Charging of plug-in electric vehicle fleets in urban environment

Juuos Lindgren
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Abstract

This thesis studies the performance and charging of electric vehicle fleets in an urban environment, using three research questions that focused on: 1) allocation of limited total charging power; 2) effect of different charging infrastructure parameters on the total distance driven in electric-only mode, and; 3) effect of cold and warm ambient temperature on the performance and charging of the fleet, respectively.

An agent-based computer simulation was employed, with parameters tuned such that the resulting vehicle travel patterns would resemble the observed behaviour of conventional cars in the city of Helsinki, Finland. Two different simulators were used: in the first one, the vehicles travel in a node network according to a stochastic trip-generation algorithm. In the second one, the vehicles' status changes according to the results of a Finnish travel survey. Two different vehicle battery models were also used: a simple linear "kilowatt-hour counter" and a more advanced battery model with temperature dependency.

It was found that smart charging power allocation can improve the total distance driven in electric-only mode compared to a "dumb" equal allocation strategy, but the gain is heavily dependent on the battery capacity. If no predictions about the future are made, the gain is small (1%), but with full knowledge on future travel patterns, it increases to over 5%. In general, more power should be allocated to vehicles that depart earlier and travel longer distances before their next charging session.

Among plug-in hybrid electric vehicles, those with small battery capacity gain the most benefit from improved charging infrastructure, in terms of total distance driven in electric-only mode. Battery capacity holds the highest potential out of all parameters tested. The second and third most important infrastructure parameters are the number of parking slots around a single charging station and the number of these charging stations. A charging station should be placed in a central location with several parking slots around it, to allow sequential charging of multiple vehicles by switching the charging cable from one vehicle to the next.

Low battery temperature has a negative impact on fully electric vehicle charging. This manifests as slightly reduced median state of charge (3–6%-units) for the vehicle fleet and significantly lower median charging rate (15% in terms of self-weighted mean charging power). Battery heating can be used to achieve higher state of charge, as well as increased charging rate for certain vehicles. Deviation from the close-to-optimal $+20^\circ C$ temperature for the cabin and the battery results in reduced efficiency (km/kWh) and eventually reduced number of planned trips that can be realized. Cabin preconditioning and active battery thermal management improve the median efficiency of the fleet around 8–9% at $-10^\circ C$ and $+40^\circ C$.

Keywords electric vehicle, charging infrastructure, charging power, battery, temperature
Tässä väittökirjassa tutkitaan sähköautolauvien ominaisuuksia ja niiden käyttökokoelmia kolmea tutkimusryhmää: 1) rajoitettun kokonaislatauksen ja kokonaismatkakulman verkostojen ja sähköauton käyttötilanteiden ja -muotojen tutkimuksen avulla; 2) erilaisen lautasdistriktin ja sähköauton käyttötilanteiden ja -muotojen tutkimuksen avulla; 

Väitöskirjassa käytettiin kahdella erilaista sähköautotila: yksinkertaisilla ”kilowattituntilaskueilta”; ja edistyneempiä ”kilowattituntilaskueilta” ja 3) kylmän ja lämpimän ympäristön käytöllä käytettiin kahdella erilaista akkumallia: yksinkertaisilla ”kilowattituntilaskueilta”; ja edistyneempiä ”kilowattituntilaskueilta”. Tutkimusmenetelmänä käytettiin agenttipohjaisen tietokonesimulaatiota, joka säädettiin siten, että simulointia tuolle syntyneet ajatiedot muistuuttavat tällisten polttoomuotoauton käyttäytymistä Helsingissä. Väitöskirjassa käytettiin kahta erilaista simulatooria: ensimmäisessä autot liikkuvat nopeiksi liikkostovien stokastisen matkagenereatorin ohjaamana ja toisessa autot muuttuvat tilaansa suomalaisen henköliikennetutkimuksen tuloksien perusteena. Lisäksi käytettiin kahta erilaista akkumallia: yksinkertaista ”kiloowattituntilaskuria” ja edistyneempää lämpötilaripuanvaista akkumallia. 

Havaittiin, että lautasdistrojen käyttöä ja sähköauton ajettua kokonaismatkaa verrattuna yksinkertaiseen lautasdistrojen tasajakoon, mutta tämä nousu on vahvasti riippuvainen lauvien akkukapasiteeteista. Jos mitään ennestään tai käytetä, kasvu on pieni (1%), mutta täydellä tietämyksellä tulevasta ajosta kasvu on yli 5%. Yleisesti ottaen, lautasdistrojen jakamisessa tuli suoria autoja, jotka ovat poistumassa aikaisemmin latauspaikalta ja jotka kulkevat pidemmän matkan ennen seuraavaa lautasdistriktia. 

Plug-in-hybridisähköautot ne, joilla on pieni akkukapasiteetti, hyötyvät niiden latausverkoston kehitettämisestä, kun mittarina käytetään täysin sähköllä ajettua kokonaismatkaa. Akkukapasiteeteilla on suurin vaikutus kaikista kokeiluista parametreista. Toiseksi ja kolmanneksi tärkeimmät parametrit ovat yhden lataustolpan ympärillä olevien pysäköintiruutujen määrä ja lataustolppien määrä. Lataustolppa on keskelle paikalle siten, että sitä voidaan hyödyntää useasta parkkuruudusta vahvamalla latauskaapelilla autosta toiseen. 

Matala akuston lämpötilaa hidastaa yksinkertaisen latauskyvyn. Tämä näkyy hieman alentuneena medianlaitaustasona (3–6%-yksikkö) ja huomattavasti alentuneena medianlaitaunsoputena (15% itsepainotetussa keskitäustehossa). Akuston lämmitystä voidaan käyttää kohottamaan latautusasoa ja nostamaan latausneuvoetta tiettojen autojen kohdalla. Kun auton sisällä ja akuston lämpötila poikkeaa +20°C:sta, autojen tehokkuus (km/kWh) laskee ja poikkeamaan kasvavalla jaotetussa matkoja joudutaan lopulta perumaan. Sisätilan esimerkiksi lämmitystä ja aktivista akuston lämmönsäätelyä käyttämällä voidaan medianitehokkuutta nostaa noin 8–9% lämpötiloissa –10°C ja +40°C. 

