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Analyzing the Correlation in the Behavior of Batteries in IoT Nodes, Powered by Solar Energy

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Title: Analyzing the Correlation in the Behavior of Batteries in IoT Nodes, Powered by Solar Energy

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Problem description:

On the roof of the Norwegian University of Science and Technology (NTNU) there are eight Internet of Things(IoT) nodes that measure the CO2-level in the air. These nodes are powered by batteries that are charged using solar energy. The IoT nodes sends information with a 10 minute frequency. This data contains information about the CO2-level, weather forecast, charging of the battery, battery usage, timestamps, and other relevant information in relations to the node or the battery. The objective of this master thesis is to analyze this data to see if there are any correlation between the behavior of the batteries in the different nodes; how they are charged by the solar energy, and how they use that power. After analyzing the behavior, the goal is to see if machine learning can be deployed to predict the future behavior of the batteries.

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Abstract

In the technological world we live in today, Internet of Things (IoT) is becoming more prominent. IoT uses sensor nodes in order to perform the intended task, and these sensor nodes need power. When powering IoT nodes, the usage of rechargeable batteries is the most common method. Batteries that are rechargeable, charges and discharges several times during their life cycle. This charging and discharging is for this project considered to be the behavior of the battery. For this master theses the object is to analyze the correlation in the behavior of batteries. To see if there is any correlation, and if there is, if this behavior can be predicted.

The experimenting conducted in this master thesis is testing whether machine learning models may be used to predict the behavior of the batteries in IoT nodes. Eight sensor nodes were placed outside on the roof, and these sensors were sending measurements at constant intervals. The sensor nodes are powered by batteries that are connected to solar power panels. These solar power panels are responsible for the charging of the batteries. There exists many machine learning models, so therefore the first task was to figure out which of these models could be used for predicting battery behavior. Six machine learning models were chosen for the testing. The testing was done by creating the models with help of programming code, and then running this code in the computer terminal. As a basis for the testing, large datasets with measurements from each of the batteries was used. These large datasets were created into training sets for the machine learning models to learn from in order to make predictions. After all the models had made their predictions, the task was to analyze these predictions to see if any of the models could be utilized for this purpose.

From analyzing the data sent from the batteries, it was evident that there might be a correlation between the behavior in batteries. This is however dependent on which way the solar panel connected the battery is facing. For northern places where the weather is unreliable, the panels have to be facing south in order for the batteries to charge correctly. Using machine learning models to predict the future behavior of batteries also proved to be plausible. Even though all the models did not work for the purpose intended, some of the models matched the actual data very well. To sum up, there is a correlation in the behavior of batteries if the batteries are charged at an even rate. This charging can be obtained if the solar panels are facing the correct way. Machine learning is a very

good tool for predicting future behavior of batteries, if the right model is chosen.

Sammendrag

I den teknologiske verden vi lever i i dag, er IoT blitt mer og mer fremtredende. IoT bruker sensornoder for å utføre den tiltenkte oppgaven, og disse sensornodene trenger strøm. For å gi strøm til IoT-noder, er bruken av oppladbare batterier den vanligste metoden. Batterier som er oppladbare, lader og utlader flere ganger i løpet av deres livssyklus. Denne ladingen og utladingen er for dette prosjektet ansett å være batteriets oppførsel. Målet for denne masteroppgaven er å analysere korrelasjonen i batteriets oppførsel. For å se om det er noen korrelasjon, og hvis det er, om denne oppførelsen kan forutsies.

Eksperimenteringen som gjennomføres i denne masteroppgaven, er å teste om maskinlæringsmodeller kan brukes til å forutsi oppførselen til batteriene i IoT-noder. Åtte sensornoder ble plassert ute på taket, og disse sensorene sendte målinger med jevne mellomrom. Sensornodene er drevet av batterier som er koblet til solcellepaneler. Disse solcellepanelene er ansvarlige for lading av batteriene. Det finnes mange maskinlæringsmodeller, derfor var den første oppgaven å finne ut hvilke av disse modellene som kunne brukes til å predikere oppførselen til batteriet. Seks maskinlæringsmodeller ble valgt for testing. Testingen ble gjort ved å lage modellene med hjelp av programmeringskode, og deretter kjører denne koden i terminalen til datamaskinen. Som grunnlag for testingen ble store datasett med målinger fra hver av batteriene brukt. Disse store datasettene ble laget til treningssett for maskinlæringsmodellene som de kunne lære av for å gjøre prediksjonene. Etter at alle modellene hadde gjort sin prediksjon, var oppgaven å analysere alle prediksjonene for å se om noen av modellene kunne benyttes til dette formålet.

Ved å analysere dataen som batteriene målte, var det tydelig at det kan være en sammenheng mellom oppførselen i batterier. Dette er imidlertid avhengig av hvilken himmelretning solcellepanelet vender. For nordlige områder hvor været er upålitelig, må panelene vende mot sør for at batteriene skal lade opp riktig. Bruk av maskinlæringsmodeller til å forutsi fremtidig oppførsel av batterier viste seg også å være troverdig. Selv om ikke alle modellene fungerte til det mente formålet, matchet noen av modellene de faktiske dataene veldig bra. For å oppsummere er det en sammenheng i oppførselen til batterier dersom batteriene er ladet med jevn hastighet. Denne ladingen kan oppnås hvis solpanelene vender i riktig himmelretning. Maskinlæring er et veldig godt verktøy til å forutsi fremtidig oppførsel av batterier, dersom riktig modell er valgt.

Preface

This master thesis is written as a result of the subject "TTM4905 - Kommunikasjonesteknologi, masteroppgave" at the Department of Information Security and Communication Technology (IIK) at the Norwegian University of Science and Technology (NTNU). This thesis is the final assignment of the 5-year Master of Science (MSc) program in "Communication Technology". The work for this thesis was conducted during the spring of 2018.

When first starting working on the master thesis, I originally had planned to conduct research on another topic. This because I had used the fall of 2017 on working on a different project, and intended to continue this for my master thesis. When realizing the actual extent of that project, I quickly decided that it was not a topic I would enjoy spending 20 weeks of my life to research. I therefore decided to change the topic of my master thesis, and has not regretted this decision. Although difficult, working with the problem behind this project has been very interesting and I have gotten a better understanding on especially machine learning. This I believe will benefit me.

Forst and foremost, I would like to thank my supervisors Frank Alexander Kraemer and Nattachart Tamkittikhun. For constructive feedback and help during the project. I would also like thank Poul Einar Heegaard and Katrien De Moor. They worked with me on the project during the fall, and helped me to change the topic of my master thesis to something I was interested in. Finally I would like to express my gratitude to my family and friends for helping me to keep my spirit up during this project, and for proofreading the master thesis.

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Karen Birgitte Ljones Fjærestad

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List of Acronyms

DTR Decission Tree Regression.

FCM fuzzy C-means.

IDE integrated development environment.

IoT Internet of Things.

K-NN K-Nearest Neighbor.

KRR Kernel Ridge Regression.

Li Lithium.

LIB Lithium-ion.

LiPo Lithium-ion Polymer.

MLP Multi-layer Perceptron.

NTNU Norwegian University of Science and Technology.

PCM Protection and Charge monitoring.

PEO Poly Ethylene Oxide.

RBFNN Radial Basis Function Neural Network.

RFID Radio Frequency Identification.

SOC state-of-charge.

SVM Support Vector Machine.

SVR Support Vector Regression.

TiS2 Titanium Disulfide.

Chapter 1
Introduction

On the roof of the Electro-building at the Norwegian University of Science and Technology (NTNU) campus Gløshaugen, there are eight Waspmote sensors nodes. Some of them have been up there since April 2017 and some since May 2017. Each of these sensor nodes are coupled with sensors that measures CO_2, pressure, humidity and temperature. These measurements are transmitted from the sensors to a computer every 5-10 minutes, where the data is stored. When measuring the CO_2 level, the sensor uses a heater in order to capture the gas density at a specific temperature. Because of the different measurements and the heater, the sensors requires a substantial amount of energy. To provide the energy, each sensor is equipped with a Lithium-ion Polymer (LiPo) battery [KAB+17]. As the sensors are active at all times, the batteries will be discharging and eventually run out of energy. To prevent this, a solar panel is connected to each of the sensors for energy harvesting and recharging of the battery. Five of the solar panels are facing south, and the other three panels are facing north. An illustration of how the sensors nodes look and their placement is shown in Figure 1.1. A deeper explanation of the sensors and their setup will be presented inChapter 4.

Figure 1.1: Five of the eight sensors placed on the roof of the Electro-building [KAB+17]

1.1 Motivation

In 2018, the world is more technological than it has ever been. Smartphones are owned by a large part of the population, and more and more services are executed online or through an application on the phone. Furthermore, smart houses and smart cities are getting more common, which means Internet of Things (IoT) is a part of the everyday life. When you turn on the light with your phone, or find available parking spaces in a city, this is IoT. IoT is explained in Section 3.2.1. When the world is evolving around technology and internet, the technology has to evolve also. For IoT sensor nodes to work as expected they, as mentioned in the Chapter 1 introduction, require energy. This energy may be provided using either wires directly connected to a power outlet, or by using batteries. When using batteries to power IoT sensor nodes, they have to be changed or recharged. Recharging may be done in several ways and one of them is by the use of solar energy. Using solar energy for recharging opens up to a broader use of sensor nodes because the devices does not have to be connected to any other power source. However, the usage of solar energy also presents a different kind of challenge; sunlight dependency. There has to be enough sunlight for the battery to never fully discharge, and often there is a lower battery percentage level that should not be exceeded. For this reason knowing and predicting when the battery recharges and discharges i.e. the behavior of the battery, is very interesting. This is the topic that will be addressed in this thesis.

1.2 Research Question

The energy consumption of a sensing node, and the prediction of solar energy are researches that have already been conducted. They will be presented in Chapter 2. For this master thesis the topic to be researched is the behavior of the batteries when discharging and recharging, and to see if there is any correlation. To predict the behavior of the LiPo batteries and their power percentage, machine learning will be deployed. Figuring out what machine learning models might be used for this purpose and which model fits the problem, is also a big part of the thesis. Is there zero, one, or several models that may be applied for the prediction? And if there is several, which is the best one? The research question for this thesis is to examine whether machine learning can be deployed to investigate the correlation in the behavior of batteries. If there is a pattern in the behavior making it possible to predict the power percentage for the battery at any time of the day. Is sunlight and weather to unpredictable and does this play an important part in the behavior?

To list up the problems that will be investigated:

- If there is a pattern in the behavior of the batteries

– Which machine learning models, if any, are applicable for the topic

– If it is possible to predict power percentage for the batteries

– If the battery power is dependent on the weather

The problems faced in this thesis requires both a theoretical and a practical approach. The theoretical approach consists of literary research regarding machine learning and the different models. Each model has to be understood and investigated thoroughly in order for them to be practiced correctly. The practical approach is to apply the models found in the literary research to a training dataset, in order to test and fit the models. Machine learning model has to be fitted in order to be able to do their predictions.

1.3 Outline

This master thesis has its basis from research previously conducted at NTNU and other research regarding battery behavior. These researches will be presented in Chapter 2 "Background and Related Work". Chapter 3 "Theory", is the theory basis for research and testing done in this thesis. The testing that has been conducted and the resources needed for the testing will be presented in Chapter 4 "Experiment", followed by a presentation of the results in Chapter 5 "Results". In the following Chapter 6 "Discussion" the results and testing will be further discussed. Also, in this chapter the usefulness of machine learning in this context is discussed. The thesis is completed with a conclusion in Chapter 7 "Conclusion", followed by the references.

Chapter 2
Background and Related Work

The usage of LiPo batteries is very widespread, but there are not many research papers for this exact topic. Most of the papers is about using Lithium-ion (LIB) in electric vehicles. There are also some papers where the energy consumption in IoT nodes, and where the solar energy prediction is investigated. Common for all these research papers are that they use supervised machine learning models for estimation.

2.1 Existing Work Regarding Electric Vehicles

In electric vehicles, a battery is the most common energy carrier and hence has an important role in the performance of the electric vehicle [HLY16]. Therefore, accurately knowing the state-of-charge (SOC) of the battery is very important. This is in order to predict the capacity of the battery, to figure out the range the electric vehicle may travel before the battery needs recharging. SOC is an indication of the remaining energy in a battery, and it helps to decide an effective management strategy which again may lead to avoiding overcharging or over discharging. The main methods used for SOC estimation is: the current integral method, the open-circuit voltage method, the equivalent circuit method, the electrochemical model-based method, the Kalman filter method, the extended Kalman filter method, and artificial neural network models [KZM14]. All of these models have disadvantages, so the main goal for the [KZM14] research is to figure out a more accurate way to estimate the SOC by developing a new neural network model.

Combining a new Radial Basis Function Neural Network (RBFNN) model with the life cycle model is expected to eliminate the effect battery degradation has on SOC estimation accuracy. RBFNN has three layers: the input layer, the hidden layer, and the output layer. The parameters for the input layer are current, instantaneous terminal voltage, and practicable capacity. In order to achieve the nonlinear transformation that happens from the input layer to the hidden layer, the hidden layer is established by a series of Radial Basis Functions. The output layer is the SOC estimation. When the RBFNN model estimates the SOC the first time, it uses a selected number of data samples to train the model. The model will then continue to adjust itself until all the data from the training set is being utilized. The combination of RBFNN and the life cycle model proves to have a good robustness against varying temperatures and the degradation of the battery. The research also found that it is possible to indirectly measure the aging cycles of the battery in electric vehicles with the running mileages of the battery [KZM14].

Another research that has been done, aimed at the same subject was the [HLY16] paper. The machine learning approach used here is a novel genetic algorithm-based fuzzy C-means (FCM) clustering technique. This approach provides a powerful means of modeling complex and nonlinear dynamic systems. Even though the offline training for fuzzy models is computationally intensive, established models can easily estimate the SOC of the battery in real time. This technique was used in the first step of the SOC estimation, and had incorporated subtractive clustering and direct search algorithm. In the second step, the back-propagation learning algorithm was exploited, in order to perform simultaneous optimization of the parameters. This approach had a much better precision than previously tested approaches, and demonstrated superiority in both average and worst cases [HLY16].

2.2 Solar Energy Prediction and Energy Consumption for IoT Nodes

A research conducted at NTNU was to predict solar energy for constrained IoT nodes, based on weather forecasts [KAB+17]. When the nodes are constrained they can not move around according to the position of the sun, and the prediction of solar energy is therefore important. This is because the resources has to be managed and utilized in an efficient way. Machine learning have for some time been used to predict solar power for large power plants. However, this research aims to predict for smaller sensors used in IoT hardware. As mentioned in Section 1.1 the deployment of IoT nodes is simpler when they have energy available at all times, which energy harvesting may provid. When predicting solar energy based on weather forecast, planning the energy-budget becomes more effective. Energy-budget planning is important when it comes to resource-constrained IoT nodes. Another observation made in this paper is which machine learning model may be used for this purpose.

