Quantitative analysis of the potential of electric vehicle utilization: methodology design and preliminary study

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at Reykjavík University in partial fulfillment
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Abstract

Alternative technologies for transport have been appearing throughout the last decades with electric vehicles showing great potential. Tools for assessing the potential of EV (Electrical vehicles) utilization are lacking. The scope of this thesis was to design such a tool and to use it for a preliminary research on the EV potential of business vehicles and fleets in Reykjavík, Iceland. A model was designed and programmed that analyzes some important aspects regarding the EV potential of conventional vehicles, based on driving data collected by the vehicles under inspection. Driving data were collected by 368 vehicles. The vehicles were divided into 3 different size classes each represented by a model EV. Two versions of the program were designed having a few differing configurations and features. Version 1 was revealed to be more error prone than version 2 with the latter giving more reliable results. The EV potential of the data collecting vehicles was assessed using version 2 only. The main program output parameters used were the failure day percentage and average daily driving. Three scales were designed each having different strictness on which vehicles are considered to have EV potential. Using the method designed and a scale which allows vehicles failing on up to 5% of days to be considered as having EV potential, 50% of business vehicles have EV potential. Class 3 has the most EV potential with 62.8% of vehicles qualifying as having EV potential while only 29% of class 1 vehicles have EV potential. Based on the 0-5% failure day scale 87.5% of businesses in Reykjavík could replace up at least 40% of their fleets with EVs and half of the businesses could replace at least 50%. Version 3 was proposed which is based on version 2 of the program with added improvements of versions 1 features which were lacking in version 2. Future improvements on the overall method, model and program are suggested.

Keywords: Electric vehicles, simulation model, Reykjavík, business vehicles.

Ágrip

Rafbílar þykja sýna merki þess að geta tekið við af hefðbundnum bílum sem ríkjandi tækni í vegasamgöngum í framtíðinni. Það er hinsvegar skortur á tólum sem gera mönnum mögulegt að meta möguleika tækninnar. Markmið þessa verkefnis var að hanna frá grunni slíkt tól og nota það til að rannsaka möguleika fyrirtækjaflota í Reykjavík á að skipta yfir í rafmagnsbíla. Hermi-líkan var hannað og forritað sem metur möguleika hefðbundinna bíla á að vera leystir af hólmi af rafbílum. Greiningin er byggð á gps gögnum sem var safnað af 368 hefðbundnum fyrirtæka bílum í Reykjavík og eru rafbíla möguleikar hvers bíls metnir. Bílunum var skipt í þrjá flokka eftir þyngd og ákveðin gerð rafbíls auðkenndur sem fulltrúi hvers þyngdarflokks. Tvær gerðir forritsins voru hannaðar. Gerð tvö reyndist töluvert betur en gerð 1 og þykir gefa marktækari niðurstöður. Rafbíla möguleiki bílanna var því aðeins metinn út frá niðurstöðum úr gerð 1 af forritinu. Þær kennistærðir sem eru notaðar eru meðal daglegur akstur og rafmagnsleysis daga hlutfall. Þrír misstrangir skalar eru notaðir til að ákvarða hvaða bílar eru taldir hafa rafbíla möguleika. Miðað við skala þar sem bílar eru taldir hafa rafbíla möguleika ef þeir yrðu rafmagnslausir á upp í 5% daga sem bíllinn er virkjaður gætu 50% fyrirtækja bíla verið rafbílar. 62,8% bíla innan flokks 3 (þyngstu bifreiðarnar) eru taldir hafa rafbíla möguleika en aðeins 29% úr flokk 1. 87,5% fyrirtækja í Reykjavík gætu skipt út að upp í 40% af flota sínum fyrir rafbíla og helmingur fyrirtækja gæti skipt út helming flota sins. Í kjölfar rannsóknarinnar er lögð fram tillaga af gerð 3 af forritinu auk þess sem kynntar eru hugsanlegar viðbætur umfram þær sem eru hluti af gerð 3.

Titill: Megindleg greining á möguleikum til rafbíla notkunar: Hönnun aðferðafræði og forrannsókn

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1 INTRODUCTION

The idea of using electric vehicles (EVs) for transport in Iceland has steadily been gaining momentum both from the government as well as private investors and the public. Both economical and environmental factors have caused this increasing interest as it is possible to generate electricity in a cheap and renewable manner in Iceland. Hydropower and geothermal heat account for more than 81 percent of the country's primary energy consumption (Rammaáætlun, 2007) with only the transport sector excluded, for which Icelanders have to rely on imported oil. The Icelandic transport sector could be largely powered by these renewable domestic sources as well, as the amount of electricity already generated is very likely to be more than sufficient to fulfil the needs of the Icelandic transport sector. An electric transport sector in Iceland, as well as in other countries, could greatly reduce the emission of greenhouse gases, although the reduction varies between different sources of electricity. Another positive aspect of an electric road transport sector in Iceland is of economical nature. The cost of importing energy is now significant. The nation is also dependent in the sense that it needs to rely on supply and prices in foreign markets. Fluctuations in the currency can also have negative effects. It is therefore possible to find both economical and environmental arguments for an electric transport sector in Iceland as well as most other countries. The government and the city of Reykjavík have both pledged to become leading parties in electric transport and various researches have been done in this field in the universities in Iceland in past few years. Iceland in the context of electric vehicles will be further explained below.

There are a few obstacles that EV manufacturers have to overcome that have hindered the growth of electric vehicles in the past. Most of these are being fought with great determination and positive results. Most of them lie with the batteries of the vehicles and it is fair to say that advancements in battery technology will determine widespread acceptance of EVs. Performance characteristics of EVs are directly related to batteries, attributes such as range and charging time. Most of the public as well as fleet managers of businesses seem to have limited knowledge and understanding on whether the performance characteristics that electric vehicles have to offer could fulfil their transport needs. Early in the thesis process the author decided to focus the research on the possibility of switching to EVs in Reykjavík. Soon it became apparent that there was a complete lack of research literature and research data available on the driving habits and driving needs of the general public and business users in Reykjavík. The focus of data sources was shifted and unprocessed driving data from a number of businesses in Reykjavík was attained from a data fleet management firm in Reykjavík called SAGAsystem. The focus of this thesis is twofold:

1. First it is on creating a method for analyzing the driving needs of vehicles and determining the possibility of whether EVs can fulfil the transport needs of the vehicles. A computer program was created that runs the driving data from vehicles through an EV energy simulation model. This gives results on how well an EV would perform at fulfilling the driving needs of the vehicle supplying the data.
2. The second focus is on applying the method created to assess whether switching to EVs for business users in Reykjavík, Iceland is a realistic possibility The aim for the research is to use the method created to answer questions such as the following:
   - *How large fractions of business vehicles in Reykjavík have potential to be substituted by electric vehicles?*
   - *Is there difference in the viability of a potential EV switch between different classes of vehicles?*
   - *What is the future outlook for firms in Reykjavík in switching towards EVs? What portion of firms could replace significant fraction of its fleets to EVs?*

In the first chapter of the thesis, the background chapter, an overview of EVs in general is presented as well as a current state with Iceland in regards to EVs. In the methodology chapter all aspects of the method created are presented. In the results chapter the results from the research are presented as well as problems with the method. The results chapter is followed by a discussions chapter. There the results are analyzed and the main research questions answered. The method created will be discussed and modifications suggested for future work in order to approve it. The final chapter is the conclusion chapter.

2 LITERATURE REVIEW

2.1 HISTORICAL OVERVIEW OF ELECTRIC VEHICLES

Electric vehicles (EVs) are far from being a novel invention and have as a matter of fact been around since before the combustion engine vehicles. The first electric vehicle was made in 1834 by Thomas Davenport (Leitman & Brant, 2009). In the 1890s ten times more EVs were sold than gasoline cars and the EVs dominated roads and dealer showrooms and remained more popular until mid 1910s. Some well known car manufacturers like Studebaker and Oldsmobile actually started out as successful EV companies before switching to combustion engine vehicles (Electric Auto Association, 2009). EVs, like other vehicles, were at that time much of a novelty item and almost exclusively used in urban areas as electricity was available there. The reason for the early popularity of EVs was due to them being quieter and less dangerous as well as being easier to drive than the combustion engine driven cars. One of best selling EVs at that time was the Columbia Runabout which could go as fast as 15 mph and as far as 40 miles on a single charge. The peak production for early EVs was in 1912 when 34,000 cars were registered. (Leitman & Brant, 2009)

EVs were a common sight until the mid-1910s until the combination of cheap oil and the non-electrification of rural areas assured the victory of combustion engine vehicles over EVs. Other reasons include the fact that volume production of combustion engine vehicles was achieved in 1910 with the motorized assembly line and the addition of an electric motor to combustion engine cars which removed the need for dangerous and difficult crank to start the engine. Due to these factors the manufacturing of the early EVs had stopped by the end of World War I. (Leitman & Brant, 2009)

From the late 60s and through the 80s, series of events paved the way for the second wave of electric vehicles. Awareness of negative environmental effects, such as smog, from combustion engines started rising in the mid 60s and resulted in the passage of the Clean Air Act in 1968. Although most of the public ignored the problem to begin with public acceptance of the problem has grown since. The public and governments of many nations realized the negative aspects of dependence on foreign oil with shortages in the 70s, 80s and 90s. Thus awareness of the negative aspects of the usage of combustion engines, arising from both economical and environmental factors, steadily rose through this period and resulted in the re-emergence of electric vehicles. Various electric vehicle prototypes have come and gone through the decades but almost all have been short lived. In the 90s some legislative and regulatory actions renewed EV development, most notably the zero emission vehicles (ZEV) program that was enacted by the Californian government to promote the use of ZEVs by requiring carmakers to make 10% of the cars they produce by 2003 ZEVs. In response to this the car manufacturers soon developed and released EV models. The ZEV program was eventually removed resulting in almost all EV models being withdrawn from the market. In most cases the withdrawn cars were destroyed which proved a highly controversial decision. (Leitman & Brant, 2009)

In the late 90s a technology very closely related to the battery EVs was introduced to the market, the hybrid. Hybrids are cars which mainly run on gasoline or diesel but are equipped with a battery that allows recapture of energy released by breaking and shutdown of the combustion engine when driving under certain speed, resulting in a one third reduction in fuel consumption. Toyota announced the Prius in 1997 which has proved a huge market success. The first hybrid to enter the U.S. market was Honda‘s Insight in 1999. Only a month after that Toyota entered the U.S. market with an upgraded version of the Prius. The Prius was in the beginning considered as an experiment with only 5% chance of succeeding. Although sales were slow in the beginning they gradually increased and soon it was clear that Toyota´s leadership and perseverance paid off as it was selling very well, and in 2005 it sold 180,000. In 2007 Toyota Prius was the 7th bestselling car in the U.S. Since then many large automakers have released hybrid models as consumers called for cars that could free them from fluctuations in fuel price. Many carmakers have scheduled releases of plug-in hybrid electric vehicles (PHEV). Plug in hybrids have smaller combustion engine but larger battery packs and electric motors and can be plugged to the electronic grid for most of their energy. Many see the hybrids and especially PHEV as a stepping stone towards full electric vehicles. (Sperling, 2008)

2.1.1 Present and future of electric vehicles

Past two or three years there has been increased excitement about EVs. Due to the economic recession in the late 2010s as well as growing gas prices and increasing environmental awareness, governments and automakers have had to reconsider the role of EVs in the car market. This could clearly be seen by the fact that nine new EV concepts were debuted in the 2009 North American International Auto Show. Recently Ford announced two new EVs which they will launch in 2010 (electric Ford Transit) and 2011 (electric Ford Focus) (Abuelsamid, 2009). Chrysler has introduced one EV and 4 PHEVs which according to them will enter markets in 2010 and 2011. Mitsubishi already released the i-MiEV in Japan and Europe and plan to introduce it to U.S. markets before 2012 and have set production goals of 2,000 units in 2009, 5,000 by 2010 and 20,000 in 2011 (Blanco, 2009). Late 2009 Nissan introduced an EV called "Leaf" which will be marketed late 2010 in North America, Japan and Europe with an expected increase in production in 2012 (Takayashi, 2009). Honda, Toyota and Mini have also announced that they plan to release EV models in the next few years. Early in the 21st century new companies were formed to take advantage of the absence of the large car manufacturers in the EV market, such as REVA in India, Th!nk in Norway, BYD in China and Miles Electric Vehicles and Tesla Motors in the U.S. All these new manufacturers have already released one or more EV models.

Governments in many countries are encouraging production and usage of EVs and hybrids. In 2009 the Obama administration allocated \$2.4 billion in grants to research and development of batteries and electric and hybrid vehicles as well as providing a \$7,500 tax credit for the for the first 200,000 families to buy EVs or PHEV (Obama, 2009). China has adopted very ambitious plans to become world leaders in production and utilization of electric vehicles. China plans that by the end of 2011 their production capacity for hybrid and electric vehicles will be 500,000 cars. Beyond planning to lead the production of electric vehicles they offer subsidies of up to \$8,800 to taxi fleets and local government agencies for every electric and hybrid vehicle they purchase and the state electricity grid has been ordered to set up electric car charging stations in Beijing, Shanghai and Tianjin (Bradsher, 2009). Israel has in cooperation with Nissan, Renault and Better Place started building a nationwide infrastructure and EV network with a goal of oil independence by 2020. Better Place has reached agreements about infrastructure building for Denmark and various states and cities in Australia, Canada and the U.S. (Better Place, 2010). The city of Reykjavík has announced plans to make the city a leader in utilization of electric vehicles and an investment group called NLE has issued plans to finish electrifying the Icelandic transport sector in 2012.

But how will electric vehicle market grow? In January 2009 Boston Consulting Group released a report where they predicted the production of EV in 2020 in Northern America according to three scenarios. In scenario 1 the situation will evolve towards lower oil prices (less than \$60 per barrel) and less concern for global warming. In that scenario both EVs and PHEV fail to reach 1% market penetration, which is a measure of the extent of the sales volume of a product (in this case EVs) relative to the total sales of all competing products. In scenario 2 the fears of climate change have intensified, price of oil has risen to \$150 per barrel and government has set legislations and regulation on emissions as well as providing tax incentives for buyers of environmentally friendly cars. For that scenario EVs reach 2.2% market penetration. In scenario 3, oil has risen to \$300 per barrel and carbon emissions have become a very urgent issue resulting in heavy government regulations and incentives to reduce the emissions. For that final scenario EVs gain 5% market penetration by 2020 meaning that 5% of vehicles sold in the US in 2020 will be EVs (The Boston Consulting Group, 2009). If the total light vehicle sold in the year 2009 in the US is used as a reference (in which 11.4 million light vehicles were sold (Bailey, 2009)), a 5% of sales being EVs would mean that 570,000 light EVs could be expected to be sold in 2020.

2.2 The benefits from EV utilization

Electric vehicles have number of advantages over the dominating internal combustion engine vehicles. The following section explores these benefits. The challenges of EVs will be described later in the chapter.

2.2.1 Lower energy consumption

It is debated whether a switch to EVs from conventional cars (CVs) would reduce energy consumption from the worlds transport sectors. If one considers only the vehicle itself EVs are far more energy efficient than CVs. For the Tesla Roadster 86% of the electricity used to charge the battery is used to power the cars motor, thus giving the car itself 86% energy efficiency (Eberhard & Tarpenning, 2006). Most CVs however convert only about 20% of the energy in gasoline into engine energy. But that does not tell the whole story as in order to determine the system-wide energy efficiency the primary source of the energy must be taken into consideration. The loss of energy from generating electricity from a primary source of energy (such as hydroelectric plant or a coal plant) and transporting it to an electrical outlet is much greater than the energy loss from extracting, refining and delivering petroleum fuel to a car. If the electricity is generated by a combined cycle natural gas-fired power plant the electricity generating efficiency can be as high as 60% (General Electric, 2009) and hydroelectric production reaches generating efficiency as high as 90%. Natural gas recovery and processing are both 97.5% efficient and the transport of electricity over the grid is 92% on average (Eberhard & Tarpenning, 2006) giving a 52.2% well-to-outlet efficiency. Charging a Tesla Roadster with electricity generated by a “top of the line” combined cycle power plant would result in a 45% well-to-wheel efficiency. It must still be noted that the EV technology is nowhere as developed as the CV technology and the efficiency could well increase with further research and development.

In addition to higher efficiency, if it is possible to charge EVs during off-peak periods, it could help load-balance the electric grid. Otherwise, the generator would just sit idle and waste excess. Furthermore, in some areas, there is no need to build more power plants to supply the electricity for EVs. In the U.S. the existing electricity infrastructure can comfortably charge tens of millions of plug-in hybrids without additional generating resources (Kromer & Haywood, 2007).

2.2.2 Reducing oil dependence

For many nations the key promises of EVs and PHEV, from a policy point of view, is the potential to reduce dependency on foreign oil. The economies of many nations depend heavily on oil which creates both economic and energy security problems. In the U.S. 40% of energy comes from petroleum and daily consumption of oil is 20.8 million barrels of which 40% goes to automobiles (Leitman & Brant, 2009). The situation is similar for many countries. As oil and fossil fuels are scarce energy resources and with increasing consumption these resources will eventually run out. Until then the prices are likely to rise steadily with oil purchasing taking a larger piece of the cake for economies around the world. As well as having negative economical effects this situation is a source for political tension. Electrification of transport would help reduce this dependency and the negative effects that follow. In Iceland the only sector relying on oil is the transport sector and although ocean and air transport solutions are not around the corner, the electrification of road transport is a promising possibility.

2.2.3 Environmental Impacts

The increasing use of EV would have significant positive impact on the environment because of the reduction of overall energy consumption and air pollution. Study performed in the U.S. (Kintner-Mayer, Schneider, & Pratt, 2007) shows that for the nation as a whole, the total GHG (green house gases) are expected to be reduced by maximum of 27% from the projected penetration of PHEV. Besides, total volatile organic compounds (VOC) and carbon monoxide (CO) emission would improve by 93% and 98%, respectively and the total NO_x emissions are reduced by 31% due to the elimination of the use of internal combustion engines (Kintner-Mayer, Schneider, & Pratt, 2007). However, electricity resource and the efficiency along the electricity generation path is the key issue in this case. A number of studies have been done on the impact of using EVs powered by electricity generated by coal power plants. Boschert (2008) did a literature review of the subject (well to wheels emissions comparisons) and compared different studies. The results of the studies ranged from 0%-59% less GHG emissions compared with ICE vehicles (two studies found 0% change; seven found 17% - 59% change) (Boschert, 2008). So even if EVs were to be powered by electricity generated using coal the emissions of GHG would still be lower although the degree of change varies with different studies. Conversely, the use of EVs could bring few slight negative impacts to environment, such as increasing amount of waste batteries, and increasing of energy demand for extracting lithium and production battery. Fortunately, the most promising lithium ion battery is more environmentally friendly than lead-acid, and Nickel–cadmium (Peter Van den Bossche, 2006). One can not only think about the emissions from the vehicle itself as obviously there are many polluting steps in the lifecycle of each vehicle. The lithium battery offers the main difference between EVs and other vehicles. Notter (2010) compiled a detailed lifecycle inventory of a Li-ion battery and produced a rough lifecycle analysis (LCA) of electric vehicles. The main finding of that study was that the impact of a Li-ion battery used in EVs for transport is relatively small. It showed that the negative environmental effect of mobility is dominated by the operation phase regardless of whether a internal combustion engine vehicle (ICEV) or an EV is used. Notter found that when an EV was compared to an ICEV, the use of an EV in transport results in lower environmental burdens. The share of total environmental impact of EVs caused by the battery is 15%. The impact of lithium extraction for the battery is less than 2.3% while the highest burden related to the battery was the supply of copper and aluminium for anode and cathode production and cables required for the battery management system (Notter, Gauch, Wager, Stamp, & Zah, 2010).

Apart from the before mentioned benefits of EVs on social level, using EVs has many upsides for users. Most regard home plugging a comfortable experience and some prefer it to the fuelling of gasoline cars and most people enjoy driving EVs because of the high acceleration at low speeds due to the high torque of the motor (Turrentine, Sperling, & Kurani, 1992). Other positive aspects for users include low noise levels and lower repair requirement than CVs.

2.3 CHALLENGES TO THE DEVELOPMENT OF THE EV

EVs have many advantages over conventional vehicles. But, why have EVs not become widespread around the world to date? Obviously, there are some challenges to overcome.

2.3.1 HIGHER PURCHASE PRICE THAN SIMILAR CONVENTIONAL VEHICLE

Although the basic EV (excluding battery) is probably slightly cheaper than the CV, battery pack would add much cost to EV at this moment. According to the California Air Resources Board Expert Panel the cost of lithium ion battery ranges from \$340 to \$420 per kWh (500MWh/year production rate) and \$240-280/kWh (2500MWh/year) based on different production amounts (Fritz R. Kalhammer, 2007). In general, the purchase price of EVs is higher than similar conventional cars. In one study, a retail cost increment of US\$ 3,000 was estimated for a midsize sedan HEV (hybrid electric vehicle). Nonetheless, if fuel cost is considered as well as maintaining cost during operation period, the cumulative cost of CV maintenance probably will exceed the EV in some cases. HEVs can provide lower cost than CVs after around 4 years and PHEVs provide lower cost than CVs after around 7 years based on 15,000 mile/year driving, gas price of \$5 per gallon, and \$0.09 cents per kWh (Simpson, 2006). In addition to private cost, conventional vehicles have some social cost, such as cost related to GHG emission, air pollution, and noise. Lipman (2003) concluded that the breakeven gasoline price based on social costs is about \$0.2 per gallon less than the breakeven price based on private cost (Lipman & Delucchi, 2003).

2.3.2 BATTERY LIMITATION

Due to breakthrough in material science, lithium batteries have made great progress since the 90s. The energy specificity and power specificity (100-150Wh/kg; 2000-4000 W/kg) of Li-ion batteries could satisfy the requirement of EVs (Fritz R. Kalhammer, 2007). Due to the more stable crystal structure, the lithium-ion battery has longer cycle life. The FreedomCAR program estimated lithium-ion calendar life at 10 years, while several commercially available batteries achieve > 1000 cycles for deep-discharge (BEV) profiles and 150,000 cycles for shallow-cycle (HEV) operation (Kromer & Haywood, 2007). However, the test data derived from laboratories are unproven under real world circumstances. The temperature, humidity, and various discharging situations would affect the capacity and performance of the battery. Another critical issue is battery safety. Concerns about Li-Ion battery safety can be limited based on the tolerance of cells and batteries to “abuse”, either electrochemical (shorting, high rate and extensive overcharging), thermal (heating to temperatures above the cell tolerance limit) and/or mechanical (destruction of physical integrity). The degree of tolerance to various abuses is serving as a relative measurement of safety as well as a guide to the development of adequately safe Li Ion cells and batteries (Doughty & Crafts, 2006).