Avainsanat: sähköauto, lainasdistriktti, latausdistro, akku, lämpötila

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I thank my instructor and supervisor Professor Peter Lund for inspiration, guidance and motivation through my studies at Aalto University. Without his positive attitude and patient encouragement, this thesis would be several years late, or in the worst case, delayed indefinitely.

In my first years of employment at Aalto University, I was instructed by Rami Niemi. I thank him for all the help and his insightful commentary on philosophy and contemporary politics.

I thank my colleagues who helped and inspired me during the research, Jani Mikkola, Jyri Salpakari and Imran Asghar. In addition, I express my gratitude to our whole research group and everyone else I worked with.

Finally, I thank my family and my friends for being awesome, understanding and supportive during the most hectic years of my life.

Leppävaara, Espoo, October 15, 2017

Juuso Joel Lindgren
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<th>Description</th>
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<tbody>
<tr>
<td>ANN</td>
<td>Artificial neural network</td>
</tr>
<tr>
<td>BEV</td>
<td>Battery electric vehicle</td>
</tr>
<tr>
<td>BMS</td>
<td>Battery management system</td>
</tr>
<tr>
<td>BTM(S)</td>
<td>Battery thermal management (system)</td>
</tr>
<tr>
<td>CCCV</td>
<td>Constant current constant voltage</td>
</tr>
<tr>
<td>CD</td>
<td>Charge-depleting</td>
</tr>
<tr>
<td>CH, CL</td>
<td>Charging at high, low battery temperature</td>
</tr>
<tr>
<td>CHP</td>
<td>Combined heat and power</td>
</tr>
<tr>
<td>CS</td>
<td>Charge-sustaining</td>
</tr>
<tr>
<td>CO₂</td>
<td>Carbon dioxide</td>
</tr>
<tr>
<td>DH, DL</td>
<td>Discharging at high, low battery temperature</td>
</tr>
<tr>
<td>EC</td>
<td>Equivalent circuit</td>
</tr>
<tr>
<td>EM</td>
<td>Electric motor</td>
</tr>
<tr>
<td>EV</td>
<td>Electric vehicle</td>
</tr>
<tr>
<td>FCV</td>
<td>Fuel cell vehicle</td>
</tr>
<tr>
<td>GPS</td>
<td>Global positioning system</td>
</tr>
<tr>
<td>HEV</td>
<td>Hybrid electric vehicle</td>
</tr>
<tr>
<td>HVAC</td>
<td>Heating, ventilation and air conditioning</td>
</tr>
<tr>
<td>ICE(V)</td>
<td>Internal combustion engine (vehicle)</td>
</tr>
<tr>
<td>LSQ</td>
<td>Least squares fitting</td>
</tr>
<tr>
<td>MOMC</td>
<td>Multiple outputs multiple cables</td>
</tr>
<tr>
<td>MSE</td>
<td>Mean squared error</td>
</tr>
<tr>
<td>NFD</td>
<td>Next free distance</td>
</tr>
<tr>
<td>Acronym</td>
<td>Definition</td>
</tr>
<tr>
<td>---------</td>
<td>-------------------------------------</td>
</tr>
<tr>
<td>OCV</td>
<td>Open circuit voltage</td>
</tr>
<tr>
<td>PHEV</td>
<td>Plug-in hybrid electric vehicle</td>
</tr>
<tr>
<td>REMI</td>
<td>Relative electric mileage increase</td>
</tr>
<tr>
<td>RQ</td>
<td>Research question</td>
</tr>
<tr>
<td>SOC</td>
<td>State of charge</td>
</tr>
<tr>
<td>SOMC</td>
<td>Single output multiple cables</td>
</tr>
<tr>
<td>SWMCP</td>
<td>Self-weighted mean charging power</td>
</tr>
<tr>
<td>V2G</td>
<td>Vehicle-to-grid</td>
</tr>
</tbody>
</table>

**Symbols**

- \( A \): Attraction function
- \( E \): Energy
- \( K \): Heat transfer coefficient
- \( L \): Scaling function
- \( M \): Heat capacity
- \( N \): Set of all nodes / Number
- \( P \): Power / Charging power / Maximum power
- \( Q \): Battery capacity / Cell capacity
- \( R \): Resistance
- \( S \): Saturation function
- \( T \): Temperature
- \( V \): Voltage / Set of all vehicles
- \( W \): Set of workplace nodes
- \( X \): Set of model parameters / Set of vehicle parameters
- \( Z \): Power allocation function
- \( d \): Distance
- \( f \): Fitness of destination candidate
- \( i, j \): Lumped capacitance thermal model element
- \( k \): Mean electricity consumption
- \( m, n \): Node
- \( p \): Heating rate of battery
$q$ Desired heat flow / Heating

