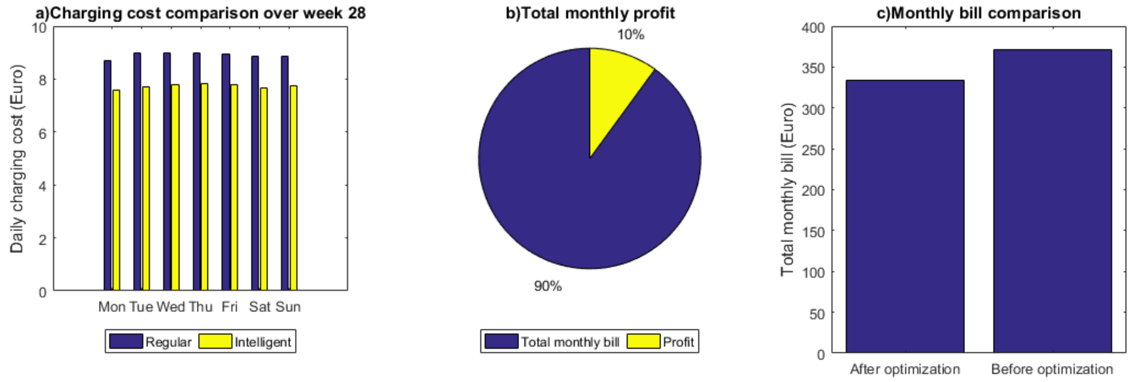


Figure 41. *Cost comparison after optimization during summer for type-6 houses*

Autumn

During the autumn, the average household consumption starts to rise with colder days approaching, but it does not go over the average wintertime daily consumptions for type-6 detached houses (Figure 16 c). Figure 42 shows the load shifting after optimization for typical weekend and weekdays of autumn.

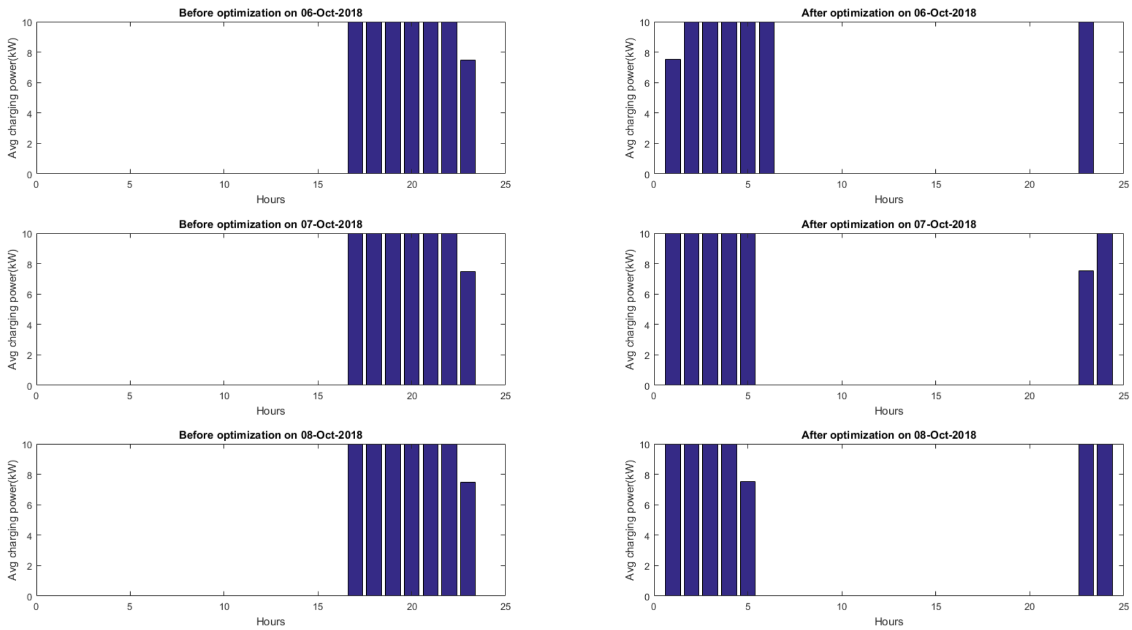


Figure 42. *Load distribution for EV charging of typical days of autumn 2018 for type-6 detached houses.*

During October, 100% of the charging load is shifted to the off-peak hours after optimization.