Another paper by some of the same authors as [KAB+17], also from NTNU, discussed energy consumption estimation for sensing applications [THK17]. Here an approach for figuring out the estimation of the energy consumption of nodes in IoT sensing applications is proposed. This estimation is important because the energy budget for the sensors determine and limits how much sensing and processing can be done by the nodes. Distinctive activities phases, that the sensors execute repeatedly was identified, and the energy consumption for these different phases were measured before the nodes were deployed. Then the total consumption was estimated by combining the measured values with the timestamps for when the application was running, i.e the nodes were sensing. The approach in this paper was done without any additional hardware to measure the energy when the nodes were deployed. This research discovered major differences in the energy consumption for the different activity phases, where the sensing activity required the largest part of the energy-budget. The accuracy of the approach was sufficient enough for it to be applicable for further use [THK17].

Chapter 3

Theory

This chapter contains the theory behind this master thesis. Here the different aspects mentioned in the previous chapters will be explained further, to better the understanding for the thesis. LiPo batteries, solar energy and machine learning are the main subjects that will be presented in this chapter.

3.1 Lithium-ion Polymer Batteries

Lithium batteries are batteries that uses the metal lithium as an anode. They are widely used in consumers portable electronic devices. These batteries are considered to be primary batteries, which means that they are disposable and not rechargeable. Lithium-ion (LIB) batteries are secondary batteries, which means that they are rechargeable. These batteries consists of lithium ions that move from the positive electrode to the negative electrode when charging, and the opposite way when discharging. In order to make LIB batteries rechargeable, they consist of intercalated[1] lithium, compared to disposable batteries which consist of metallic lithium.

LiPo batteries are also rechargeable batteries. Unlike a LIB battery, which uses a liquid electrolyte, a LiPo battery uses a polymer electrolyte. This polymer is a semi solid electrolyte, which can be described as gel, that has a high conductivity. Conductivity is a measurement for a material's ability to conduct electric current. The use of polymer electrolyte causes these batteries to be light in weight, as other lithium batteries. In difference from other lithium batteries that is not high performance energy sources, LiPo batteries have a high voltage and the ability to supply high current [Gib09].

3.1.1 History of Lithium Batteries

The progression of any device is influenced by its past history [Scr13]. This is also the case for lithium batteries. In 1800 a dispute between professors Alessandro Volta

[1] Intercalation is the insertion of a ion (or molecule) into materials with layered structures

and Luigi Galvani was the initial start of electrochemical science, that eventually led to the lithium battery that is widely used today. As a result of Volta's work, many electrochemical systems was invented: zinc-manganese oxide cell invented in 1866, lead-acid rechargeable battery invented in 1859, and rechargeable nickel-cadmium battery invented in 1901. All of these systems are still used for developing commercial batteries designed for different applications, by making changes to the original concept. An example of this is the common alkaline battery. In this battery type the zinc-manganese oxide cell form 1866 was altered by changing the electrolyte from a liquid to a mixed manganese dioxide-carbon paste. The zinc rod was changed to a core of mixed powdered zinc and electrolyte paste, and the container was changed to consist of stainless steel. Alkaline batteries are widely used and billions of units are produced every year. Lead-acid batteries have also been altered and are mostly used for car lighting and ignition [Scr13].

After discovering lead-acid, nickel-cadmium and alkaline batteries the innovation regarding batteries decreased. Only minor changes were made with the already existing battery types. This continued until the 1960s when the demand for energy to portable devices triggered a series of innovation. When the demand for portable electrics escalated, there was a need for batteries with a high energy density. Until now, conventional batteries had a low energy density because of their electrode combinations. The electronic combinations in the original batteries could only offer a limited specific capacity value, measured in ampere-hours per gram (AH/g), which gives a low energy density. Figure 3.1 is an illustration of the relation between energy density and specific density for a variation of batteries. Batteries that have a high energy density have more energy for each weight unit, which makes it light in weight. Batteries that have a high specific density have more energy in a specific space, which makes it small in size. A battery intended for the electronics marked should both have a high energy density and a high specific density, in order to be as light and small as possible. This means that the batteries closest to the upper right corner, which are lithium batteries, are the preferred batteries for portable devices and are also the most promising for electrical vehicles. The previously mentioned batteries that were invented in the late 1800s, are located in the bottom left corner and are considered to be big and heavy. Therefore, they are not ideal for the new technology that was evolving [Scr13].

Initially, lithium batteries was developed as primary batteries. When technology developed further, and the lithium batteries became a success, the interest in secondary rechargeable batteries increased. To create rechargeable batteries, difficulties had to be acknowledged and changes had to be made. Lithium ions formed when the battery discharged were expected to plate back onto the lithium metal in charge. Therefore, the anode side was considered to have no apparent difficulty. Focus was thus directed to the cathode side. The intent here was to find materials that would

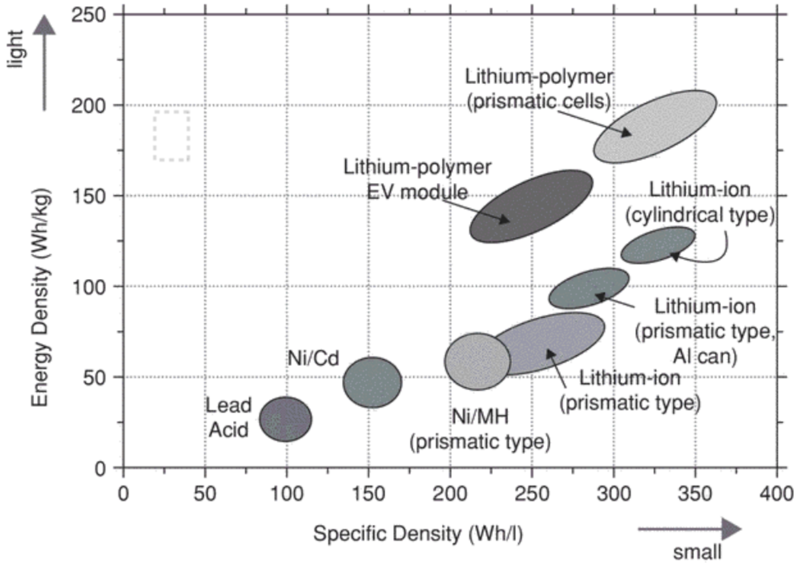

Figure 3.1: Energy density vs. specific density for several types of batteries [Scr13]

have a long life cycle. In 1978 intercalation electrodes were developed. This was a compound that reversibly accepted and released lithium ions from their open structure. These conditions was met by, for instance, Titanium Disulfide (TiS2). Li-TiS2 was therefore a good alternative for the cell in a rechargeable battery. The process of a Li-TiS2 cell involves lithium oxidation at the anode, which is when lithium ions forms and travels through the electrolyte to the cathode where the ion is inserted into the layered structure [Scr13]. This structure and process is shown in Figure 3.2.

After rechargeable lithium batteries became a success, the development of new types of rechargeable lithium batteries started in the 1980s. One of the ideas that was discussed was to use conducting polymers as positive electrodes. The interest around this faded some when it was discovered that polymer had a poor electrochemical behaviour. First the use of polymer electrolyte was examined as a solid state. This was done by forming an aggregate between a lithium salt and a coordinating polymer like PEO. During the process, the lithium salt is dissolved in the Poly Ethylene Oxide (PEO) matrix. The main difference from liquid electrolyte is that in liquid ions can move in their salvation shell, but this is not possible in PEO because of the large size and constraints of the polymer chains. Transport of ions in the polymer electrolytes therefore requires a flexibility in the PEO chains, so that the ions can move from one loop to the other. Fast ion transportation may only happen when the polymer is

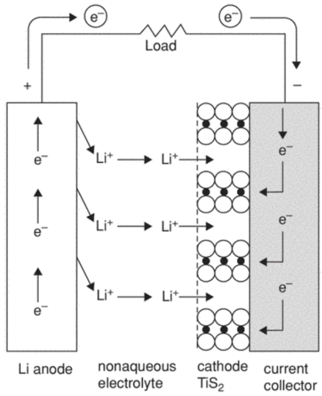

Figure 3.2: The structure of a Li-TiS2 cell [Scr13]

in amorphous state, which happens when it goes above 70°C. This condition makes PEO-based polymer batteries less applicable. After realizing that solid polymer electrolyte based on PEO had a low conductivity, the development of gel polymer electrolytes started. To create the gel, liquid electrolyte is introduced in order for the polymer to be softened. This produces solid polymer electrolyte with a high conductivity, almost as high as with liquid electrolyte. This gel based electrolytes are the base of today's lithium batteries that are used in electrical consumer product e.g. cell phones, tablets and other highly technological devices [Scr13].

3.1.2 Properties of a Lithium-ion Polymer Battery

LiPo cells are made up of several thin plates that are connected in parallel. This makes the internal resistance in the cells low, and LiPo batteries are therefore suited for high discharge rates. Therefore, a LiPo battery with the same weight as a nickel based battery will contain much more stored energy. In a LiPo cell, as shown in Figure 3.3, there are three components: the anode, the cathode, and a separator. The anode is the negative plate and the cathode is the positive plate. Both plates are primarily made of lithium, and the separator is made of polymer with a conductive electrolyte. Because the plates are very thin and the case around the cells is simply thin foil, LiPo batteries are easily damaged by impacts [Gib09].

Table 3.1 gives a comparison of a nickel based battery and a LiPo battery, and their different properties. Here it is visualized that a LiPo battery has a bigger ability to sustain a high discharge rate, because of its ability to have a low internal resistance. But, it is also more risky if not used correctly. LiPo cells are unable to release any of the pressure that can build up inside the cell. The case around the cell will therefore "puff up" when the battery is under pressure. This can happen for several reasons,

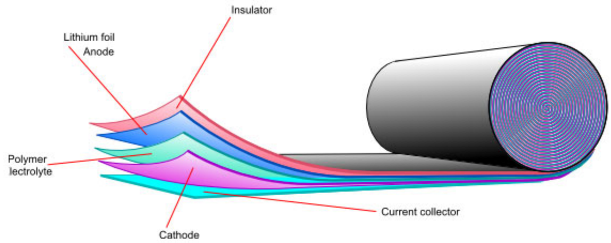

Figure 3.3: The structure of a LiPo cell [Kai13]

Table 3.1: A comparison of a nickel based battery versus a LiPo battery [Gib09]

Property	**NiMH**	**LiPo**
Nominal voltage per cell	1.2 Volts	3.7 Volts
Internal resistance	Moderate	Can be very low
Normal maximum continuous discharge current	Up to 10C	Up to 30C
Normal maximum charge current	1C-2C	1C (or higher if approved)
Capacity per weight unit	Moderate	Very high
Overall safety	Very high	Much lower if not used correctly
Overcharging	Allowed at C/10 only	Dangerous
Tolerance to over-discharging	Limited	Very poor
Life cycle (durability)	Limited	Good

for instance overcharge and damage to the battery. If the pressure is to much for the container, the cell may blow up and burn. As seen in Table 3.1, normal voltage for a LiPo cell is 3.7V which is far higher than for several other battery types. When it is fully charged the voltage increases to 4.2V, and decreases to 3.0V for whent it is fully discharged. This small difference in voltage makes it difficult to decide the state of charge (in percent) by measuring the voltage. Internal resistance is related to the battery's state of charge. When the battery is in a high state of charge the internal resistance will be low, and the other way around. LiPo batteries are sensitive to the temperature and the internal resistance is lowest when the battery is warm. They are therefore considered to have a poor performance when they are too cold [Gib09].

When LiPo batteries are charging the cells have two requirements: charge current has to be limited to a safe value, and the cell voltage must not exceed 4.2V per cell. Because of these requirements, LiPo batteries have a different technique for charging than other cell types and must use a charger intended for LiPo batteries. The charging process has three phases. The first phase is when the charging starts, some chargers skip this phase. Here the charging current increases gradually until it reaches the required value. The battery voltage rises throughout this phase. In the second phase the charging current shifts to consistent. but the voltage continues to rise towards the maximum safe value of 4.2V. The last and third phase is when charging happens at a almost constant voltage. The battery is now almost fully charged, so the charge current is reduced to approach the maximum voltage at a safe pace. Even though this phase is said to have a constant voltage, the voltage is still increasing only very slowly. When the charge current is approximately C/20, the battery is considered to be fully charged and the charging process is completed. Figure 3.4 shows this charging process, with the different colors representing charging current, voltage, and energy capacity. Normally the charging rate used for LiPo batteries is 1C, and this was the maximum charging rate until recently. To extend the battery life it is recommended to not charge at the maximum rate. The batteries should not be charged if they are very warm or very cold, this could be dangerous [Gib09].

When LiPo batteries are discharging, they should never have a voltage level lower that 3.0V. In the earlier years 2.5V was considered to be the lowest voltage level, so it is expected that 3.0V will be considered to be a too low voltage in the future. To increase the battery's life expectancy, it is recommended to not go any lower than 3.3V. A slightly over discharge, only happening once, is not likely to have any effect on the battery. Although, if a damage does occur it can not be reversed, and the battery is therefore permanently damaged. This damage may happen if the battery is frequently over discharged or if it has been very over discharged. The discharge rate is affected by the available capacity of the battery. When the discharge rate is faster, the capacity is lower. In comparison to nickel based batteries, LiPo batteries can keep their charge over a longer time when it is not being used. When a battery is discharging it is recommended to not discharge lower than 20% to give it a longer life expectancy.