2.3.3 EV INFRASTRUCTURE

Not all people can park their vehicles in a private driveway, garage, or carport, especially in urban areas. Moreover, when charging a midsize EV (20kWh capacity) on 220 volts, 15A outlet at 90% energy efficiency, it takes approximately 6.7 hours. It is clear that sufficient EV infrastructure is required to make charging battery become as convenient as possible for everyone and everywhere. According to a recent research report, the average infrastructure installation cost is from $4,000 per charger (level 2 residential charger) to $6,300 (commercial charger) including (charger, installation labor, permits, tax) (Boyce, 2009). This is clearly a very large investment and nobody knows if or when they will start to get profit.

2.4 EVS AND ICELAND

This section focuses on aspects that are in some ways relevant to the implementation of EVs in Iceland, aspects that either will influence or be influenced by the transition to EVs in Iceland

2.4.1 ENERGY IN ICELAND

Iceland’s energy profile is somewhat unique. In 2008 approximately 80% of the total energy demand of Iceland was met with domestic renewable energy resources, consisting mainly of geothermal energy and hydroelectric sources (Rammaáætlun, 2007). But this is not quite this simple. 80% of the energy goes to heavy industry, namely aluminium smelters. Those smelters are owned by foreign companies but are built here as Iceland can supply them with cheap electricity. It is therefore fair to say that the electricity supplied to the aluminium industry could be identified as indirect export of energy. With heavy industry included, the portion of energy demand fulfilled with domestic energy is roughly 85% but with heavy industry excluded this portion is 65-70% (Ministry of Industry, 2008). The latter is more relevant in the context of this subject. Figure 2-1 shows that with the aluminium industry excluded the portion of primary energy demand supplied by fossil fuels is quite high (37%) (Ministry of Industry, 2008). Note that the numbers shown are for primary energy supplied and therefore do not take conversion efficiency into in to the equation.

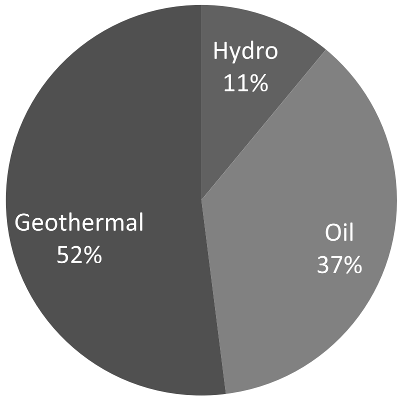

Figure 2-1 Primary energy demand in Iceland with demand for heavy industry excluded

Iceland has become worldwide poster child for “green energy”. In fact Iceland still relies heavily on imported fossil fuels for certain sectors. When it comes to the consumption of oil per capita Iceland is one of the largest consumers of oil worldwide with consumption of oil per capita reaching 69.95 barrels of oil consumed daily for each 1000 habitants. That consumption is similar to nations such as the USA and Canada which on the other hand are also producers of oil while Iceland has to rely completely on imported oil for consumption. (Ministry of Industry, 2008)

2.4.2 Economic effects

Most of oil imported is used for automobiles and other road vehicles. Second highest oil consuming sector is fishing vassels, followed by airplanes (National Energy Authority, 2007). A switch from imported oil to domestic energy for cars would have a considerable impact on the Icelandic economy. On top of savings from less import the refilling costs for vehicle owners could decrease by up to 90%. Sigurðsson in 2010 showed that consumers with average or higher annual driving distances will benefit from purchasing EVs (Sigurðsson, 2010)

In a report made for the Icelandic ministry of industry in 2008 it is concluded that a transition from conventional vehicles to EVs would be economically benefitial for Iceland. As less fuel is imported trade balance will improve as well as economic growth as domestic energy is used. In the 2008 report it is further stated that positive trade balance will improve the currency rate (Ólafsson, 2008). In 2010 Sigurðsson reached a different result, showing that EV implementation would impact trade balance in a negative way. The negative contribution results entirely from the high import prices of EVs compared to conventional vehichles. The trade balance will remain towards deficit until import prices of EVs are low enough to equal subsequent decrease in gasoline and maintenance imports (Sigurðsson, 2010).It is clear that things are moving in that direction with ever increasing fuel prices and mass production of EVs around the corner.

2.4.3 Energy demand for electric vehicles

It is assumed that the charging of electric vehicles would by the largest part take place during night. The electric system is designed and operated to be able to supply peak power needs. The demand of electricity is lowest during the night and it is beneficial from the point of view of efficient use of the system to charge vehicles at those times. Whether the current system is sufficient to supply electricity for an electric transport system is on the other hand yet to be seen. Based on the sum of imported cars in 2007-2009 and average net annual electricity required for an EV Sigurðsson (2010) showed that if 100% of these vehicles had been EVs the total increase in energy needed to power the cars would have been 61 GWh (Sigurðsson, 2010). Sigurðsson further concluded (also based on future projections) that the added load was not significant enough to require increase in the electric generating capacity of the country. Orkustofnun (2009) projected that by 2030, 90% of vehicles would be electricity driven resulting in an annual electricity demand of 145 GWh (National Energy Authority, 2009).

2.4.4 PAST, PRESENT AND FUTURE OF EVS IN ICELAND

The history of electric vehicles in Iceland ranges back to the Second World War, when one EV was apparently operating in Iceland, although the author did not find any documents mentioning its role or brand (Jónsson, 1996). Work on EVs in the scientific community in Iceland ranges back to the 70s when, Steinn Sigurðsson and Gísli Jónsson, worked separately on EV related projects. In 1975, Steinn Sigurðsson received an award in an EV design competition held by the American magazine Popular Mechanics for his vehicle “Rafsi”. Gísli Jónsson had the first EV imported to Iceland (Jónsson, 1996). This vehicle was a so called Electro Van 500 which is converted Subaru 500 van which offered a 20 horsepower motor, 80 km/h max speed and a 40-50 km range. Gísli Jónsson was a professor at the University of Iceland and had the car imported for research purposes. In 1984 Jónsson published his report based on his experience with using the car. He notes two major positives regarding EV implementation in Iceland, less emission and positive economic effects from using domestic energy. His results were that EVs would be technically feasible and their characteristics would be sufficient to fulfil “a large part” of urban driving needs and calls for action from the government (Jónsson, Notkun rafbíls á Íslandi, 1984). Little information regarding EVs in Iceland is available and until the latter part of the 2010s, with the exception of four Peugeot 106 EVs that Orkuveita Reykjavíkur and Landsvirkjun purchased in 1998.

In the late 90s and the beginning of the 21 century, hydrogen vehicles were introduced to the scene and the concept of the hydrogen economy was on everyone’s lips. Iceland pledged to become frontrunners in the utilization of hydrogen for transport and very ambitious projects were lunched such as the building of the world’s first commercial hydrogen pumping station and hydrogen powered buses in Reykjavík. Although the mirage of the hydrogen economy slowly disappeared from scene it still helped paving the way for other alternatives in Iceland. The actions in this field in Iceland got the attention of the research community and media around the world.

Following the success of hybrid vehicles around the world and the recent wave of EVs, Iceland made sure not to miss the boat. Private investors have already issued very ambitious plans to set up the infrastructure for EVs in Reykjavík by 2012. A number of EV models are to be available from early 2011 both from dealerships offering well known brands (Mitsubishi, Nissan, Volvo etc.) as well as an specialized EV dealership introducing new brands (Reva, Smith and Tesla). In the universities in Iceland a number of studies have been done (and are being done) on the many aspects related to EVs in the past two years and a few EVs have been built. In the University of Reykjavík an EV car sharing organization is operating where students and teachers of the school can borrow an electric vehicle.

As stated above Iceland’s research and actions with hydrogen did draw global attention and to some extent placed Iceland among the frontrunners in the field of green transport around the world. The Icelandic government pledged in 2007 to keep its seat among the leaders in that field as using domestic renewable energy for transport could have considerable positive effects on the Icelandic economy (Ministry for the Environment, 2007). It was further stated that Iceland had a reasonable chance in becoming the first fossil fuel free industrialized nation (Ministry for the Environment, 2007). In order to reach this goal a number of actions have been issued to be made of which some have already been made. One example of such action is that on the 1st of January 2010 a new law passed that puts a carbon tax on all fossil fuels in Iceland (Ministry of Finance, 2010). This indirectly gives people incentive to purchase low emission vehicles. Another example of governmental actions in this is that it has been decided that public parties and institutions will use environmentally friendly vehicles when possible. For example the ministry of industry in 2008 announced that it was to start working with the Japanese car manufacturer Mitsubishi and start using iMiev EVs. Today the official vehicle of the minister of industry is an iMiev (Ministry of Industry, 2010).

The city of Reykjavík has ambitious plans when it comes to environmental issues. A new city council was elected in 2010 and one of its main priorities is a transport system transition with focus on electricity (City of Reykjavík, 2010). The goal is that in 2020 half of the vehicles on the streets of the city shall be powered with green fuel. The council will show initiative in the utilization of environmentally friendly vehicles by renewing its vehicle fleet with green vehicles (City of Reykjavík, 2010). This has already been done to some extent. For example the Reykjavík city garbage trucks are all fuelled by methane and the vehicle of the mayor is a hydrogen vehicle. Reykjavík is one of 7 cities to reach the finals in a European contest to become the “Green capital of Europe” (City of Reykjavík, 2010).

It thus seems as if all required parties in Iceland such as the government of Iceland, the research community, the city of Reykjavík and private investors have similar ambitions and when it comes to shaping of the future of the Icelandic transport system, with all of them putting special emphasis on electric transport. It is fair to say that the transition towards an electric transport system in Iceland is already underway although it is currently nowhere near the finishing line with a very long way to go.

3 METHODS AND MATERIALS

As stated in the introduction to the thesis the scope (goal) of the thesis is twofold. Firstly it represents a new methodology for assessing whether the driving distance needs of a vehicle could be fulfilled by an EV. To do this a model was developed and programmed which compares driving data collected by vehicle for a single day with the performance characteristics of a similar sized EV. Secondly, this method was used to research whether and how well EVs could replace ICE business vehicles in Reykjavík. The method is shaped around using GPS data from vehicles gathered using data loggers. The simulation model designed in correspondence with the format of the GPS data.

In the first part of this chapter the data gathered for the research is described. An overview of the approach that was used for the research is presented as well as a thorough description how data was collected and how it was processed before being used for the EV model created. The second part describes the EV model which was created and programmed, through which the driving data gathered was run in order to assess whether each data gathering vehicle could have been an EV through the sampling period. The model vehicles and the charging information used for the model are described, before an overview of the program is presented. Finally the analytical procedures that were used to draw conclusions based on the information gathered are described.

3.1 DATA FROM VEHICLES

In this part the driving data gathered to assess whether the driving needs of vehicles in Reykjavík could be fulfilled by EVs (via the model programmed and presented later in the paper), is described. The sample is described thoroughly as well as the process of how data was collected. The data format is then presented as well as how it was processed before being used.

3.1.1 SUBJECTS

The data were acquired through a company called SAGAsystem which is a privately owned company, founded in 2000. SAGAsystem is a patented application service solution in the telematics industry. The patents are for Driver Assessment Program, a driving behavior formula developed to monitor and better individual driving behaviour in order to improve vehicle and employee performance, productivity and reduce fleet operating cost. SAGAsystem has been developed and thoroughly tested for over 8 years, mainly in the Icelandic market but also in other Scandinavian countries, since 2001. Currently there are more than 130 companies using the system in rapidly growing number of vehicles in 4 countries.

SAGAsystem works in the following manner. Positioning information is collected from the GPS network through a data logger that is installed in every vehicle. The data logger resends the information, in real-time, via GSM or GPRS network, to a nearby SAGAsystem Control Centre. The four main attributes that are used to determine driving behavior are calculated at the control centre. These are speeding, acceleration, deceleration and gravitational force when turning. The location of the vehicle at any given time is logged and stops are located, measured and categorized. This information is processed and presented to the client through a user friendly interface where the driving behavior and pattern of each vehicle can be closely monitored by the client.

SAGAsystem was contacted as a possible data source early in the thesis progress and were immediately willing to cooperate. From the clientele of SAGAsystem a number of companies were initially identified as possible co-operators of which 17 ended up supplying data from their vehicles, hosted at Saga System. A few things were kept in mind when co-operators where chosen. The total group of firms needed to be diverse, representing disparate employment sectors. The companies were then identified on the basis of preferably having a large vehicle fleet, composed of vehicles with varying roles and daily driving distances. Saga System hosts the data for its clients but cannot give access to it without the client's permission. In order to get access to it a confidentiality contract had to be signed by the author and a representative

The data was gathered by business vehicles driving in Reykjavík over a 100 days phase from May to June 2010. The vehicles are equipped with data logging devices that logs information about the driving. A total of 368 vehicles gathered the data used for this research. These 368 vehicles belong to 17 companies operating in Reykjavík. The companies operate in a broad array of business sectors such as postal service, cargo transport, wholesale firms, public organizations and dairy product manufacturers to name a few. The sample size is thus limited to the amount of SAGAsystem customer businesses willing to cooperate and to the number of vehicles within the fleets of these businesses. Whether the research results are statistically significant is unclear. It is important for readers to take this fact into consideration when the results are analyzed. Even if it would have been possible to increase the sample size it was not possible to get information on the number of vehicles in Reykjavík belonging to businesses and it would therefore have been not possible to assess the significance. The sample is still large and even if it is not statistically significant the results will point in the right direction. However the research performed in this thesis is mainly meant to test the method created and to unveil its shortcomings so that it can be improved in the future.

All the 368 vehicles were put into three separate “classes” based on their gross weight. The classes are -2500 kg, 2500-4000 kg and +4000 kg. A list of all vehicles from those of SAGAsystem clients which were willing to cooperate was acquired through SAGAsystem. Knowing the brand and exact model of the 368 vehicles they could be divided into these categories. In table 3-1 the total vehicles and in which class they have been put to can be seen. The companies to which the vehicles belong are encrypted and marked with a letter from A to R, due to confidentiality issues. The vehicle fleet of the companies ranges from 2 to 112 vehicles. In total data was gathered by 118 vehicles under 2500 kg, 165 vehicles weighing between 2500 and 4000 kg and 85 over 4000 kg. Initially the vehicles were roughly 450 but some of the companies downsized their vehicle fleet during the data gathering phase and returned data loggers to SAGAsystem. It was decided not to use vehicles that were not equipped with data loggers throughout the whole period.

Table 3-1 Number of vehicles from each class from each fleet

Company	Vehicles	Class 1	Class 2	Class 3
A	28	11	1	16
B	17	14	2	1
C	4	0	4	0
D	3	0	0	3
E	19	2	15	2
F	19	11	8	0
G	26	2	7	17
H	22	13	1	8
I	11	1	3	7
J	9	6	2	1
K	62	23	31	8
L	15	2	11	2
M	11	0	9	2
N	5	0	0	5
P	4	0	2	2
Q	4	3	1	0
R	112	30	70	12
Total	368	118	165	85

3.1.2 DATA

The following section contains description of how the data was acquired as well as why certain data format was chosen rather than another. A description of the data format follows.

3.1.2.1 ACQUIRING AND SELECTING DATA

The data gathered by the vehicles was acquired at SAGAsystem's headquarters. The data format is SQL tables and Microsoft SQL Server 2005 was used. By connecting to the SAGAsystem local network the author could access SAGAsystem servers master database and import the data gathered by all vehicles gathered over the decided research period from the companies which had accepted to supply data for the research. SAGA holds its data on a few different ways. One format (which I will refer to as 2-second tables) is such that each vehicle has a table which holds data for last three months. Data is logged approximately every 2 seconds and a number of variables recorded. When the vehicle stops (showing 0 km/h) data ceases to flow into the 2-second table. Instead the stop period information regarding the stop period is analyzed and logged to a separate table for that same vehicle. SAGA also stores so called RT Packets in tables where information is logged every 15 seconds. RT packet tables hold fewer variables then those above but still include all the variables needed for the EV model created for this research. RT Packet tables are not limited to holding 3 months worth of data like the 2-second tables. However when signing contracts with companies the period agreed upon was limited to the approximately three month period held in the 2-second tables. The RT Packet tables logs stops, so instead of showing a single 0 km/h log and having a separate stop report table, 0 km/h is logged every 15 seconds of the stop period. Initially the plan was to use data from 2-second tables (hence the 100 day data collecting period) but in the end it was decided to use RT Packet tables due to a few reasons:

- The biggest advantage of the RT packet table was the fact that data for all the vehicles could be exported in one large table. This would save great amount of time and effort as with the 2-second tables each vehicle would need to be in two separate tables (table holding data and a different one for stop reports). Therefore instead of having 740 tables for the data from the vehicles there could be one holding all the data. The transfer of each table takes quite some time and needs to be done manually. Also, using only one table instead of hundreds makes the program written run much faster.

- Logging data every 15 seconds is sufficient to acquire reliable results. Also most of the variables in the 2-second tables were not required for the model. The result is a smaller amount of data due to fewer logs and variables.

Apart from the RT packets table containing all the driving data, a table was created by programmers at SAGAsystem which simply holds a list of the vehicles. This table contained a blank column for "Class", which was later filled with the corresponding class (described above) of each vehicle on the list from each company. When the data had been acquired and the most convenient format been identified the author could start to shape the model and program which play the largest part in the methodology designed.

3.1.2.2 DATA FORMAT AND DESCRIPTION

As stated earlier the data is kept in SQL format. The following section shortly describes the data that was used, its format and main variables. *RT Packets*: This table is holds the main information needed for the research, it was acquired from SAGAsystem. The data used is the RT packet table which contains all the data gathered by the 368 vehicles over a 100 day phase. A screenshot of a section of the table is shown in table 3-2.

Table 3-2 An example of a short segment from the RT_Packets table

RTpacketID	IMEI	TimeDate	Lat	Lon	Speed	Course	Customer_FK	Plate
1407212264	001101300007565	22.4.2010 07:35:24	64,0795	-21,925	0	289	9999999999	XX-123
1407212350	001101300007565	22.4.2010 07:35:43	64,0795	-21,925	0	289	9999999999	XX-123
1407212685	001101300007565	22.4.2010 07:35:58	64,0794	-21,9252	20,7	206	9999999999	XX-123
1407213062	001101300007565	22.4.2010 07:36:13	64,0785	-21,9243	36	135	9999999999	XX-123
1407213196	001101300007565	22.4.2010 07:36:28	64,0788	-21,9225	43,2	42	9999999999	XX-123
1407213306	001101300007565	22.4.2010 07:36:43	64,0784	-21,9191	59,4	126	9999999999	XX-123
1407213411	001101300007565	22.4.2010 07:36:58	64,0772	-21,9166	24,3	110	9999999999	XX-123
1407213525	001101300007565	22.4.2010 07:37:13	64,0782	-21,9142	44,1	42	9999999999	XX-123
1407213638	001101300007565	22.4.2010 07:37:28	64,0773	-21,9127	50,4	161	9999999999	XX-123

This table shows about two minutes worth of data from a vehicle with the license plate number XX-123, which is owned by a company with the social security number 999999-9999 (column *Customer_FK*). Both the plate and the social security numbers have been encrypted due to a confidentiality agreement. Information for the vehicle is logged every 15 seconds as can be seen in the column *TimeDate*. Every log contains information on the location (latitude, longitude), speed (in km/h) and course of the vehicle. In total this table (all 368 vehicles included) has over 22 million logs.

The table "*docks"* was created from data contained by the RT_Packets. A simple program was created using Python which identified the 5 most common stop locations for each vehicle. The purpose of this table is to identify the "docks" or "home" for each vehicle. A dock is a location where each vehicle will be allowed to charge its battery pack in the model. Originally each *lat* and *lon* log was more precise (had more decimals). It was important that the locations were not too precise so that two locations perhaps 50 meters apart would be counted as the same location. This is because each vehicle will only have two docks where it can charge (the dock count can be changed in the program). It is important that the two most common stop locations are not two different locations on the same car lot but rather two definitely separate locations, such as two outposts belonging to the same company, or a company's headquarter and the drivers home (in many cases cars are kept at drivers home over night). The aim with the docks method was to make a vehicle at least be able to charge at its overnight locations.

Table 3-3 A segment from the locations table. The 5 most common stop locations of two vehicles are shown.

Plate	Lat	Lon	stops
XX-123	63,9849	-22,5462	4973
XX-123	63,9858	-22,5412	3800
XX-123	63,9929	-22,5481	691
XX-123	63,9774	-22,5472	408
XX-123	63,9934	-22,5559	405
XX-111	64,1142	-21,932	1166
XX-111	64,1146	-21,9064	42
XX-111	64,1349	-21,9092	41
XX-111	64,1327	-21,8982	9
XX-111	64,1377	-21,8942	5

Overview: The *Overview* table is simply a list of all the vehicles used in the project. The class of each vehicle is identified in this table. The main program created to run the model accesses this table in order to identify to which class each vehicle belongs, in order to determine which constants to use for the model calculations (see under the *model vehicles* section below).

Table 3-4 The format of the Overview table

Plate	Customer_FK	Class
XX-111	9999999999	2
XX-112	9999999999	3
XX-113	9999999999	1
XX-114	9999999999	3
XX-115	9999999999	1

3.2 THE MODEL

The following chapter describes the EV model. The model vehicles chosen to represent each category are first presented. This is important as some of the characteristics of the model EVs will serve as constants for the EV model. Next the charging of the vehicles is described. Lastly the model and the program written will be presented.

3.2.1 MODEL VEHICLES

Different size and role vehicles have very different performance characteristics. The vehicles that gathered data for this research are of very different sizes, ranging from small subcompact vehicles (such as Toyota Yaris) to light commercial vehicles (such as VW Transporter) and large trucks. It is not possible to use the same model for a small vehicle and a large truck as those classes offer very different characteristics. For example a small van EV has a much smaller battery capacity than a large truck and therefore takes shorter time to charge. In order to get more realistic results the sample vehicles were divided into three different classes based on their gross weight (unladen weight plus full cargo). The three groups are as follows; -2500 kg, 2500-4000 kg, +4000 kg. The vehicles chosen were identified on the basis of being new models, based on well know models from well known brands, having similar batteries and having similar charging characteristics. The following EVs have been chosen to represent each weight category.

-2500 KG: PEUGEOT EPARTNER™

The Peugeot ePartner (see figure 3-1) represents the model for vehicles under 2500 kg gross weight. The ePartner is an electric version of the Peugeot Partner which is a van and leisure activity vehicle made by the French vehicle manufacturer Peugeot. The vehicles are manufactured by Allied Electric, a Glasgow based vehicle manufacturer, which combines the latest in battery technology and electronic management software with a range of vehicles produced by Peugeot.

Figure 3-1 The Allied Electric Peugeot EPartner

2500 – 4000 kg: Allied Electric Peugeot eBoxer™

Like the Peugeot ePartner the eBoxer (see image 3-2) is a vehicle manufactured by Allied Electric, based on a well known Peugeot model (Peugeot Boxer). The eBoxer is a larger vehicle than the ePartner. Its specifications can be seen in table 3-5.

Figure 3-2 The Allied Electric Peugeot EBoxer

4000+ kg: Smith Newton™

The vehicle representing data collecting vehicles of 4000 kg and more is the Smith Newton. Smith Newton is a truck manufactured by Smith Electric, the world's largest manufacturer of commercial EVs. Smith electric has manufactured EVs since 1920. Smith Newton is the largest electric truck on the current market and the exact model used for this project has a gross vehicle weight of approximately 10 tonnes.