Figure 43 (a) shows the cost comparison for different charging events during week 41. The average cost profit after optimization for all the charging events happening during October is 19.5% for type-6 houses.

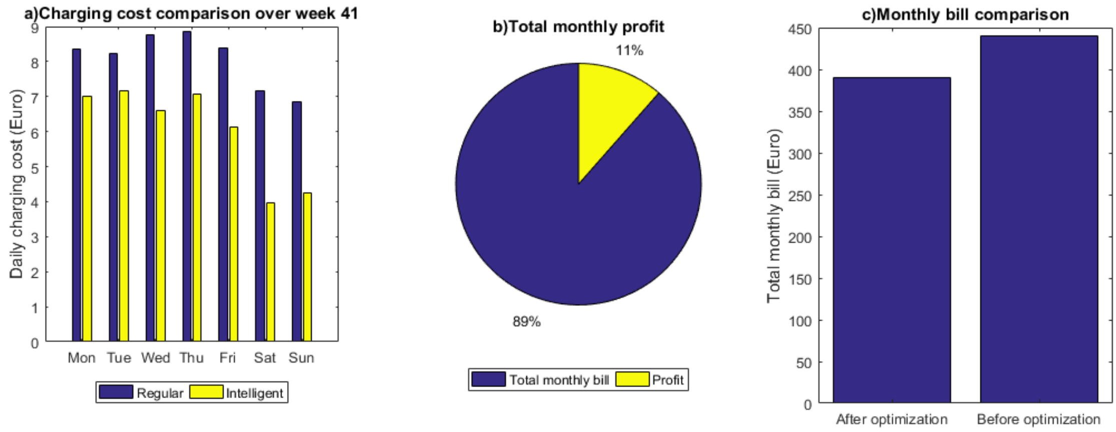


Figure 43. *Cost comparison after optimization during autumn for type-6 houses*

The overall data for the whole year for type-6 detached houses is as follows,

- 100% of the charging load gets shifted to off-peak hour zone during the whole year.
- Average cost for one optimized charging event is 6.86 € (not including the fixed distribution price component) and average profit is 1.49 € per event compared to regular charging.

6.2.4 Type-7 detached house

Type-7 detached houses have the highest consumption among all the four house types. Assuming the average load profile as actual average hourly load, simulation was done for all the days of 2018. In this process, all the other starting parameters remain same as other house type simulations. This house type has a yearly average consumption of around 16MWh. The installed fuse rating for this house type is like other house types, 3x25A.

Winter

Load profiles in winter days have a significant effect on optimized results for type-7 detached houses. Figure 44 shows some typical days load distribution comparison for a single charging event in January 2018. That includes a typical public holiday, weekend and a weekday into study.