3.1.3 Safety Regarding Lithium Polymer Batteries

Since the invention of LiPo batteries, the safety regarding them has been widely discussed. These batteries, if not used correctly and carefully, can be dangerous. Because of the usage of LiPo batteries in many electrical consumer products, it is important to be aware of the uncertainties regarding the batteries. When in an electrical product, such as cell phones and tablets, each individual LiPo cell is carefully monitored and controlled by Protection and Charge monitoring (PCM) circuits. These circuits are there to prevent the battery from exceeding the safe voltage range, or to prevent it from being mishandled. Because of the PCMs and

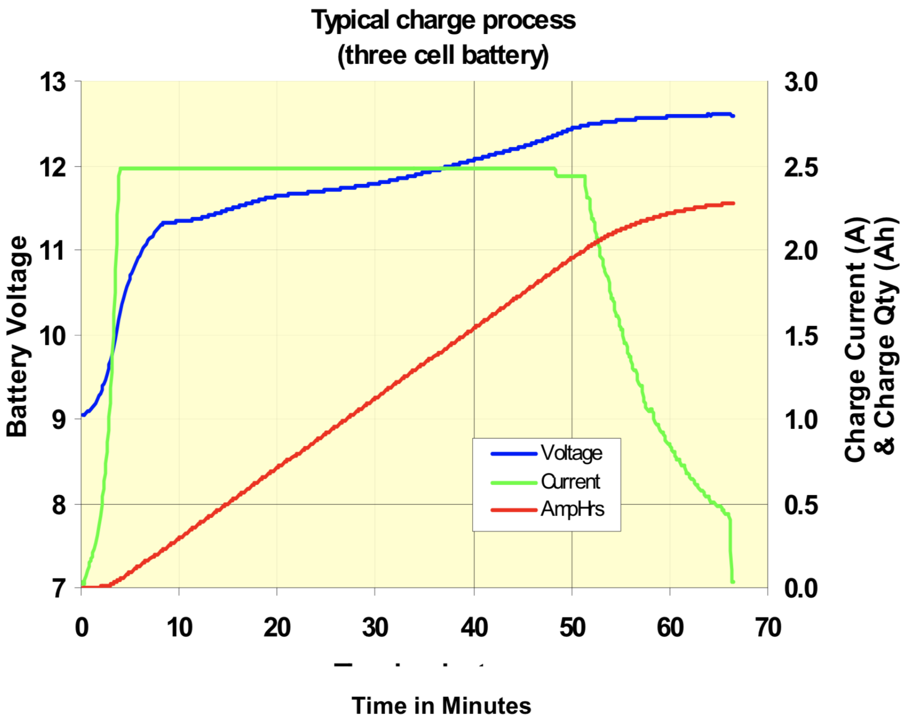

Figure 3.4: The charge process of a LiPo battery. The green line is the charge current, the blue line is the voltage, and the red line is the energy capacity of the battery [Gib09]

the low charge and discharge rate, accidents regarding LiPo batteries in consumer products are very rare. However, if an accident does occur, the possible consequences of a LiPo battery accident is more serious than with other battery types. For instance if a nickel based battery overcharges it might get hot, but if a LiPo battery overcharges it might start to burn [Gib09].

A fire in a LiPo battery may happen due to of several causes. When the battery is overcharged in voltage, i.e. the voltage exceeds 4.2V, this might result in damaging the cell. This again may result in an internal short circuit which can cause the battery to be set on fire. Over discharging is another cause for fire in a LiPo. At best over discharging only results in a capacity loss, but it is known for causing the battery to "puff up", get hot and even start to burn. In a battery there can be several cells. To not cause the battery to overcharge or over discharge, it is important to make sure that the battery is balanced. This is done by using balancing equipment to prevent two neighboring cells from not having a similar state of charge. As mentioned in

Section 3.1.2, batteries can operate with different discharge rates. If the rate is to high, this might cause the battery to overheat or "puff up". The most sever result could be a short circuit in the battery. Short circuits happens when the positive and negative wires in the battery come in direct connection with each other. In this case a high current can flow quickly, making the battery very warm. Short circuits have to be avoided because they cause a high risk of damage and fire. The safety concerns mentioned in this section has all been internal in the battery, but causing damage to the external of the battery may also lead to dangerous situations. The casing of the LiPo battery can handle a minor damage, but if the damage is to severe this may damage the cells of the battery resulting in a short circuit. Batteries should also not be stored in a warm place, because this may lead to overheating and fire [Gib09].

3.2 Solar Power

In 1839, a discovery was made by Edmond Becquerel. He observed that if two different brass plates, that was submerged in liquid, would produce a continuous current if they were exposed to sunlight. This is the first known discovery of solar cells, which evolved into the solar cells known today. In the late 1970s and early 1980s solar power was mostly used for remote locations where utility power was unavailable. In the early 1990s, solar power started to be utilized in suburban and urban homes and office buildings. Today, solar cell electricity is considered to be the cheapest and best way to generate electricity for most power needs [FP10].

Solar power is the conversion of sunlight to electric current. The sun and sunlight is filled with energy. This energy is free of charge and will not run out, at least not as we know. When the sunlight hits an object the energy is converted to heat, which is why being in the sun is warmer than being in the shadow. But for certain objects, the energy is not converted into warmth but rather converted into electrical current. This electrical current can be harvested and stored for power. The solar technology developed in earlier years used large crystals made of silicone. This produces electricity when it is struck by light, because the electrons in the crystal move around when exposed to light instead of only wiggling in the same place to make heat. Crystals made of silicone creates a lot of electricity from the light, but is expensive to use because big crystals are hard to grow. Newer solar technology uses smaller and cheaper crystals, e.g. copper-indium-gallium-selenide, that can be shaped into a flexible film. This technology however, is not as good as silicone for turning the light into electricity [Loc08].

Figure 3.5 is an illustration of the process of harvesting solar energy. In a crystal in the solar sell, bonds are made of electrons that are shared between every atom in the crystal. When the cell absorbs the light, one of the electrons gets excited and reaches a higher energy level. The result is that this electron can move around in the

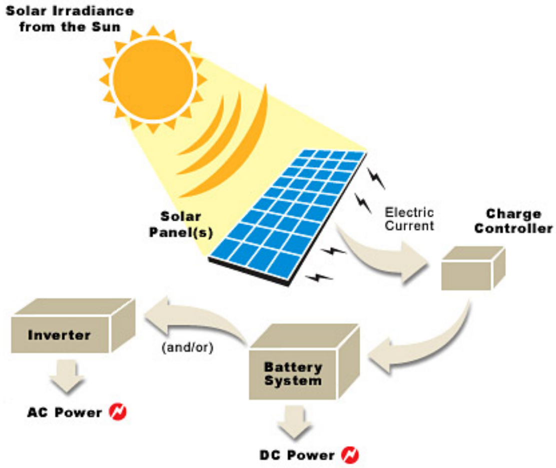

Figure 3.5: An overview of the process regarding collecting solar power [Kit11]

crystal more freely, which leads to current [Loc08]. After the sunlight is converted into electric current the current is transferred to a charge controller. This controller helps to properly manage the voltage flowing to the battery, making sure that the battery does not overcharge. The energy is then stored in the battery, which may be charged and discharged several times. When converting sunlight into electricity, direct current is the result. However, if the desire is to power devices that is plugged in to the wall, the current has to be alternating current. To convert the current from direct to alternating, an inverter is used.

3.2.1 Solar Power in Connection to Internet of Things

IoT was a term first used to describe a system where physical objects could be connected to the Internet using sensors. The term was used to illustrate the power of connecting Radio Frequency Identification (RFID) tags to the Internet to count and track goods without needing human intervention. Today, IoT is a popular term to use for describing scenarios where Internet connectivity and computing capability is extended to a variety of devices, sensors, and everyday objects [MP16]. There are a lot of definitions to describe IoT, and this is one of them:

> *The term "Internet of Things" (IoT) denotes a trend where a large number of embedded devices employ communication services offered by the Internet protocols. Many of these devices, often called "smart objects," are not directly operated by humans, but exist as components in buildings or vehicles, or are spread out in the environment [MP16].*

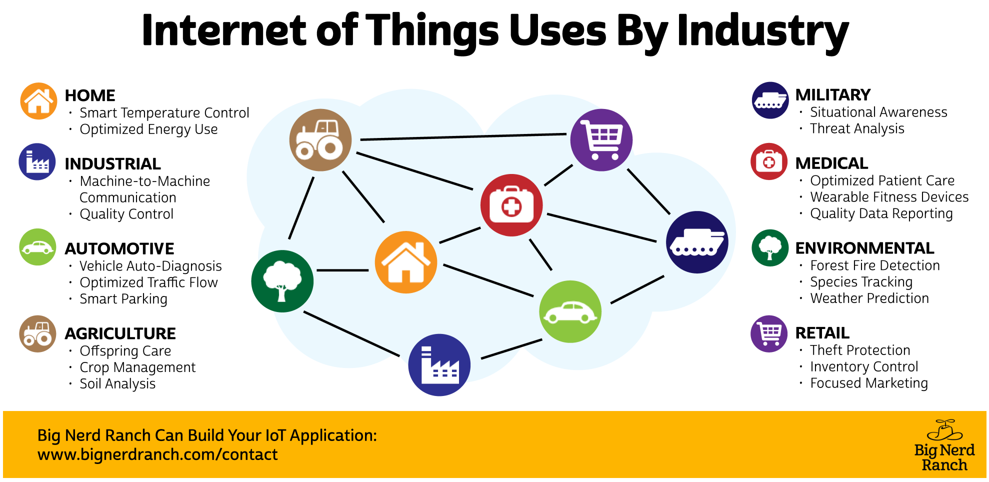

Figure 3.6: An illustration of the usage of IoT by different industries [Hil16]

The utilization of IoT may be very diverse. Figure 3.6 contains several industries and the way IoT may be deployed in that particular industry. Here the diversity of IoT is very evident. IoT may be used in a private home, in business or the industry, or may even be used in the military. Because of the world developing rapid in terms of technology, embracing and developing IoT for a business is crucial in order to compete in the market.

For an IoT device to function, it needs power. Often these devices are powered with batteries, which would need to be recharged when empty. This is where solar power enters the picture. If the IoT device has to be active at all times, it would also need to be powered at all times. Solar energy is, in most cases, a dependable source of energy. The sun is always up during the day, and even on light cloudy days the solar panels will gather some light and convert this to power. There are negative sides of solar power also. Solar panels are very dependent on sunlight, and if the panels are located in a area where the sunlight is limited this could cause problems. The angle and tilt of the panel is also included in the factors that may affect the utilization of solar panels [KAB+17].

3.3 Machine Learning

A process of learning includes acquiring new knowledge, organizing the new knowledge, developing new cognitive and motoring skills through practice, and discovering new facts and theories through observation and experimentation [MCM13]. Since the invention of computers, the capability of learning have been attempted to be implemented in computers. This process of computers having the capability to learn is called machine learning.

Machine learning is revolved around the problem of predicting the future. This became feasible when researchers started approaching intelligent tasks in an empirical way, instead of using the procedural way. Machine learning predictions does not respond well to hard-wired rules, but rather training by using known datasets and making functions from these training data. The purpose of using machine learning is to discover structures and patterns in data, and to generalize this discovery. It fits complex and flexible functional forms without overfitting [MS17]. Machine Learning is now so widely known that there are simple explanations for every model that exists and how to use them. This makes machine learning a very applicable tool, in order to do predictions and analyzing data.

There are three main areas machine learning can be divided in to: Task-Oriented Studies, Cognitive Simulation and Theoretical Analysis. Task-Oriented Studies is also known as the "engineering approach" and is a method to improve the performance in a fixed set of task by analyzing learning systems. Cognitive simulation is when the computer is taught to simulate the learning process of a human. The last area is Theoretical Analysis which is an exploration of the possible learning methods and algorithms independent of the application domain [MCM13]. It is preferable to utilize only one of these approaches, however the progress of one approach often leads to the progress of another approach.

3.3.1 Types of Machine Learning Models

Machine learning is a wide term that includes many different algorithms, or methods, that may be used for different purposes. These methods may be divided into two main areas: supervised learning, and unsupervised learning. Unsupervised learning may again be divided in three: feature learning, generation, and clustering. Supervised learning could be divided into: regression, and classification. These different areas is illustrated in Figure 3.7. As mentioned in Section 3.3 machine learning is used for prediction based on training datasets. In supervised learning or "learning with a teacher", the predictions are based on a training set from previously solved cases. The previous solved cases have known values that are created by joining all variables. A training set is created by the machine learning algorithm predicting an already known output (answer), and is then told whether it is correct or not. In unsupervised learning or "learning without a teacher", the algorithm has a set of known observations, but the correct output is not known [HTF09]. For this section the focus will be on regression from the main area of supervised learning.

Regression is the process of figuring out and estimating the relationship between

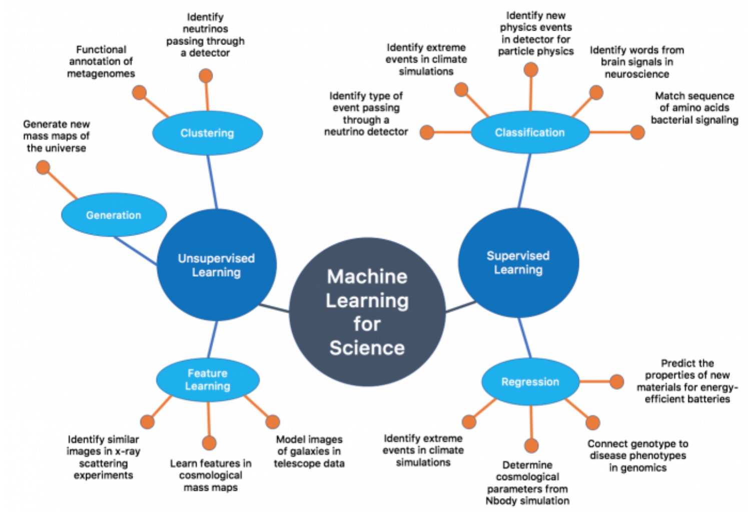

Figure 3.7: The different areas in machine learning [NERwn]

several variables. It focuses on the relationship between a dependent variable and independent variables, also called predictors. Regression is a way of figuring out how the dependent variable will change when one of the independent variable changes. Next, the machine learning models used for this thesis will be presented.

Linear Regression

In linear regression the goal is to predict a linear(straight) line, which fits the points in a given dataset in the best way possible. One variable, called criterion variable, is predicted using another variable, called the predictor variable. If there is only one predictor variable, the method is called simple regression. This is the method that gives the straight line, which is called a regression line. When using linear regression the predicted regression line may have an error to the actual points in the dataset. This error is calculated by subtracting the predicted point value from the actual point value. The best fitting regression line will be the line with the lowest sum of the squared error values. Figure 3.8 shows an example on how a plotted linear regression might look. The black points are the dataset input for the regression, and the red line is the fitted regression line output [Gér17].

Support Vector Regression

Support Vector Machine (SVM) is a very adaptable and powerful machine learning model. This model can perform classification, regression, and outliers detection. This is one of the more popular machine learning models to utilize [Gér17]. SVM

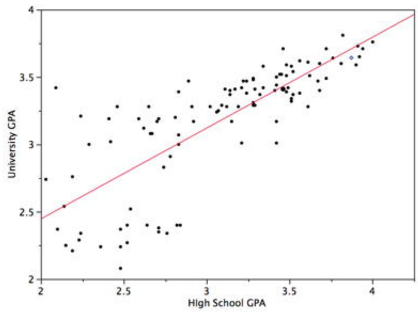

Figure 3.8: An illustration of a Linear Regression prediction plot [Lan03]

are effective in high dimensional spaces, even when the number of dimensions is higher than the number of samples. The model uses a subset of the training points, called support vectors, in the decision function. Therefore, the model is very memory efficient. A disadvantage with SVM is that it does not directly provide probability estimates. The estimates are calculated by using an expensive cross-validation [PVG+11].