$q'$ Actual heat flow

$r$ Random number

$s$ Saturation factor

$t$ Time / Time step

$v$ Vehicle

$w$ Weight parameter

$x$ Model parameter

$\Gamma$ Scaling function

$\delta$ Error scaling parameter

$\eta$ Efficiency

COP Coefficient of performance

NFD Next free distance

Subscripts

$o, A, B$ Charging power allocation strategy $o$, $A$, $B$

BTMS Battery thermal management system

C Charging half-model / Power allocation strategy C

CH Charging at high battery temperature quarter-model

CL Charging at low battery temperature quarter-model

Coul Coulombic

D Discharging half-model / Departure

DH Discharging at high battery temperature quarter-model

DL Discharging at low battery temperature quarter-model

HVAC Heating, ventilation and air conditioning

M Model

OC Open circuit

SWM Self-weighted mean

a Ambient
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>b</td>
<td>Battery</td>
</tr>
<tr>
<td>c</td>
<td>Cabin</td>
</tr>
<tr>
<td>cable</td>
<td>Charging cable</td>
</tr>
<tr>
<td>cell</td>
<td>Battery cell</td>
</tr>
<tr>
<td>char</td>
<td>Charging</td>
</tr>
<tr>
<td>cool</td>
<td>Cooling</td>
</tr>
<tr>
<td>disc</td>
<td>Discharging</td>
</tr>
<tr>
<td>draw</td>
<td>Attempted draw</td>
</tr>
<tr>
<td>eff</td>
<td>Effective</td>
</tr>
<tr>
<td>end</td>
<td>Charging or discharging ends</td>
</tr>
<tr>
<td>exact</td>
<td>Exactly known</td>
</tr>
<tr>
<td>heat</td>
<td>Heating</td>
</tr>
<tr>
<td>high</td>
<td>Higher limit</td>
</tr>
<tr>
<td>int</td>
<td>Internal</td>
</tr>
<tr>
<td>inv+EM</td>
<td>Inverter and electric motor in series</td>
</tr>
<tr>
<td>keyon</td>
<td>Vehicle being driven</td>
</tr>
<tr>
<td>low</td>
<td>Lower limit</td>
</tr>
<tr>
<td>max</td>
<td>Maximum</td>
</tr>
<tr>
<td>mean</td>
<td>Mean or average</td>
</tr>
<tr>
<td>min</td>
<td>Minimum</td>
</tr>
<tr>
<td>normal</td>
<td>Obtained from normal distribution</td>
</tr>
<tr>
<td>pack</td>
<td>Electric vehicle battery pack</td>
</tr>
<tr>
<td>park</td>
<td>Parking</td>
</tr>
<tr>
<td>parked</td>
<td>Time spent at current location since arrival</td>
</tr>
<tr>
<td>pole</td>
<td>Charging pole</td>
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<tr>
<td>propulsion</td>
<td>Vehicle propulsion</td>
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<tr>
<td>s</td>
<td>Transition region</td>
</tr>
<tr>
<td>Term</td>
<td>Definition</td>
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<td>------------</td>
</tr>
<tr>
<td>sat</td>
<td>Saturation</td>
</tr>
<tr>
<td>series</td>
<td>Cells in series configuration</td>
</tr>
<tr>
<td>simult</td>
<td>Electric vehicles charging simultaneously at a specific charging pole</td>
</tr>
<tr>
<td>slot</td>
<td>Parking slot in a charging pole's area of service</td>
</tr>
<tr>
<td>socket</td>
<td>Electric vehicle charging station</td>
</tr>
<tr>
<td>standby</td>
<td>Vehicle in standby state</td>
</tr>
<tr>
<td>start</td>
<td>Charging or discharging begins</td>
</tr>
<tr>
<td>total</td>
<td>Total</td>
</tr>
<tr>
<td>vehicle</td>
<td>Electric vehicle</td>
</tr>
<tr>
<td>$i, j$</td>
<td>Lumped capacitance thermal model element</td>
</tr>
<tr>
<td>$v$</td>
<td>Vehicle</td>
</tr>
</tbody>
</table>
List of publications

This doctoral dissertation consists of a summary and of the following publications which are referred to in the text by their Roman numerals.


III. Lund, Peter; Lindgren, Juuso; Mikkola, Jani; Salpakari, Jyri. Review of energy system flexibility measures to enable high levels of variable renewable electricity. Renewable & Sustainable Energy Reviews 45, 785–807 (2015). DOI: 10.1016/j.rser.2015.01.057


Author’s contribution

**Publication I:** *Effectiveness of smart charging of electric vehicles under power limitations*

The author was responsible for building the model, conducting the experiments, analysing the data and co-writing the article.

**Publication II:** *Identifying bottlenecks in charging infrastructure of plug-in hybrid electric vehicles through agent-based traffic simulation*

The author was responsible for upgrading the model in Publication 1, conducting the experiments, analysing the data and co-writing the article.

**Publication III:** *Review of energy system flexibility measures to enable high levels of variable renewable electricity*

The author was responsible for writing sections 4, 5 and 7.3 of the article.

**Publication IV:** *A hybrid lithium-ion battery model for system-level analyses*

The author was responsible for designing, training and validating the model, as well as co-writing the article.

**Publication V:** *Effect of extreme temperatures on battery charging and performance of electric vehicles*

The author was responsible for building the model, conducting the experiments, analysing the data and co-writing the article.
1. Introduction

Transportation is an essential part of life. It takes us to work and back, shopping, to buy groceries, and to visit friends and family. Even if in some modern cities, it is now possible to work remotely from home, to order groceries to your front door, and to socialize with people online, most people still need to move themselves from one place to the next. Moreover, in emerging economies, the need for energy-intensive transportation is rapidly growing [1].

One of the most popular and robust solutions for personal transportation is the car. Cars offer freedom and flexibility that public transportation cannot yet match. The downside is that cities are often plagued by traffic congestion, air pollution, traffic noise and parking space demand for vehicles that are stationary 90–95% of the time [2,3]. These cost society both time and resources to manage or maintain.

The all-electric car, an innovation dating back to the late 19th century, helps solve at least two of these challenges, namely, air pollution and traffic noise, while consuming less energy per unit distance. The all-electric car relies on a relatively silent electric motor connected to a rechargeable battery. Because there is no exhaust, there are also no tailpipe emissions, although there may well be significant CO₂ emissions involved in producing the required electricity [4].