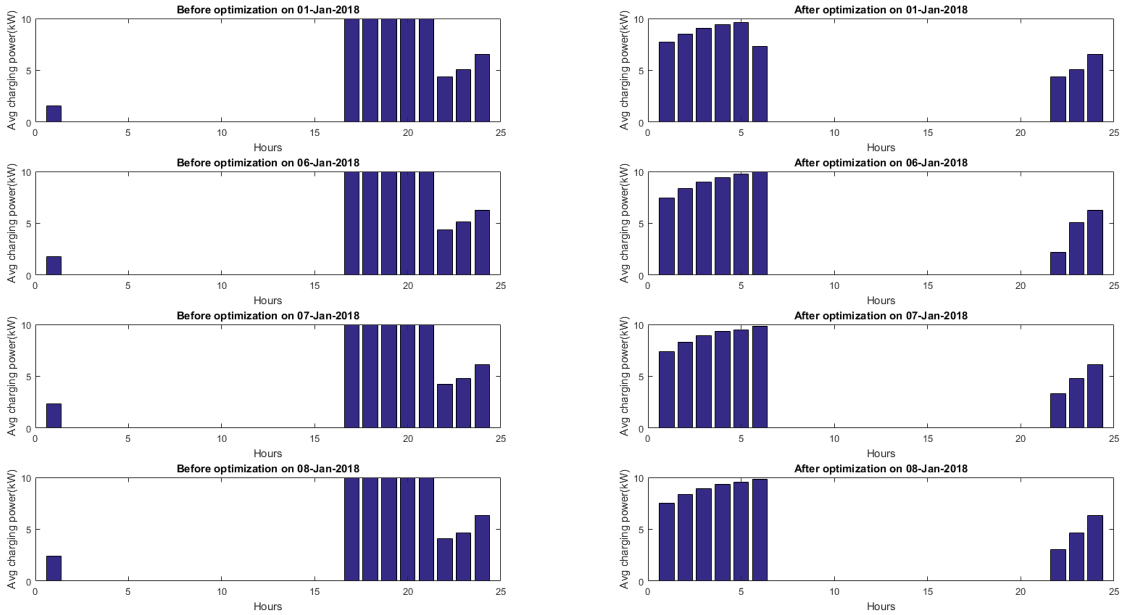


Figure 44. *EV Charging load of some typical days of winter 2018 for type-7 detached houses*

The first pair of graphs are taken for a public holiday (1st January, new year holiday). Depending on the starting time, most of the charging events takes place during the peak hour for regular charging. After optimization, all the charging events are shifted to the off-peak hours, but during the off-peak hours the charger does not get enough charging power to charge the EV with maximum power. It happens because the household electric load during those hours are high. Therefore, the algorithm uses all the available power slots from off-peak hours first. Then one of the lowest price hours from typical peak hours is used to charge the remaining energy needed for the EV battery. This event is an example of all the charging events when maximum power available during off-peak hour are not enough to charge the battery to full.

For the remaining typical weekday and weekends all the charging power is shifted to the off-peak hour, but there are some hours when the charging power is less than maximum because of the unavailability of maximum power after the general usage of house.

The simulation results show that, total 99.46% of the charging load is shifted to off peak hours during January-April and November-December for type-7 detached houses.

The daily charging cost comparison for a segment (one week) of wintertime is presented in the Figure 45 a as an example. The values are taken for the first week of January (1st – 7th January 2018).

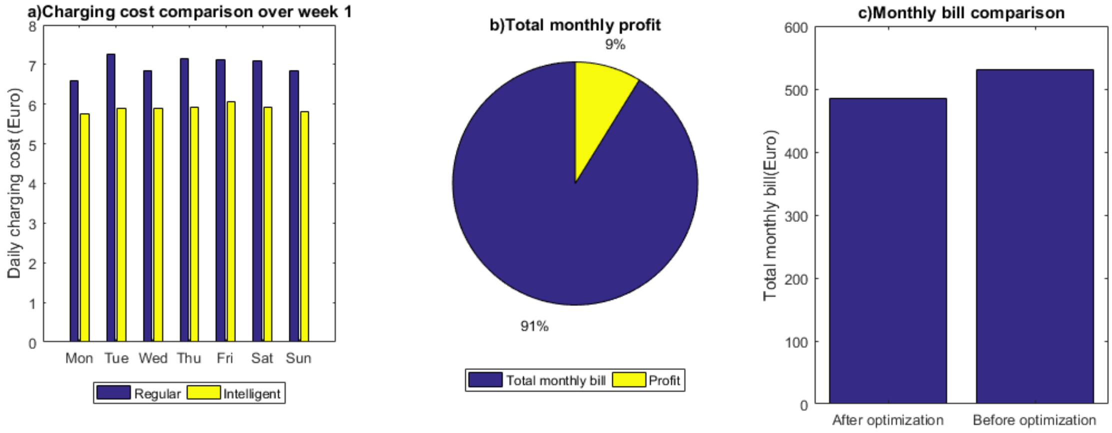


Figure 45. *Weekly and monthly cost and profit comparison of January 2018 for type-7 houses.*

All the charging events are cheaper with the intelligent charging. This week contains a public holiday (new year day). The nature of the day (holiday or weekend) does not have much effect on the results. The optimized charging cost is almost similar for all the days of the week. The average charging cost profit for charging events happening during January-April is 17.10%. Figure 45 (b and c) shows the effect of regular and intelligent charging over the monthly bill. It is calculated considering the average hourly load profile as the actual load during the month. The monthly profit shown in total bill is 9%.