SVM can, as mentioned, perform more than one task. One of these is regression. This is called Support Vector Regression (SVR). SVR may be both linear and nonlinear. The linear model only considers the linear kernels, while the non-linear model considers all kernels. Instead of trying to fit the largest possible street between two classes, SVR tries to fit as many instances possible on the street. The model that SVR produces, predicts by only using a subset of the training data. This is because the cost function for building the model does not care about the training point that lies to close to the model prediction. The model predicts with two chosen values: epsilon (ϵ) which defines a tolerance margin where errors are accepted without a cost, and gamma (γ) which decides how strict the model fits to the training set. A too strict model could result in overfitting [PVG+11].

Kernel Ridge Regression

Ridge regression is a regulated version of linear regression, where a regularization term is added to the cost function. This results in the algorithm not only fitting the data, but also making the model weight as small as possible [Gér17]. Kernel Ridge Regression (KRR) is an regression algorithm that combines Ridge regression with kernels. It learns a linear function in a space generated by the kernels and the dataset. The form of the KRR creates is identical to the form SVR creates, but the models use different loss functions. KRR uses a squared error loss, and SVR uses ϵ-insensitive loss. Fitting KRR is typically faster for medium sized datasets, and the fitting can be done in closed-form. More precisely, fitting KRR is about seven times faster for medium datasets than SVR. However, the model is non-sparse and uses all the points in the training data for prediction. Therefore, it is slower than SVR, which is sparse, on large datasets [PVG+11]. The reason for the KRR being slow for large datasets is because when computing the regression, the kernel matrix has to be inverted. This requires large costs in time and memory [ZDW13]. The model predicts with two chosen values: alpha (α) which helps the conditioning of the problem to improve and reduces the variance of the estimates, and gamma (γ) that also here represents how strict the prediction is [PVG+11].

K-Nearest-Neighbor

K-Nearest Neighbor (K-NN) is a prediction algorithm that stores all available data and makes a prediction based on a similarity measure. This method was utilized already in the 1970's for statistical estimation and pattern recognition, but as non-parametric. One approach when using K-NN regression is to calculate the average of the numerical target of the K nearest neighbors. Another is to use inverse distance weighted average of the K nearest neighbors. The regression method uses the same distance function as K-NN classification. The difficult part of K-NN regression is to choose the optimal value for K. This could be done by inspecting the data first. A larger K value will be more precise as it reduces the noise, but the distinct boundaries in the feature space will be blurred [Say10]. To figure out which points are the nearest neighbors, metric distance is used to calculate the distance. Any measure method may be used, but Euclidean distance is the most common. Methods based on neighbors are non-generalizing machine learning methods, because they remember all the training data [PVG+11].

Decision Tree Regression

Decission Tree Regression (DTR) is to fit a sine curve with observing noisy addition. The main difference from decision tree classification is that instead of predicting a class in each node the regression predicts a value. DTR predicts the average target value of the training dataset. The algorithm in the model splits each region in the training set which makes most training instances as close as possible to the predicted value. DTR is prone to overfitting and has to be regularized in order to prevent this [Gér17]. Overfitting happens when the maximum depth of the tree is set to high, which leads to the decision tree learning too fine details of the training data and therefore learn from the noise [PVG+11].

Multi-layer Perceptron

Multi-layer Perceptron (MLP) is a neural network machine learning model. The algorithm learns a function by training on a dataset with a decided number of input dimensions and output dimensions. Between the output and input layer there can be, in difference to logistic regression, one or more nonlinear layers. These layers are called hidden layers. The input layer consists of a set of neurons that represents the input data. In the hidden layer each neuron transforms the values from previous layers with a weighted linear summation that is followed by an activation function that is non-linear. Finally the output layer receives the value from the last hidden layer and transforms these values into output values. The MLP has the potential to learn non-linear models, and to learn models in real-time. MLP also has some disadvantages. Because of the hidden layers, the MLP have a non-convex loss function where more than one local minimum exists. This can cause different random weight initialization which can lead to different accuracy for validation. MLP also requires determining a number of hyperparameters, for instance the number of hidden neurons, layers, and iterations [PVG+11].

Chapter 4
Experiment

An important part of this master project is the testing of the different machine learning models found in the literary review to see if they are usable for the intended purpose. The sensors that were presented in Chapter 1 were the basis of the project. As mentioned, they transmitted data every 5-10 minutes that included measured CO_2 level, pressure, humidity and temperature. This was not the only data transmitted from the sensors. To keep track of the resources connected to the sensors, all the statistics involving time and date, and energy power was also transmitted. This included among others battery percentage, battery voltage, seconds from midnight, solar charge, sunrise and sunset. These latter measurements are the ones used as parameters for creating the different machine learning models.

The IoT sensor nodes from the roof had been transmitting data for a long period of time. Therefore the datasets that were the basis for the training set were very large. They also had some missing data at some points and were not homogeneous. So the first step before actually starting to design the models, was to clean the datasets and make them homogeneous. From viewing the large datasets it was decided that the results would be more straightforwardly if the batteries was tested separately. This was because even though the batteries shared behavior, they had different battery percentage at different times and it would not be possible to fit the machine learning models.

To create the machine learning models the programming language python was chosen. PyCharm was used as the python integrated development environment (IDE), and the models was inspired by the Scikit-learn library. Running the tests was done by using the computer terminal to run the programming code. The machine learning models used for testing are the ones presented in Section 3.3.1. The figures for this chapter is based on only one battery that is facing south. However, in Chapter 5 the results from one battery facing north will also be presented.

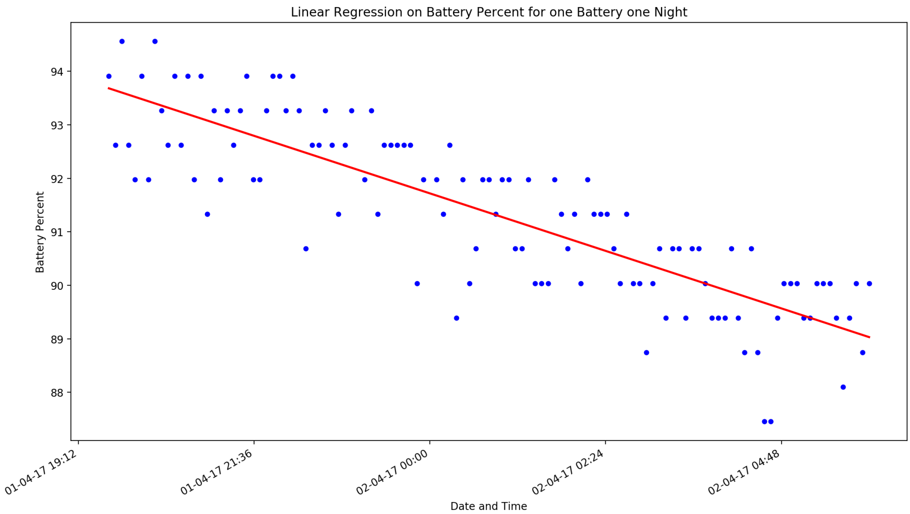

Figure 4.1: One night with linear regression

4.1 Testing During Nighttime

The first part of the testing was conducted using only data from when the sun was down. During nighttime the battery would not recharge because of the lack of sunlight and this would make it easy to get an overview of the discharge rate. Figure 4.1 is a presentation of the dataset for one battery during nighttime with a linear regression model applied.

4.2 Testing During Daytime

After looking at the data for the battery during nighttime, viewing the data only when the sun was up was the next step. This was to better understand the charging and discharging during daytime, and to better understand the curve. Figure 4.2 presents the dataset for the charging and discharging only when the sun is up. The dataset in the figure is combined with linear regression, KRR, and SVR. Linear regression is the red line, KRR the yellow line and SVR is the green line.

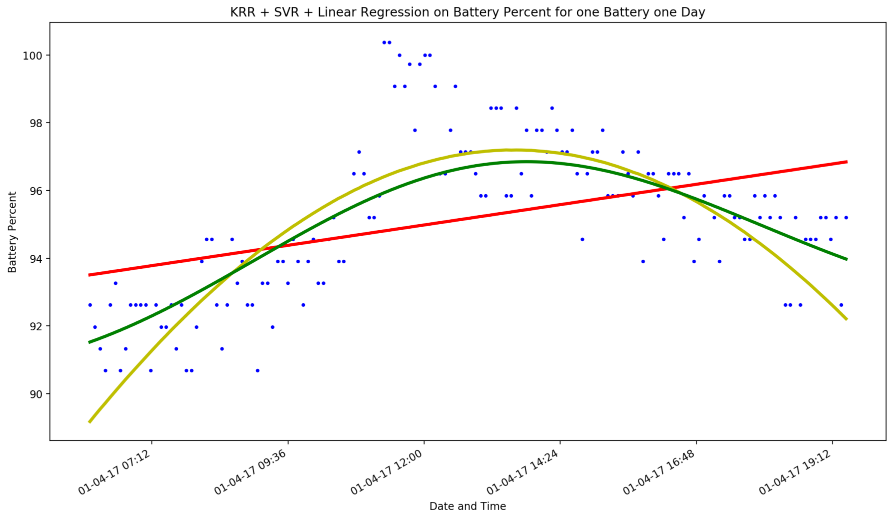

Figure 4.2: One day with linear regression, KRR, and SVR

4.3 Testing for Entire Days

When both nighttime and daytime had been viewed and tested separately, it was time to combine the two and look at the entire day. This was to view the data in a unified way, and therefor get a better understanding of the behavior of the battery. The behavior of to consecutive days are illustrated in Figure 4.3 in combination with linear regression (red line), KRR(yellow line), and SVR (green line).

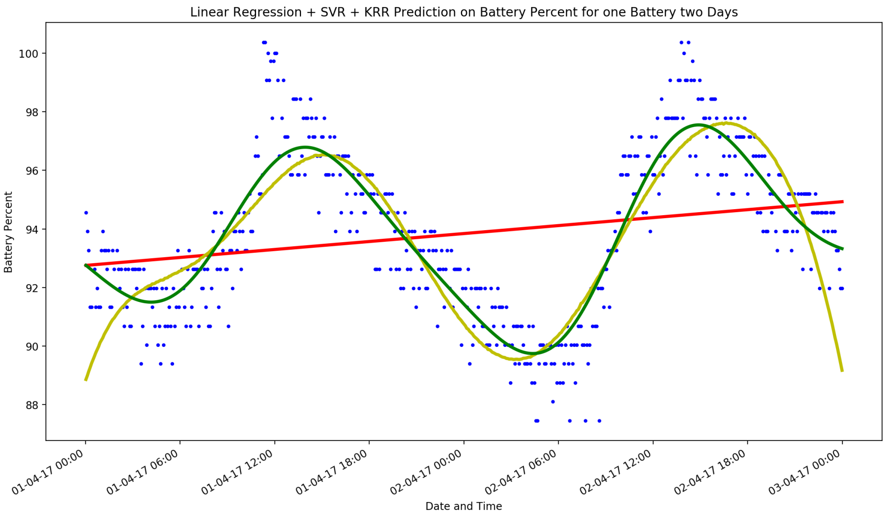

Figure 4.3: Two entire days with linear regression, KRR, and SVR

4.4 Expanding to Weeks and Months

Expanding the entire day was the next step. First a whole week was tested, to see if there was a pattern in the behaviour for longer than the two days that was viewed in Section 4.3. Figure 4.4 represents a week of data combined with KRR, and SVR. Second, an entire month of the dataset was applied. This was also to check for a possible pattern that could be applied to the machine learning models. An illustration of the entire month with KRR and SVR is shown in Figure 4.5.

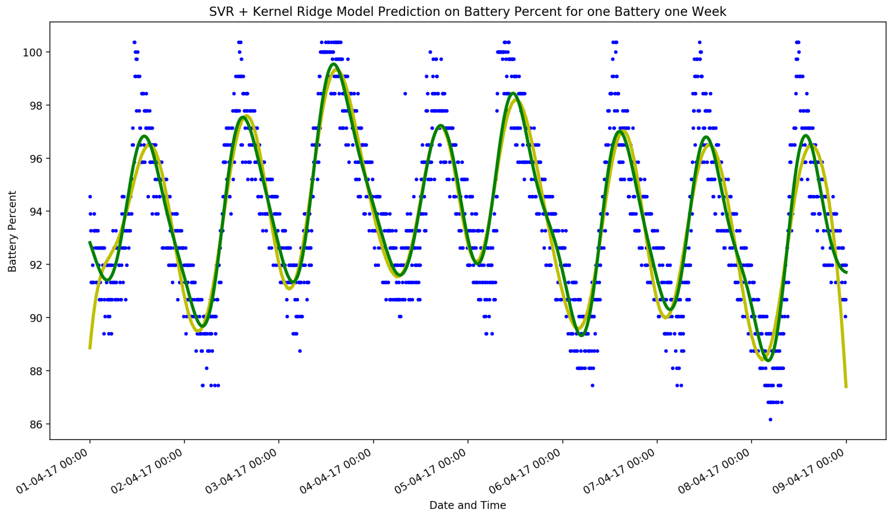

Figure 4.4: One week with KRR(yellow line) and SVR(green line)

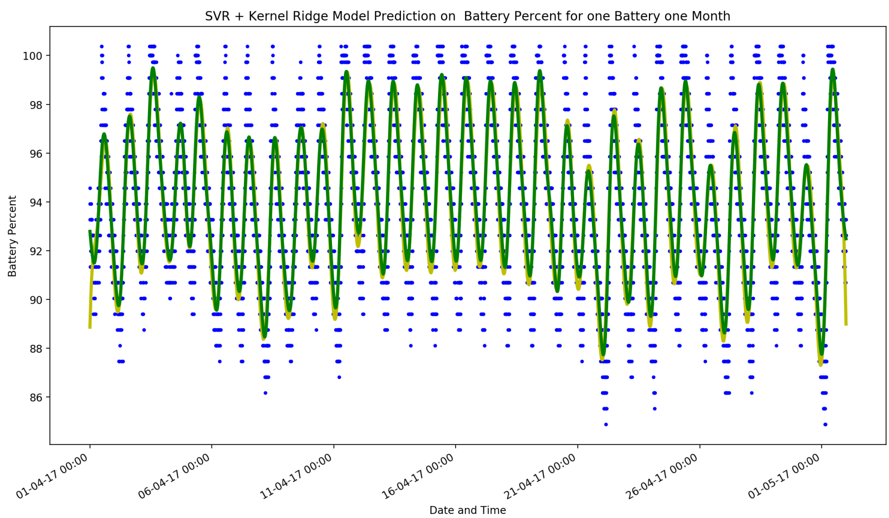

Figure 4.5: One month with KRR(yellow line) and SVR(green line)

4.5 Fitting the Models

After viewing the dataset in different intervals, the models had to be fitted. Here it was important to fit the models enough without overfitting. The different machine learning models had different parameters for the fitting. For this part of the testing the goal was to change the values of the different parameters and choose the parameter value that was most suitable for the specific model. Figure 4.6 shows the SVR model not highly fitted with gamma value 1.0, Figure 4.7 shows the model more fitted with gamma value 4.0, and Figure 4.8 shows the model highly fitted with gamma value 8.0. The values used to fit here does only apply for the visualization on how fitting is done, and does not represent the actual values used for prediction.