In terms of efficiency, the all-electric car has a 4-to-1 advantage over conventional cars, which are limited by Carnot inefficiency [5]. Furthermore, electric cars capture some of their kinetic energy during braking, and their motor and power electronics are lighter than the counterpart in a traditional car [6]. Finally, using electricity in place of fuel allows decoupling of personal transportation from carbon emissions [7–10].

This innovation, which is old and advantageous, yet still underused, also brings its own challenges. From the driver’s point of view, electric cars are costly [11], have small operational range [12], have longer “refuelling” times [13,14], and, at low temperature, their performance is reduced drastically. On the societal level, large numbers of electric cars charging simultaneously may necessitate investments in larger power transfer capacity, or developing means to control their charging.

Despite these shortcomings, electric cars are rapidly becoming a more and more relevant part of the transportation system. This relatively recent development could be an early signal of a paradigm shift in transportation, and is driven by many factors, including climate change mitigation, energy security, growing air pollution problems and lower cost of battery technology. Thus, we should be
prepared to find efficient ways to ensure their smooth integration into our transportation and power systems.

Climate change mitigation efforts also drive countries to adopt new and sustainable methods to produce energy, such as solar photovoltaic power, wind power and wave power. Contrary to conventional power production methods, these energy sources are variable, and require supporting flexibility measures to integrate them into a general energy system in which supply and demand must always match. Electric cars are one potential source of such flexibility, as they can be charged at variable power rates and also function as a moving, distributed electricity storage.

This thesis studies some of the unique challenges of integrating large numbers of electric cars (electric car fleets) into urban environments, specifically: i) electric power allocation when total charging power at a location is limited; ii) bottlenecks to the utility of an electric car fleet when planning charging infrastructure, and finally; iii) performance and utility of electric cars at low temperatures.

For simplicity’s sake, in the following, the term vehicle is used to refer to cars, meaning that e.g. electric trains and trams are not considered electric vehicles. Further, fuel cell vehicles are beyond the scope of this thesis.

1.1 Objectives and scope

In this thesis, three different aspects of electric vehicle (EV) fleet charging are investigated, namely, limited power allocation, charging infrastructure and ambient temperature, and their effects on the society-level benefits gained from traffic electrification. The following three research questions are central for the thesis:
1. How should limited charging power be allocated between several simultaneously charging plug-in hybrid electric vehicles (PHEV) to maximize the distance driven in charge-depleting mode (CD), the mode in which PHEVs consume mainly electricity in place of gasoline?
2. How do different charging infrastructure parameters affect the distance driven in CD mode by a fleet of PHEVs?
3. How is the utility, performance and charging characteristics of a battery electric vehicle (BEV) fleet affected by extreme ambient temperatures?

These three research questions are answered in Publication I, II and V, respectively. In the following, we refer to these publications as the main publications. Publication III provides the “big picture” in which EV charging is considered and Publication IV provides the groundwork for Publication V. The relations of the dissertation articles are shown in Figure 1.
The scope of the thesis is on PHEVs and BEVs only, i.e. plugless hybrid electric vehicles (HEV) or fuel cell vehicles are not included in this study. This is because plugless HEVs cannot be charged from an external power source, making them irrelevant for the three research questions. Fuel cell vehicles are not charged directly from the power grid, but instead refuelled with hydrogen.

The power grid, while playing a major role in the power limitation of Publication I, is not explicitly modelled in this thesis. For simplicity, we keep the focus of our study on the EV fleet. Basically, power grid is considered here as an abstract limitless energy storage, which can be tapped into at specific locations.

1.2 Thesis outline

The remainder of thesis is structured as follows. Chapter 2 provides the general background and motivation of EV fleet studies. Chapter 3 reviews the existing studies on the subject. Chapter 4 presents the research method, including the different models, such as fleet movement model and battery model, used in the publications. Chapter 5 collects the results obtained by applying the research method and is divided into three subsections according to the three research questions. Chapter 6 discusses the implications of the results and their reliability. Finally, Chapter 7 summarizes and concludes the thesis.
2. Background and motivation

2.1 Motivation

The transport sector is responsible for around a quarter of worldwide total CO₂ emissions, and three-quarters of these emissions are attributable to cars and trucks [15]. The sector is growing rapidly due to increasing mobility demand of emerging economies. By 2050, IEA expects road transport to double, energy use to increase by 70%, and greenhouse gas emissions to increase by 50%, if no new policies are introduced [16]. Note that greenhouse gas emissions include not only CO₂, but also e.g. water vapor and methane.

Another major cause of concern, especially in urban areas, is airborne particle pollution, which affects the health of more than 90% of world’s population according to World Health Organization [17], and is suspected to kill more people worldwide than AIDS, malaria, or tuberculosis [18]. In China, 4 000 people die every day due to complications from air pollution [18]. Figure 2 shows a photograph taken in Beijing in 2014.

Figure 2. Sanlitun, Beijing, China on February 22, 2014. A photo taken by Flickr user Kentaro IEMOTO [19]. Licensed under the terms of the CC BY-SA-2.0 [20].
These growing problems drive us to develop alternatives to conventional transportation, such as electric mobility [21–23], modern on-demand transportation and ridesharing solutions (e.g. Lyft) and telecommuting [24]. Several countries, including U. S., Canada, Australia, New Zealand, China and multiple EU members have established EV adoption targets, along with policies and plans to reach them [25,26]. In this thesis, the focus is on private EVs.

EVs exhibit several favourable qualities over traditional, internal combustion engine-powered vehicles. They have superior efficiency in terms of distance travelled per unit energy consumed, potential for zero CO₂ emissions, no tailpipe emissions, low noise and low maintenance costs. For some countries, electric vehicles can also reduce dependency on imported oil [27]. Figure 3 lists some of the drivers behind EV technology. Among the EV benefits, we focus on the potential of EVs on reducing CO₂-intensity of travel.