Spring

During the spring, (end of April - May) household power consumption goes lower than winter as the heating load reduces (Figure 16 d). The charging power distribution for regular and intelligent charging for a holiday and typical weekdays are shown in Figure 46. Here, in most of the cases there are some power remaining in the peak hour region for smart charging. The load profile during spring has lower spikes than in wintertime. Additionally, during May 2018, there are some hours during off-peak hour region that have a higher cost than some of the peak-hours during daytime as explained in Figure 22. That leads the algorithm to choose those low-price hours from peak-hour region over the off-peak higher price hours for charging in some cases. That causes some aberrance to load shifting to typical off-peak hours. 100% of the charging loads are shifted to off-peak hour during May for type-7 detached houses.

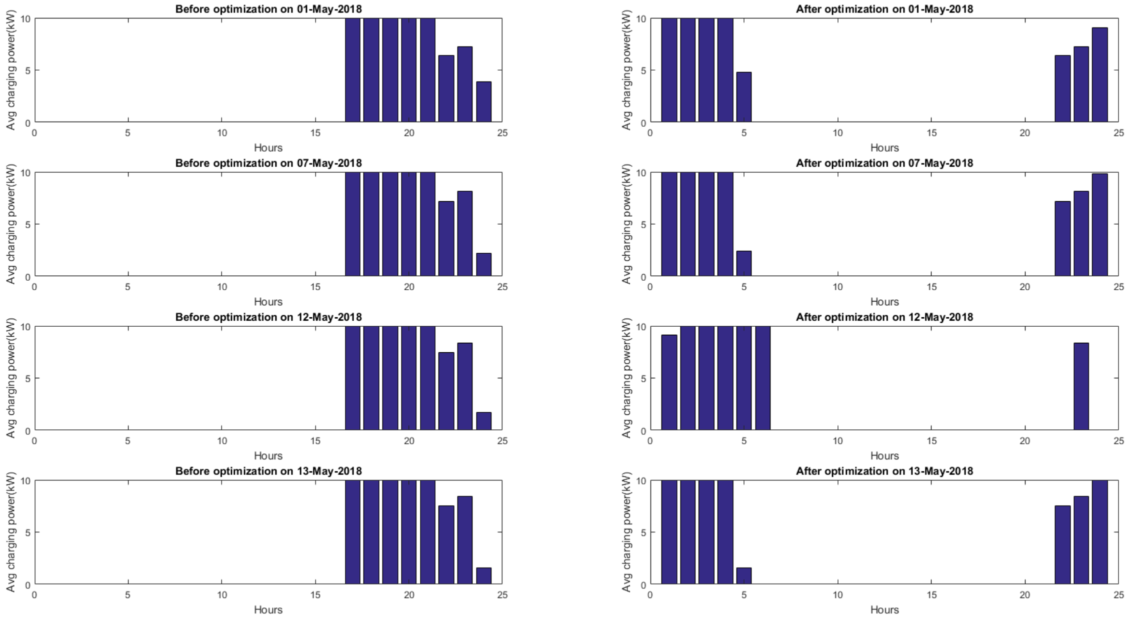


Figure 46. *EV Charging load distribution for some typical days of spring 2018 for type-7 detached houses*

The charging cost comparison graph over a week (Figure 47 a) of use shows that there are significant differences in charging cost optimization during the week. The data is taken for week 19 (7-13 May 2018). The difference in cost profit ratio is irregular in this period because of the irregular hikes in energy prices during May 2018. Average cost profit for the events in May is 22.91%. The monthly profit visible in total bills is 14% (Figure 47 b).

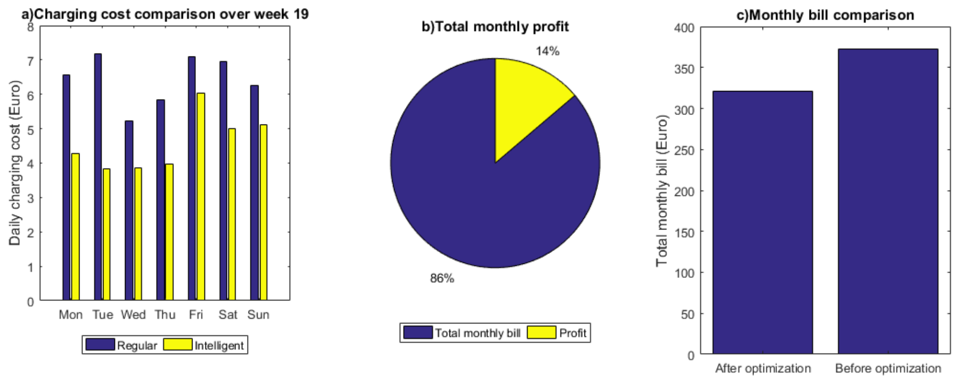


Figure 47. *Weekly and monthly cost and profit comparison of May 2018 for type-7 houses*