Figure 3-3 The Smith Newton

Relevant characteristics of these vehicles are identified and used as constants for the three models created. Each of these vehicles represents one of three classes of vehicles that the data collecting vehicles were grouped into, and for each class a separate model is created. Although the model is basically the same, different constants are used based on the model vehicle representing each class. The main specifications of the vehicles can be seen in table 3-5 below.

Table 3-5 Overview of characteristics of the model vehicles chosen to represent the different classes

	Peugeot ePartner (Class 1)	**Peugeot eBoxer (Class 2)**	**Smith Newton (Class 3)**
General vehicle specifications			
Vehicle type	Van	Van	Truck
Gross weight (kg)	2185	3500	9990
Electrical specifications			
Peak output (kW)	30	60	120
Battery Type	Lithium-Ion ferrite	Lithium-Ion ferrite	Lithium-Ion Phosphate
Cell count	84	84	NA
Battery Capacity (kWh)	27	56	80
Nominal battery Voltage (V)	268	268	NA
On board charger Type	3 phase 32 amp	3 phase 32 amp	3 phase 32 amp
Range (km)	96	128	160
Charging time	3 hours	7 hours	8 hours

3.2.2 Model constants

The model is simple and is made to simulate the model EVs. There are three constants in the model which vary between the model vehicles. These are energy usage, max energy and charging power.

Max Energy (E_{max}): The max energy constant sets an upper value to the maximum energy that can be "pumped" into each of the model vehicles and is simply the battery capacity of each vehicle. The unit is kJ so the kWh (battery capacity in table 3-5 is in kWh) must be multiplied by 3600 in order to gain kJ.

Max energy for the model vehicles is the following:

$$Class\ 1\ (Peougot\ ePartner):\ \ 27\ kWh * 3600 = 97{,}200\ kJ$$

$$Class\ 2\ (Peougot\ eBoxer):\ \ 56\ kWh * 3600 = 201{,}600\ kJ$$

$$Class\ 3\ (Smith\ Newton):\ \ 80\ kWh * 3600 = 288{,}000\ kJ$$

Energy usage: For the model energy usage is assumed to be uniform, meaning that the model EV is always using the same amount of energy if it is driving. Acceleration is not taken into account, nor is change in the topography of the driving route. The self discharge rate of the batteries is not taken into account for this first version of the model as it's effect would be minimal especially as lithium ion batteries have the lowest self discharge rate of all batteries (Simpson C. , 2010). The energy usage is found using the battery capacity of the vehicles and the advertised range of the vehicles. This range is widely regarded as being lower when the vehicles are in actual use. For example users of Mitsubishi iMiev have complained about the range being much lower under actual usage than the official vehicle range. The energy usage is measured in kJ per meters driven. Then the maximum battery capacity is divided with the official range. The energy usage (has the symbol "p" in the model) of the model vehicles is the following:

$$Class\ 1\ (Peugeot\ ePartner):\ \frac{97{,}200\ kJ}{96{,}000\ m} = 1.012\ kJ/m$$
$$Class\ 2\ (Peugeot\ eBoxer):\ \frac{201{,}600\ kJ}{128{,}000\ m} = 1.57\ kJ/m$$
$$Class\ 3\ (Smith\ Newton):\ \frac{288{,}000\ kJ}{160{,}000\ m} = 1.8\ kJ/m$$

Charging power (c): The batteries of all the model vehicles are lithium-Ion batteries. Li-Ion batteries are unique when it comes to charging. They are charged under constant voltage charging, where the voltage source is fixed and current limited. The voltage in the battery is forced up to a set-point voltage (normally 4.200 mV). When set-point voltage is reached the current is limited to hold the voltage at the set-point voltage. The charging cycle is divided into two phases; current limit and constant voltage. In the current limit phase maximum charging current is flowing into the cell (1 c in figure 3-4), as the voltage is below set-point. During this phase about 65% of the total capacity is charged. When set-point is reached the charging current is reduced. A typical charging profile for a Li-Ion cell can be seen in figure 3-4.

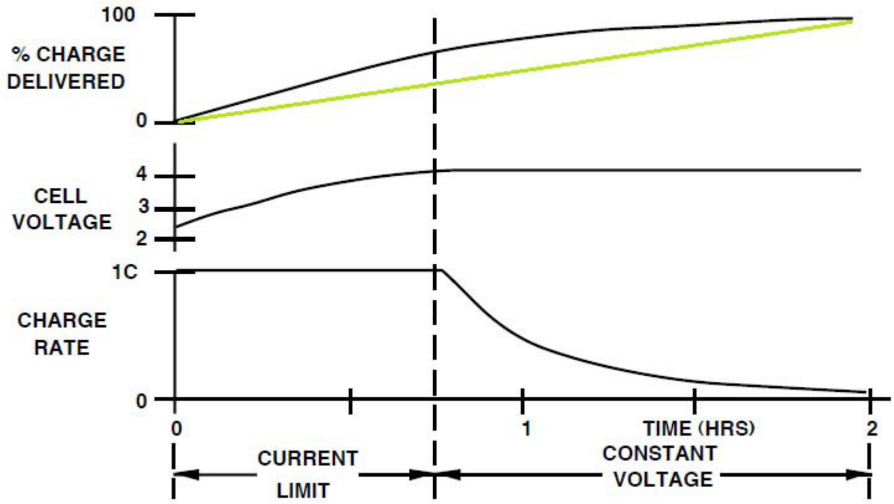

Figure 3-4 Typical charging profile for a Li-Ion battery (figure from Simpson, 2009). The green line was added by the author to represent the charging profile used for the model.

It was decided that the charging profile would be a straight line for the EV model, represented by a green line on figure 3-4 above. The whole charging period will be as long but the first 65% will happen slower than normally while the last 35% of the charging will be faster. All the model vehicles have 3-phase on board charger and it is assumed that these can be used to their full extent in all cases. Initially the plan was to use information on the vehicles to obtain the charging power for each of the vehicles but it was not possible to obtain the all information regarding electrical specifications that was needed for those calculations. Instead it was decided to use the information given by the vehicle manufacturers on the charging time of the vehicles. This is a very simple approach where max energy capacity is divided with estimated full recharge time.

$$Class\ 1\ (Peugeot\ ePartner):\ \frac{97{,}200\ kJ}{12{,}150\ sek} = 8\ kW$$

$$Class\ 2\ (Peougeot\ eBoxer):\ \frac{201{,}600\ kJ}{25{,}200\ m} = 8\ kW$$

$$Class\ 3\ (Smith\ Newton):\ \frac{288{,}000\ kJ}{28{,}800\ sek} = 10\ kW$$

3.3 Model and computer program

The model created simply shows the energy capacity of a theoretical EV battery pack as a function of time. The real code is not used for the sakes of convenience of explanation. The code can be seen in appendix 1. In the first section some constants and options in the program created, that can be modified to yield different results, will be identified. Then the model and program is described and finally the different versions of the program are presented. The program was written with the assistance of Jón Brynjar Stefánsson, a software engineer.

3.3.1 Model configurations and constants

There are a few options to the model that are very important for the research and different values at each of those will yield different results. These need to be configured at a certain value for the research in order to give realistic results as possible. These are „dock count", a so called „delta docks“ value, „charge wait“ and the class constants showed in the model vehicle section of this chapter; max energy, charging constant and discharge constant. The following configurations of the program were used for this study.

Dock count: 2

A dock is a location at which a car can be charged. It was decided to give each car two locations (hence, docks count equals 2) where it could be charged during stops.

In many cases companies have more than one outpost and also in many cases employees take the vehicle home over night. The two most common stop locations of each vehicle are identified as its docks. This will hopefully be sufficient to make sure vehicles are always charged overnight.

Delta docks: 0.005

This option decides the accuracy of longitude and latitude values. If this value is 0.005 (as was decided), two locations approximately 200 meters apart are considered as the same location.

These values cannot be to precise for the sakes of identifying charging docks. For example the three most common stop locations could be three locations of the same parking lot outside company headquarters if the locations are too precise. By allowing for approximation of the locations, all these three locations become one and the same location, where the car could be charged.

Charge wait: 240 seconds

This value sets for how long a car needs to stop at a dock in order for it to start charging. It was decided to make this value 4 minutes. This is done to exclude very short stop durations where it is not realistic that drivers would charge the vehicles.

Class Constants

These are the model constants for each class as defined and calculated above. In the brackets the symbol used for each constant in the model is shown.

Table 3-6 Class constants used

	Max energy (Emax)	Charging (c)	Discharge (p)
Class 1	97,200 kJ	8 kW	1.012 j/m
Class 2	201,600 kJ	8 kW	1.57 j/m
Class 3	288,000 kJ	10 kW	1.8 j/m

3.3.1.1 Model and program

This section shows how the model as well as presenting a simplified way of how the computer program runs. The program was written using the Python programming language with help from Jón Brynjar Stefánsson, software engineer. As stated above the model calculates the state of a battery pack of a model EV as a function of time using the actual driving data collected by real vehicles. The main purpose of this is to see whether or how often each vehicle would have run out of energy at any point during either the whole research period or each day, based on the different versions of the program. The actual code of the computer program created to run the model can be seen in appendix 1. The program starts by accessing the overview table where the cars are ordered alphabetically by number plates. It runs through one vehicle at a time using the configurations identified, and using information on docks from the docks table. From the overview table the program knows the class of the vehicle it is currently working with. Knowing the class it will use the class constants defined in the program for its model calculations. Two versions of the model/program were created. The difference is described in the section following this one.

Having been configured in a certain way, knowing the class of each vehicle and where it can be charged, the program starts working its way through the driving data for the cars from the RT_packets table which is ordered by time and date, calculating the current state of the battery pack at each point.

In the beginning (T_0), before the first log of each vehicle, it has a full battery pack, E_{max}.

$$E(T0) = Emax$$

At every TimeDate log (T), that is each row in the RT_Packets table, the E(T) is calculated. At every T the program looks at the speed (v) logged in that same row. If the speed (v) is >0 it means the vehicle is driving. When speed is >0 the following function is used

$$E(T_n) = E(T_{n-1}) - (T_n - T_{n-1}) * pv \qquad (1)$$

Where $E(T_n)$ is the energy state after the log, $E(T_{n-1})$ is the energy state at last log before. $T_n - T_{n-1}$ is the time between the the current log (T_n) and the log before in seconds (T_{n-1}), p is the energy usage of the car (based on the vehicle class) and v is the speed in m/s. The location of the vehicle does not matter while the speed is above 0. Every time that the $E(T_n)$ reaches zero the program documents one failure. The E can go below zero. This is done in order to give the possibility of calculating the capacity required for every vehicle (a feature of version 1). The program goes through the rows in this way, calculating the energy state of the model vehicles battery after each log until it encounters v=0.

If at T_n the speed (v) is 0 there are two possibilities based on the location of the vehicle and the duration of the stop. If the location does not match one of the docks defined for the vehicle there will be no change in the state of charge on the battery meaning

$$E(T_{n-1}) = E(T_n) \qquad (2)$$

If the location is at one of the two locations defined as a dock for the corresponding vehicle there are two possibilities based on the duration. If the duration of the stop (ΔT), that is time difference from the first v=0 log until the last v=0 log, is shorter than 240 seconds the vehicle will not be charged.

However if ΔT > 240 seconds the vehicle will be charged. The following function is used for every log during the stop duration

$$E(T_n) = E(T_{n-1}) + c(t_n - t_{n-1}) \qquad (3)$$

Where c is the charging constant defined for the class of the vehicle. The charging will stop if the energy reaches the maximum energy capacity, E_{max}. If the current energy status is below zero when the vehicle starts charging it will start at zero. The two versions of the model differ in one aspect of charging. Version 2 of the model/program automatically charges vehicles at midnight (regardless of location), while version 1 does not.

The program keeps doing this until reaches a new plate number. It then plots the whole data collecting period (where E is a function of time) for the vehicle using Matplotlib which is a plotting library for Python and its NumPy numerical mathematics extension. The program also creates a row dedicated to that vehicle in a result SQL table. The plots and result tables will be presented in another section of the methodology chapter. Once a new plate is reached the routine starts again for the next vehicle from the overview table.

3.3.1.2 PROGRAM VERSIONS

The text above describes the model and the corresponding model in a very simple way. It does not show any of the programming code nor does it show all the mechanisms lying behind the calculations. There are two versions of the model/program. The description above fits both of them and all the same calculations apply for both of the versions. The difference lies in whether or not the whole research period is segmented into smaller base research periods or not and if the vehicles are automatically charged overnight.

- Version 1: The program runs through all of the data gathered for the whole research period as a whole giving results from the whole period at once. For this version the energy level can go beneath zero and can go infinitely low. Every time a vehicle goes below zero over the research period one failure is documented. While the E remains under zero no failures are recorded.

- Version 2: The research is divided into 24 hour segments and results are documented for each of those 24 hours for each vehicle. At midnight a new day will start for the vehicle and the battery will go to E_{max}. In this version the energy level cannot go below zero. The decision to “automatically” charge the vehicle overnight proved vital.

Version 1 will look at the data for the whole 100 days and yield results based on that period time. The author identified a few questions which was hard to answer from results from version 1. These were questions such as “What is the mean driving distance per day for each vehicle”. Version 1 cannot give answers to questions such as “how many days could this car be an EV”. One other reason for version two being created is that the author decided that there might be a slight problem with the “docks method” used for charging in the model. In some cases a vehicle will not be at its dock identified for it for a long time and during that period the vehicle will keep going downwards until it finally stops at its dock again. A vehicle might for example always spend the night at an employee’s house and spend long hours each day at one of the company’s outposts. If the vehicle would for some example be relocated to start operating from another outpost of the company or if the employee would move, those locations would not count as docks and the vehicle would very rarely be charged. Therefore a new version of the program was created, where the period is divided into days and analyzing whether the car could have operated each day from a full battery pack.

3.4 PROGRAM OUTPUT DESCRIPTION

As stated above, once the program finishes running the driving data from each vehicle through the model it does two things; plots E as a function of time and summarizes the entire the results from the model in a row in a result *SQL* table. The results from the two different versions of the model/program differ. The following section will give description on how the results for each car are presented to the author. These results can be considered raw results as they are simply the results from each car while the main results of the thesis are acquired from statistical analysis of these results.

3.4.1 VERSION 1 PROGRAM OUTPUT

After running the entire data for a vehicle through the model the program plots the results. The plot has the energy status (E) of the vehicles battery in kJ on the y-axis and the time on the x-axis. An example of a plot created by version 1 of the program can be seen in figure 3-5.

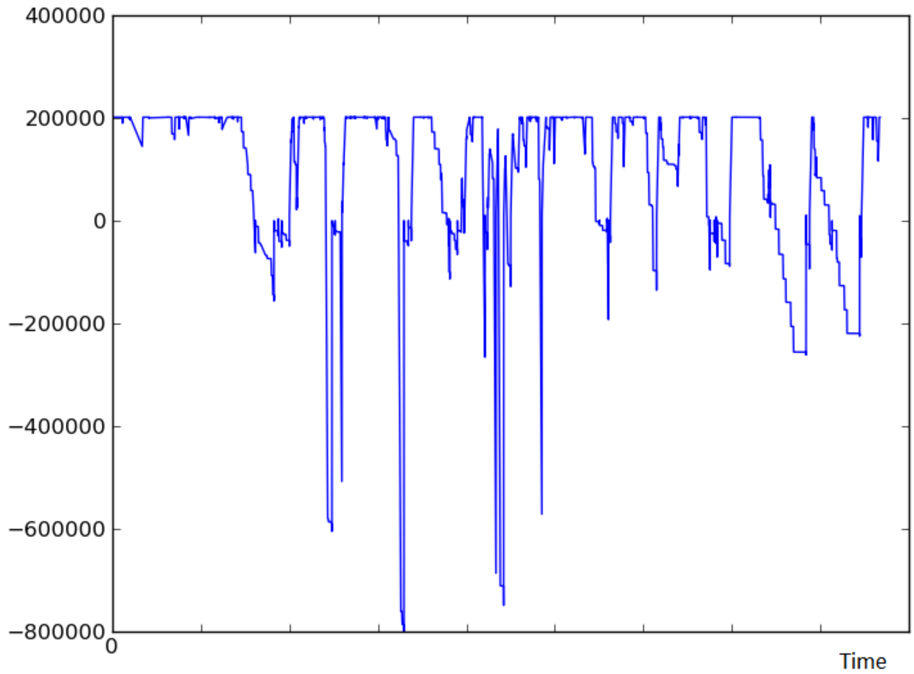

Figure 3-5 Output plot from a vehicle showing the whole research period from version 1 of the program. The y axis is the battery energy [j] while the y axis is time (the entire research period of each vehicle).

The program then summarizes the results of each car into a SQL table. There is one table for each of the model versions. A short section of the table for version 1 can be seen in table 3-7 below.

Table 3-7 Short section of the result table from version 2 of the program/model

Plate	Customer_FK	Failures	CapacityRequired	Class
XX-123	9999999993	9	329365	2
XX-124	9999999993	45	1329658	1
XX-125	9999999993	0	252614	3
XX-126	9999999993	61	179166	1
XX-127	9999999993	14	539514	1
XX-128	9999999993	0	54140	2

From table 3-7 the columns plate, customer and class are self explanatory. The failure column shows how many times the vehicle failed during the research period. One failure is documented every time the plot crosses the zero line on a negative slope. The “cap req“ (short for capacity required) column shows how much battery capacity would have needed for each car in order for it to be able to take its longest trips each day without running out of energy. This value is simply the difference between E_{max} and E_{min} (the lowest E value recorded for the vehicle).

Running all the data through the model using the version 1 of the program takes roughly 9 hours.

3.4.2 Version 2 program output

The plots created by version two are by most parts the same as the ones from version 1. The dissimilarity lies in the difference described before being that every midnight the battery pack jumps to Emax for version 2. The program notes every time this happens (every midnight) if the car did fail or throughout the day. An example of a plot created by version 2 of the program can be seen in figure 3-6. The same instruments are used for the plotting as in version 1.

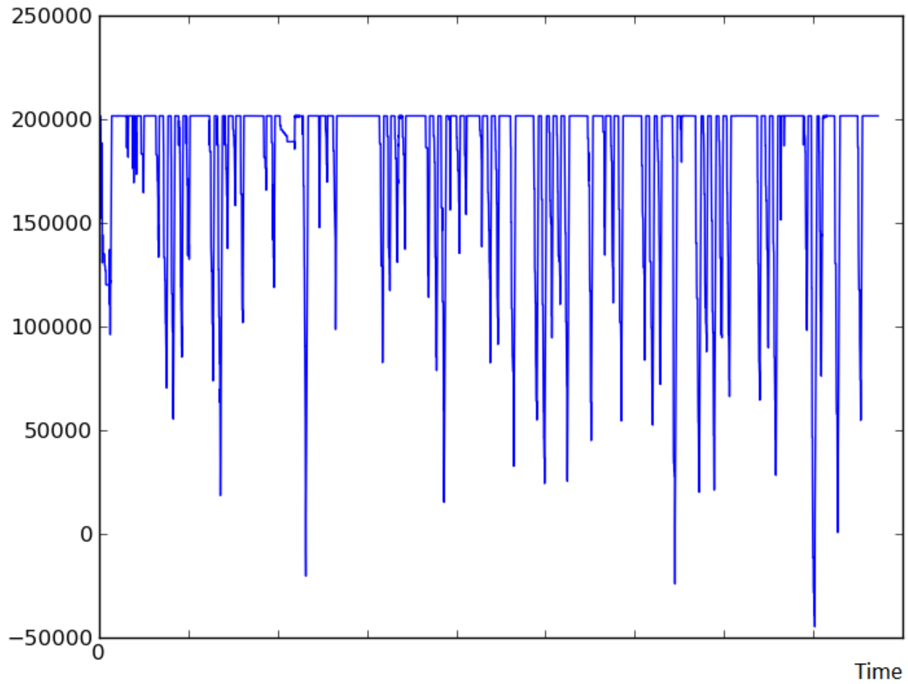

Figure 3-6 Output plot from a vehicle showing the whole research period from version 2 of the program. The y axis is the battery energy (j) while the y axis is time (the entire research period of each vehicle).

As with version 1 the program summarizes the results from each car into a SQL table. A short section of the table for version 2 can be seen in table 3-8 below.

Table 3-8 Short section of the result table from version 2 of the program/model

Plate	Customer_FK	Class	FailureDays	TotalDays	MeanDistPerDay
XX-123	9999999993	2	7	101	39
XX-124	9999999994	1	12	56	102
XX-125	9999999995	3	0	101	52
XX-126	9999999996	1	5	101	65
XX-127	9999999997	1	6	101	66
XX-128	9999999998	2	0	98	146

The columns in the two tables are mostly the same. The table from version 2 of the program does not include failures column. It however includes a column for the total amount of days on which the vehicle was used and a column for days without failure for each car. Finally it includes the average distance driven per day. The average calculations do not include days on which the vehicle did not move.

Running all the data through the model using the version 2 of the program takes approximately 16 hours.

3.5 Result processing and analysis

Results will be presented in the next chapter. This section will present how the result data (program output) will be analyzed in order to answer the main research questions such as;

- *How large portion of business vehicles in Reykjavík have the potential to be substituted with electric vehicles?*

- *Is there difference in the viability of a potential EV switch between different classes of vehicles?*
- *What is the future outlook for firms in Reykjavík in switching towards EVs? What fraction of firms could replace large fraction of its fleets to EVs?*

The result chapter will simply present the results without analyzing or discussing them. All discussion on the results and answers to the research questions will be in the discussion chapter that follows the results. The discussion chapter will also contain sections where the model, its shortcomings and future steps for improving it are presented.

The results are presented in three different sections, each dedicated to a certain way to group the vehicles. At first all the vehicles will be analyzed as one group. In that section the vehicles are not divided into any groups and simply show results based on data from all the vehicles, without aligning them into groups based on companies or classes. Next each of the vehicle classes are analyzed. Each class will be analyzed separately (the same kind of analysis will be used as for each class group as for the *all vehicles* group) and the results for different classes compared. In the *companies* section the vehicles from each company are analyzed and compared. All these groups are composed of the same vehicles and the data used for this is the model results of each car from the result SQL tables.

3.5.1 AVERAGE DAILY DRIVING ANALYSIS

Version two of the program calculates the average daily driving of vehicles. For every day that a vehicle which supplies data for the model is active the driving distance is recorded. The mean driving distance for all active days is then calculated. This feature will give information that was lacking for the research as there seems to be hardly any information available on the driving distance needs for vehicles in Reykjavík. Note that this parameter has in fact nothing to do with the model EVs or EVs at all but is simply a value calculated directly from the data from each vehicle, without adding any kind of EV model simulation. Apart from giving interesting and vital information about driving habits of business drivers in Reykjavík, this value for each vehicle gives rise to the simplest method of assessing the potential of a switch to an EV for that vehicle. Given that a vehicle could only be charged overnight it is possible to assess whether the driving range of a same class EV would be sufficient to supply the driving distance needed to get through the ”average day” before being charged again over night. After the data was run through the model, knowing the class of the vehicle, it is simple to see if the average daily driving distance value for each vehicle was under the official driving range of the same class model EV. Based on whether the average daily driving distance of each data collecting vehicle is lower than the official range of the model EV or not it is applied a “yes” or “No”. If a vehicle is applied a yes it regarded as having EV potential. Statistical analysis of the results for average daily driving analysis includes mean, median, maximum and minimum values, standard deviation and a depiction of the frequency distribution.