EV CO₂ emissions (gCO₂/km) can be defined as the product of vehicle energy consumption (MJ/km) and fuel carbon intensity (gCO₂/MJ) [4], and EVs aim to reduce CO₂ emissions by lowering both. Electrification could, in theory, reduce the energy consumption of transport to one fifth of its current level [28]. However, the quality of electricity plays a major role in reducing CO₂ emissions: it is entirely possible that grid electricity is so carbon-intensive that overall CO₂ emissions increase, regardless of the improved efficiency [4]. It is thus important to not only facilitate EV adoption, but also to shift electricity production towards lower carbon intensity.

In recent years, electric vehicles have started becoming more and more mainstream around the world; in 2015, the worldwide EV stock reached 1.3 million, almost double that in 2014. IEA expects this figure to exceed 150 million by 2040 [29].

The rapid penetration of electric vehicles into the transportation sector also introduces new challenges for the power grid. Foremost, the behaviour of modern working people is very synchronized, which will lead to high peak electricity demand when many EV drivers begin charging their vehicles at the same time, i.e. when arriving home. If the charging is not controlled or the grid is not reinforced, large-scale EV charging can lead to grid overloading [23,30–35].
Figure 3. Drivers of electric vehicle technology (not an exhaustive list).
2.2 Background

2.2.1 Electric vehicle history

The electric vehicle was born in 1837 [36], shortly after the invention of primary battery and electric motor. In the early stages of consumer car market, EV had a strong advantage over internal combustion engine vehicles (ICEV). This was because, unlike their gas counterparts, EVs did not produce noise, exhaust, or require difficult and dangerous hand-cranking. Their performance was also very high; the first car to exceed the prestigious ‘mile a minute’ speed (100 km/h) was electric. In fact, one hundred years ago, there were more electric cars than gasoline cars [37]. However, after breakthroughs in oil and mass production and, ironically, after the rechargeable battery was employed in an ICE self-starter, the situation changed in favour of the ICEV. By 1920, the ICEV had won the race against EV in the consumer car market [37]. EVs could not compete further due to high cost of batteries [6]. Even today, the high cost of batteries is considered one of the main obstacles to widespread adoption of EVs [11,38,39]

The second wave of EV adoption began in 1996, when electric cars were launched in California by several automakers. However, only 10 years later, they were almost completely gone.

In 1990, California Air Resources Board (CARB) passed the Zero Emissions Vehicle mandate, which required all automakers in California to offer vehicles with no exhaust. ICEV-prefering car companies fought against the mandate, and CARB made a compromise, allowing the companies to build and market EVs according to demand, which incentivized car companies to make the case that there was no demand for EVs. This conflict of interest resulted in “innovative” marketing and public relations strategies which are chronicled in the 2006 documentary Who Killed the Electric Car?. Ultimately, the second wave of the EV was also a failure, and ICEVs prevailed for another 20 years.

The third wave, which we are currently experiencing, is fuelled by improved technology, cheaper batteries, and growing concerns of climate change and energy security. As mentioned earlier, a major remaining obstacle to large-scale EV adoption is battery technology. Batteries are costly, have low energy density compared to gasoline, and require special measures to prevent explosion if the battery is damaged in a traffic accident [40]. Currently in Finland, the consumer price of Nissan Leaf, one of the best-selling electric cars of all time, is around 34 000 – 42 000 € (new), or 18 000 – 22 000 € (used), depending on features and model year [41,42].

2.2.2 Electric vehicle types

Vehicles are typically categorized based on their power train, and this is also the case for EVs. Depending on occasion, electric vehicle may describe a vehicle that is either fully or partially powered by an electric motor (EM). Battery electric vehicle (BEV), in contrast, is used to refer specifically to those vehicles that are fully electric, i.e. ones that do not have an internal combustion engine. In this
thesis, electric vehicle refers to any vehicle that is at least partially powered by an electric motor. Hybrid vehicles (HEV) refer to vehicles that have both an electric motor and an internal combustion engine (ICE). However, a hybrid vehicle may not necessarily allow its traction battery to be charged externally via a plug. Instead, the battery is recharged during driving. In order to refer specifically to those hybrid vehicles that allow the battery to be charged from the power grid, the label plug-in hybrid electric vehicles (PHEV) is used [43]. Because PHEVs are less dependent on charging infrastructure than BEVs, they are considered a bridging technology towards the BEV [44].

Both hybrids, the HEVs and PHEVs, are divided into subcategories based on their drive train configuration. In a series hybrid, the ICE is always online while driving and provides the bulk of the power required, while the EM acts in a supporting role. In a parallel hybrid, both the ICE and EM can independently power the vehicle. There are also more exotic variations on these basic methods, but for the purposes of this thesis, this categorization is sufficient.

2.2.3 Range anxiety and range margin

Range anxiety refers to the fear of fully depleting a BEV’s battery in the middle of a trip, leaving the driver stranded [45,46]. This phenomenon is typically observed in BEV drivers, as BEVs currently still suffer from operational ranges lower than ICEVs. PHEVs are often regarded to have no range anxiety issues, as they can operate in charge-sustaining (CS) mode after their all-electric range is expended [43,47].

Range anxiety is an important part of EV fleet modelling, because high range anxiety leads to underutilization of BEV’s mileage [45]. It may also slow down the adoption rate of EVs, as car drivers are typically not accustomed to having to calculate distances, tolerating long recharge times and keeping a close track of their vehicle’s energy level. Therefore, the shift from ICEV to EV introduces some undesirable hassle to most drivers [27].

Range anxiety can be alleviated by expanding the charging infrastructure, as there are then more opportunities to charge and consequently, to maintain a higher average vehicle energy level. Range anxiety is also lowered by driving EVs, as the driver will, with experience, become familiar with the BEV’s characteristics and limitations.

Range margin refers to the minimum remaining range the vehicle must have when it finishes its trip or tour (a sequence of trips), for that trip or tour to not be cancelled. It reflects the range anxiety of the driver, i.e. a driver with a high range anxiety would also have a high range margin. Therefore, range margin can be used to model range anxiety. Some authors call the range margin the comfort level of the driver [48].