Summer

The simulation results starting from June changes because of the load profile as it becomes warmer than past months. Figure 48 shows one weekend and a typical weekday of summer, respectively. The storage heater load gets to its minimum of the year during the summer. Therefore, the available charging power during off-peak hours gets higher than the past cold months. As a result, the charging power load portion that is shifted to the off-peak region increases during summer.

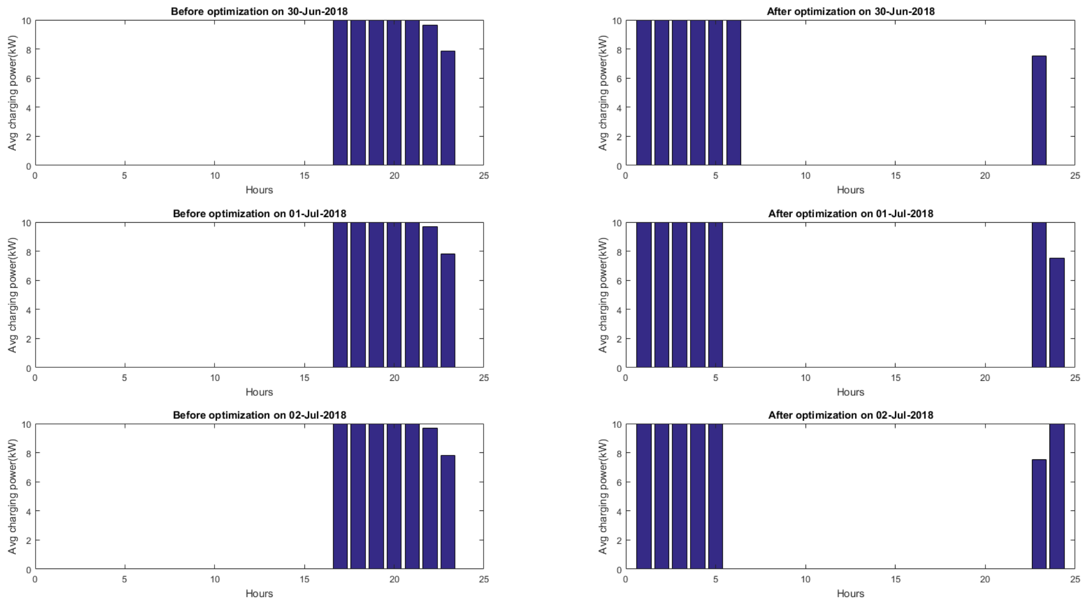


Figure 48. *EV Charging load distribution for some typical days of summer 2018 for type-7 detached houses*

Total 100% of the charging load is shifted from peak to off-peak hours during June-August.

Daily charging costs over different days of the week during summer looks steady from Figure 49 (a). The data were taken for week 28 (9-15 July 2018). The price curve looks steady during the month July 2018 (Figure 17). As a result, there is a comparatively smaller number of unusual high or low prices during the peak and off-peak hours. That explains the steady cost optimization in Figure 49 (a). The monthly profit visible in monthly bill is 10% for the month July (Figure 49 b). It is less than the spring, because of the lower volatility of the prices than in May (Figure 17). The average charging cost profit per event during June-August is 17.28%.

The effect of optimized charging shown in Figure 49 (b and c) for the month July 2018.