3.5.2 FAILURE DAY ANALYSIS

Version 2 of the program gives results for how many days a vehicle failed (that is went below 0 in battery capacity). Not all vehicles supply results for an equal amount of days throughout the research period. Therefore instead of simply looking into the number of failure days the fraction of failure days per total days is calculated from the results of each car. This gives rise to a parameter labelled „failure day percentage“. This parameter is very important for the research as it plays an instrumental part in analyzing the potential of an EV switch for the research vehicles and answering the research questions. Statistical analysis of the results for average daily driving analysis includes mean, median, maximum and minimum values, standard deviation and a depiction of the frequency distribution. From the frequency distribution the percentages of vehicles belonging in the ranges 0%, 0-5% and 0-10% failure days percentage is calculated. This is done for the total vehicle sample as a whole and the class grouping of the vehicles. A frequency distribution column chart is not depicted for the company division of the sample. Instead the percentage of the total vehicle fleets in each the range, 0%, 0-5%

and 0-10% failure day percentage is calculated for each company. For example a certain company might have 12% of its vehicle fleet having 0% failure day percentage.

Based on the results from the statistical analysis of failure day percentage it is possible to assess which vehicles could possibly have been replaced with electric vehicles throughout the research period. Three different scales were designed.

0%: In this scenario only vehicles which did not fail on a single day are considered to have the potential switch to an EV. Using this scale, companies and drivers would not need to modify their driving behavior or reorganize their fleet at all. Vehicles could be used in completely the same way as before.

0-5%: The second scenario includes all vehicles which failed in the range of 1% to 5% days from the total days (on top of course the vehicles that have 0% failure days). It is clear that for these vehicles the EV range is sufficient for majority of days with rare exceptions. As these days are clearly exceptions it is possible to plead that these vehicles could be replaced with EVs by a few ways. Substituting vehicles failing up to 5% of days with EVs would require some action and driving optimization from drivers. But even though some of these vehicles would have experienced problems on a few days had they been EVs those were clear exceptions. Obviously in the case of vehicles failing at some point, this would require some change in the utilization of the vehicles. For one, slightly changing the driving pattern and time management of the drivers could have drastically reduced failure frequency. These changes in time management and driving pattern can for example be to make sure to spend lunch time at dock when the EV is close to running out of energy, or taking a long trip after a pause instead of before it and charging the vehicle during the pause. And this kind of optimization would only be required on a maximum of 5% of days, and on the other days the vehicles could be used without any change in habits. It is thus likely that had the drivers known they were driving an EV on the few occasions that they failed, they would have easily be able to escape those failures by only slightly modifying their routine on the days that these exceptions from the norms took place. But not only how the day is organized, and how the driving route is optimized can allow those vehicles to be EVs, but also the driving behavior/style of the drivers. Some studies have been done showing how very effective a change in driving behavior can be, for example by using so called EcoDriving. Three different EcoDriving instructors and 16 students performed a trial in three different locations with the goal to see if EcoDriving had an impact on emissions and fuel consumption of a vehicle. A 1998 gasoline vehicle was used, equipped with data loggers, measuring factors such as engine parameters, driving style/behavior, and position. Fuel consumption of the vehicle was then calculated. The students drove twice each along a 10 km route that possessed some high speed limit roads, first without the EcoDriving instructions and then again after receiving EcoDriving instructions. In the second trip, the fuel consumption was reduced by an average of 10.9% (Johansson, Farnlund, & Engström, 1999). This underlines how small changes in driving behavior can be very effective. It does thus not seem too optimistic to conclude that vehicles which on 5% of days failed, would have not failed had they actually been driving EVs and adopted their daily schedule and daily routine as well as driving behavior and style according to the characteristics of EVs.

0-10%: The third scenario includes also vehicles which failed between 6-10% of days. The same logic is used for the expansion as with the 1-5%, that by optimizing the use of the vehicle by modifying its schedule and driving route, so the vehicle would not fail at any point. In this case the effects of such modifications are expected to allow vehicles which fail on up to 10% on days to qualify as having EV potential. On top of optimizing the daily routine, schedule and driving style/behavior of drivers, in order to be able to expand the range up to 10 %, the company might have to reorganize and optimize its fleet. This might for example be done assigning a conventional vehicle to take the longest trips or add vehicles to its fleet. Doing so should at least allow vehicles which fail up to 10% to erase the 10% exceptions from the norm from their driving. It has been shown that fleet planning using different fleet management tools can have significant effects. For example using fleet optimization models can expose possibilities of reducing fleet size by 25% (Lockledge, Mihailidis, Sidelko, & Chelst, 2002). By reorganizing and optimizing fleets using effective management tools, and changing driving behavior/style and routines, it should not be impossible to eliminate all failures recorded from vehicles failing up to 10% of days.

3.5.3 Failure Frequency analysis

Version 1 of the model counts how frequently each vehicle crossed the zero line for battery capacity (cross only counted when the slope is negative, not on the way up). The failure frequency is counted for the entire research period. This parameter is important for the research as it plays an instrumental part in analyzing the potential of an EV switch for the research vehicles and answering the research questions. Statistical analysis of the results for average daily driving analysis includes mean, median, maximum and minimum values, standard deviation and a depiction of the frequency distribution. From the frequency distribution the percentages of vehicles belonging in the ranges 0, 0-5 and 0-10 failures throughout the research period is calculated. This is done for the total vehicle sample as a whole and the class grouping of the vehicles. A frequency distribution column chart is not depicted for the company division of the sample. Instead the percentage of the total vehicle fleet in each the range, 0, 0-5 and 0-10 failures is calculated for each company. For example a certain company might have 12% of its vehicle fleet having 0 failures and 40% of the vehicles could have between 0 and 10 failures.

As with the failure day analysis, there are different scenarios regarding what vehicles could qualify as having EV switch potential. These are 0 failures, 1-5 failures and 6-10 failures. The same logic is used as with the failure day percentage when the range is expanded upwards between scenarios.

3.5.4 Capacity required.

Capacity required is calculated by version 1 of the program. The capacity required is calculated for each vehicle and is simply the difference in Emax and the lowest recorded energy level. This is done only for the class grouping of the vehicles. This value can give information on how large the capacity is required to be for vehicles not to fail at any point of the day.

4 RESULTS

In this chapter the results for the research are presented. The aim was to assess using the model created whether business vehicles, that gathered driving data for a 100 day period in Reykjavík, could have performed equally well had they been EVs. First a few problems and errors that occurred from the program will be shown, followed by resulting modifications of the research sample. Then the research results will be presented. They will follow the outline presented in the last section of the methods chapter.

4.1 MODEL CHALLENGES

It seems as if the model and programs created did not work correctly in all cases and thus not all the vehicles delivered functional results. The sample had to be re-evaluated due to these visible problems/errors in order to yield reliable results. Version 1 of the model/program offered more problems. The likely reasons for the errors will not be analyzed in this chapter, but in a separate section in the discussion chapter where future modifications of the program and model will be proposed.

4.1.1 PROBLEM 1

This problem results from version 1 of the program. An output graph for a vehicle experiencing this problem can be seen in figure 4-1. The vehicle never comes close to reaching a full charge. There are 17 of these cases. Those will not be used for the result analysis. The reason for this problem is discussed in chapter 5.

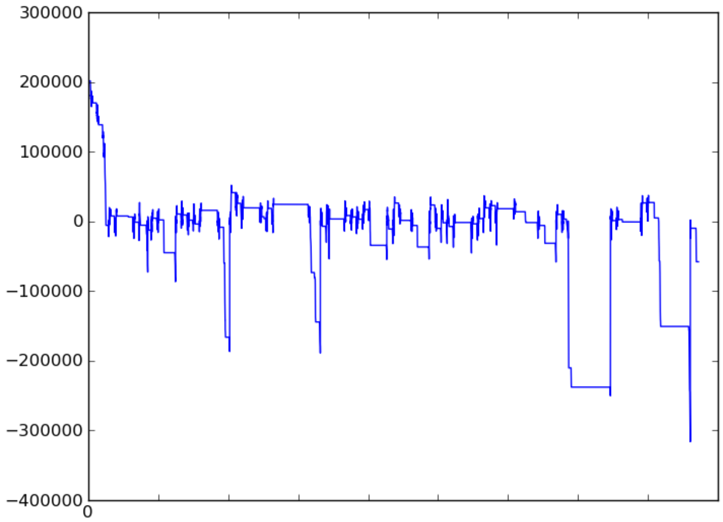

Figure 4-1 Plot where problem 1 occurs. The y axis shows the battery energy (j) while the y axis is time (the entire research period of each vehicle).

4.1.2 PROBLEM 2

A high number of vehicles showed a very similar pattern as the one in figure 4-2. The problem is that an extreme case of dip in the capacity is recorded resulting in very extreme cases of “capacity required” being registered in the results table for version 1 of the model/program. Apart from these extreme lows in the capacity the results from these vehicles are normal. The results from these vehicles are used for everything except for analysis of the capacity required. There are 61 recorded cases of this pattern. The reason for this problem will be discussed in chapter 5.

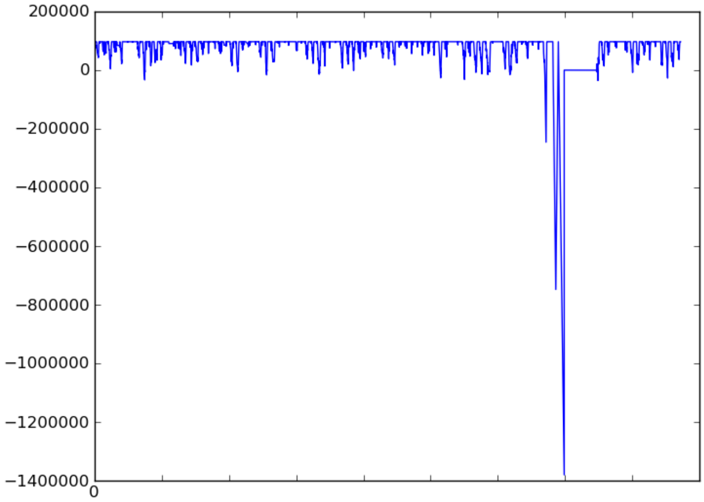

Figure 4-2 A plot from a vehicle that portraits problem 2. The y axis shows the battery energy (j) while the y axis is time (the entire research period of each vehicle).

4.1.3 PROBLEM 3

Few vehicles showed peculiar results from version 2 of the model. One of the parameters that version 2 calculates is the average daily driving distance of each vehicle. For a few vehicles the program gave results that seem very unrealistic, such as average daily driving distance over a 101 days period of 1828 km. The plots from these vehicles do not seem to fit these very high average driving distance values. 6 cars show these results and will be left out of all calculations. This problem, like the other two, will be further discussed in the discussion chapter.

4.2 TOTAL VEHICLE SAMPLE

In this section results based on the whole vehicle sample is presented. A few different aspects are analyzed; average daily driving, failures for the overall period, daily failure percentage and capacity requirements.

4.2.1 AVERAGE DAILY DRIVING

Version 2 of the program includes a feature which calculates the average daily driving distance of every vehicle. Based on this value for every vehicle in the sample, figure 4-3 was plotted. The final sample is 346 vehicles. Note that only days when a vehicle is moved are used for the calculations.

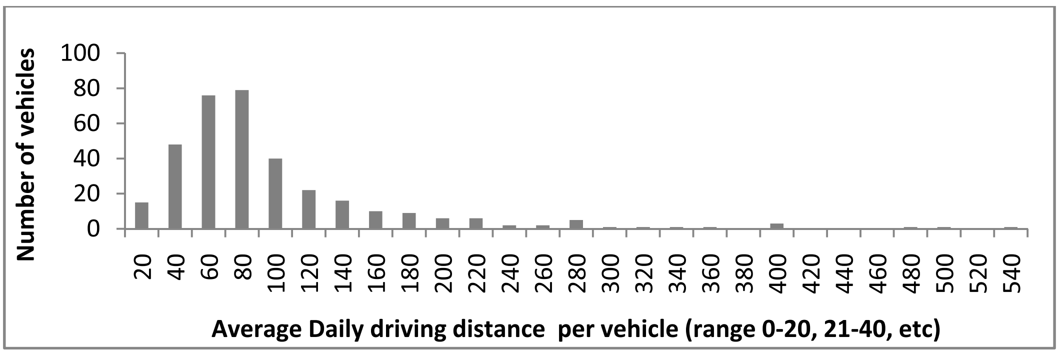

Figure 4-3 Frequency distribution for average distance driven by all the vehicles in the sample. Every column represents a certain array of km driven, the first one 0-20 km, the second one 21-40 km and so on.

Figure 4-3 shows the frequency of average daily driving distance for the whole sample. The frequency distribution shows a Poisson shape. The most common average daily distance is 61-80 km, but 79 of the vehicles have an average daily driving distance in that range. Second most common range is 41-60 km, containing 77 vehicles. The mean average driving distance for all the vehicles is 91.78 km and the median 69.5 km. The lowest value is an average of 5 km driven daily while the highest value is 524 km. The standard deviation for the distribution is 78.43.

4.2.1.1 Possibility of EVs based on average daily driving distance.

Knowing the average daily driving distance of each vehicle and its class in the model it is possible to see if the distance driven daily on average exceeds the driving range of the corresponding model EV. Each vehicle was either assigned a "yes" or "no" based on whether the range of the EVs would be adequate for the average daily driving distance. For the overall sample (346 vehicles) the average daily driving distance is under the EV range for 78% of the vehicles. This means that if vehicles would drive their average daily distance every day, only charging during the night, the EV range would be sufficient for 78% of vehicles.

4.2.2 Failure frequency over whole period

Version 1 of the model/program counted the times the model EV would have failed throughout the entire research period. At each time the model crosses 0 on a negative slope, the program counts 1 failure, a point at which the model EV runs out of energy on its battery pack. The sample used to give the results is composed of 346 vehicles.

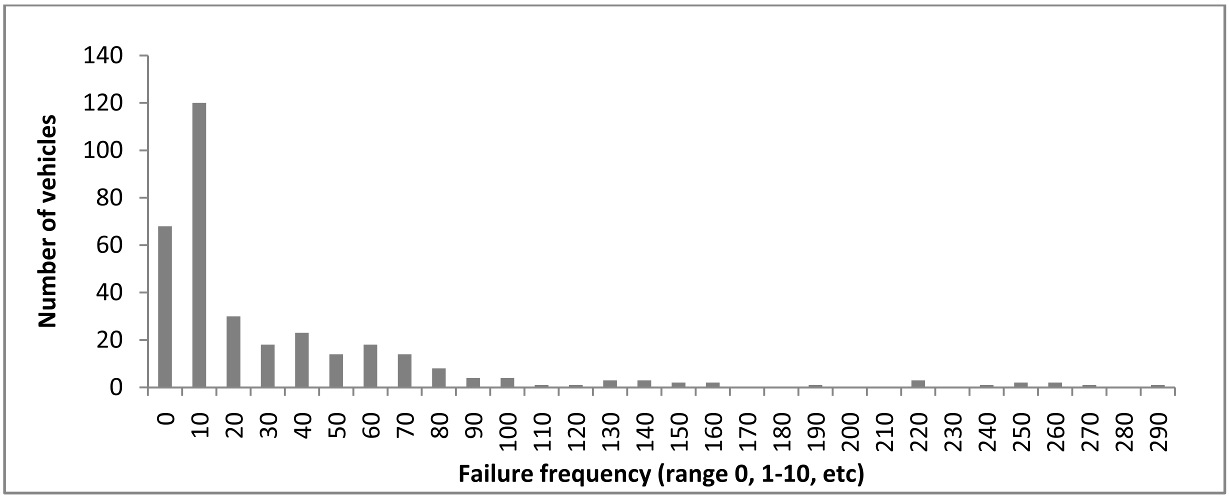

Figure 4-4 Frequency distribution for the failures of all 346 vehicles in the sample over the entire research period of 101 days. Every column represents a certain array (range) of failures throughout the period such as 1-10 and 11-20, except for the first one, zero, which shows only vehicles which never ran out of energy.

Failure count for the entire research period can be seen in figure 4-4. It is most common that the failure count is in the range between 1 – 10 failures (120 vehicles), followed by 0 failures (68 vehicles). A total of 154 (44.6%) vehicles fail 0-5 times and a total of 188 (54.5%) fail 0-10 times. The failure count then steadily goes down from the 1-5 range. The mean failure frequency is 30.75, while the median í 8. The largest failure frequency recorded was 285 failures while the lowest was zero. The standard deviation is 51.81.

4.2.3 Failure days

In version 2 of the model/program the total failures are not counted, but rather days which include failures. In the methodology chapter the difference between the programs are described and those will not be restated here. Not all vehicles gave data for all of the 100 days. The failure days are divided with the total active days to give a fraction of failure days from total. That percentage is then used for the result analysis. The total sample used for the failure day analysis is 346 vehicles.

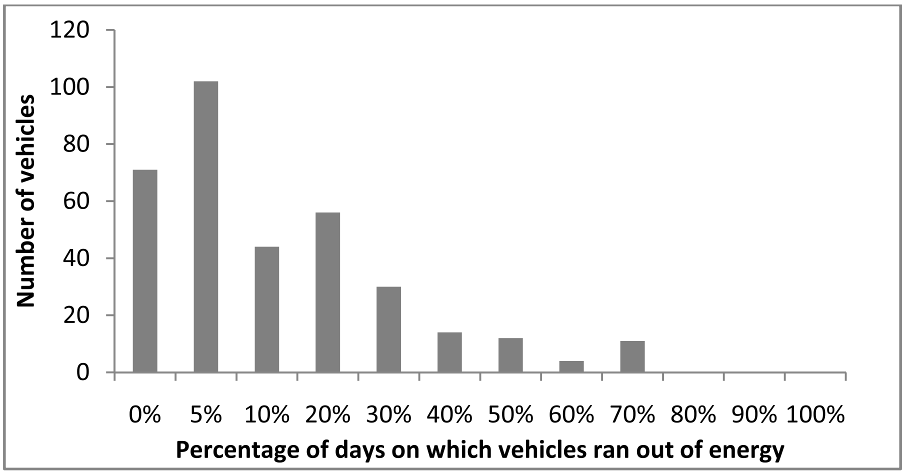

Figure 4-5 A frequency distribution for the percentage of failure days per vehicle of all the 346 vehicles. Every column represents a certain range of failure day percentages throughout the whole period such as 1-10% of days ending with a failure. The first column, zero, however does not represent a range but only vehicles only vehicles that did not run out of energy at any of its active days.

Figure 4-5 above shows the failure day percentage of all the vehicles in the sample. 71 vehicles never failed throughout the research period, or 20.6%. A total of 173 vehicles have failure day percentage between 0-5% (50.1% of vehicles) and a total of 253 (62.9% of vehicles) have a failure day frequency between 0-10%. The average failure day percentage is 11.79% while the median is 4.95%. The highest failure day percentage recorded is 67.7% while the lowest is 0%. The standard deviation is 16%.

4.2.4 Capacity Required

The capacity required was not calculated for the whole sample, but for each class separately. See below under “classes”.

4.3 Classes

In this section the results for each class of vehicles are presented. This is done in order to be able to analyze the difference between the three classes and possibly identify whether one class is better suited for being an EV than the others.

4.3.1 Average daily driving of classes

4.3.1.1 Class 1:

The sample for class one is 115 vehicles. The frequency distribution for the average daily km driven per vehicle for class one is showed in figure 4-6.

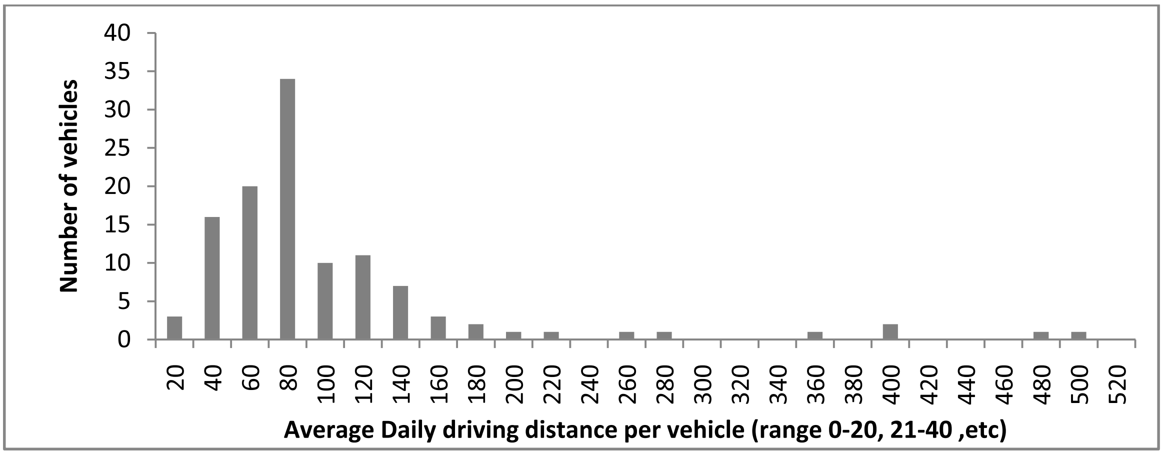

Figure 4-6 The frequency of the average daily driving distance of the vehicles from class 1.

It steadily rises from the 0-20 km range until it peaks at the 60-80 km. There are 34 vehicles from class 1 that have an average daily driving distance of 60-80 km. The second largest range group the 40-60 km into which 20 vehicles fall while 20-40 km is comes third with 16 vehicles. The mean average daily driving distance for group 1 vehicles is 93.18 km and the median is 68 km. The highest value is 467 km average daily while the lowest is 12 km. The standard deviation is 83.99.

4.3.1.2 CLASS 2:

The sample for class 2 is 153 vehicles. The frequency distribution for the average daily km driven per vehicle for class one is showed in figure 4-7 below.