2.2.4 Battery

Battery is an electrochemical energy storage device, dating back to year 1800 [49], where electric energy is stored based on differences in electron affinities
of two electrodes. In basic terms, the battery is charged by expending energy to force electrons to the electrode with lower electron affinity. The battery is discharged by allowing electrons to flow naturally back to the electrode with the higher electron affinity. This latter flow of electrons is used to power mobile devices, including EVs. Lithium-ion is currently the most common EV chemistry due to its high specific energy, high energy efficiency, high power density, fast charging capabilities, wide operating temperature range, long cycle life and low self-discharge rate [50].

A battery pack refers to a group of several battery cells (basically small batteries) connected in series and in parallel to each other. For brevity, in the following, the term “battery” is used to refer to the battery pack in the EV.

**State of charge**
The energy level of the battery is measured with *state of charge* (SOC), which is a dimensionless value between 0 and 1, where 0 refers to a fully discharged battery and 1 refers to a fully charged one. SOC cannot be easily directly measured without destroying the battery, so it is usually estimated instead, by tracking the amount of charge coming in and out of the battery.

**C-rate**
Because battery packs come in a great variety of capacities for different applications, their discharging rates are typically given not as amperes but instead as dimensionless *C-rates*. Basically, C-rate is the current in amperes divided by the rated capacity of the battery in ampere-hours. For example, a battery with a rated capacity of 5 Ah discharged with a current of 5 A is discharged at a rate of 1C. A C-rate of 0.5C and 2C would then refer to currents 2.5 A and 10 A, respectively [51].

**Ageing**
As complex chemical devices, batteries also experience unwanted reactions that cause their performance to degrade, a phenomenon called *battery ageing*. Battery ageing mechanisms are still being studied, but they can be divided into calendar ageing and cycle ageing.

Calendar ageing refers to irreversible loss of battery capacity during storage, which is accelerated by elevated battery temperature and SOC. Cycle ageing refers to degradation that occurs due to the battery being actively used, and is affected by several factors, e.g. voltage and SOC variation during a cycle [52]. In the scope of the current thesis, the most important notion is that degradation can be reduced by limiting the effective capacity, or the SOC window, of the battery [43]. In practice, this means that the battery is never fully charged or fully discharged, but the operational range is limited to a certain SOC region, e.g. between SOC of 0.15 and 0.85, creating a SOC window of 0.70 [53].

**Operation in PHEV**
PHEVs can operate in CD in which propulsion power is mainly drawn from the battery and little to no fuel is consumed [54]. Basically, the PHEV battery operates in CD mode until a certain minimum SOC is reached. At this point the electric range is considered exhausted, and driving continues in CS mode. In CS
mode the main power source is the ICE, while the battery acts as an intermediary to improve efficiency and its SOC fluctuates within a narrow window [54], much like in an HEV [43].

**Effect of temperature on performance**

The operation of an EV battery is heavily dependent on its temperature [55,56]. Consequently, the performance of EV, in terms of e.g. efficiency (km/kWh) and charging power, are heavily dependent on temperature as well. Moreover, when the outside temperature deviates strongly from the comfortable room temperature (around +24°C), more power is consumed due to the increased use of air conditioning. In cold climates such as Finland, the outdoor temperature may vary from −30°C to +30°C. Therefore, a realistic EV fleet study in such environments should include temperature considerations [57].

Cold affects the performance of the battery and the vehicle in several direct and indirect ways:

- Cold air has higher density than warm air, thus air resistance is higher at cold temperature. This increases power consumption during driving.
- Vehicle windows need to be defrosted for safety of the driver and others on the road. This consumes additional power.
- Driver typically activates air conditioning to keep cabin temperature and air quality at a comfortable level. This consumes additional power [58,59].
- All chemical processes slow down at cold temperature, which increases the electric resistance between battery terminals. This increases thermal losses, slows down charging and reduces vehicle performance, as explained further below.
- Regenerative braking is hampered by increased battery electric resistance. This negatively impacts power recovery during driving and effectively increases mean power consumption per unit distance.

Battery charging is slowed down in cold (below 0°C) because low battery temperature increases battery resistance [60–62], which in turn increases battery voltage during charging. The maximum voltage of the battery is therefore reached earlier [63], and charging current must be limited to a lower absolute value to prevent damage to the battery [64]. Lower absolute current implies less stored charge per unit time, and thus, charging time increases.

In a similar fashion, the operational SOC range of the battery is reduced by cold because cold decreases battery voltage during discharging. Now the minimum voltage of the battery is reached earlier with the same discharging current. This situation can be handled in basically two ways. The first solution is to reduce the absolute current [6], which will inevitably affect e.g. the acceleration capability of the vehicle. This can cause dangerous situations if the driver is not informed. The second solution is to tell the driver that the battery’s minimum usable SOC has been reached and that the vehicle will shut down to ensure safety.

High ambient temperature (>+40°C) also causes increased air conditioning load [65], but increases the speed of chemical processes. Therefore, charging and discharging performance generally remain good [66]. Downsides of high
temperature include the unwanted chemical processes of faster degradation (ageing) and self-discharging of the battery [6,65].

Because temperature has such drastic effects on the battery, it is desirable to maintain battery temperature in a range where unwanted effects are minimized. The vehicle’s own battery thermal management system (BTMS) is responsible for cooling and heating the battery, as well as maintaining a reasonably uniform temperature profile within the battery. BTMS can be implemented in various different techniques, see Ref. [67].

**Battery management system (BMS)**
The battery management system (BMS) is an electronic system that manages a rechargeable battery pack. Its purpose is to protect the battery from damage, improve its efficiency and prolong its life.