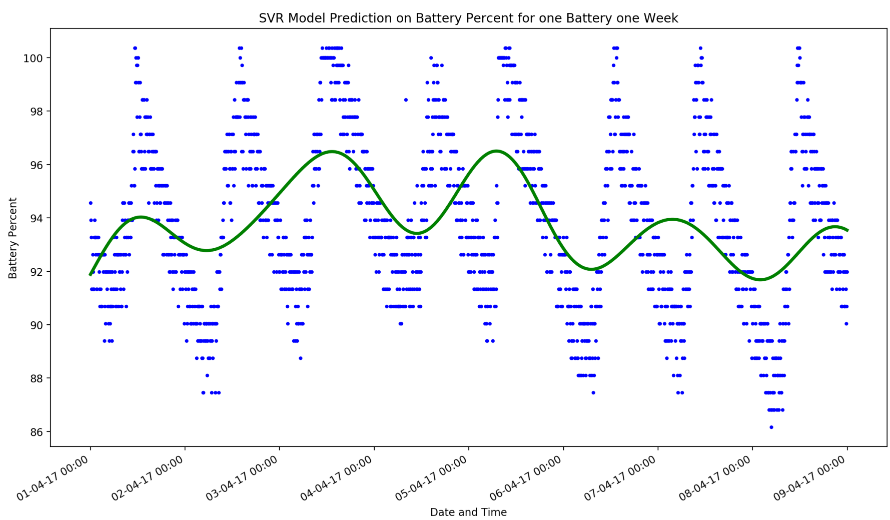

Figure 4.6: SVR model fitted with gamma = 1.0

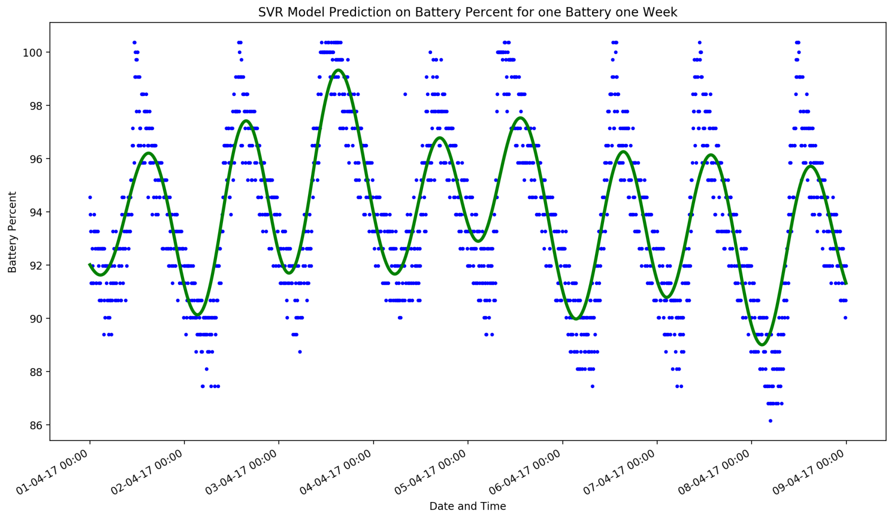

Figure 4.7: SVR model fitted with gamma = 4.0

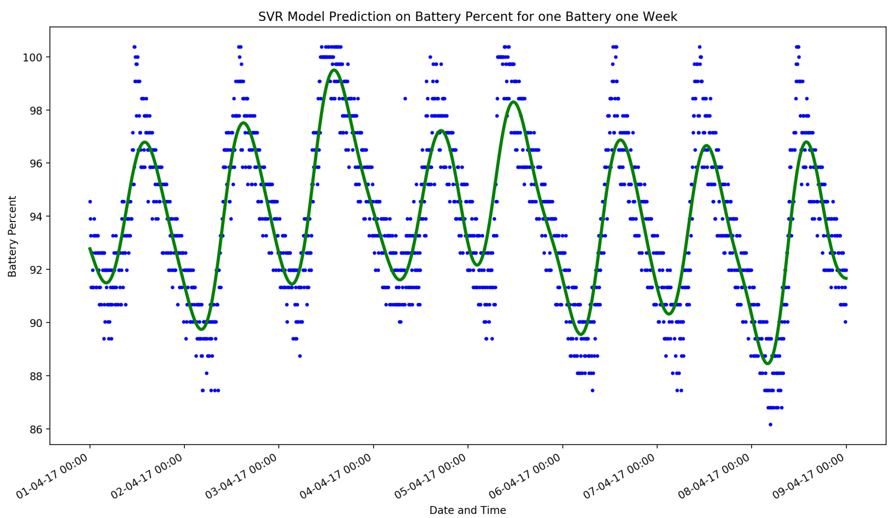

Figure 4.8: SVR model fitted with gamma = 8.0

4.6 Decisions for the Testing and Predictions

When going through the different intervals for the dataset, it was clear that a large interval was to unclear to be able to get good results from. It was therefore decided that the visualization for the dataset would be for only two days. Of those two days, the first day would be the representation of the actual data for that day, and the second day would be the prediction. The training dataset was created by generalizing all of the previous days up to the predicted day. Generalizing is to take all days and creating the data based only on the seconds passed midnight, meaning that it will appear to only be one day.

Chapter 5
Results

The purpose of the experiment presented in the previous Chapter 4, was to use different machine learning models. These models were used to see if there was any correlation in the behavior of batteries, and if there was a possibility to predict the future behavior of the same batteries. The decision of which machine learning models to use was decided based on the theory, and the usage of the machine learning models. As already explained in Chapter 2, Section 2.2 the sensor nodes have different activity phases. The entire phase cycle is completed when the sensors send information, and therefore the decent in battery percent is linear when the battery is not charging. However, when the sun is up, the battery may be charging and discharging. This is dependent on the whether there is sunlight or not.

Training data has been the input for each of the models mentioned in Chapter 3, and predictions have been made. The models have been created using python programming. In this chapter, the result from the predictions will be presented. First each model separately, then some and all models together. As explained in Chapter 4.6 the result will be presented as two consecutive days. When viewing the figures showing the different result the blue dots will represent the previous day, and the black dots will represent the actual registered data for the predicted day. The x-axis of the graph the time and date, and the y-axis is the battery percent.

5.1 Prediction Data

When making a prediction, a machine learning model has to have data to learn from. As mentioned in Chapter 4 the dataset received from the sensor nodes had to be cleaned in order to be homogeneous. This means no missing data or wrongly registered data. After cleaning the data, two of the batteries were selected. One of them had the solar panel facing south, and the other had the panel facing north. Even after cleaning the datasets, the data may still vary depending on the charging during a certain period of time. The different models were fitted with the same values for both the south and north facing battery. This means that the models are fitted on a general purpose, and not for one specific battery.

Figure 5.1 shows the entire dataset for the battery facing south. It shows that the data in general follows a specific pattern. However, sometimes the data points are far from the general pattern. This data is the basis for the training set, and is generalized to become one day of data. Figure 5.2 is the illustration for the training set of the battery facing north. This dataset has a less recognizable pattern. Generalizing to create the training set for one day is also conducted to this dataset. Even though these figures only represent two batteries, the remaining batteries had a similar dataset to the battery where the solar power panel was facing the same way.

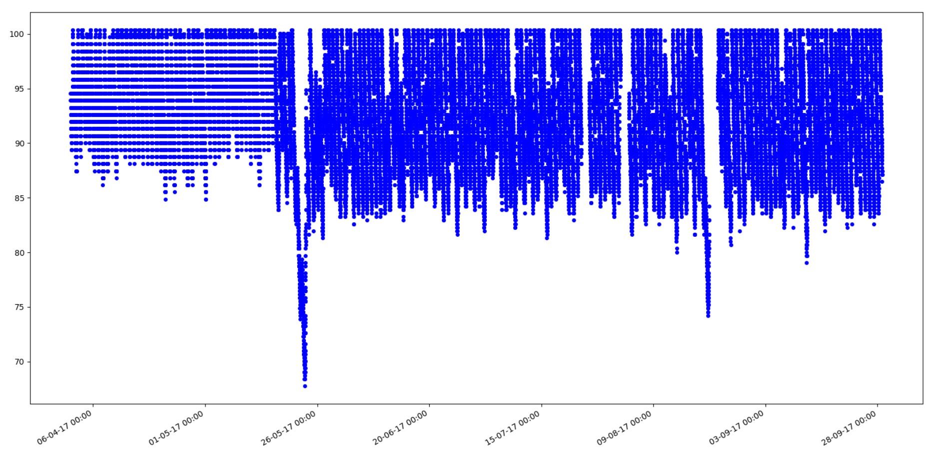

Figure 5.1: The training set used for prediction on the battery facing south

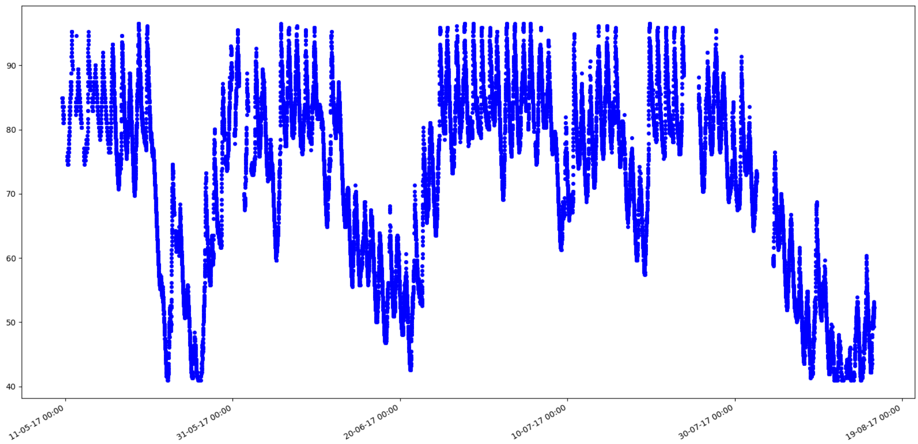

Figure 5.2: The training set used for prediction on the battery facing north

5.1.1 Linear Regression

Prediction using linear regression will, as explained in Section 3.3.1, provide a straight line. However, if fitted it can provide straight lines between points, and the point may then create a dynamic line. Linear regression does not have any variables to set, and does only take the parameters into consideration when predicting. When looking at Figure 5.3 and Figure 5.4 it is visible how linear regression may appear like a dynamical line. Figure 5.3 is an illustration of the prediction with linear regression for the battery facing south. The yellow dots represent the predicted values. It is clear that the yellow dots follow the curve of the actual data to a certain extent, but it does not reach either the lowest or highest battery percent of the actual graph. The prediction is not very noisy, and at some point not noisy at all.

Figure 5.4 is the illustration of prediction with linear regression for the north facing battery. Also here are the yellow dots a representation of the predicted values. The curve of the predicted values follows the curve of the actual values very well. However, the entire predicted curve lies on a higher x-value and does not match at any point. Noise is nearly non-existent, only at points where the actual data is noisy as well. The predicted curve is a better match to the training data, shown in blue. This could be caused by several reasons. The maximum effect of the battery may be decreasing, the actual day might have had very bad weather, the training set created

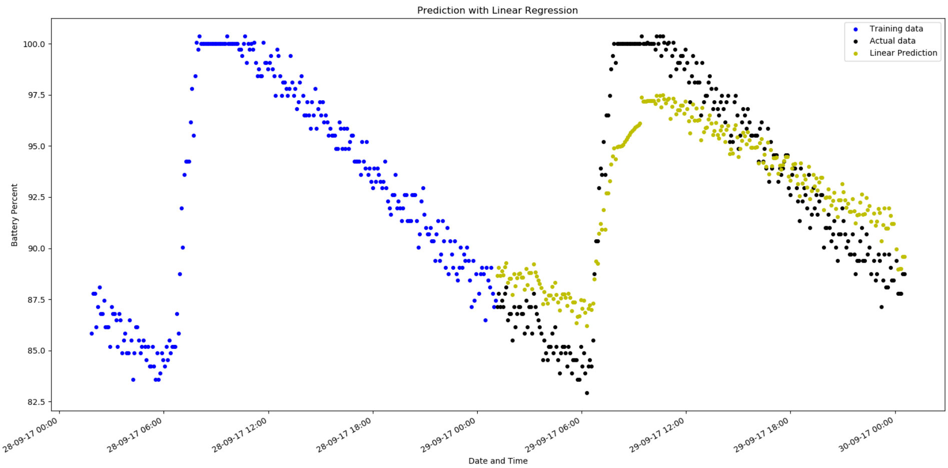

Figure 5.3: Results of the prediction model using linear regression on the battery facing south

by the model may be wrongly created, or the dataset used for the training set may be so varied that the prediction is difficult to perform.