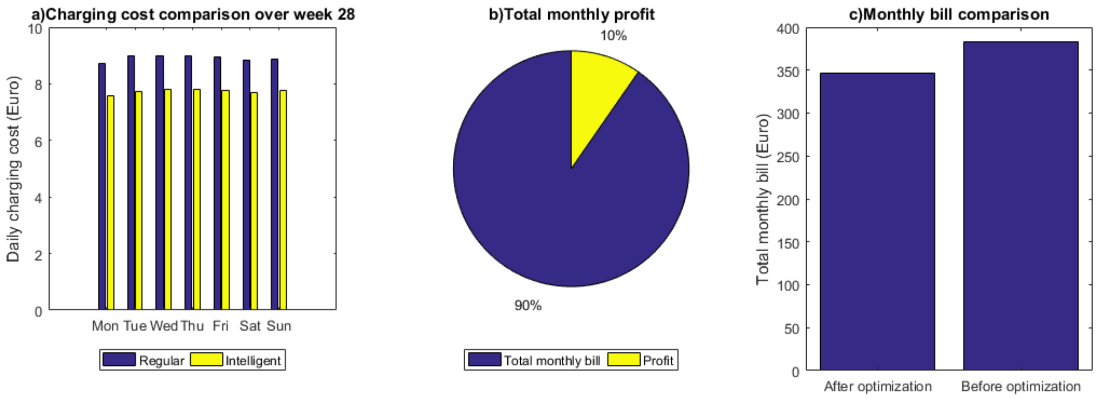


Figure 49. *Weekly and monthly cost and profit comparison of July 2018 for type-7 houses*

Autumn

Colder days approaching in autumn results an increase in electricity consumption for the household. A typical autumn week of October data shows that, intelligent charging shifts most of the peak-hour charging loads to the off-peak hour region (Figure 50). The data were taken for an autumn weekend and a weekday respectively. Total 99.81% of the load is shifted to off peak hours during October for type-7 detached houses.

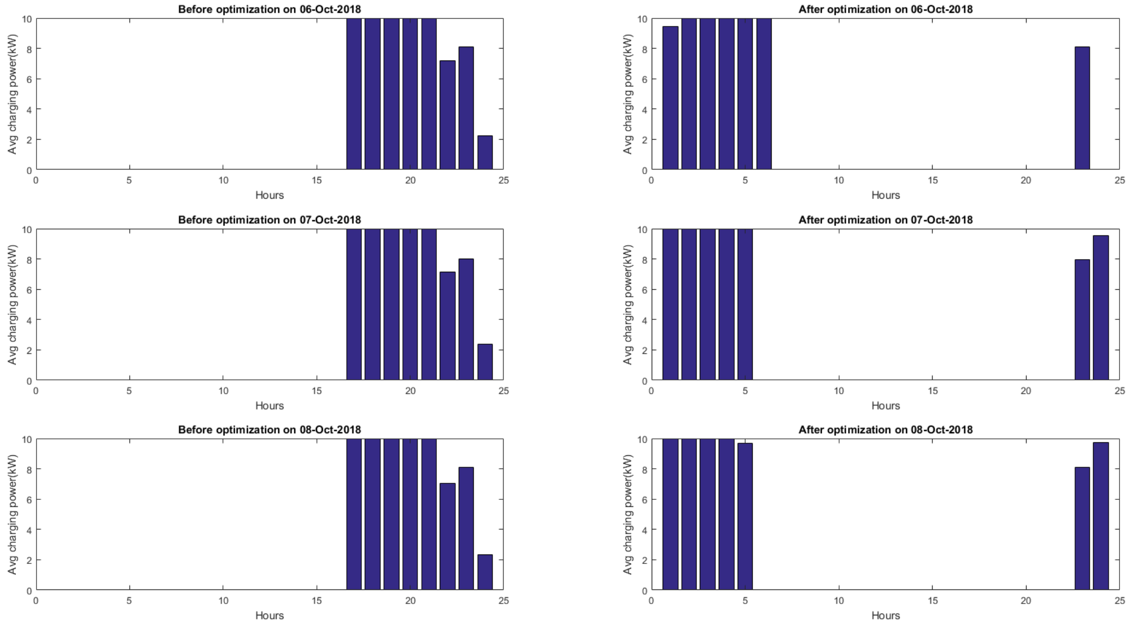


Figure 50. *EV Charging load distribution for some typical days of autumn 2018 for type-7 detached houses*

Figure 51 (a) shows cost comparison between different days of week 41. The example shows that the optimized cost is lowest during weekends. The average cost profit for charging events happening in October is 19.11% for type-7 customers. The effect of optimization over the monthly bill is shown in Figure 51 (b and c). The data is taken for the month October.