One of the core functions of the BMS is to periodically balance internal SOC differences in the battery pack. Inside the pack, cells are practically never in the same exact state, due to manufacturing differences, unequal ageing and unequal temperature distribution. These differences result in some cells having higher or lower SOC than others. This SOC deviation process is divergent, and if left unchecked, will eventually lead to reduced battery capacity, or in the worst case, complete battery stack failure [68].

In addition to balancing SOC within the battery, the BMS is also used for regulating charging and discharging current so that voltage limits are not violated, maintaining the temperature within limits using the BTMS, and providing relevant status information about the battery pack [68].

### 2.2.5 EV power consumption and charging

EV power consumption is determined by a variety of factors, e.g. battery temperature, utilization of auxiliary loads such as heating, ventilation and air conditioning (HVAC), driving speed, road friction, wind and air resistance. These are discussed in more detail in Section 3.3.

As EVs consume energy from their batteries, they also require some means of charging them. When the vehicle is parked, the battery is charged using an external power source, but EVs also charge their battery on the road via regenerative braking. Moreover, series-PHEVs operating in CS mode charge their battery with the ICE during driving. As external charger-based charging is the most relevant form of charging in terms of scale, from now on, we use the term “charging” to refer to external charging.

Charging is generally carried out by simply connecting the EV to the power grid via an intermediary off-board EV charging station (or charging pole). Thus, investments in charging infrastructure are necessary to make EV driving a practical alternative to owning a conventional ICEV. The lack of EV charging infrastructure is considered one of the most critical barrier to successful deployment of EVs at large scale [69], together with high cost of EVs.

Charging at home is an attractive option for several reasons. For the individual, there is the practical incentive: the driver requires rest and there is rarely
Background and motivation

need to use the vehicle during the night, so the vehicle can easily charge in preparation for the next day [70]. There is also an economic incentive as electricity is generally cheaper during the night than during the day [71]. On the societal level, the night provides an around 14 hour window on average to schedule the charging of a large EV fleet, although the variance between different vehicles may be large [43].

Charging power is determined by several factors, including battery voltage, number of electric power supply phases used and maximum current supported by the associated electric cables. One must also consider the maximum charging power allowed by the charging pole, and possibly other larger-scale limitations, such as the total combined charging power of all charging poles in the same area. Table 1 shows some common charging power levels, and their nicknames. Note that the International Electrochemical Commission’s international EV charging standard defines 4 different modes of charging: 3 modes for AC charging and 1 mode for DC charging. These do not directly translate to the power levels shown in the table [72,73].

In Finland, the normal consumer phase voltage is 230 V. The charging power is around 3.6 kW for single-phase charging at 16 A, 7.4 kW for single-phase charging at 32 A, 11 kW for three-phase charging at 16 A, and 22 kW for three-phase charging at 32 A. Charging stations for all four above variations are currently sold to the Finnish consumer [74], with price range of around 1 000 – 1 500 € per station at the time of writing. The *de facto* standard charging plug type in EU is the “Type 2” or “Mennekes” socket outlet, which also has the official backing of the European Commission. All public EV charging stations in Finland are legally required to support Type 2 charging [73,75,76].

EV batteries are mainly charged using the *constant current constant voltage* (CCCV) method (see Figure 4), which consists of a *constant current* (CC) phase and *constant voltage* (CV) phase. In CC phase, the charging current is kept at constant value while the voltage builds up. After voltage reaches a *cutoff value*, the CV phase begins and the current is reduced to keep the voltage at the cutoff value. CV phase ends when the charging current drops below a given *saturation value*. 

Table 1. Charging power levels. Values are from Ref. [45] unless indicated otherwise.

<table>
<thead>
<tr>
<th>Nickname</th>
<th>Description</th>
<th>Voltage and current</th>
<th>Power</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>Home charging [27], residential charging [47], 1-phase slow charging</td>
<td>120 V, 15 A</td>
<td>1.5 kW</td>
<td>Uses on-board charger. Can be plugged directly to wall outlet at home [47]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>120 V, 16 A [70]</td>
<td>1.92 kW [70]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>120 V, 15 A [44]</td>
<td>2.4 kW [27]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>120 V, 12–16 A [47]</td>
<td>1.44 kW [44]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1.3–1.9 kW [47]</td>
<td></td>
</tr>
<tr>
<td>L2</td>
<td>3-phase slow and fast charging</td>
<td>240 V, 32 A</td>
<td>6.5 kW</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>208-240 V, 12-80 A [70]</td>
<td>7–21 kW [27]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>240 V, 30 A [44]</td>
<td>6.0 kW [43]</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>240 V, &lt;80 A [47]</td>
<td>2.5–19.2 kW [70]</td>
<td></td>
</tr>
<tr>
<td>L3</td>
<td>High-power DC charging / 3-phase fast charging</td>
<td>480 V, &gt;123 A &lt;400 A [70]</td>
<td>6 kW [77]</td>
<td>Uses off-board charger. Requires dedicated cooling equipment</td>
</tr>
<tr>
<td></td>
<td></td>
<td>480 V, &lt;80 A [47]</td>
<td>&lt;19.2 kW [47]</td>
<td></td>
</tr>
</tbody>
</table>

Figure 4. Constant current constant voltage (CCCV) charging.

Scheduling
Electricity in the power grid is generated by different power plants at different times and thus, the carbon intensity of electricity varies by time of day and season. If one wishes to reduce CO₂ emissions using EVs, it is then important to consider the timing of charging [78].

The evening spike in electric power consumption (non-EV electricity consumption) on a weekday is caused by people arriving home and turning on the lights, appliances (e.g. TV, computer) and cooking equipment. If EV owners were to attempt to charge their vehicles immediately after arriving home, EV load would coincide with this evening peak, making the peak worse and causing the increased demand to be likely met with peak power plants, e.g. by natural gas [4,79]. This is one of the many symptoms of dumb charging, a.k.a. uncontrolled charging, in which EVs begin charging immediately upon arrival, trying to fully charge their batteries [80].