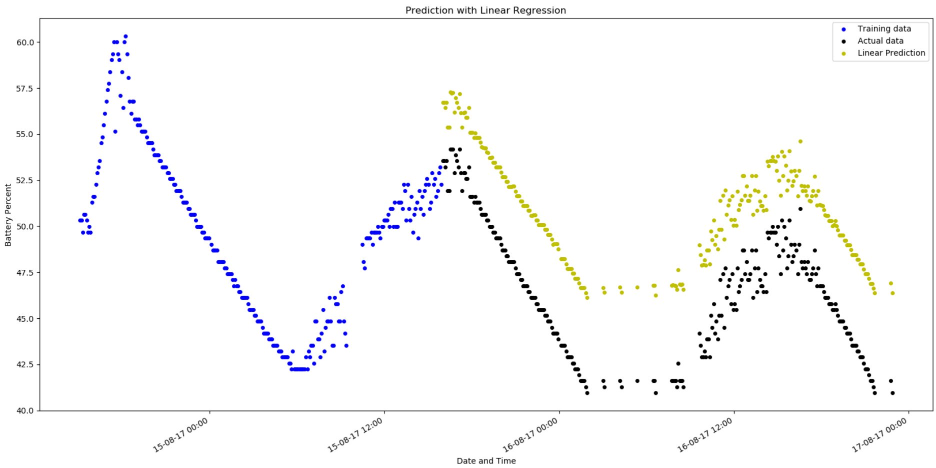

Figure 5.4: Results of the prediction model using linear regression on the battery facing north

5.1.2 Support Vector Regression

Prediction with SVR and how it works is explained in Section 3.3.1. SVR only uses a part of the training set in order to make the prediction. For this prediction the values used for fitting is: $\epsilon = 0.1$, and $\gamma = 0.000001$. Figure 5.5 shows SVR performed on the battery facing south, where the red dots represent the prediction. The prediction curve follows the curve of the actual data very well, and it is only missing the actual data when recharging. Noise is almost non-existent in the prediction, only a small amount at the peaks. For the SVR prediction performed on the battery facing south, a validation curve was also created. This is shown in Figure 5.6 and shows how the training score performs in relation to the γ value used.

An illustration of the prediction for the north facing battery is shown in Figure 5.7. Predicted values are, in this case also, represented with red dots. The prediction values are not as closely gathered here as they are in the south facing value, meaning more noise points. Even though this prediction is more noisy, it still follows the curve of the actual data to a certain degree. At some points the prediction is on the actual data curve, but for the most part the prediction is at a higher x-value than the actual data.

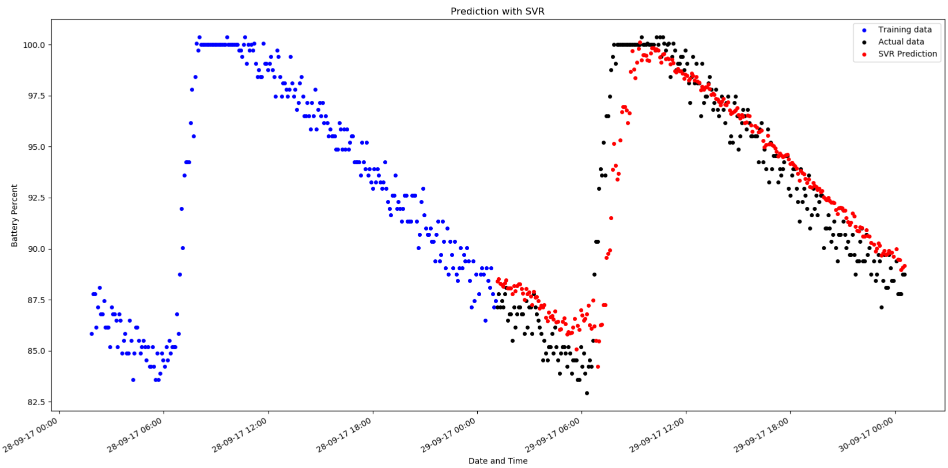

Figure 5.5: Results of the prediction model using SVR on the battery facing south

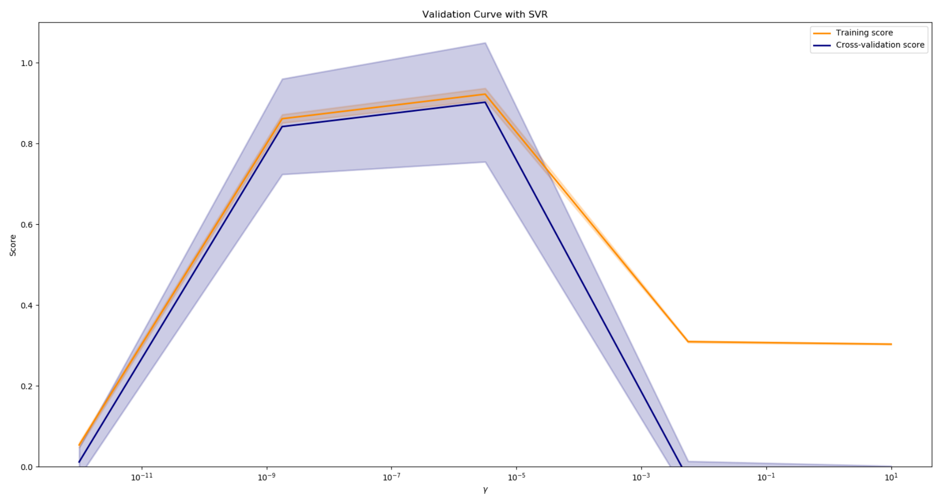

Figure 5.6: A validation curve for SVR on the battery facing south

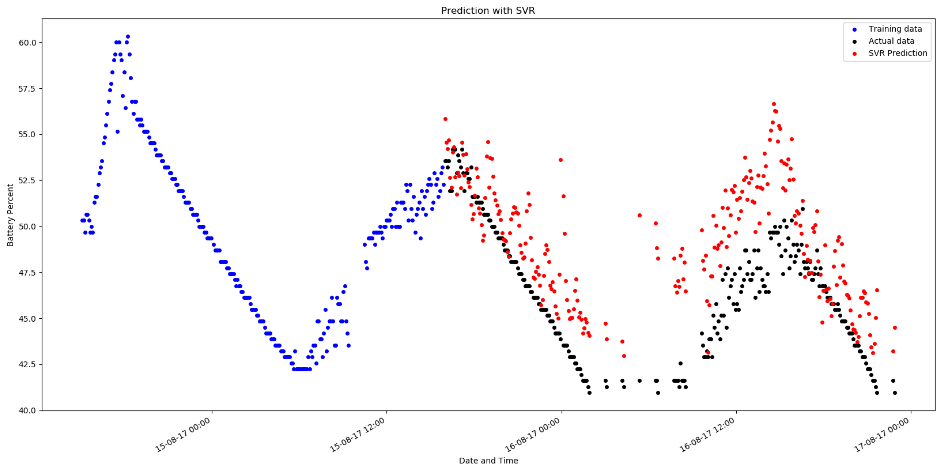

Figure 5.7: Results of the prediction model using SVR on the battery facing north

5.1.3 Kernel Ridge Regression

KRR, which is presented in Section 3.3.1, is not a sparse model. This means that the model uses the entire data set for training rather than a selected amount of training points. For this prediction the values used for fitting is: $\alpha = 0.04$, and $\gamma = 0.000001$. Figure 5.8 is a representation of the prediction done for the battery that is facing south. The purple dots are the prediction from KRR. It is visible that this prediction model follows the curve of the actual data for most of the graph. However, it does not reach the highest values on the x-axis, which means that the model does not predict that the battery will be fully charged. The prediction does not appear to have any noise.

Figure 5.9 shows an illustration of the prediction for the battery facing north, where the purple dots are the KRR prediction. It is very clear that the KRR model misses the predicting with a quite large margin. The predicted curve matches the actual to some extent, but the prediction is not correct for this specific day. Noise is also a part of the prediction, but it is not severe.

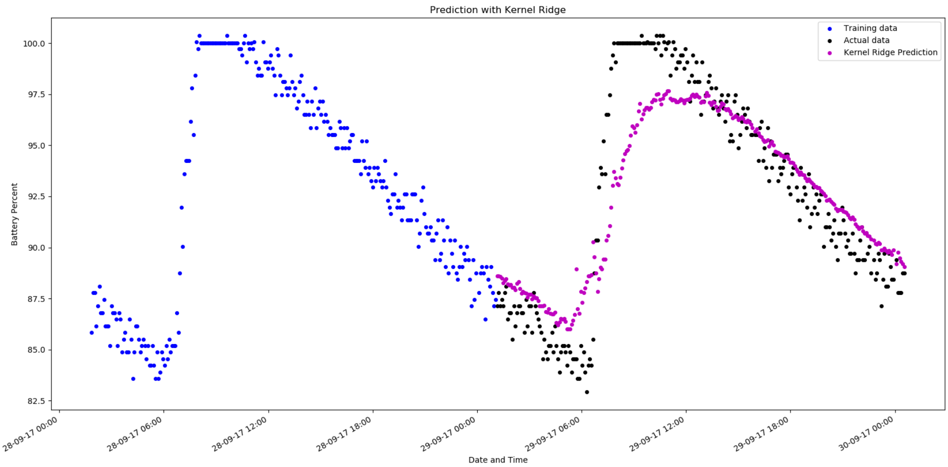

Figure 5.8: Results of the prediction model using KRR on the battery facing south

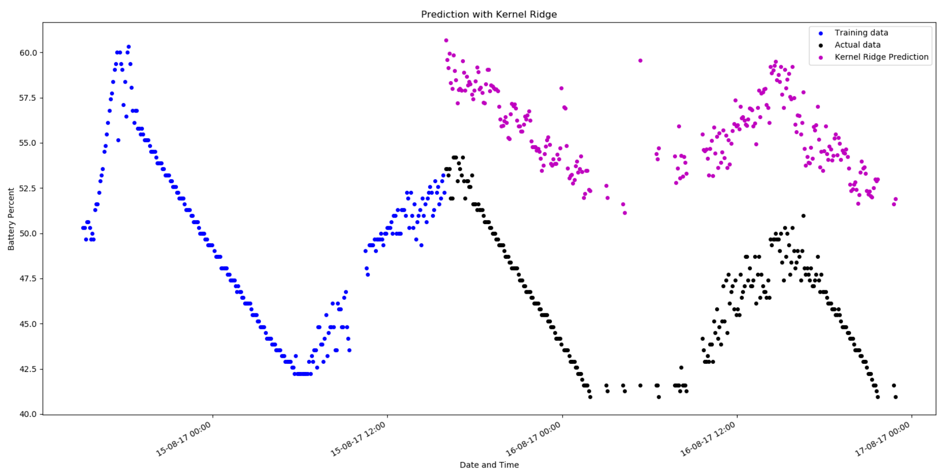

Figure 5.9: Results of the prediction model using KRR on the battery facing north

5.1.4 K-Nearest-Neighbor

The K-NN algorithm bases its prediction on a chosen number(K) of selected neighbors. This is explained further in Chapter 3.3.1. The larger the K-value, the less noise in the prediction. For this prediction the value used for the number of neighbors, K = 10. Figure 5.10 illustrates the K-NN prediction for the south facing battery, with the predicted dots are represented in turquoise. The curve of the prediction follows the curve of the actual data at almost any point in the graph. Noisiness however is an issue, and the noise makes the prediction harder to read because of the large spaces between the extremities.

The representation of the prediction for the north facing battery is Figure 5.11, with turquoise dots as the prediction. There is really no noticeable curve in the prediction, and difficult to even see what is predicted. This is because of the enormous amount of noise points in the K-NN prediction. Some of the predicted points fits some points in the actual data curve, but this is far from enough to get a good prediction.

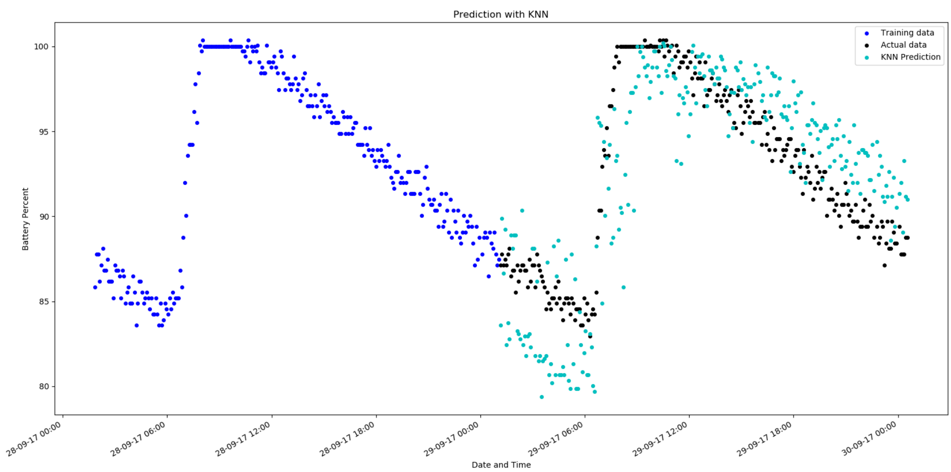

Figure 5.10: Results of the prediction model using K-NN on the battery facing south

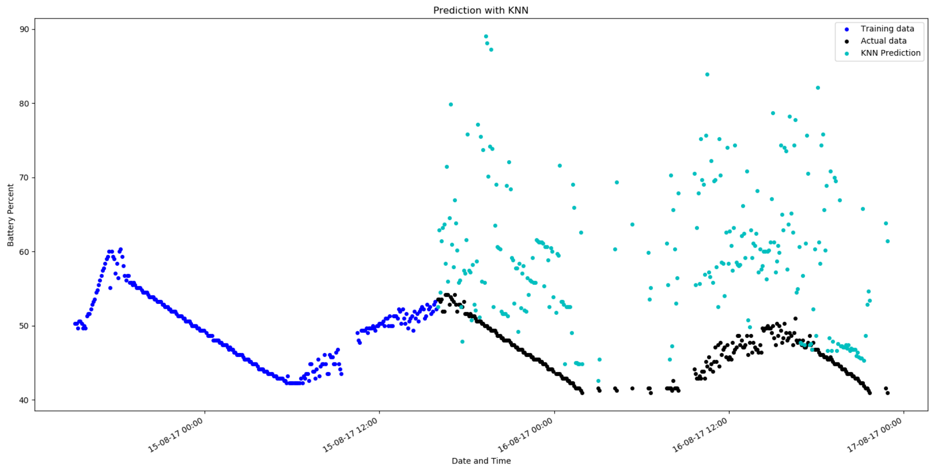

Figure 5.11: Results of the prediction model using K-NN on the battery facing north

5.1.5 Decision Tree Regression

DTR bases its prediction on the average value of the training set, which is explained in Section 3.3.1. This regression model bases its prediction on the decided maximum depth of the tree. The deeper the tree, the more fine details is taken into consideration. Maximum depth for this prediction is set to, max_depth = 10. An illustration showing the prediction for the battery facing south is Figure 5.12. The predicted points are presented with maroon dots. This illustration shows that the predicted curve follows the actual curve in a very good way, and it is only at the high peak that the prediction misses by a small margin. The noisiness in the curve is also good, meaning not a lot of noise points.

Figure 5.13 shows the prediction done for the north facing battery, also represented with maroon dots. This prediction however, it not as good as the one for the south facing battery. The predicted curve is not visible, and is replaced with a clustered presentation. Clustering is not the type of prediction wanted for regression. Noise points are also the majority of the prediction, where some of the noise points are very far from the actual data.