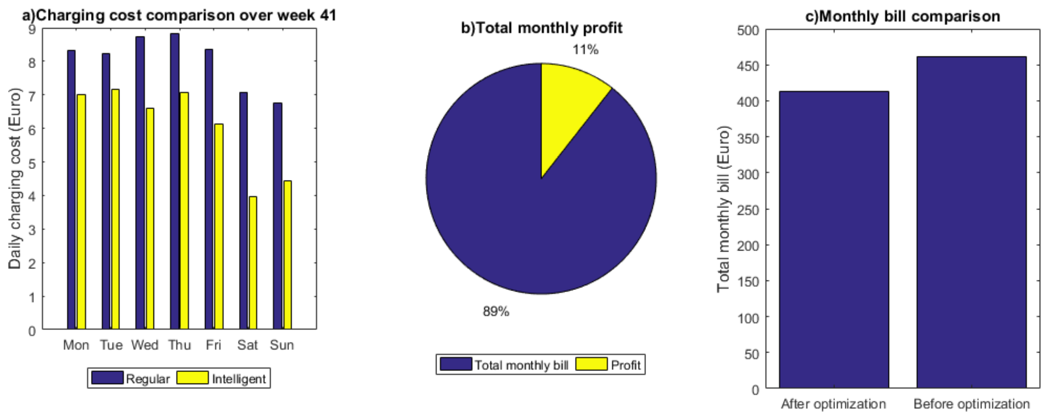


Figure 51. *Weekly and monthly cost and profit comparison of October 2018 for type-7 houses*

The overall data for the whole year for type-7 detached houses is as follows,

- 99.71% of the charging load gets shifted to off-peak hour zone during the whole year.
- Average cost for one optimized charging event is 6.88 € (not including the fixed distribution price component) and average profit is 1.44 € per event compared to regular charging.

Table 5 shows the summary of simulation results for 10 kW charger.

Table 5. *Simulation results summary for 10 kW charger.*

House type	Winter		Spring		Summer		Autumn	
	Load shifting	cost saving per event	load shifting	cost saving per event	load shifting	cost saving per event	load shifting	cost saving per event
Type-4	100%	18%	100%	23%	100%	17%	100%	19.5%
Type-5	100%	18%	100%	23%	100%	17%	100%	19.5%
Type-6	100%	18%	100%	23%	100%	17%	100%	19.5%
Type-7	99.71%	17%	100%	22%	100%	17%	99.81%	19%

In addition to the simulation presented so far, another simulation was conducted to validate the results. The second simulation was done with different charger rating of 7.5 kW. Rest of the simulation settings remained unchanged. Similar kind of results were found from this study. The summary of this study is shown in Table 6.

Table 6. *Simulation results for 7.5 kW charger.*

House type	Winter		Spring		Summer		Autumn	
	Load shifting	cost saving per event	load shifting	cost saving per event	load shifting	cost saving per event	load shifting	cost saving per event
Type-4	99.29%	13%	97.10%	15%	99.97%	12%	98.18%	13%
Type-5	99.29%	13%	97.10%	15%	99.97%	12%	98.18%	13%
Type-6	99.29%	13%	97.10%	15%	99.97%	12%	98.18%	13%
Type-7	91.44%	12%	96.89%	15%	99.97%	12%	96.61%	13%

The summery table for 7.5kW charger validates the similar results found for 10kW charger.

6.3 Limitations

The simulation was analyzed assuming that it was done with the actual data from real life. Some limitations of the simulation work are stated below.

- *Load profile data:* The average hourly load profile data used for different type of house types are the average electricity consumption in Finnish detached houses. Meaning that these profiles do not model the consumption of an individual houses as such. The size of the house, the number of occupants, and other variables that influence on the yearly energy consumption vary a lot in real life. In real life, the hourly energies vary a lot. In the used load profile list, the variability of the hourly energies is assumed to be normally distributed and standard deviation for each hour is given.
- *EV arrival time and departure time*: EV arrival time and departure time of the vehicle from facility is more random than regular in real life. Though if users would leave at the same time for work during weekdays, the assumption of this thesis would be closer to reality, but during weekend and holidays the available charging hours are more dependent on the lifestyle of the user.
- *Initial SoC*: The initial SoC can be different for EV batteries as the charging mode and driving habits are different depending on the user.