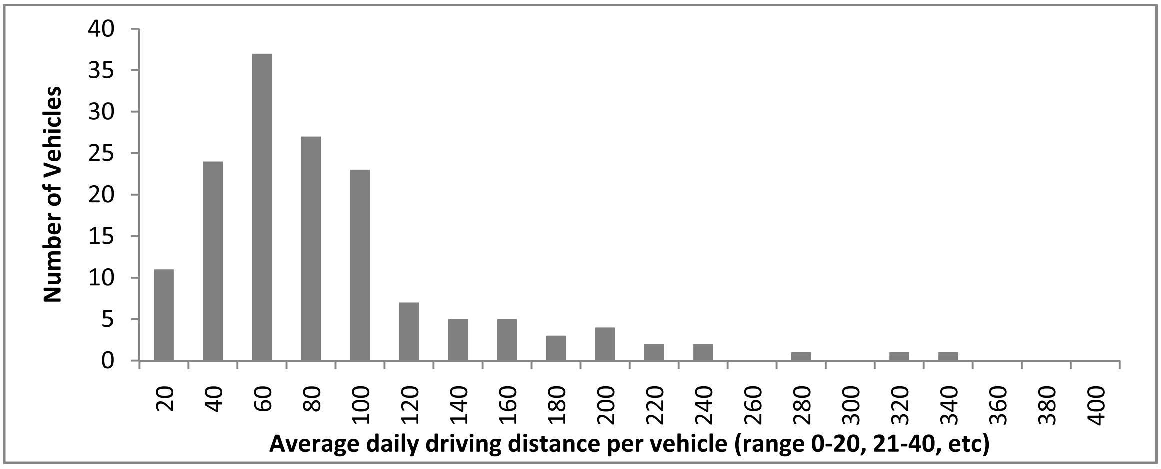

Figure 4-7 The frequency of the average daily driving distance of the vehicles from class 2.

Most of the vehicles in class 2 have an average daily driving distance in the range of 40-60 km. This is different from group 1 where the peak of the distribution was at 60-80. There are 37 vehicles which fall into the 40-60 range while there are 27 vehicles from class 2 that have an average daily driving distance of 60-80 km. What also differs quite a lot from class 1 is the high number of vehicles driving under 20 km on average daily. The mean average daily driving distance for group 2 vehicles is 77.8 km and the median is 65 km. The highest value is much lower than for class 1 and is 335 km average daily while the lowest is 5 km. The standard deviation is 42.55.

4.3.1.3 CLASS 3:

The sample for class 3 is 78 vehicles which is the smallest of the classes. The frequency distribution for the average daily km driven per vehicle for class one is showed in figure 4-8.

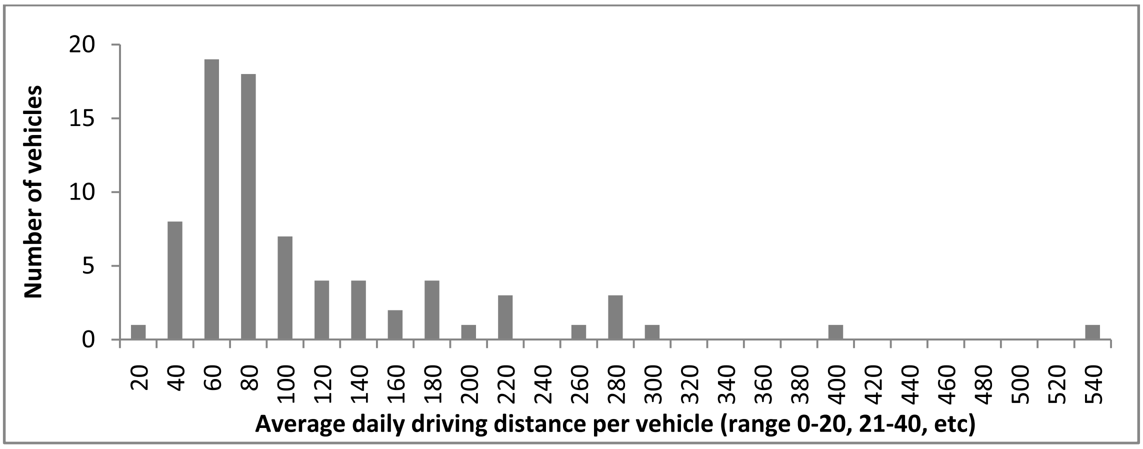

Figure 4-8 Frequency distribution of the average daily driving distance of the vehicles from class 3.

Most the vehicles in class 3 have an average daily driving distance in the range of 41-60 km. There are a total of 19 vehicles which fall into the 41-60 range followed very closely by the 61-80 km range with 18. The mean average daily driving distance for group 3 vehicles is 105 km and the median is 78 km. The highest average daily distance is 524 km and the lowest is 15 km. The standard deviation is 73.36. The vehicle driving 524 km on average daily is the vehicle which had the highest recorded average daily driving value in the whole sample.

4.3.1.4 Possibility of EVs based on average daily driving distance.

As was analyzed for all the vehicles as one single group, the possibility of a vehicle being to be an EV, from the point of view of EV range, was analyzed for each of the class groups separately. The result can be seen in figure 4-9 below.

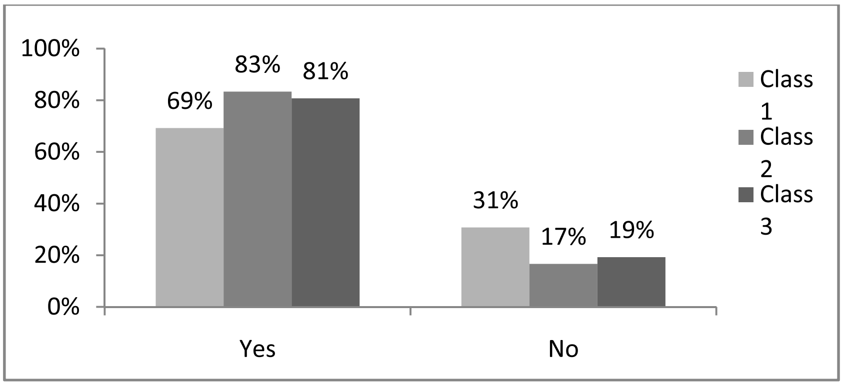

Figure 4-9 Portion of vehicles from each vehicle class considered to have EV potential based on their average daily driving.

As can be seen the highest EV potential fraction is for class 2, with 83% of vehicles are considered to have EV potential based on their average daily driving. Class 1 has by far the lowest percentage considered to have EV potential.

4.3.2 FAILURE FREQUENCY OVER WHOLE PERIOD

4.3.2.1 CLASS 1:

The sample for class 1 is 117 vehicles for the failure frequency over the whole period calculated by program version 1. The frequency distribution for the failure count of vehicles in class 1 is showed in figure 4-10 below.

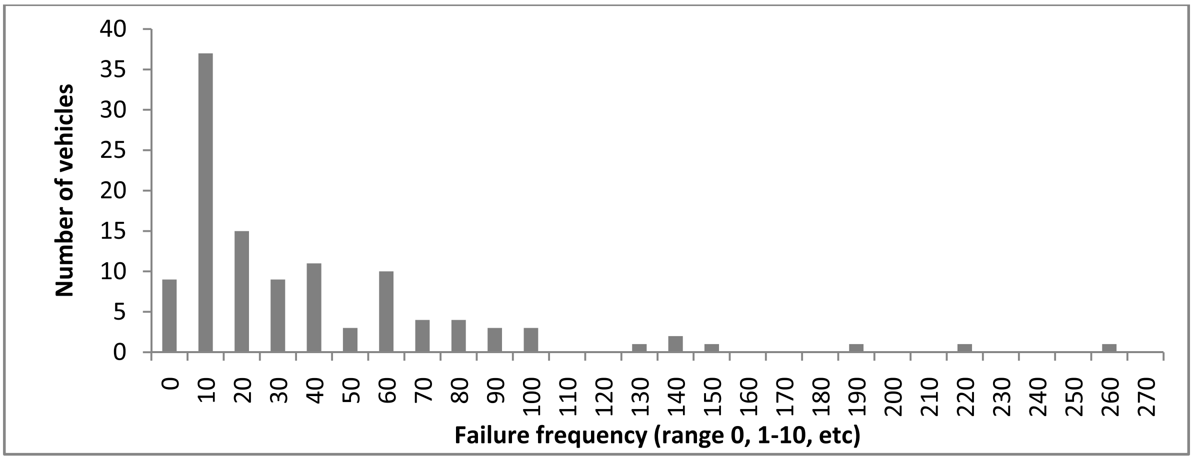

Figure 4-10 Frequency distribution of total failure count throughout the entire research period for class 1 vehicles.

8 vehicles from class 1 did not fail at any time throughout the research period. The range that has the most vehicles (37 vehicles) is the 1-10 failures range. It should be noted though that the range is larger than for those with lower failure frequency. The second largest group is in the 11-20 failure range, in which there are 15 vehicles. 30 vehicles (25.8%) have a failure frequency between 0-5 failures and a total of 46 vehicles (39.6%) have a failure frequency between 0-10 failures. The mean failure frequency for group 1 is 37 failures and the median is 16.5. The lowest failure frequency value is 0 and the highest is 254 failures. The standard deviation is 51.5.

4.3.2.2 CLASS 2:

The sample for class 2 is 153 vehicles for the analysis of failure frequency over the whole research period. The frequency distribution for the failure count of vehicles in class 2 is showed in figure 4-11.

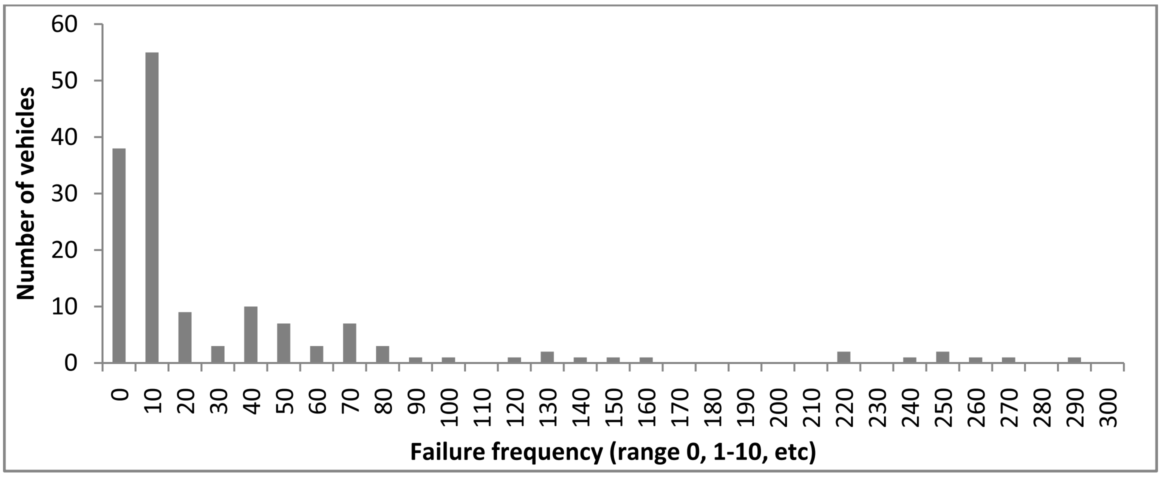

Figure 4-11 Frequency distribution of total failure count throughout the entire research period for Class 2 vehicles.

For class 2 a total of 38 vehicles did not fail at any point throughout the research period. Most vehicles fall into the 1-10 failure range, a total of 55 vehicles. A total of 79 vehicles (52.3% of total vehicles) have a failure frequency between 0-5 failures and a total of 93 (61.5% of total vehicles) have a failure frequency between 0-10 failures. The average failure count is 32.4, and the median is 5. For class 2 the lowest value is 0 but the highest 285 failures. The standard deviation for class 2 is 59.8.

4.3.2.3 Class 3:

The sample for class 3 is 78 vehicles for the analysis of failure frequency over the whole research period. The frequency distribution for the failure count of vehicles in class 3 is showed in figure 4-12 below.

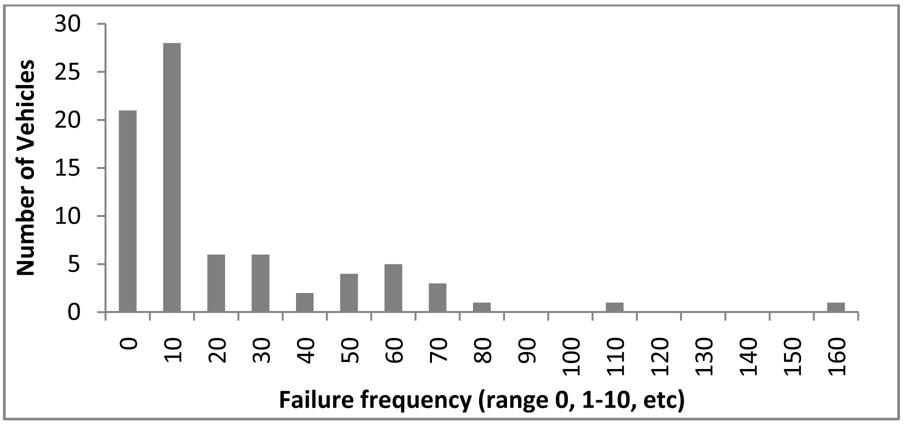

Figure 4-12 Frequency distribution of total failure count throughout the entire research period for class 3 vehicles.

A total of 21 class 3 vehicles did not fail throughout the entire period. Most vehicles fall into the 1-10 failure range, a total of 28 vehicles. A total of 45 vehicles (57.7%) have a failure frequency between 0-5 failures and a total of 49 (62.8%) have a failure frequency between 0-10 failures. The mean failure count for class 3 is 17.19 and the median is 2.5. The highest failure frequency value is 154 and the lowest 0. The standard deviation for class 3 is 28.05.

4.3.3 Failure day analysis

4.3.3.1 Class 1:

The sample for class 1 is 117 vehicles for the analysis of failure days. The frequency distribution for the percentage of failure days for vehicles in class 1 is showed in figure 4-13..

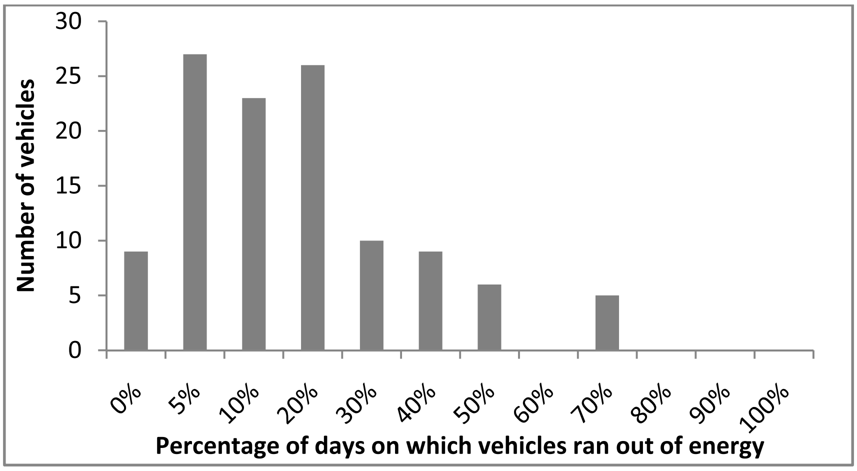

Figure 4-13 Frequency distribution of class 1 vehicles for the percentage of days from the total active days on which vehicles failed.

9 vehicles of the 117 from class 1 did not fail at any day throughout the research period, resulting in a 0% failure day percentage. The most common failure day percentage for class 1 is the range from 1-5%, with 27 vehicles having a failure day in that range. The range from 11-20% follows very closely with 26 vehicles and 6-10 with 23 vehicles. A total of 36 vehicles have a failure day frequency between 0-5% (31.3% of total class 1 vehicles) and a total of 59 between 0-10% (51.3% of total class 1 vehicles). The mean failure day percentage for class 1 is 16.1% and the median is 9.9%. The highest value is 66.3% and the lowest is 0%. The standard deviation for class 1 is 16.4%.

4.3.3.2 CLASS 2:

The sample for class 2 is 153 vehicles for the analysis of failure days. The frequency distribution for the percentage of failure days for vehicles in class 2 is showed in figure 4-14 below.

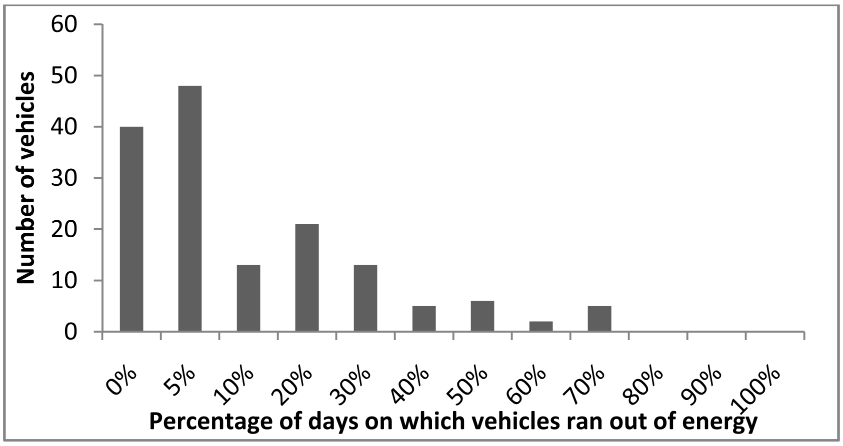

Figure 4-14 Frequency distribution of class 2 vehicles for the percentage of days from the total active days on which vehicles failed.

Figure 4-14 shows that 40 vehicles of the 153 from class 2 did not fail at any day throughout the research period. The most common failure day percentage for class 1 is the range from 1 - 5%, with 48 vehicles having a failure day in that range. The 0% failure day group follows very closely. A total of 88 vehicles (57.5%) have a failure day frequency between 0-5% and a total of 101 between 0 - 10% (66%). The mean failure day percentage for class 2 is 11.3% and the median is 9,9%. The highest value is 67.7% which is also the highest value overall, and the lowest is 0%. The standard deviation for class 2 is 16.1%.

4.3.3.3 CLASS 3:

The sample for class 1 is 78 vehicles for the analysis of failure days. The frequency distribution for the percentage of failure days for vehicles in class 3 is showed in figure 4-15 below.

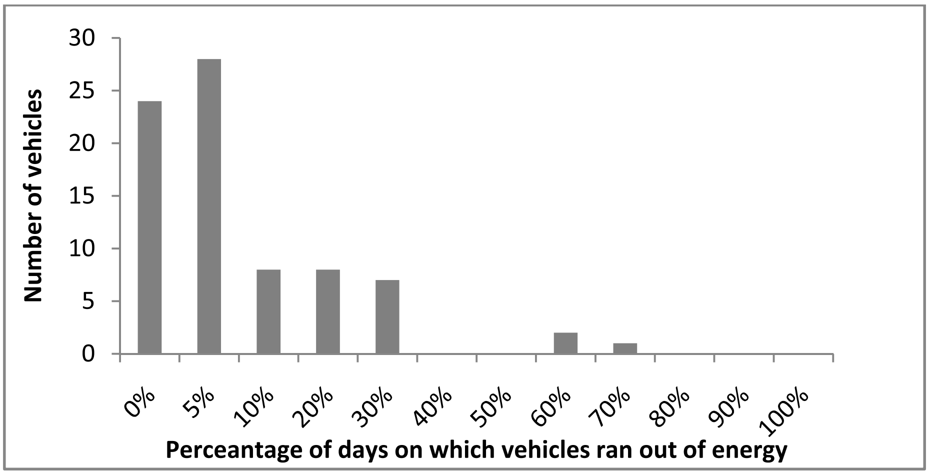

Figure 4-15 Frequency distribution of class 3 vehicles for the percentage of days from the total active days on which vehicles failed.

As with class 2, the largest groups are the 0% and 1-5%. In group 3 the case is more extreme with a total of 70% of the vehicles having a failure day percentage in those two groups. The 1-5% group has 25 vehicles while the 0% has 24 vehicles. A total of 49 vehicles (62.8%) have a failure day frequency between 0-5% and a total of 56 (71.7%) between 0-10%. The mean average failure day percentage is 7.1% and the median is 2%. The highest value is 64.4%. The standard deviation for class 3 is 12.3%.

4.3.4 CAPACITY REQUIRED

The capacity required parameter was calculated by version 1 of the program/model for each vehicle. This value is simply the difference between Emax of each vehicle and the lowest energy state recorded throughout the whole research period. Note that the energy level is allowed to go below 0. That configuration was added to the program simply in order to be able to acquire this value (capacity required) for each vehicle. The results for all the classes are shown in table 4-1 below.

Table 4-1 S The main results of some statistical parameters for the capacity required for the 3 classes of vehicles.

Parameter	Class 1	Class 2	Class 3
Sample size	117	153	78
Model EV cap.	97,200 kJ	201,600	345,600
Mean	619,757 kJ	1,015,294 kJ	1,257,206 kJ
Median	219,966 kJ	345,357 kJ	519,912 kJ
Max	5,571,726 kJ	8,788,552 kJ	9,266,463 kJ
Min	26,741 kJ	43,121 kJ	111,190 kJ
Standard Dev.	953,432 kJ	1,768,338 kJ	1,719,514 kJ

Class 1 has the lowest average capacity required for its vehicles, 619,757 kJ. Class 3 has the highest mean, 1,257,206 kJ. The highest recorded capacity required is 9,266,463 kJ for a vehicle in class 3. Class 2 has the highest standard deviation and therefore the most disperse distribution of capacity required values among the vehicles in its group.

4.4 COMPANIES

For this part the vehicles were grouped based on the companies they belong to and results gathered for each of them. The purpose of this analysis is to be able to approximate how many companies in Reykjavík, using this group of firms as representatives for firms in Reykjavík, could replace considerable parts of their fleets to EVs.

4.4.1 AVERAGE DAILY DRIVING AND EV POSSIBILITY

The results from a statistical analysis of the average daily driving distance of the vehicles from the companies which supplied data for the research can be seen in table 4-2 below.

Table 4-2 The results for the average daily driving and the EV possibilities of the fleets of all the companies which supplied driving data for the research

		Average daily driving distance				
Company	Sample	Mean	Max	Min	st.dev	% EV possibilities
A	26	150.80	400	15	121.31	57.7%
B	17	89.88	174	41	35.44	58.8%
C	3	59.3	84	46	21.65	100.0%
E	19	57.89	232	0	51.45	94.7%
F	19	79.68	202	11	46.14	78.9%
G	26	98.23	281	53	55.31	88.5%
H	22	92.95	197	41	41.45	68.2%
I	11	61.27	174	26	52.98	81.8%
J	9	88	140	42	33.48	55.6%
K	60	81.23	496	0	92.03	86.7%
L	15	106.6	203	37	58.21	60%
M	7	193.57	314	135	62.96	0%
N	5	219.2	524	48	192.74	40.0%
P	2	81.4	116	46	49.49	100%
Q	4	59.1	89	33	24.38	100%
R	101	71.14	274	5	48.64	88%

The average daily driving distance for the companies varies greatly, ranging from 59 km average daily driving up to 193 km. 6 of the mean average daily driving distance for the 16 companies are in the range of 80-100 km. Based on the method of comparing the average daily driving distance and the maximum range of a same class EVs, all the firms with the exception of two could replace more than 50% of their vehicle fleet to EVs. 8 of the 16 firms could replace more than 80% of their vehicles with EVs, based on this approximation.

4.4.2 FAILURE FREQUENCY OVER ENTIRE PERIOD

The results from a statistical analysis of the failure frequency of the vehicles from the companies which supplied data for the research can be seen in table 4-3 below.