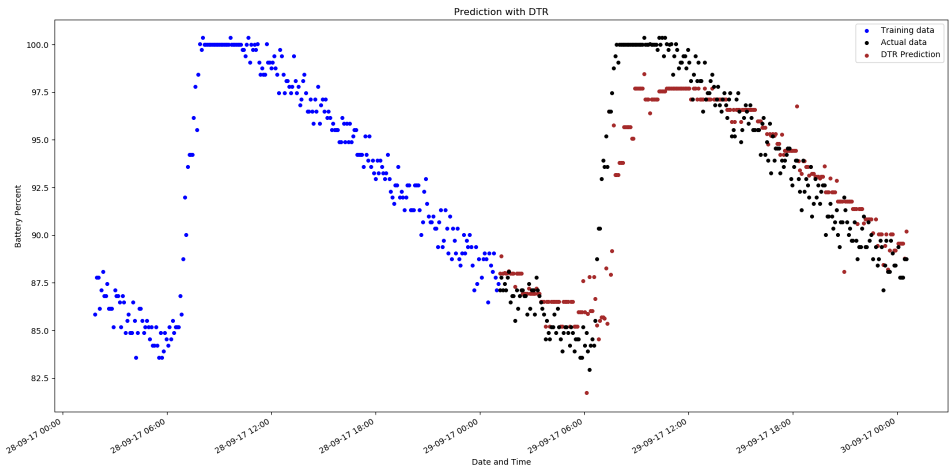

Figure 5.12: Results of the prediction model using DTR on the battery facing south

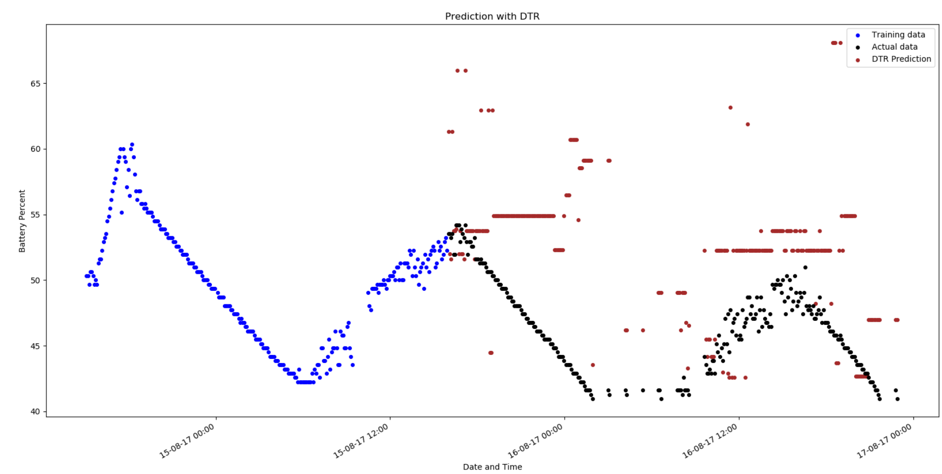

Figure 5.13: Results of the prediction model using DTR on the battery facing north

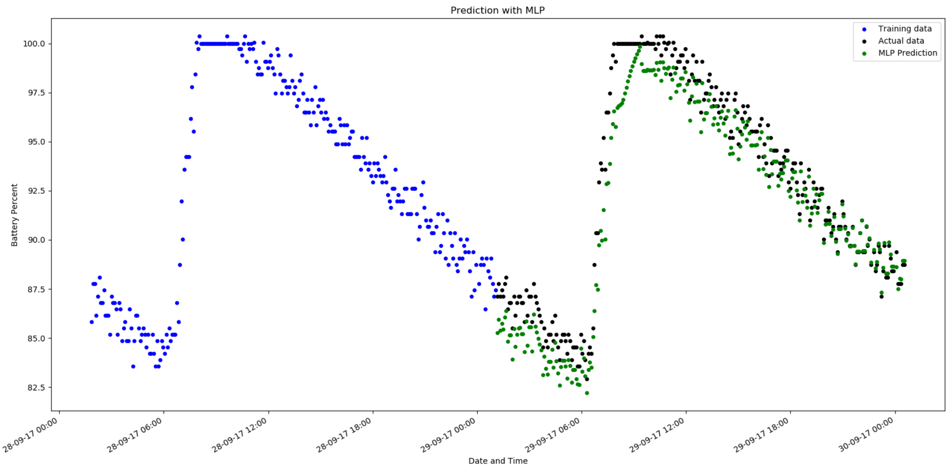

Figure 5.14: Results of the prediction model using MLP on the battery facing south

5.1.6 Multi-layer Perceptron

The MLP prediction model bases its prediction, which is presented in Section 3.3.1, on a decided number of input and output dimensions. The model consists of several layers, where at least one layer is hidden. Figure 5.14 shows the prediction created with using MLP prediction on the battery facing south. This prediction is shown by the usage of green dots. The predicted curve fits the actual curve almost perfectly with only very small differences. It also reaches the high an low peaks of the actual data. There is some noise to the predicted data, but not more than what exacts in the actual data.

Figure 5.15 shows the prediction done with MLP on the north facing battery. Also this represented with green dots. The predicted curve follows the curve of the actual data to a certain extent, but misses quite clearly in some points. For the peaks of the actual graph, the prediction is a little lower on the x-axis for both the highest and lowest point of the graph. There is also some noise in some of parts of the prediction, while other parts have no noise.

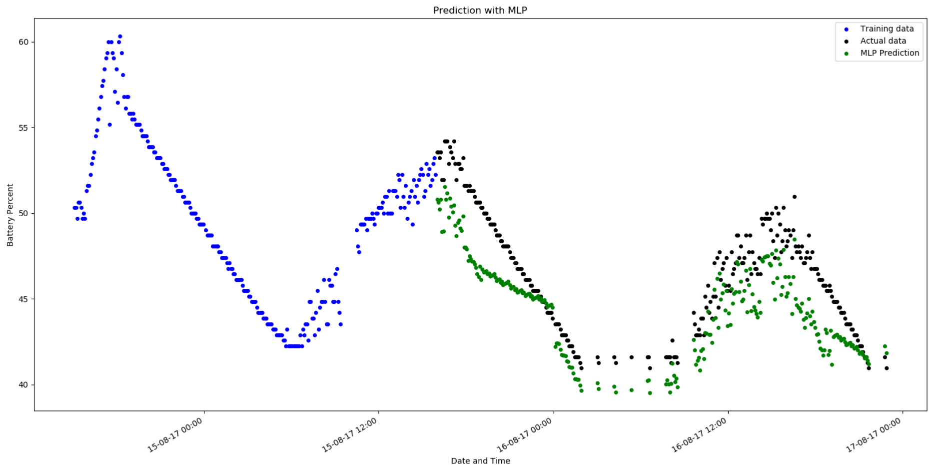

Figure 5.15: Results of the prediction model using MLP on the battery facing north

5.2 Combination of Several Models

For this part of the results, more than one of the machine learning models used in this project will be presented in the same figure. This is to illustrate how the different models behave and performs compared to the other models. Values used for prediction in the previous section, are the same for the prediction in this section. The colors used to represent the different predictions are also the same as they were in the previous sections.

In Figure 5.16 all of the models used to predict for the south facing battery is combined. The figure also has a box with which model is which color, to make it easier to see the differences. All of the prediction models used for the south facing battery is very similar. This could be because of the homogeneous training set for this battery, which can be seen in Section 5.1. From the figure it is visible that the most accurate models are SVR and MLP. However, the MLP prediction is a bit noisy and the least noisy models are SVR and KRR. When it comes to the models that has the worst prediction, this is K-NN and linear regression for this battery.

Figure 5.17 is a illustration of a combination of all of the models used to predict for the battery facing north. This figure also has the box showing the different colors used for the different models. The similarities between the prediction curve for the

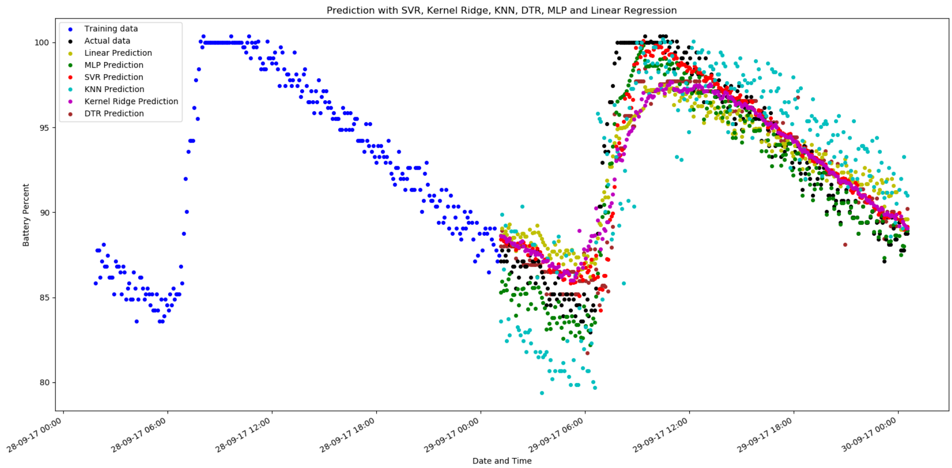

Figure 5.16: Results of the prediction model using all previously mentioned machine learning models on the battery facing south

different models are not so apparent for this battery as they were for the south facing battery. This might be because of the training set for the north facing battery was more volatile, making predicting more difficult. From the figure it is visible that the models that are most accurate in their predictions are SVR and MLP. The least noisy models are MLP and linear regression. When it comes to the least accurate prediction models it is clear that K-NN is the model that is furthest from the actual data curve, and by far the noisiest.

Viewing all models in one figure is very unclear when the models look quite similar. In Figure 5.18 and Figure 5.19, respectively presenting the south facing and the north facing batteries, three and four models are selected to be displayed. It is more clear in these figures the differnce in the different machine learning models. Figure 5.18 shows how SVR is the most accurate prediction and how K-NN is a lot more noisy than KRR. It also shows that the difference is not so huge for the predictions because of the homogeneous training set. Figure 5.19 shows how much more difference there can be in predictions when the training set is less homogeneous. It also shows that the prediction from DTR does not have a curve compared to the other predictions, and is therefore more diffucult to read results from.

When the different machine learning models predict, they test their models fitting

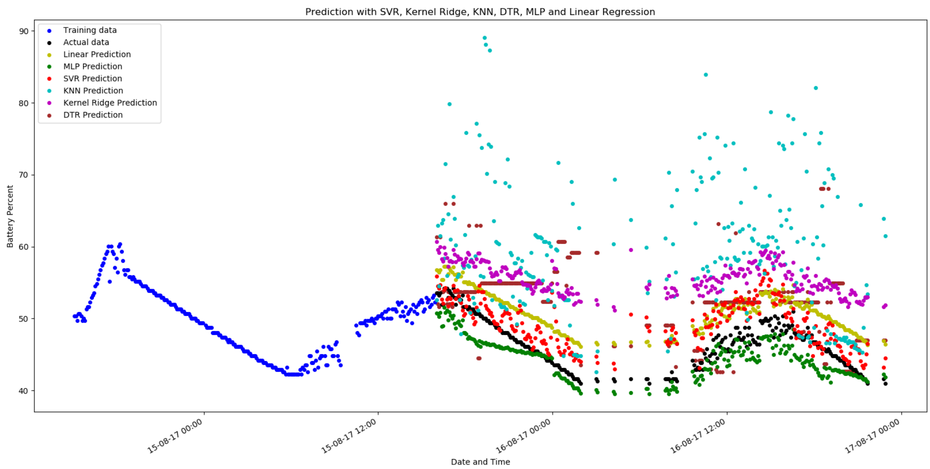

Figure 5.17: Results of the prediction model using all previously mentioned machine learning models on the battery facing north

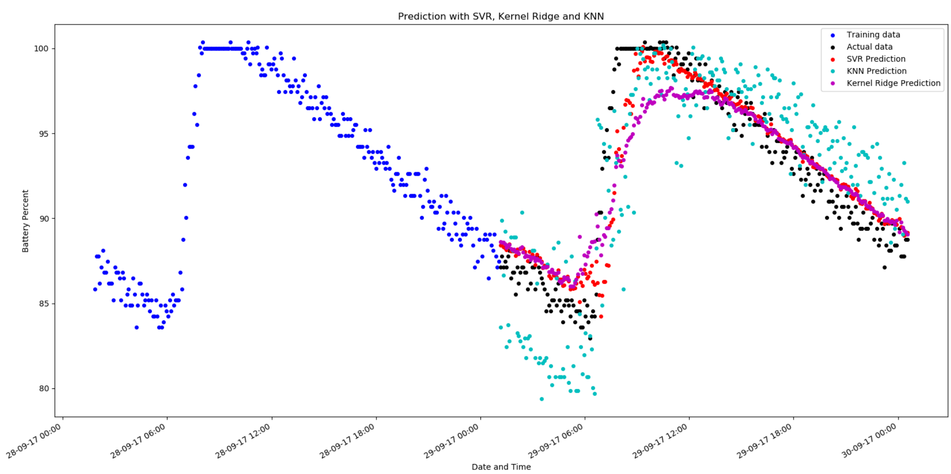

Figure 5.18: Results of the prediction model using SVR, KRR, and K-NN on the battery facing south

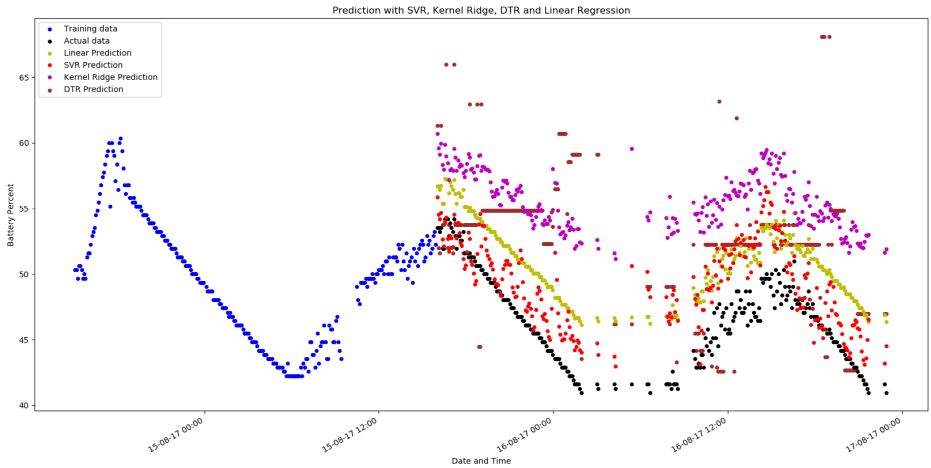

Figure 5.19: Results of the prediction model using SVR, KRR, and K-NN on the battery facing north

by checking the confidence level. This is done by splitting the training data in to separate parts where the first part(80%) is tested to predict the second part(20%). How well it is fitted is then represented by a confidence value. The confidence level will vary a lot, depending on how big the dataset used for prediction is. As the dataset increases, the confidence level will decrease. This is because it is difficult to be as precise in the prediction when the data points used for training are so many, because of the difference in the data. Table 5.1 is an table that shows the confidence level for the different machine learning models used in this project. It is presented one value for the north facing battery and one value for the south facing battery. Confidence level 1 is the highest possible level to reach, and confidence level 0 is the lowest possible value.