7. CONCLUSIONS

The challenges coming with electrification of transportation are significant. The existing electric generation and distribution system is very unlikely to change overnight, but with the emerging congestion of electrical power caused by charging of the newly introduced electric vehicles, a smart solution is inevitable. The solution might include the adaptation of certain behavioral changes for users. Therefore, creating enough value for the solution to user end is equally important. In this chapter the summary of the thesis is discussed, key findings from the simulation work is pointed out and future research possibilities of the topic is discussed.

Different intelligences applied to electric vehicle charging algorithm was researched in this thesis and a smart charging algorithm was developed including multiple intelligences.

The algorithm calculates the total energy and distribution unit cost for all the hours. Then it creates a charging schedule by selecting the lowest possible price timeslots for charging available within certain time, before the vehicles leaves. During this process, it calculates the available power for charging after the other domestic electricity usage of the facility (house). The hourly energy and distribution prices are set in a way that higher demand or low supply hours have higher price and lower price hours are usually the off-peak hours. By allocating charging power usage towards the low-price hours means that the algorithm takes part in demand response (DR). The developed algorithm is implemented in MATLAB.

For studying the effect of this algorithm implementation, a case study was investigated by simulating four different type of Finnish detached houses having electric vehicles in use. The houses have load profile of different ranges. These are labeled as Type-4, Type-5, Type-6 and Type-7 house. Type-4 have the lowest consumption of all house types and type-7 have the highest. An EV having 75 kWh battery with a charger rated 10kW for all types of detached houses was modeled producing large amount of result data.

After analyzing all the charging schedules found from the simulation events for EV charging the summary is listed in Table 7.

Table 7. Summary of simulation results.

Battery capacity	75 kWh			
Charger rating	10 kW			
Type of house	type-4	type-5	type-6	type-7
Load shifted from peak hours to off-peak hours (whole year)	100%	100%	100%	99.71%
Cost saved per event	17.81%	17.81%	17.81%	17.43%
Charger rating	7.5 kW			
Type of house	type-4	type-5	type-6	type-7
Load shifted from peak hours to off-peak hours (whole year)	99.14%	99.14%	99.14%	95.11%
Cost saved per event	12.81%	12.81%	12.81%	12.13%

The investigation of the whole year data suggests that the load shifting is quite successful for all the house types for different charger rating scenarios. For 10 kW charger more than 99% of the loads are shifted to off-peak hour for all the house types in general. Type-7 houses have a bit lower success rate because of unavailability of enough charging power during the low-price hours. Related to that, the cost saving scenario is kind of similar for type-4, type-5 and type-6 houses. Type-7 house cost savings are slightly low because of using more power during the high price hours.

The seasonal analysis of load distribution shows that type-4, type-5 and type-6 detached houses have similar effect of the optimizing algorithm. The optimized charging load distribution and cost saving percentages are similar for these three house types during different seasons, but for type-7, the numbers are a bit lower.

From the seasonal results, it is seen that the typical load shifting is different in cases when hourly prices do not follow the regular peak/off-peak hour pattern. Typical load shifting is referred here as the electrical load shifting from hours 7:00-22:00 to nighttime (22:00-7:00 h). This irregularity does not affect the monetary profit for customer achieved by algorithm, but it changes the expected load profile for the charging load.

The study of simulation segment from different seasons of the year shows that during the spring the algorithm has highest proportional cost saving for intelligent charging over regular charging method. After winter, the average cost benefit increases during spring to highest. Then it decreases as the summer approaches. After the hot days of summer end, the cost benefit increases again in autumn.

The aim of this thesis was to study possibilities of different intelligences related to EV charging and research them to be used in a smart charging system that establishes a good cooperation between the EV and electricity market. The rapid integration of EVs to the grid demands smart behavior from EVs as a load. New possibilities like vehicle-to-grid (V2G) integration makes the smart interaction between the grid and vehicle more important. V2G is a technology where EV can be used as an electrical energy storage. EV owners can buy the electricity from the grid and sell it back to the grid incentivized by different types of earning models. This thesis is an addition to establishment of the smart infrastructure related research that could help enabling “market based V2G technology” in the future.

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