Table 4-3 The results for the failure frequency analysis of the company fleets

Failures frequency through research period								
Company	Sample size	% of vehicles in fleet in failure frequency range			mean	max	min	st.dev
		0	1-5	6-10				
A	25	21%	17%	0%	41.3	216	0	50.89
B	17	6%	11%	6%	30.2	81	0	22.06
C	3	0%	68%	33%	2.7	6	0	3.06
D	2	50%	50%	0	2	4	0	2.83
E	17	41%	41%	12%	2.5	15	0	3.87
F	19	11%	5%	5%	45.8	150	0	42.34
G	26	15%	35%	15%	14.7	63	0	18.88
H	22	5%	27%	5%	42.7	121	0	37.80
I	11	72%	0%	0%	8.0	36	0	14.06
J	9	11%	44%	11%	11.9	46	0	16.01
K	60	17%	35%	15%	15.4	154	0	26.36
L	16	0%	13%	13%	46.6	160	2	45.10
M	8	0%	0%	0%	168.4	263	62	85.70
N	5	40%	0%	0%	26.6	53	0	26.26
Q	4	50%	0%	0%	13.0	25	1	13.86
R	101	24%	26%	12%	34.1	285	0	66.73

As can be seen in table 4-3 the highest mean failure frequency for a company is 168 failures while the lowest is only 2 failures. Of the 16 firms, 8 have an average failure frequency under 20, and all except one (which is stunningly high), have an average failure frequency under 50. The highest fraction of vehicles failing 0 times throughout the entire period for a company is 72% but the lowest 0% (meaning all vehicles failed at some point for that company). Most companies have fewer than 10% of vehicles not failing throughout the research period. If the failure range is increased up to 5 failures (meaning how large fraction of the vehicle fleet of each company failed 5 times or less throughout the period), the highest value is 100% but the lowest 0%. A frequency analysis for a fraction of company vehicles failing 5 times or less revealed that 4 companies have between 50 and 60%, which is the most common range, followed by 30-40% with 3 If the failure range is further increased up to 10 times the highest and lowest values are the same as for 5 failures. The most common range of number vehicles failing 10 times or less is 60-70% with 5 companies, meaning that from the total 16 firms 5 companies had 60-70% of their fleet failing 10 times or less.

4.4.3 Failure days analysis

The results from a statistical analysis of the failure days of the vehicles from the companies which supplied data for the research can be seen in table 4-4.

Table 4-4 The result of the failure day percentage analysis for the company fleets.

Failure day percentage									
Company	Sample size	% of company vehicles with failure day percentage in range			mean	max	min	st.dev
		0%	1-5%	6-10%				
A	26	19.2%	23.0%	11.5%	17.7%	64.3%	0.0%	20.4%
B	17	5.0%	23.0%	11.7%	12.9%	47.5%	0.0%	16.1%
C	3	66.7%	33.3%	0.0%	1.7%	5.0%	0.0%	2.9%
E	19	47.0%	31.5%	5.2%	3.5%	17.6%	0.0%	5.2%
F	19	10.5%	10.5%	26.3%	13.8%	48.5%	0.0%	12.0%
G	26	19.2%	38.5%	19.2%	6.1%	23.0%	0.0%	7.0%
H	22	9.1%	36.4%	13.6%	16.0%	62.6%	0.0%	18.5%
I	11	72.7%	0.0%	0.0%	5.7%	27.3%	0.0%	10.1%
J	9	0.0%	33.3%	22.2%	15.3%	43.5%	2.0%	14.1%
K	60	18.3%	33.3%	18.3%	10.0%	65.3%	0.0%	13.7%
L	15	0.0%	26.7%	6.7%	14.8%	27.8%	2.1%	8.7%
M	7	0.0%	0.0%	0.0%	48.4%	58.2%	40.7%	6.1%
N	5	40.0%	0.0%	0.0%	13.6%	26.6%	0.0%	12.6%
P	2	50.0%	0.0%	0.0%	13.9%	27.7%	0.0%	19.6%
Q	4	25.0%	25.0%	0.0%	6.4%	12.9%	0.0%	6.9%
R	101	22.8%	37.6%	10.9%	10.9%	67.7%	0.0%	17.3%

The highest mean failure day percentage for a company is 48.4% while the lowest is 1.7%. The highest fraction of company vehicles having 0 failure days is 72.7% but the lowest is 0%. Most (9) companies have between 0% and 20% of their vehicle fleet not failing on a single day. When the failure day percentage range is increased to 5% the lowest value for a firm is 0% but the highest is 100% (meaning all the vehicles from that firm fail on 5% of active days or less. A frequency analysis for a fraction of company vehicles having 5% or less failure days revealed that 4 companies have between 70% and 80% failing less than 5% of days, which is the most common range.

5 DISCUSSION

As stated in the introduction and throughout the thesis the scope of the thesis is twofold. First it was to create a method from scratch which would allow one to analyze whether a conventional vehicle could be replaced by an EV. Secondly the method created and described in detail in the method chapter was used to research the possibility of switching from conventional vehicles to EVs for business users in Reykjavík. Apart from attempting to answering important questions regarding the transport sector of Reykjavík, a vital factor for doing the research is to test the method. By using the method its shortcomings could be identified and possible solutions provided. First is a review of the method. Second are the results of the research and third are suggested improvements of the method in order to make it more precise and reliable. It is important that the model and method is reviewed before the research results are discussed so that the shortcomings of the method can be taken into account when the research is discussed afterwards.

5.1 METHOD REVIEW

In this section the method created is reviewed. The errors and problems, which became apparent after the program had run and the results were being analyzed and were presented in the first section of the result chapter, will be further discussed and possible solutions presented. The different features of the model and program will be critically reviewed. The different ways of assessing EV potential are compared.

5.1.1 ERRORS, PROBLEMS AND POSSIBLE SOLUTIONS

5.1.1.1 PROBLEM 1: CAUSE, EFFECT AND POSSIBLE SOLUTION

Problem 1 represents perhaps the biggest flaw in the current methodology. This error is characterized by the vehicles never reaching Emax when charging, showing very short charging sessions, extreme amounts of failures and often extreme lowest capacity value. From looking at the program output graphs the vehicles affected by this error could be identified. A total of 17 vehicles showed this fault. A few vehicles gave an extreme amount of failures from version 1 of the program and when the graphs were analyzed they showed the same characteristics. The cause for the error has roots in the method for how the docks for the vehicles were identified. A program identified the most commonly logged stop locations for each vehicle and listed the five most common ones for each vehicle (latitude and longitude values) in a SQL table labelled “docks”. This method was supposed to make sure that the locations where each vehicle spent most of its time so that the vehicle would be charged where it stayed overnight and during long pauses throughout the day. However, the author was unaware of the fact that after a vehicle had been stopped at a location for half an hour or more the location was logged only once every hour, instead of every 15 seconds. Due to this change in logging frequency the docks were not identified correctly (each vehicle has two docks, two locations where a stop was logged most frequently). Therefore in the case of these 17 vehicles the headquarters of the company or the home of the drivers were not identified as docks but instead perhaps a traffic light which the vehicle stopped on frequently for short durations at a time. This caused the vehicles to be charged for only very short durations at a time causing it not to reach Emax at any point. The programs are designed in such a way that if a model vehicle is below zero in energy capacity when it starts charging it immediately jumps to zero and starts charging from there. This however means that after charging for a very short duration the car would only have to drive a very short distance to go below zero again and a failure to be counted, resulting in extreme counts of failures for these vehicles. However it seems this method worked in almost all cases and that even though the stop logs were not frequent during nights and longer duration pauses these logs were sufficient for the docks to be correctly identified.

As stated above a total of 17 vehicles were identified having been clearly affected by this problem. It is however not completely impossible that some vehicles might have gone under the radar. For example the method might have been sufficient to identify one of the docks correctly but not both of them, resulting in a normal looking graph but incorrect results. As stated above, this is the single most critical deficiency of the current method.

The solution for this problem is not a complicated one although the author has not performed the changes. The idea is that instead of identifying the docks on the basis of the frequency of stop logs, simply identifying them on the sum of stop duration at each location, and identifying the docks as the locations on which a vehicle spent most of its time while not moving. This is a bit more complex and adds a new dimension to the method for docks identifications but should make sure that the docks of each vehicle would be correctly recognized.

5.1.1.2 Problem 2: Cause, effect and possible solution

This common problem was first identified when the results from the capacity required of a number of vehicles showed extreme values from program 1. When the graphs for these vehicles were analyzed it could be seen that were deep dips occurred in the energy status of these vehicles (see figure 4-2). This kind of dip occurred only once in most cases for the vehicles throughout the entire period, and apart from this error looked normal. The cause for this is in fact very simple. This problem occurs simply when vehicles do not get to a dock for a long period of time. This happens for example when a vehicle takes a trip outside Reykjavík for a number of days or when a dock (headquarters, driver's home, etc) is moved. This affects mainly the capacity required value for vehicles and was surprisingly common with at least 60 vehicles showing this error. A side effect of this is that during periods where a car is not charging at all and is under the zero capacity value it does not fail. This therefore could also result in a lower failure frequency for a vehicle.

The capacity required value was meant to show the required capacity for each vehicle to be able to take its longest single trips. The idea was basically to show the required capacity for the car to be able to operate on a single heavy working day. Instead with problem 2 the capacity required value shows the amount of energy needed for the vehicle to run for many days without being charged. Even in mild cases of this problem the capacity required is extreme (10 times larger than the actual battery capacity is not uncommon). One possible solution for this problem can be swiftly identified. The capacity required is only calculated in version 1 of the program. In version 2 a feature was added where every night at midnight the energy status of the vehicle jumps to Emax. The solution is simply adding the capacity required feature to version two. This way the extremes resulting from many days without charging is erased due to the fact that in version 2 the vehicles start every new day on a full battery pack. Also it might be interesting to see the most extreme exceptions for every car erased so that the result would represent heavy but still normal days rather than the extreme exceptions.

5.1.2 Model and program features review

5.1.2.1 Failure analysis approaches

In the method there are two ways to analyze the EV potential of a vehicle based on failures; the failure frequency parameter from version 1 of the model/program and the failure day percentage parameter from version 2.

The failure frequency parameter in version 1 was initially regarded as the most important factor for assessing the possibility of a vehicle being replaced by an EV (before version 2 was created). This parameter does give the user a quite clear idea of how easily a vehicle could be replaced by an EV. It is clear that a vehicle with 0 recorded failures throughout the research period could easily have been an EV based on its driving distance and time spent at dock, and on the other hand a vehicle that fails 200 times can hardly be considered as having EV potential. As presented in the final section of the method chapter, in one scenario vehicles failing below 10 times are considered to have EV potential. However it is hard to use this feature and parameter to assess the possibility of vehicles which fail in the area of 10-30 times and possibly higher. This is due to a problem not mentioned above. In version 1 when a vehicle goes below the 0 line in the model it is counted as one failure. When the vehicle keeps driving it will go lower until it stops at a dock. Then it instantly jumps to zero and starts being charged. However there is no limit for how long the vehicle needs to be charged before it starts driving again. Therefore the vehicle can have stopped at a dock and charged for 2 minutes before keeping on driving and instantly getting another failure recorded. Therefore the failure frequency can be an exaggerated value for vehicles. When looking at the raw data from the vehicles it can be seen that the vehicles which have under 10 failures do not seem to be influenced by this problem, and that vehicles failing very often would not have had EV potential anyway. It is however vehicles failing 10 to 50 times which might have failed much fewer times and could possibly have qualified as having EV potential would they for example have been made to reach a full charge before being “allowed out” again.

Soon after version 1 was created the author decided to create a new version of the program with a few different features than version 1. It was decided that the new version might use a different parameter to evaluate the EV potential of vehicles than to simply count the failures (which could happen many times through the same day, something that would hardly take place in reality) and the failure day method was created. The failure day method seems to work like it was supposed to and no visible errors were found. The problem identified above which is coupled with the failure frequency parameter is no longer an issue. With this approach a vehicle either fails or not in a given timeframe. Applying that approach for the failure frequency over the entire research period would have been to simply see if the vehicle failed or not through the entire period. That however would not give a very clear picture of the overall possibility of business vehicles in Reykjavík as there is a clear difference between failing 1 and 133 times. The failure day parameter is not only less prone to errors and problems but also this approach probably more illustrative than the failure frequency. That is, for some people it might be difficult to understand what the failure frequency value really describes (partly because it lacks the dimension of time) and what a difference in this value for two vehicles tells you about the driving need of the two vehicles. The failure day parameter is very clear and tells a very simple story. There is one possible problem with the failure day approach of version 2. It is possible that in some cases the fact that every midnight the model EVs battery pack jumps to Emax could skew the picture. In some cases it might be that the vehicle would not have reached a full charge throughout the night. This means that a car starts driving at 5 in the morning with a full tank he might not have had if the energy amount had he not jumped to Emax at midnight. This would however be rare as the vehicle is stop overnight for at least 8 hours in almost every case. This feature is considered to be working correctly and for further versions will not need to be changed.

If one looks at failure parameters from the program output tables of the two different versions of the program it can still be seen that the results are in most cases similar. In every single case that a vehicle has failure frequency value of 0 the same vehicle has a 0% failure day percentage. However this does not apply to the other way around. In a few cases a vehicle which has 0% failure days has some recorded failure frequency. This can for example be on occasions when the vehicle is not spending the night at a dock in version 1 and starts driving the next day on half a tank, while in version two he starts the day with a full tank and does not fail the following day. It seems that a rise in one of the failure parameters means rise in the other one as well. A correlation analysis of the two parameters confirms this and gives an R value of 0.83. In quite a few cases there is a very great difference in the two parameters for the same vehicle. For example one vehicle has a failure day percentage of 5% but a failure frequency of 61. When the raw data for this vehicle is analyzed it can be seen that this problem is down to the problem identified above, with multiple failures taking place in a very short time period due to short charging sessions. Based on the fact that in most cases the results of the two failure analysis parameters are similar, and most large dissimilarities arising from faults in version 1 of the program, only the failure day analysis will be used for the failure assessment of the research result discussions. It is likely that with further development of this method and future versions of the program will only contain the failure day method.

5.1.3 OTHER MODEL FEATURES

5.1.3.1 AVERAGE DAILY DRIVING AND EV POSSIBILITY

When the author was searching for data for the thesis it was discovered that information regarding the average daily driving of vehicles in Reykjavík is very scarce. Therefore it was decided to include a feature which would calculate the average daily driving of the data collecting vehicles, as this is a useful parameter. It was later realized that this parameter would be interesting to compare with the failure assessment parameters. Further it is possible to compare this value for each vehicle to the maximum range of a corresponding model vehicle to get a helpful parameter in assessing the EV potential of vehicles. Obviously the average daily driving is not able to provide reliable answers regarding the EV potential of vehicles on its own, as there are the exceptions from normal driving distances which in most cases limit the EV potential of vehicles. It however is able to supply information that the failure day application cannot provide. This feature gives one an idea of what the norm is. In the case of failures it hints at how big of an exception they are. For example two vehicles might both only have a failure day percentage of 1% throughout the study period with one of the recording considerably higher average daily driving that might be close to the model vehicle range. This hints at that vehicle often coming very close to failing and that even though it has a low failure day % is not at all as well suited for being an EV than most vehicles with a 1% failure day percentage. Failure day percentage and average daily driving offer very different information but together provide information which in most cases is sufficient to answer questions regarding the EV potential of vehicles.

The average daily driving feature of version 2 works well, and it is only in very rare cases that it returns unrealistic values, and in those cases that is not down to errors in the program but due to glitches in the raw data which is not hard to scour from the sample. Future versions of the program will likely contain an unmodified version of the average daily driving application.

5.1.3.2 CAPACITY REQUIRED

The idea with the capacity required was find the amount of battery capacity required for the each vehicle not to fail at any point of the research. This feature was only included in version 1 of the program. This feature failed. When the feature was designed it was thought that the method for assigning docks to all vehicles would be sufficient to make sure that all vehicles would at least always charge overnight. The result was different and in reality it seems many vehicles did at some point of the research spend a night away from a dock. This resulted in periods of time when the vehicle was not charged at all, for example when going out of town for a prolonged period of time. When version 1 was designed it was decided that the battery capacity would not jump to Emax but would have to charge be charged to get there. This might not sound like a unfair configuration, but with the prolonged periods of no charging that occurred for a surprisingly high number of vehicles this resulted in the capacity required parameter to be unrealistic. Had all vehicles always charged overnight, this parameter would likely have worked. The parameter is interesting and if working would give a value for how far off an EV is from being able to completely replace a conventional vehicle. It was a mistake not to include this feature in version 2 of the program, where vehicles are automatically charged overnight regardless of location. The capacity required was only analyzed for the class results and due to the deficiencies discussed here the results for the capacity required will not be discussed in the result discussion section.

5.2 RESEARCH RESULTS

In this section of the thesis, the results from the research performed using driving data from roughly 368 business vehicles in Reykjavík is presented. The method created and used has been discussed above and this section takes into account the results from the previous analysis of the method, the model and the program when discussing the research results, and answering the research questions. The discussions will follow the same outline as the result chapter, beginning with discussing the results from the whole sample, then the results for the three different classes of vehicles will be discussed and finally the results for the companies that own the vehicles will be discussed and compared.

5.2.1 All vehicles

In this section the results for the whole research vehicle sample is presented. This section should reveal how many vehicles are regarded to have EV potential, as according to the method created in this thesis. The section will discuss the results from the average daily driving analysis and the failure day analysis.

5.2.1.1 Average daily driving

The average daily driving of the whole usable sample can be seen in figure 4-3 in the results chapter. As expected the average daily driving of vehicles is rather widespread, with a standard deviation of 78.43 km. What was though surprising was the sheer scale of some of the vehicles which were driving the furthest. A total of 4 vehicles drove more than 400 km on average each day. When looking at the raw data for these vehicles they all have in common to be travelling out of Reykjavík very frequently. A rather high percentage of vehicles drive more than 100 km on average daily, or 26%. A lot of these vehicles (driving more than 100 km on average) belong to the same companies with class 3 vehicles being most common. The number of vehicles driving less than 40 km daily on average is quite low, with 18% of vehicles falling into that range. Most vehicles drive between 40 and 80 km each day, or 45%. It is surprising how high the mean for the average daily driving value of all the vehicles is, 91.78 km. This high mean is very likely down to the high number of vehicles driving above 100 km on average and how high this value tends to get.

Based on the average daily driving, the EV possibility was evaluated. This was done by comparing the average driving value with the official range of the model EV. It has to be said that the staggering amount of vehicles, qualifying as having EV potential based on this parameter is surprising. 273 vehicles have EV potential while 74 have not, meaning that 78.4% of the drivers of vehicles could switch to EVs without ever running out of energy. That is of course if they could fully charge their EV overnight and would never drive a greater distance then their average daily driving in one day. This is obviously a great simplification of the reality, and in fact the EV potential of vehicles cannot be determined by the average daily driving parameter alone. It is the essence of many phenomenons to be limited by exceptions rather than the norm. That applies to EV potential based on driving distance requirements. This value still gives a very good idea of the EV potential of the vehicles as a lot of people seem to think about its driving needs in the timeframe of a single day. If a driver knows his average daily driving value to be well under the official range of an EV on the market, he might be encouraged to switch. Drivers should keep in mind that the official range of these vehicles tends to lower in reality and is reduced slightly through usage. The driver noted above might feel that he could easily skip the exceptions (the longest trips) or use another vehicle for those trips since his average value is well under the driving range of a certain EV. So that even though the high percentage (78.4%) is not telling the whole story it does indeed give a positive sign for EVs.

5.2.1.2 Failure day analysis

A frequency distribution of failure day percentages of the total vehicle sample can be seen in figure 4-5 in the result chapter. It shows that the distribution of the failure day percentage of the vehicles is not very widespread, underlined by a standard deviation of 16%. What is surprising is the low number of vehicles having a recorded failure day percentage above 20%, with a mere 20.5% having a recorded failure on more than 20% of its active days. Even with this low percentage some vehicles recorded very high failure day percentage, with the highest one failing on 67.7% of total active days. This vehicle drove out of Reykjavík on almost all of his active days, thus frequently surpassing the model EV range. This vehicle quite clearly could never have been an EV and his role does not fit the characteristics of EV at all. A very high fraction of the whole sample fails on 5% or fewer days, or 50.4%. Still the average failure day percentage is 11.79%, which is surprisingly high. This is likely due to the extreme values going very high and due to a rather high number of vehicles failing in between 10% and 20% active days.

In the method chapter, 3 different EV potential scales were presented, based on how high the failure day % of vehicles could go in order for them to be considered to have EV potential. These scales are 0%, 0-5% and 0-10% failure days. This section is intended to answer one of the research questions, being *"What fraction of business vehicles in Reykjavík could be EV".*

0% failure days

In total 70 vehicles, or 20.5% of the whole sample never failed throughout the research period. It is clear that these vehicles all have EV potential. A vehicle not driving more than the range of a same class EV on a single day over a 100 day period could have definitely have been an EV. It should also be noted that obviously the driving pattern of the vehicles was not adapted to EV characteristics but still would have had no problems going about its business with a max range limited to a same class EV. Thus with the strictest possible limitations for which vehicles have EV possibility this research suggests that 20.5% of business vehicles could be EVs. It should be noted that that all these vehicles are regarded to have EV potential, based on their average daily driving. This of course is not surprising but simply points towards the program working correctly.

0-5% failure days

For the 0-5% failure day scale, all vehicles failing between 1% and 5% of total days are added to the collection of 71 vehicles not failing at all. A total of 173 vehicles failed on 0-5% of their active days. This marks 50.1% of the total research sample. The adding of these vehicles (vehicles experiencing 1-5% failure days) to the potential EV group of vehicles is reasoned for on the basis of the driving habits (trip lengths, stop durations and stop locations) of the data collecting vehicles having not been adapted in any ways towards the characteristics of EVs. Thus it seems reasonable to include vehicles which fail on very few days which seem to be exceptions from the normal driving habits of the vehicles, to the set of vehicles regarded to have EV potential. These are vehicles which are regarded by the author not to have had any problems with being EVs if their driving routine and schedule, and stop locations were to be modified only slightly. If for example a case of a theoretical driver which had his driving needs and habits analyzed is considered, where he learned he would have had problems on only 3% of his active days had he been driving an EV, without modifying his driving pattern or habits the slightest bit. It is likely that if he would regard EV as a possibility for himself and is would evaluate his situation as such that he would have no problem in removing those 3% of days from the equation with slight modifications of his driving. If this scale for EV potential is used 50% of business fleet vehicles in Reykjavík could be EVs. When the EV possibility evaluated from the average daily driving of these vehicles is analyzed it can be seen that 3 of the 102 vehicles failing 1-5% of days, are regarded not to have EV potential. What this means is that these vehicles, although failing on 5% of days or less, these vehicles constantly become very close to failing and when they fail, do so in a quite heavy manner. When the data for these vehicles is closely inspected they are revealed as having an average daily driving value which exceeds the model EV range by a very small margin, but still do so due to constantly going very close to failure. It makes sense to remove those 3 vehicles from the EV potential collection, resulting in the 0-5% failure day collection being reduced to 49,7% of the total sample.