Table 5.1: A table showing the confidence level for each of the machine learning models

Machine learning model	South facing battery	North facing battery
Linear regression	0.4	0.67
SVR	0.47	0.66
KRR	0.49	0.62
KNN	0.22	0.27
DTR	0.5	0.72
MLP	0.25	0.64

5.3 Sources of Error

The testing done in this level may have some errors. One of the major errors are the fitting of the models. The models should be fitted correctly without being overfitted, which happens if the model is fitted to precisely for that exact battery. This is attempted to be prevented by using the same fit for the north and south facing battery, and using the fitting values that is best for both batteries. Another error that may occur in this project is the decision on which part of the data for the batteries to use for training. The data was cleaned to the best attempt, but may still contain errors affecting the prediction models. Choosing which batteries to use for the testing may also be a source of error. The batteries chosen were the ones that looked like they contained the most data available for testing, but this may be incorrect.

Chapter 6 Discussion

The subject of this master thesis has been to analyze the correlation in the behavior of LiPo batteries. For the project and testing conducted, the purpose was to see if machine learning models could be used to predict the future behavior of the batteries. In the project there has been both a theoretical approach as well as a practical approach. This chapter will contain a discussion on the background theory and the experiment conducted. The utilization of machine learning in combination with battery behavior prediction, and also the placement of the solar power panel will be the main focus for the discussion.

6.1 Discussing the Theoretical Background

When viewing the information presented in Chapter 2 and Chapter 3 the behavior of LiPo batteries should be similar. The batteries are created in the same way, and charge and discharge in the same way. However, if the batteries are using different devices for charging, this may lead to overcharging or over discharging. The life cycle of the batteries then might be different. If a battery is damaged in any way it may loose some of its effect, and will therefore not be able to reach the same voltage level as an undamaged battery. When using a large enough dataset of battery behavior, these possible damages should be visible and thus be taken into consideration. Machine learning models have already been applied to predict the energy consumption of a battery in electric vehicles, and to predict the solar energy for constrained nodes. This means that a combination of these to should be feasible.

6.2 Discussing the Usage of Different Machine Learning Models

In Section 3.3.1, all the different machine learning models used for testing is presented and their approach is explained. All of the models were chosen because they were regression models, and for this project regression appeared to be the best fit. This is because the representation of the battery behavior would be a presented as a graph. When deploying different models that have the same purpose they might end up looking very similar. They will however often have a difference in the noise they generate and the speed of executing the prediction. This is based both on the values chosen for the fitting of the models, and the amount of the training set they use for the prediction. When testing if machine learning may be utilized for a certain purpose it is smart to look at several models and not just one or two. For this thesis, six models have been reviewed and tested. This is in order to get several different predictions to be able to collect the best possible results. I thought six would be an appropriate number of models to get enough references and predictions, to be able to solve the problem for this project. Based on the results collected, this number was a good decision.

6.2.1 Figuring out Which Models to Utilize

For this part of the discussion, each of the machine learning models will be discussed separately based on the results presented in Chapter 5. After all the models are presented, there will be a summary with decision of which models work best for the purpose of this master thesis.

Linear Regression

The linear regression model prediction could be usable for the battery facing south. Here it fits in some of the data points. It does however miss on both the high and low peaks, and would therefore not be able to tell if and when the battery is fully charged. As this is considered to be essential information, the linear regression model is not as usable for predicting as it could appear from Figure 5.3. With a confidence level of 0.4, the model it self is not very confident in its own prediction, and this for a good reason. Because the training set for the south facing battery is very homogeneous, the error in the prediction done by the linear regression model is to big.

For the north facing model the prediction misses for the entire graph completely. Even though it follows the curve, this would not help in a real world situation. If you are expecting the battery to have a power percentage of 46% and the real percentage is 41%, this could have a big impact. You could expect the sensors to be able to send a specific amount of measurements, however the number would be lower which could have an effect on the results of the measurements. The confidence level for the linear regression on the north facing battery is 0.67, meaning also that the model expects to predict much better than it actually does. This could be because of the non homogeneous training set for this battery, or the battery might be getting worse in performance. The performance might sink because of outer damage, over charging, or over discharging. The error in the prediction might also be because of bad weather causing the battery to not charge as much. However the model is taking solar charge in as a parameter and should therefore know the amount the battery has charged.

Support Vector Regression

When viewing the figures presented in Section 5.1.2, it is very clear that the SVR prediction model is very suitable for the battery facing south. It fits the curve at every part and the prediction is very gathered and not noisy. This means that the SVR model could be utilized to predict for a model when the battery has a homogeneous training data. When creating the model certain values were decided. For the south facing battery the confidence level for SVR is 0.47 which is not so high. Even though the model fits quite well, it did not have a big confidence for its ability to predict correctly.

Since SVR only uses a part of training set it is faster than other regression models. This on the other hand might cause errors when the dataset is not homogeneous. For the north facing battery this effect is very visible. The SVR prediction matches the curve and matches almost the lowest points and does match with the highest points of the graph, but it is very noisy. Since the training set for this battery is quite variable, this could result in more noise when only selecting a part of the training set. The confidence level for the north facing battery is 0.66, which is a fairly high score. Even though it does not look like it, the model fits the actual data to some extent, but with a lot of noise points.

The γ value chooses how strict the prediction should be, a bigger value will cause overfitting and a too small value will make the prediction not fit the actual data. Even though the fitting could be better for the north facing battery, it would have been bad to make it stricter because then the prediction for the south facing battery would be incorrect. The ϵ value that allows more errors the higher the value was set to be low in order for the prediction to be very accurate. This could have been even lower for the north facing battery, but then it would have been too low for the south facing battery. It is still clear from the results that SVR is a possible model to use for the purpose of predicting the behavior of any battery.

Kernel Ridge Regression

Since KRR is a regulated version of linear regression that uses kernels, I expected it to have similar results as the linear regression model. This was not the case. For the south facing battery the prediction i almost not noisy at all. It also fits the curve of the real data pretty well. The only similarity to the linear regression model is that it does not reach the high and low peaks. Confidence value for the south facing battery is 0.49. This is not a very good value, but the prediction is better than the model expects it to be. The prediction for the north facing battery on the other hand is not as good. Even though it hits the same curve it does not mach at any point and is noisy. This could be a result of the model not being strict enough when predicting, or that the training set for this battery is not good enough to predict from. The confidence value for KRR for the north facing battery is 0.62. Because the curves are similar this confidence is eligible, but the curve misses the actual data.

Because the model uses the entire training set and also inverts the training set, this is by far the slowest of the chosen models. This is negative when dealing with large data sets, but the model is possible to use if the number of training points is below 100. The value chosen for α is low but positive, this resulted in the conditions for the south facing battery to improve. It did not have a very big effect on the north facing battery. The γ value was also, as with SVR, chosen not to be any stricter because this would cause overfitting and the results for the north facing battery would then be wrong. This would prevent that the model might be used for any battery and not just one specific. When viewing the results, KRR does not seem to fit the intended purpose of creating a prediction for any battery. It can work for a chosen battery, but the model would have to be fitted for each battery which would cause a lot of work.

K-Nearest-Neighbor

The results presented in Section 5.1.4 shows the K-NN regression for both the north and south facing battery. Although slightly noisy, the model fits the actual data for the south facing battery to a certain extent. It reaches both the high and low peaks of the actual data, and it could be used to predict this battery. For the south facing battery the confidence level is 0.21. This could be explained with the model being somewhat noisy, but the model predicts better than it expects to.

The prediction for the north facing battery on the other hand is really not readable. Prediction point are all over the place and there is no visible curve, only noise. This could be because of the training set or because of the chosen K value. As it is presented, the model is not usable for the north facing battery. The confidence level for the north facing battery is at 0.28, which means that the model did not have a hig confidence in the prediction it would perform. This with a good reason.

When predicting with K-NN the only value to be chosen is the K value of how many neighbors the average should be calculated from. When viewing Figure 5.10 and Figure 5.11 it is clear that K value could be much higher for the north facing battery. This would affect the boundaries for the south facing battery, making that prediction worse. The K value which was chosen for the tests were the best value for the model to work for both batteries. As seen in the figure, the K-NN regression model is not feasible for both batteries and therefore not really feasible for the intended purpose of this project.

Decision Tree Regression

Figure 5.12 and Figure 5.13 illustrates the prediction performed with DTR. The prediction for the south facing battery is fitting the actual data very well with little noise. It only misses at the highest peak. This could result in thinking that the battery is not fully charged when it actually is, which again could lead to overcharging and damaging the battery. The confidence level for this model for the south facing battery is 0.5. The model anticipated for the prediction to be worse than the actual result which is good.

For the north facing battery the prediction is very bad. The predicted point are all over the place, and it is not possible to read a result from this prediction. It does not have a recognizable curve, and even though it matches the actual data in some points this is just a coincidence. The confidence level for the north facing battery is 0.72. The model anticipated to give a good prediction, but as the figure shows this was not the case.

When predicting with DTR the value that is chosen is the maximum depth. When the depth is increased the models takes more fine details into consideration for the prediction. If this value had been lower, the prediction for the north facing battery might have been better, but this would affect the prediction for the south facing battery making it worse. As the figures illustrates the DTR prediction model will work well for the south facing battery but not for the north battery. This means that this is not a general model than may be used for any battery.

Multi-layer Perceptron

The MLP regression consist of at least three layers. This is further explained in Chapter 3.3.1. The prediction for the south facing battery is almost spot on for every part of the actual data graph. This is a very good prediction, with just a small amount of noise points. For the south facing battery the confidence level is 0.25. This is a very low number of confidence considering how good the model predicted. The number could be explained by the fact that the training set is very large making the model less secure of its prediction abilities.

The prediction done for the north facing battery is also quite good. It misses the actual data curve in some parts, but matches for the most parts. This prediction is a little noisier than the one for the south facing battery, but it is still a good prediction. The layers in the MLP model might be the reason for the good prediction for both batteries, because they filter out the usable information and creates a prediction based on this. Confidence level for the north facing battery is 0.64 which is a better value than for the south facing battery. Figure 5.14 and Figure 5.15 illustrates the prediction for both batteries and shows that the model is feasible for the purpose of this master thesis.

6.2.2 Summary

The review of the machine learning models used in the experiment for this master thesis shows both small and big differences between the values. Some of the models can be used for the purpose intended without large alterations, while others will not be usable even with alterations. The best suited model to predict for both batteries, and therefore any batteries are MLP and SVR. Both of these models predictions matched the actual data well. MLP was the model that matched the best, but SVR also matched only with slightly more noise for the north facing battery. These to models, I believe, can be used for further development when it comes to predicting the behavior of batteries charged with solar power.

When it comes to the different batteries, the models had a much harder time predicting the behavior of the north facing battery. If Figure 5.1 and Figure 5.2 is reviewed it is easy to see why. While the training set for the south facing battery is almost homogeneous with some abnormalities, the training set for the north facing battery has no real pattern. This could be because of the battery used, but when looking at all the batteries this was the case for all. The batteries facing south had a repeatable homogeneous pattern, and the batteries facing north had no recognizable pattern. Because of these findings I think it would be a good idea to face all the solar power panels towards south.

Chapter 7
Conclusion

The basis for this master thesis was to find a correlation in the behavior of LiPo batteries, and to see if machine learning models could be utilized to predict future behavior. IoT and the always developing technological world was the motivation for deciding to work on this task, as well as analyzing data. Machine learning is becoming more and more familiar, and the areas use of machine learning models are increasing.

7.1 Possibility for Deployment in IoT Nodes

In Section 1.2 a research question was proposed, with some underlying problems to investigate. When using IoT sensor nodes they need power to be able to sense, make measurements, and send these measurements. To generate this power rechargeable LiPo batteries can be used, and these batteries can be recharged with the help of solar power. When using such rechargeable batteries for power, and solar energy for recharging it is beneficial to know how the battery will behave. This could be used for knowing how much energy is consumed by the node, and how fast the battery will recharge. It could also say something about when the maximum effect of the battery will be low, so that it is time to change the battery. Using machine learning models to predict this behavior is a possible solution, and with the testing conducted it is also proven to be feasible. However, not every machine learning model can be used for this purpose, because it requires a high match in the predicted values. This is because a battery may be damaged or even completely ruined if it overcharges or over discharges.

Some of the solar panels connected to the batteries were facing south, while others were facing north. When looking at the different datasets for the different batteries it became clear that there was a correlation in the behavior of the batteries facing south. However for the batteries facing north, the correlation was not so clear. So, when the solar power is being used in a northern place where the weather is considered to be unstable, the solar panels charging the batteries should be facing south. The behavior therefore appears to be dependent on the weather, but there is a correlation in the behavior of the batteries when the batteries are facing the correct way.

Through testing and literary review, six machine learning models have been investigated to see if they fit the purpose intended for this master thesis. Using machine learning to predict the future behavior of batteries proved through testing to be possible. This by using previously registered battery percent, time of day and solar charge values as parameters for the models. The models should not only be applicable for one specific battery, but for any battery. predicting future behavior using machine learning models proved to be achievable. However it is somewhat dependent on the training set for the prediction to be homogeneous.

Using regression models for the prediction was the best fit because the data was presented as a graph. From all of the six models tested, there were only two models that would be recommended for this purpose. This is because they would fit the actual data very well for both batteries, without being overfitted. The two models possible to use for battery behavior predicting is MLP and SVR, where MLP was the absolute best mach. Other models could be used for this purpose as well, but they would maybe have to be fitted for each battery creating a lot of work.

7.2 Further Work

For future work it would be natural to include the weather forecast more. It could be to combine data for cloudiness, positioning of the sun, and other weather data to the models. This to see if the models would be even more precise and maybe the dataset used for training would not have to be cleaned before using it. There could also be research on the factors that makes the battery decrease in maximum effect, and maybe it could be possible to merge this into the models to be able to predict when exactly the battery need to be changed. This could be usable for IoT sensor nodes deployed in places where they are hard to reach.

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