0-10% failure days

For this scale the 44 vehicles failing between 6% and 10% of active days are added to the EV potential collection based largely on the same reasoning as the former added range. If a firm was to replace these vehicles with EVs it would obviously require more adaptation than for those failing between 1-5% of days as failures for these are less of an exception from the norm than the 1-5% vehicles. It is likely that for these it might not be enough to optimize driving routine and stop locations.

It might be required for the firms owning those vehicles to reorganize its fleet and for example assign conventional vehicles to roles which require longer distances to be driven with less frequent pauses in order for these vehicles to qualify as having EV potential. The 0-10% failure day collection counts a total of 217 vehicles, 62.8% of the total sample. Without taking the average daily driving of these vehicles into account a maximum of 62.8% of business vehicles in Reykjavík could be EVs according to this scale. 6 of these 44 added however do not qualify as possible EVs based on average daily driving, resulting in the maximum possible 61.2% of business vehicles to be regarded as having EV potential.

5.2.2 Classes

In this section the results for the different classes will be discussed. This discussion is expected to yield an answer to the question of whether there is any difference between classes of vehicles when it comes to EV potential.

5.2.2.1 Average daily driving

The frequency distributions for the different classes of vehicles are quite different one from another, and can be seen in figures 4-6 (class 1), 4-7 (class 2) and 4-8 (class 3) in the result chapter. The highest recorded value for all classes is over 300 km driven daily on average. The highest value for class 1 is 469 km, for class 2 it is 335 km and for class 3 it is 386 km. Class 1 has the highest single recorded average daily driving value. The author anticipated class 1 to have rather low average daily driving values, as many of the class 1 vehicles are vehicles which are not specially designed delivery vehicles. That however was not the reality and an example of a class 1 vehicle that drove very far regularly can be seen in figure 5-1. In fact class 1 has the highest portion of vehicles which exceed 300 km in average daily driving distances or 3.5%. Although not a large portion, it is when compared to class 2 with 1.3% and 3 with 1.2%. Although having the highest fraction driving extreme distances it does not for rather high distances such as +100 km daily on average. Class 3 has 30.7% vehicles driving more than 100 km on average daily, class 1 has 27.2% and class 2 only 20.2%. Knowing the capacity required would be very interesting for comparison to the analysis of the average daily driving but cannot be used due to deficiencies in the program as previously stated.

The high percentage of class 3 vehicles driving in excess of 100 km daily is not surprising as a lot of the vehicles in that group are large trucks which frequently drive out of Reykjavík and in general take long distance trips. When the raw data is inspected one can see that the class 3 vehicles do not take trips as frequently as the other two groups but these trips tend to be much longer in distance. These are vehicles which frequently carry a lot of cargo which takes a lot of time to load into them. It seems due to this that in many cases they take only 2-4 trips per day or less. It is therefore unexpected to see the low percentage of vehicles driving more than 300 km on average in that class as when compared to class 1. The same pattern shows when one inspects the fraction of vehicles in each class driving very low distances on average, under 40 km daily. Class 2 again seems to be driving short distances on average daily with 22% of vehicles driving 40 km or less on average, while a 16% fraction of class 1 drives under 40 km daily and 11% of class 3. Class 3 has the highest mean average daily driving distance which is 99.5 km. Class 1 follows close behind with 93.18 but class two has an astonishingly low mean of 77.85 km. Class 3 having the highest mean is not unanticipated due to the reason noted above with long but rather infrequent trips. However the author is surprised to see the great difference between class 1 and class 2 and if anything those two were if anything expected to the other way around. Class 2 is composed mainly of delivery vans. One would have expected those vehicles to travel just as frequently and possibly longer distances than class 1 vehicle. This on the other hand is not the reality and one has to wonder. There is no real difference in trends to be seen in the raw data and graphs for these classes. One possible reason for the low mean average driving distance of class 2 vehicles is that these vehicles combine two aspects which could possible cause this trend. As they are able to carry more cargo than class 1 vehicles they might not travel as frequently due to the time it takes to load them, while class 1 vehicles carry less but take a lot of trips and are constantly driving around. On the other hand they (class 2 vehicles) cannot carry as much as class 3 vehicles and therefore are not used to take the long trips that characterize a lot of the class 3 vehicles. This is only a conjecture and it seems hard to judge whether there is any foundation for it based on the raw data and graphs.

The average daily driving distance of the vehicles showed somewhat surprising results. When the EV possibility of the vehicles belonging in each of the groups is evaluated by comparing the distance driven and the maximum range of the model EVs the surprising results become apparent. Note that the maximum range of the Peugeot ePartner vehicle representing class 1 is 96 km, the class 2 model vehicle eBoxer has 128 km range and the class 3 vehicle, Smith Edison, has a max range of 160 km. Class two vehicles have the highest EV possibility portion with 83% of vehicles having an average daily driving distance below the max range of its corresponding model vehicle. The results above showed that the class 2 vehicles on average drove substantially less distances than the other classes. The combination of the low driving distances and the moderate model EV range result in encouraging results for class 2 vehicles. Class 3 gives very similar results with 81% of vehicles acquiring the EV possibility rating based on the average daily driving method. Although the vehicles in this class had a much higher recorded mean average daily driving than class 2, the fraction of vehicles considered to have EV potential is similar. This if course due to the substantially higher maximum range of the class 3 model vehicle. Class 1 seems to be worst suited for possible switching to EV based on the average daily driving. This is due to a combination of the high recorded average daily driving of the class and the low maximum range of the model vehicle. It is quite obvious how heavily the characteristics of the model vehicles chosen to represent each class affect the results. If for example the vehicle representing class 1 had a max equal to that of the class 2 vehicle (which is definitely available on the market) the results would without a doubt have been quite different. It would have been interesting to run the program based on different model vehicle constants to see how that would have affected the results. In fact one of the proposed add-on to be included in a future version of the program and method, which is described in later section of this chapter, a feature where users will be able to easily switch between model vehicles and choose among different sets of vehicles. This will give users a chance to see how different types of vehicles affect their results and which vehicles best suit their needs.

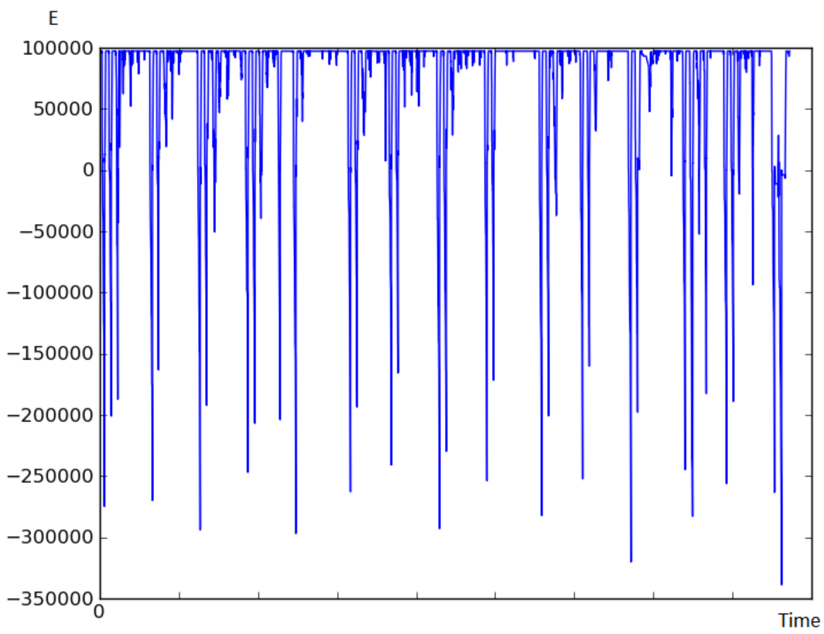

Figure 5-1 An example of a class 1 vehicle which drove very far regularly. The y axis shows the battery energy (j) while the y axis is time (the entire research period of each vehicle).

5.2.2.2 FAILURE DAY ANALYSIS

The frequency distributions for the failure day percentage of vehicles of the three classes can be seen if figure 4-13 (class 1), figure 4-14 (class 2) and figure 4-15 (class 2). When the highest failure day percentages are examined it becomes apparent the overall highest failure frequency value belongs to a vehicle in class 2, 67.7%. In the discussions about the whole vehicle sample it was noted that a surprisingly low fraction of vehicles had a failure recorded on more than 20% of days. There is a clear difference in the fraction of vehicles from the separate classes which fail on more than 20% of its active days. A total of 26.7% vehicles form class 1 fail on more than 20% of days, while a surprisingly high fraction of 21% of class 2 vehicles do and Only 12.8% vehicles from class 3 do. What is surprising about these results, when compared to the average daily driving results, is the high fraction of class 2 vehicles failing relatively often. When the most extreme values (40% failure days and more) are inspected the same trend is apparent with class 1 leading, closely followed by class 2 and with class 3 falling far behind. This seems peculiar when compared to the average daily driving values where class 2 had by far the lowest mean. The reason seems to be that when some class 2 vehicles fail, they do so very regularly and only by a small margin. For example a certain class 2 vehicle fails on 35.6% of days but still has a relatively low average driving value of 101 km. This pattern is more common with class 2 vehicles than with the other two classes. One other reason becomes apparent when one analyses the frequency of the lowest failure day percentage values of the classes. It can be seen that class 2 has a low fraction of vehicles within the failure day percentage range between 6% and 20%. Class 1 has 42.3% of vehicles failing between 6% and 10% of total active days. Class 2 has much lower fraction of vehicles within that range, 22.2% and class 3 only 15.3%. So even though class 2 has a rather high fraction of vehicles with failure day percentage above 20%, it also has a lot of vehicles with a percentage of 5% and lower. One possible reason for class 2 vehicles clustering at the extreme poles could be the following. In the discussion about the average daily driving of the classes it was noted that it could be that class 2 vehicles have such a low average daily driving due to way that firms utilize this class of vehicles. The theory is that the large delivery vans that make up for the majority of the class 2 sample do not travel as frequently as class 1 vehicles and when they do, they do not travel as far as class 3 vehicles which tend to take relatively few trips daily which tend to be long distance trips. This could be the case for the majority of the vehicles in class 2, which cluster in the <5% failure day range. However, the rest of them might be vehicles which are utilized in a way similar to that of the class 3 vehicles. Due to the lower range of the class 2 model EV the vehicles being utilized in this way would record a high number of failure days.

When it comes to the number of vehicles with 0% failure days the class with by far the fewest vehicles is class 1 with only 7.8% of vehicles. 26% of class 2 vehicles did not fail on a single day and 31% of class 3 vehicles. It is clear that class 1 seems to have the least potential when it comes to EV possibility which can be quite clearly seen in the 16.1% average failure day percentage. Class 2 also has a rather high average failure day percentage, 11.2% but class 3 seems to be by far best suited for the switch with a 7.3% failure day% on average. Perhaps the most unanticipated result is the rather high number of class 2 vehicles with a high failure day %, especially when the low average daily driving results are considered. The results of the frequency distribution for class 1 and class 3 hardly comes as a surprised as both follow the results from the average daily driving quite closely. As with the results of the evaluation of EV possibility based on average daily driving values it seems clear that the range of the model EVs play an instrumental part in the determination of the results. Had the range of the class 2 model vehicle been the same as that of the class 3 model vehicle the results might have been very different. Let’s next consider the different scales of EV potential for the results for the classes.

0% failure days

7.8% of vehicles from class 1 did not fail over the entire period which is by far the lowest % of vehicles having 0% failure days. Class 2 has 26% of vehicles with 0% failure days and class 3 31%. As stated in the discussion section for the failure days for the entire vehicles sample is the strictest possible way of identifying vehicle that have EV potential. It is amazing how low fraction of class 1 vehicles has 0%

failure days. One has to wonder if this large gap between class 1 and 2 is caused simply be the lower range of the model EVs. Class 1 of course was showed to have higher average daily driving and difference is so great there that there has to be a difference in the role of these two classes of vehicles at companies in Reykjavík. One possible explanation could be (this is just a theory) that class two vehicles take less frequent trips than the class 1 vehicles, resulting in lower average daily driving distance and longer periods spent at dock where the vehicles get recharged. Class 1 vehicles on the other hand are constantly taking short distance trips and coming back to dock only for a short period of time before going out again. Based on this EV potential scale there is a very great difference in how well suited the different classes of vehicles are for a possible EV switch. Class 3 shows encouraging results with 31% of vehicle definitely having EV potential while class 1 shows worrying results with only 7.8% of vehicles qualifying as having EV potential if judged by this stern scale.

0-5% failure days

Class 1 rises from 7.8% to 30,4% when the scale for EV potential is increased up to 5% failure days. The other classes also show steep rises. Class 2 rises from 26% to 57.7% while class 3 rises from 33% to 62.78%. It can be clearly seen how much the broadening of the scale changes the results for all the classes. When the average daily driving value results are taken into account the results do not change for class 2 and 3 but two vehicles from class 1 that have a failure frequency between 0% and 5% were considered not to have EV potential based on their average daily driving values lowering the percentage of vehicles from 30.4% to 28.7%. Thus with slight optimization of driving habits and time organization 28.7% of vehicles from class 1, 57.5% from class 2 and 62.8% from class 3 of commercial vehicles in Reykjavík could be considered to have EV potential.

0-10% failure days

When the potential scale is broadened up to 10% failure days the number of vehicles increases. The largest increase with the further broadened scale is for class 1 which increases from 30.4% (with average daily driving not taken into account) up to 50.4%. That is double the increase for the other classes. Class 2 goes up to 66% of vehicles qualifying as having EV potential and class 3 up to 71.8%. However 4 of the 8 vehicles added to the EV potential pool for class 3 by the broadened scale did not qualify as having EV potential based on the average daily driving, and is thus the percentage for class 3 is reduced to 67.7%. It is unclear why such a high portion (50%) of class 3 vehicles which failed between 6% and 10% of active days were considered not to have EV potential based on average daily driving, while the other classes did not contain any vehicles showing this trend.

One of the scopes of the research was to try to answer the question of whether, among commercial vehicles in Reykjavík, all classes had equal potential to be EVs. Based on this research method and the model EVs chosen to represent the classes it seems there is quite high difference between the three classes. It seems that large vehicles over 4000 kg in weight are best suited for this switch. Class 2 vehicles, vehicles which weigh between 2500 kg and 4000 are next best suited, and do not fall behind class 3. Class 1 vehicles got the worst result on whether being regarded to have EV potential.

5.2.3 Companies

In this section the results for the vehicles will be analyzed from the point of view of the companies they belong to. One of the research questions was what fraction of firms in Reykjavík can change a large fraction of its fleet to EV. The answer to that question among other aspects of the future outlook for firms in Reykjavík in regards to EVs will be discussed in this section.

5.2.3.1 Average daily driving

The results for the average daily driving of the vehicle fleet of companies can be seen in table 4-2 in chapter 4. There is a very clear difference in the average daily driving of fleets, with the mean of average daily driving values ranging from 27 km to 219 km driven on average daily. Still as stated in the result chapter a many of the fleets fall within the range of 80-100 km, or 7 of the total 16 fleets used for the research. It is interesting to inspect the fleets on the different poles as it is quite obvious that there is a great difference in the driving patterns and needs of fleets.

The three highest mean average daily driving values for fleets are those of firms A (150.8 km mean average daily driving), M (193.5 km) and N (219 km). Company A is a food and beverage manufacturer and importer and has a fleet made up of mainly class 1 and 3 vehicles. The distance driven by the vehicles varies greatly, from 15 km to 400 km driven daily on average. However, and as the average of 150 km points to, most vehicles drive very far on average and 15 of 26 vehicles drive more than 100 km on average daily. There seems to be no connection between class and distance driven for this firm. Firm M has a mean average of 193,5 km driven daily. This firm specializes in express delivery of goods and all of the vehicles in its fleet are class 2 vehicles. All the vehicles in this fleet have a very high average daily driving distance, the lowest being 135 km and the highest 314 km. This company shows remarkably uniform results and it is quite clear that EVs do not at all suit this particular firm. The fleet of company M has the highest mean average daily driving, a noteworthy 219 km. This is a gas company and all of its vehicles are large trucks which fall under class 3 of this research. This firm has only 5 vehicles in its fleet (that have data loggers), two of them driving under 100 km on average daily but the other 3 over 200 km, one of those having the overall highest value in the research 524 km. When the raw data from these vehicles is inspected it seems as the two driving under 100 km on average tend to be operating inside Reykjavík more often than not while the other three very regularly drive far outside the city, to other regions of the country.

The three fleets which have the lowest average daily driving distance are those of firms C, E and Q. The fleet of E has the lowest mean average driving distance of 57 km driven daily on average. Company E is a commercial enterprise. The driving distance differs greatly between lowest and highest values, ranging from 10 km on average to 232 km driven daily on average. However only 2 vehicles of the total 19 drive more than 80 km on average and 11 of them under 50 km daily. This is quite different from all other companies and if it was not for the high value of 232 km the mean for the fleet would be significantly lower. A large fraction of the vehicles are class 2 vehicles. It seems that the overall role of vehicles in this company is well suited for being EVs. Company C and Q both have fleets which drive 59 km on average daily. Company C is a super market chain. All the vehicles are class 2 vehicles and all are driven less than 90 km on average. The vehicles of this company do not seem to be driven very frequently, explaining the low average daily distance. Company Q is meat processing company. All the vehicles of this company are class 3 and all are driven under 90 km on average. The pattern of how the vehicles are driven is very similar to company C, with vehicles taking very frequent trips and not leaving the city at any point.

When the EV possibility of fleets is inspected it shows a pattern which could be expected based on the values shown for the average daily driving of vehicles within the fleets. The possibilities range from 0.0% to 100%. Overall all companies except two are regarded to have the possibility of replacing more than 50% of their fleets with EVs when based on this method. Half of the companies are considered to have the possibility of switching 80% on more of their fleet to EVs. Three firms are evaluated to have the possibility of switching their entire fleet to EVs. These are C and Q which had their fleets described above due to having low average daily driving distances recorded. The third firm is firm P. Even though firm P was not one of the firms being identified as having the lowest mean average daily driving distances (its fleet on average drives 81 km daily) it is considered to have the possibility of switching their complete fleet to EVs. Still due to its fleet being mostly class 3 vehicles none of the firm's vehicles has an average daily driving distance above the maximum range of its corresponding model EV. Company E was not considered to have 100% EV potential but became very close with a 94.7% EV potential. Only one of its 19 vehicles was regarded not to have EV potential but that vehicle had by far the highest average daily driving distance. One firm was very extreme when it comes to having low EV potential. This is company M which was discussed above. Based on this method not a single vehicle from this firm is regarded to have EV potential. All its vehicles are class 2 vehicles and all travel very far on average each day. The firm which has the second lowest value is N which has only 40% EV possibility. It should be noted that this firm has only 5 vehicles in its fleet and thus the results of a single car drastically would change this percentage. The third lowest EV possibility percentage is 55.6% for company J. This is a dairy product company which has a fleet characterized by a high portion of class 1 vehicles. All the vehicles not regarded to have EV potential according to this method for company J are class 1 vehicles, but only half the class 1 vehicles of this company fail to do so. The fleet of company A which was noted above as having one of the highest average daily driving manages to reach 60% EV possibility despite having an average daily driving of 150 km. This is no doubt due to the large fraction of class 3 vehicles in its fleet. Still 4 of its 16 class 3 vehicles are considered not to have EV possibility, while 7 of its 9 class 1 vehicles are not possible EVs.

To summarize, the average daily driving of business fleets in Reykjavík varies greatly. When using the average daily driving of vehicles to determine the possibility of switching from conventional vehicles to EVs, the average driving of company's fleet obviously matters heavily. But it is not only the average driving that decides the EV potential but also the composition of the fleet with regards to vehicle class. Using this method yields results which indicate that a very large part of companies in Reykjavík could have most of its fleet composed of EVs. Based on average daily driving of the 16 company sample used it seems 87.5% of companies could replace at least half of its fleet with EVs and half of the companies could replace 80% of its fleet with electric vehicles.

5.2.3.2 Failure day analysis

When looking at the failure day percent for the fleets it can be seen that there is quite a difference between the different poles. The highest mean failure day percentage of a fleet is 48.8% while the lowest is 1.7%. 50% of companies have an average failure day percentage between 10% and 20%. The highest recorded failure day percentages are 48.4% for company M, 17.7% for company A and 16% for H. 48.8% is a very extreme fraction and is close to 3 times the next highest. This fleet is the same which has one of the highest average daily driving and based on that value has not a single vehicle in its fleet which is considered to have EV potential. All the vehicles are from class 2 and none of them have a failure day percentage under 10%. An example of a company M vehicle can be seen in figure 5-2. The fleet with the second highest mean failure day percentage is the one of company A. Company A, like M, was noted above for having high average daily driving. It has mainly vehicles from class 1 and 3. There is a very visible difference in the failure day percentages between the two classes with the class 1 vehicles having only one vehicle (of 9 class 1 vehicles) with a recorded failure day percentage under 20%. From the total 16 class 3 vehicles from the fleet of company A only 3 fail on more than 10% of active days. This is a unusually clear difference between the failure percentages of two classes within the same fleet. Even though company A has such a high average failure day percentage 19.2% of its vehicles never failed, all of which are from class 3. The clear difference in the dissimilarity between the overall potential of the three separate classes becomes very apparent in the case of company A.

On the other pole the lowest average failure percentage for companies are those of company C (1.7%), company E (3.5%) and company I (5.7%). Both C and E were among the three companies with the lowest recorded mean average driving distance and the low failure percentage is without a doubt largely down to the low daily driving. In fact more than 50% of fleet of these companies never failed throughout the research period. The fleet of company I on the other hand does not have a particularly low average daily driving distance but does have a high portion of class 3 vehicles which tend to drive rather far but on the other hand do not fail frequently. The highest fraction of a single fleet recording no failures through the research period is the one of company I. Based on the failure days of the vehicles within the company fleets, the EV possibilities of the companies can be assessed.

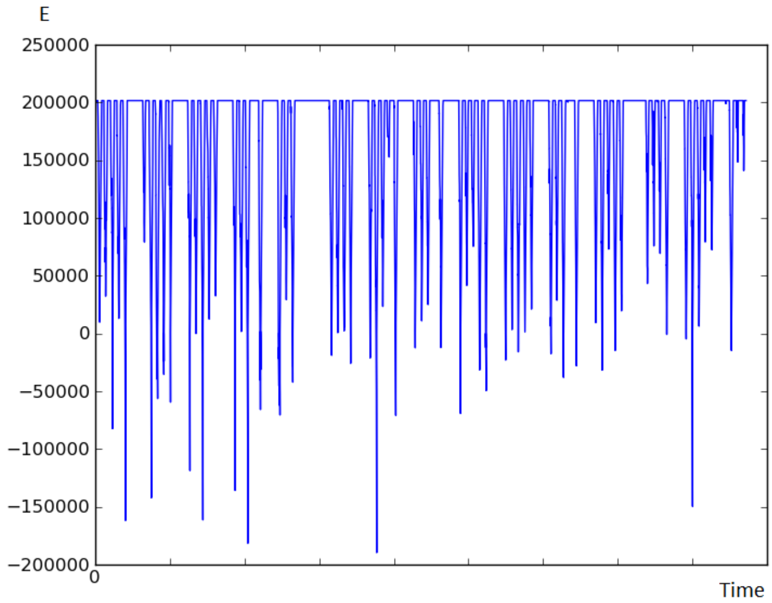

Figure 5-2 An example of a vehicle from company M. Note how often the vehicle fails. The y axis shows the battery energy (j) while the y axis is time (the entire research period of each vehicle).

0% failure days

If this most limiting way of determining whether a vehicle has EV potential is used, results for companies vary greatly, ranging from 0% of company fleet up to 72%. If this method for identifying EV potential is used, 56.25% of companies could replace 20% of their fleet with EVs. If the companies which are identified as having this possibility would take this step that could prove to be an immense boost for the possible transition to electric mobility in Reykjavík and Iceland. Due to these vehicles not failing at any point had they been EVs, the drivers of the vehicles should be not have do modify their habits in any way and the transition to EVs should be very smooth. It is likely that due to how painless this transition could be, switching to EV is likely to be a positive experience for companies and drivers. That could perhaps encourage them to reorganize and modify their fleet in order to further increase the fraction of EVs in their fleet. 25% of companies could replace 50% of their fleet with EVs based on this EV potential identification method. All of the vehicles recording zero failures were regarded to have EV potential based on the average daily driving method.

0-5% failure days

If the scale for possible EVs is increased to 5% failure days the results change significantly. 87.5% (14 out of 16) could replace 40% of their fleet with EVs based on this scale. Half of the companies could replace 50% of the fleet with EVs. If either would take place, obviously the transition to electric mobility would gain very significant momentum. But as stated before, substituting vehicles failing up to 5% of days would require some action and fleet optimization from companies. But even though some of these vehicles would have experienced some problems had they been EVs those were clear exceptions. Note that had these vehicles have been EVs they would have possibly failed on a very few occasions, but that is when they were used as if they were conventional vehicles. Obviously in the case of vehicles failing at some point, this would require some change in the utilization of the vehicles. But the changes are likely to be very minimal for example making sure to spend lunch time at dock when the EV is close to running out of energy, or taking a long trip after a pause instead of before it and charging the vehicle during the pause.

0-10% failure days

As stated above the broadening of the EV potential scale up to 10% failure days is reasoned for by the same way as the increase to 5%. Obviously the change from 5% to 10% is significant and would require greater effort from companies and drivers. What is added is the possible requirement of a overall reorganization of vehicle fleet with vehicles being assigned more specialized roles based on vehicle characteristics, such as assigning conventional vehicles to take all longer distance trips. Such a modification of a fleet added to the optimization of driving routes, stop locations and driving habits should enable the drivers of vehicles failing on up to 10% of days to remove the failure days from the results. Based on this scale the possible EVs are increased further. From the total 16 companies 11 could swap more than 50% of its fleet with electric vehicles. The author regards this as a definite possibility, but something that would clearly not be as effortless as substituting vehicles which never failed, as basing the fraction of vehicles substituted on the 0-10% failure scale would require greater effort.

To summarize, companies in Reykjavík have the possibility of replacing a large fraction of their vehicle fleets to EVs. Based on the efforts that drivers and fleet managers are willing to put into optimizing fleet organization and driving patterns and behaviors, different result may be gained. Even without any modification of driving behavior and patterns, half of businesses in Reykjavík could replace more than 20% of vehicles with EVs. If companies are willing half of them could without too much struggle replace up to 50% of vehicles with EVs, based on the 0-5% failure day percentage scale.

5.3 SUGGESTED FUTURE MODEL AND PROGRAM DEVELOPMENT

Before discussing the future development of the method a summary of the current method is presented, taking together which features did not work as planned which did and will be used to answer the research questions for the Reykjavík business fleet research. The next steps in the development of the method and program are suggested under section labeled version 3, discussing which aspects of the current method will provide the foundation, which aspects will be modified and added. Version 3 will not offer any breakthroughs and perhaps simply is a program which would have been designed for this thesis had the author known what he learned from the thesis about the current method and program versions. After that some ideas for future modifications and add-on‘s will be described.

5.3.1 CURRENT METHOD DEFICIENCY SUMMARY

One large problem with the current method is the way that docks were assigned to vehicles. This problem forced the author to remove a number of vehicles from the sample. It is not impossible that the error could have affected vehicles that remained in the sample. Version 1 of the program had some problems. The failure frequency feature in most cases worked well. There was however a problem with the failure frequency of vehicles being exaggerated. It was very hard to determine whether vehicles were affected by the problem. Also not all vehicles were active for all the research days, something that this parameter failed to take into the equation. The author also regards the failure frequency parameter to lack descriptive value. That is, for some people it might be difficult to understand what the failure frequency value really describes, partly because it lacks the dimension of time, and what a difference in this value for two vehicles tells you about the driving need of the two vehicles. Another problem with version 1 was that due to vehicles not being automatically charged during night, there were sometimes large periods of time where vehicles were not charged. This was quite common, resulting in huge dips in battery energy. This caused the capacity required feature to be very unrealistic in many cases, eventually causing its drop from the research tool kit for the research. Version 2 however was not as error prone as its predecessor. The failure day percentage is a very self explanatory parameter, which allows for easily understandable and explanative comparison. Due to the added configuration of automatically giving vehicles a full battery in the beginning of each day the problem with periods where the vehicles did not spend nights at a dock was solved. The former problem described with version 1 (exaggerated failure frequency) does not affect version 2 of the program. This is due to the fact that failures during the day are not counted, but instead the vehicle either failed or not during each day. The average daily driving feature of version provides interesting information which can be used for a very basic assessment of EV potential.

Version 2 of the program/model provides features which are less error prone and which together can give a very good idea of the EV potential of vehicles, and can be used for result analysis and discussion.

5.3.2 Version 3 proposal

Based on what has been discussed above a new version of the method and program created will be presented. First changes in the basic method will be suggested, notably how the docks for the vehicles are identified from the raw data. Features of the proposed program will then be described. Version 3 is based on what has been learned from this thesis, and presents simply a version which seems like a step in the correct direction, without making drastic changes in the method or program. It offers slightly modified and fixed features from the old versions, and takes no giant steps from the current method and program. It could be described as the method and model/program which would have been designed had the author already learnt about the problems related with the current method and programs.

5.3.2.1 Dock identification

This aspect is not really a part of the program or model but rather a part of the preparation of data before it can be used for the model and program. It will still be described as it will definitely be done in a different manner in the future. In the current method the docks for vehicles are identified based on the log frequency of locations where the vehicles are stopped. However when this was designed the author failed to note that after a certain amount of stop logs at a location, the logs cease to be made every 15 seconds and start being logged once every hour. Due to this the locations at which vehicles spend most its time and should have been made docks could fail to be assigned as a dock for the vehicle. This caused an error which caused a number of vehicles to be removed from the sample for the research. The way which docks are assigned needs to be changed from the current method. The idea is that instead of assigning the docks based on which stop locations are logged most frequently, to identify the docks based on the locations at which each vehicle spends most of its time. This could be done by using the current small program created to find docks to list the most frequent stop locations. From there a code would need to be added to the program which would sum the durations of all the stops on each of the listed locations and listing them again based on at which locations the car spent most of its seconds when not on the move. How many locations the program would need to list based on frequency to make sure not to miss the locations at which a vehicle spent most its time is not clear. Based on the fact that it seems that in most cases (note that the wrongly identified docks were only rare exceptions, that is in most cases the most frequent locations were also the one where the car spent most its time) the old method worked, so the program would hardly need to calculate the time spent at more than the top 10 most frequently logged locations, in order not to miss the “correct” docks. Changing the docks identification method should erase the problem described in earlier section and chapters as problem 1, from the methodology.

5.3.2.2 Main program features

Version 3 will be based on version 2 of the program created. The model will work the same way between those two versions meaning that the vehicles will be automatically charged at midnight. Version two provided less error prone results than version 1, largely due to the fact of gathering result data on daily basis and the car always having a full tank at midnight. As was noted when discussing the different failure assessment features of the two models there is one problem with the automatic charging. In some cases it might be that the vehicle would not have reached a full charge throughout the night in reality but still starts the next day with a full battery pack. This means that a car starts driving at 5 in the morning (after having been in operation until 23 the night before) with a full tank he might not have had if the energy amount had he not jumped to Emax at midnight. This problem could be fixed simply by not making the car jump straight to Emax but instead, automatically start charging from where he ended at midnight and charging until the he starts driving the morning after. The automatic charging is important for the model, as periods when a vehicle is not at dock during the night will skew the picture. It is very likely that an EV owner would charge his vehicle anyway if keeping the vehicle away from dock during night and planning to use it the next day, and therefore this configuration is hardly unrealistic.

Like version 2 of the program, version 3 of the program will provide the failure day percentage as well as finding the average daily driving value for each vehicle. These two features will not need to be modified except for two very minimalistic changes. In the case of the failure day analysis the program would be made to calculate the failure day percentage automatically, something it does not do now (it simply gives the total amount of active days and the failure days). The change for the average daily driving feature is also very nominal, being to automatically determine the EV possibility of each vehicle based on the maximum range of the matching EV. In version 2 this has to be done manually from the result table.

Although version 3 will be based on version 2 it will adopt two features from version 1. The failure frequency and the capacity required. Both of the features need to be redesigned in order for them to fit the model (automatic charging, etc) and to erase the problems accompanying them in version 1 of the program.

Failure frequency in version 3

Even though it is not used for result analysis in the thesis, due to a few problems, the failure frequency is an interesting parameter, which offers slightly different information than the daily failure percentage. It is likely that a failure frequency feature will be included in version 3, which will be an improved version of the feature from version 1. Although the failure day and average daily driving features are based on assessing each day separately, it does not mean that all the features for the version have to be designed in such manner. The failures can easily be counted for the whole research period. At least two problems accompanied the failure frequency function in version 1. One was that on periods when a vehicle was away from a dock for an prolonged period of time and was not charged for a long time, the battery level line could stay below zero for many days. During these time periods no failures occurred, something that makes the results less reliable. However with the automatic charging configuration of the model in version 3, this problem is out of the way. The second problem, which was more serious, was the exaggerated failure frequency problem caused by vehicles being charged for a very short time before starting to drive again. There is a solution to this problem. In version 1, when a vehicle started being charged after having failed, there was no limit as for how long the vehicle had to be charged before starting to drive again. In version 3 this will be changed in such a way that a vehicle is kept being charged until the battery has at least been charged up to 50% of battery capacity. This will stop multiple failures being counted during a very short time period.

Capacity required in version 3

The capacity required feature for version 1 was eventually dropped due to the high number of vehicles displaying problem 2. As with the failure frequency for version 3 this parameter will be found looking at the whole research period. Problem 3 will not exist in this version due to all vehicles being automatically charged over the night. Therefore there will be no prolonged periods without charging which result in the huge dips in energy level that characterize problem 2. It might also be possible to list for example the five highest capacity required vehicles for each vehicle, occurring over the entire period in order to be able to determine whether the largest value is a large exception from the other values or not.

5.3.3 FURTHER IMPROVEMENT IDEAS

In this section some possible future add-ons and improvements on the methodology and model/program will be discussed. These are simply ideas which have come up through the thesis work which have yet to be planned to full extent.

5.3.3.1 IMPROVING MODEL CONSTANTS AND PHYSICS

The model used in the current methodology is very basic and many of physical factors are neglected. It still gives a good idea about the EV potential of vehicles, although it could obviously be more realistic. In this section a few modifications that would improve the reliability of the model are presented.

Energy usage

For the current model the energy usage of vehicles is constant. It was found simply by using the maximum range of each of the model vehicles and the total battery capacity. One factor that would definitely improve how realistic the model is would be to include topography into the model. In the current model the vehicles are always driving on a flat surface. In reality topography affects vehicles substantially, and the effect is even more for electric vehicles than for conventional ones (as EVs can be charged when braking). Obviously the energy usage of a vehicle is higher when driving upwards due to gravity. The author has yet to closely ponder how the effects of topography should be included in the model, but its addition would surely complicate it. One problem, which is the main reason for topography not being a part of the current method, is that SAGAsystem does not include topography in its data or calculations. The SAGAsystem data would thus need to be combined with topographical maps in order for this to become a possibility.

In the current method, acceleration of vehicles is not taken into the account. It is clear that accelerating is energy costly, and including acceleration in the model would make it substantially more realistic. Although acceleration is not logged by SAGAsystem it is very simple to calculate the acceleration and adding this aspect to the model and program should not be very difficult.

Charging and infrastructure

Currently the charging function is constant and is simply found using the official charging time of the model vehicle and its battery capacity. In reality, as presented in the method chapter, this is not as simple. In fact the first 70% of the charging take place very fast, until a certain voltage is reached, and the final 30% take much longer time. The idea is to add the correct charging function of every vehicle to the model. Another aspect of charging that could be added is what has been noted above, that when going downhill batteries get charged. This would likely be a complicated add-on but indeed possible. Finally electric vehicles are charged when braking as the kinetic energy of the vehicle is transformed into mechanical energy through the shaft and to electric energy in the motor and used to charge the vehicles battery pack. As with other possible development aspects for the method, it is not yet realized how adding brake charging to the model would be carried out. In the current method the infrastructure for charging was not regarded as an issue and it was simply assumed that the infrastructure in place at a dock was sufficient to supply energy for the maximum allowed charging rate possible for the charger of the vehicles. This is a simplification as different types of charging infrastructure offer different charging characteristics. It would be very interesting to see how different types and models of infrastructure would affect the research results.

5.3.3.2 OTHER POSSIBLE IMPROVEMENTS AND MODIFICATIONS

Meteorology

It is a widely known fact that temperature affects batteries. In the current methodology this is not taken into account. It would be possible to add the dimension of weather to the model by using research data on the effect of temperature on batteries and the average daily temperature of each day. This would likely mainly affect the maximum battery capacity of the vehicles in the model. Based on research data and temperature the program could shift the Emax constant of vehicles in the beginning of each day in the model. For example if -5 °C would be known to limit the maximum capacity of the vehicle battery to 80% of highest possible capacity. So the program would, at the beginning of a day which had an average -5°C temperature set the maximum battery capacity to 80% of the maximum value, and the vehicle could not be charged but up to this value. Adding this aspect to the model and program would significantly increase its reliability and allow for more realistic results.

Model vehicle sets

The model vehicles chosen for the model are absolutely instrumental for the research. Different kind of electric vehicles offer different characteristics, and choosing one vehicle to represent a certain class could significantly affect the final results of the research. The idea with the model vehicle sets is to include a feature for the user of the program to be able to swiftly change between sets of model vehicles. There could be many different kinds of sets. For example a few of them might be made only of vehicles from certain manufacturers, or if someone would be interested in finding out what brand of class one vehicle he should buy for his firm, there could be a set consisting of many different class one vehicles. It is important that it is easy to change and one would simply choose a set from description, labelled for example simply as set 2, which would then be used for the model and to create results.

Infrastructure location analyzer

One aspect of this method and program which has not been touched upon in this thesis is the possibility of using it as a tool for infrastructure planning. This method could be a powerful tool for firms, cities, zones or other parties who might be working at setting up or organizing an infrastructure system. In the current version of the methodology, model and program, vehicles can only be charged at docks. The idea would be to add a feature to the program which would help those interested to find traffic hotspots in cities or regions to help them find the optimal locations to locate EV infrastructure. This would possibly be done in a completely automatic manner with a program which would be designed, and likely based on the proposed version 3, to identify a number of locations (not including vehicle docks) within a previously decided area that would give the highest potential amount of potential EVs from the total vehicle sample used. If not done automatically it would be possible simply to create a program which would list the locations at which the vehicles from the sample spend most time, excluding the docks, and manually add them to the program as charging locations for all the vehicles and see how adding theoretical infrastructure to different locations would affect the results from the version 3 program features. A MSc student at Reykjavík University has already proposed the design of this tool as a possible MSc thesis. The idea for the thesis is to couple a tool such as this one above (and base it on the method and program created in this thesis) with information of the electrical grid in Reykjavík and use those two to propose a infrastructure system in Reykjavík.

6 CONCLUSIONS

Overall, the main objectives of the thesis were achieved. A method was successfully created that allows the user to assess the EV potential of a conventional vehicle. The method may however be further improved and its minor shortcoming became apparent when the results of the research were analyzed. The method created used real data collected by approximately 380 business vehicles from 16 businesses to assess the potential of each of the vehicles in being substituted by an EV. All vehicles were put into 3 separate groups based on their weight and a model vehicle representing each of these groups was identified. A model was designed and programmed to simulate an EV and the data from the vehicles was run through the model to yield results on a few different aspects. Two versions were created, referred to as version 1 and version 2 in the thesis. Version 1 was rather error prone and none of its features were used for the assessing the results in order to answer the research questions. Version 2 on the other hand ran smoothly and was less prone to errors and problems. It gives results for how many days a vehicle would have failed from its total active days throughout the research period. Version 2 also has a feature where it calculates the average daily driving of each vehicle for all its active days. These two features were eventually used to answer the research questions. Three different scales were introduced to identify vehicles consider to have EV potential; 0% failure day, 0-5% failure days and 0-10% failure days. When these scales are compared to studies done on the effects of optimization of driving behavior and fleet management these scales appear to be strict.

One of the research questions was "*What is the potential for business vehicles in Reykjavík when it comes to the potential to be substituted by electric vehicles?"* 20.5% of business vehicles in Reykjavík are identified as having the possibility of being substituted for an EV based on the 0% failure day EV potential scale, after taking into account the results from the daily driving analysis of the vehicles. This scale is very strict and perhaps not entirely fair as concluding that a vehicle could not be an EV if it fails on 5% of days, when driven completely without taking into account the characteristics of EV is harsh. Still, the portion of business vehicles that could be substitutes to EVs without experiencing any problems at all throughout a 100 day period is 20.5%. This portion of vehicles rises to 49.7% of the whole usable sample (174 vehicles) based on the 0-5% failure day scale. When the broadest scale for identifying EV potential is used vehicles which can be substituted for EVs in Reykjavík rises to 61.2%. Due to the strictness of the first identifying method it is likely that in reality at least half of business vehicles in Reykjavík could be substituted for EVs.

Another of the research questions was "*is there difference in the viability of a potential EV switch between different classes of vehicles?"* There appears to be quite a difference in the possibility of the three classes when it comes to being substituted for EVs. Interestingly there is a significant difference in the average driving of the three classes. The model vehicles chosen had very significant effects as the results for the EV potential of the class very closely correlated with the maximum battery capacity of the vehicles. Using the 0% failure day scale 7.8% of vehicles from class 1 did not fail over the entire period which is by far the lowest percentage. According to this research and based on the model vehicles chosen to represent the three classes, class 3 vehicles are best suited to be EVs in Reykjavík, followed closely by class 2 vehicles. Class 1 vehicles on the other hand seem to have the least EV potential. It would be interesting to see how changing the model vehicles would have affected the results. A feature to easily compare results based on different model vehicles is among proposed added applications for the method.

The final identified research question was "*What is the future outlook for firms in Reykjavík in switching towards EVs, and what portion of firms could substitute considerable parts of its fleets to EVs?"* Companies in Reykjavík have the possibility of replacing a large fraction of their vehicle fleets to EVs. Based on the efforts that drivers and fleet managers are willing to put into optimizing fleet organization and driving patterns and behaviors, different result may be gained. Even without any modification of driving behavior and patterns (0% failure day scale), half of businesses in Reykjavík could replace more than 20% of vehicles with EVs. If companies are willing, they could without too much struggle replace (based on 0-10% scale) up to 50% of vehicles in approximately 70% of cases. It might be interesting in the future to compare different sectors and see which business sectors are best and worst suited for EVs. This was not possible in this research due to the low number of companies willing to give away driving data and one company from most sectors hardly significant enough for such a comparison.

Designing the methodology and creating the program to run the model proved a challenging job for the author but very educating. Version 2 of the model ended up being considerably better than its predecessor and it is fair to say that its errorless and smooth results were ahead of the author's brightest hopes. Solutions to the problems with version 1 are provided and a proposed version 3 of the program includes the improved features of both the versions. It would have been very interesting to see the results from the capacity required feature of version 1 and seeing the results from the failure frequency analysis from would have been useful for comparison to the results from the daily failure analysis. Despite the minor deficiencies of the methodology created the author believes the features and results of version 2 to be sufficient to answer the research questions in a reliable manner.

This method can be used as a tool for companies and whoever might be interested in learning the EV potential of a vehicle fleet. In fact the author has plans to found a small scale consultancy business based on offering firms to get the EV potential of their fleet assessed. A tool such as this could prove instrumental for parties which work on the various aspects on transport technology transition, such as governments, EV manufacturers and dealerships, and infrastructure designers. In Iceland there is for example a business which plans to lead the transition to electric mobility in Iceland. Among other aspects, they import EVs. They have experienced problems when it comes to encouraging companies to commit to buy EV. According to them this is mainly down to people not being familiar with the characteristics of EVs and on top of that having poor understanding of their own transport needs. Businesses are therefore reluctant to buy the electric vehicles. For firms such as the Icelandic one described above being able to offer companies to have the EV potential of their fleet scientifically evaluated could prove instrumental in selling their product. The evaluation of company fleets would include analyzing which vehicles could be substituted, how much that would save the company and how they could reorganize their fleet in order to increase their overall EV possibilities.

But before the method and program created for this thesis can be applied for purposes such as those above it needs to be improved. A version 3 of the program is proposed in the thesis, which is based on what has been learned from this thesis. It is based largely on version 2 but includes improved features from version 1. Version 3 will not offer any giant leaps and simply is the program which would have been designed for this thesis had the author known what he learned from the thesis about the current method and program versions. Also proposed are other future add-ons, which are not expected to be featured in version 3. These include improving the model physics, taking meteorology into account and allowing for easily changing the model vehicles used for the research. One final use of the tool created is to utilize it for infrastructure planning. The method and program created for this thesis is expected to provide the foundation for a multinational research on EVs in three Scandinavian cities. Hopefully a grant will be provided which would allow the author to work full time on improving the many different aspects of the methodology created, with the support of multiple other parties.

This thesis has achieved its objectives by producing a method for assessing the EV potential of vehicles. Although being far from perfect it does provide a solid foundation for further development and is, even in the current slightly flawed state, able to yield results which could answer the research questions asked for an analysis of the EV potential of businesses in Reykjavík, Iceland. The author believes that the improved versions of the method and program created can prove very helpful in the transition to electric mobility. The results of the research yielded overall positive results which will hopefully play some part in pushing Iceland towards an electrically driven transport sector.

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REYST

Reykjavík Energy Graduate School of Sustainable Systems (REYST) combines the expertise of its partners: Reykjavík Energy, Reykjavík University and the University of Iceland.

Objectives of REYST:

- Promote education and research in sustainable energy
- Attract talented graduates into the important field of sustainable energy
- Provide industry and academia with qualified experts in engineering, business and earth sciences

REYST is an international graduate programme open for students holding BSc degrees in engineering, earth sciences or business.

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HÁSKÓLI ÍSLANDS

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