Dumb charging may lead to several adverse effects on the distribution system, including phase imbalance, current harmonics, transformer failures, and fuses
blowouts [81], as the distribution system was not designed for the extra load caused by EVs [33]. There are two main ways of counteracting these effects; reinforcing the grid by upgrading the infrastructure and deploying new generation (including energy storage [79]) and scheduling the EV load optimally using smart charging [33,79]. Smart charging simply refers to a solution that aims to manage the charging of the EV fleet so that the negative impacts of uncontrolled charging can be avoided. The individual consumer may also benefit from smart charging, e.g. by taking advantage of cheaper electricity [82]. Researchers have come up with numerous ways to implement smart charging. These are discussed in Section 3.5.

It should be noted that smart charging need not be centrally governed, as informed consumers with real-time electricity pricing and a means to control their electricity consumption automatically in response to price signals could achieve the same objectives. This would likely have higher public acceptance and could also reduce communication requirements [40,80].

Sources of electricity
As noted previously, the quality of electricity plays a major role in EV CO₂ emissions [10]. Depending on the share of coal in power generation, EV carbon emissions can vary up to 300% (including vehicle manufacturing emissions). In India, for example, a BEV has emissions comparable to a 12 l/km petrol car, while in France, EVs can more than halve total vehicle emissions [7].

To estimate the true CO₂ impact of EVs, one should consider marginal grid CO₂ intensity, the increase in CO₂ intensity resulting from the additional production (marginal generators) brought online to meet the additional demand by EVs, instead of average intensity [9]. These marginal generators are the most expensive plants to operate and likely the least efficient [4]. In UK, for example, marginal intensity can be around 60% higher than the average intensity [9]. Because wind and nuclear are typically producing nearly 100% of their availability, this incremental demand is often met using fossil fuels [9].

With smart charging combined with weather and baseload forecasting, it is possible to schedule EV charging in such a way that e.g. wind power and solar power production peaks can be better exploited. This would improve the utilization of renewable energy and simultaneously reduce the carbon intensity of the electricity used to charge EVs.

Vehicle-to-grid (V2G) and ancillary services
EVs are parked for most of the time: on an average weekday at 17:00, only 15% of the vehicles are on the road, and over 75% of the vehicles are parked at all times [83]. Because EVs have such low utilization for their main function of transport, they are attractive for providing additional services, such as load levelling [84], minimizing power losses [85] and performing frequency regulation [86].

Vehicle-to-grid (V2G) is essentially the reverse operation to charging; it refers to the process of feeding electric power from the vehicle to the grid. We differ-
entiate V2G from smart charging by requiring that smart charging does not involve reverse power flow from vehicle to grid, while V2G must involve reverse power flow.

With V2G operation, the EV fleet would become a kind of distributed, moving electric energy storage device. This would enable a range of services, e.g. scheduled energy, reserve power, emergency load curtailment, energy balancing and renewable energy integration [86–89]. However, suitable equipment and vehicle aggregators would likely be required to achieve sufficient scale [90,91].

Because V2G involves additional charging and discharging cycles for the battery, the battery ages more rapidly, putting the owner at an economic disadvantage [92]. If increased battery ageing is accounted for, the profit from V2G services may be very small [92,93].

Smart charging, on the other hand, would not cause additional ageing, because the battery experiences no additional discharging: in smart charging, by our definition, one is only allowed to change the timing of charging and the magnitude of the charging power. This method would still allow performing e.g. demand response services, emergency load curtailment and renewable energy integration, without negatively impacting battery life [90].

**Alternatives to onboard battery charging**

An alternative to charging the onboard battery is to simply switch a depleted battery to an already charged one. This battery swapping approach requires a high amount of standardization in e.g. battery access, type and dimensions, and a high amount of storage space for multiple units of several different battery types. The business model is therefore extremely capital-intensive, and may not be economically feasible in the current EV culture. The most well-known battery swapping service provider, **Better Place**, which collected almost $1 billion in funding, filed for bankruptcy in 2013 [94].

Another alternative to conventional battery charging is pursued by the company **Tanktwo**, the developer of string battery. Here the battery is formed by a multitude of automatically self-organizing modular cells. The placement of the cells in the battery enclosure can be entirely random, which allows for rapid “refuelling” by simply ejecting depleted cells and pouring in charged ones. They claim that the process would take less than 3 minutes [95].
In this section, the research gaps targeted in this thesis will be matched with relevant existing scientific literature. Due to the extensive scale of EV fleet research, it is not practical to cover all the connected literature. Instead, we focus on the main subsets of research that are necessary to answer the research questions introduced in Section 1.1, such as battery dynamics and large-scale driver behaviour.

Figure 5 shows how the literature review is structured. First, we cover traffic generating models and explain their requirements and how they can be divided into two categories. Traffic generating models generate EV movement, which generates EV power consumption during driving. We then cover the most common methods of modelling EV power consumption, focusing on battery dynamics and HVAC. The power consumption, in turn, generates charging power demand when the vehicle is parked. The optimization of this charging demand is the goal of most EV fleet studies. Thus, in the final section, we review how researchers have optimized charging for the EV fleet.
3.1 Research gap identification

EV fleet research is a relatively new, complex and broad topic that ranges all the way from molecular chemistry of the battery to society-level behaviour. It consists of several subsets of research, including battery dynamics and large-scale behaviour of drivers. As a result, it also spans across multiple scientific disciplines. Depending on the depth and scope of the study in question, EV fleet research may connect disciplines such as power engineering, social sciences, psychology, chemistry and thermodynamics. Figure 6 shows how these disciplines connect to the subsets of EV fleet research with practical examples, in the scope of this thesis.
Due to the great variety in the scope and depth of EV fleet research studies, there are numerous gaps in knowledge. The three research gaps identified in this section are diverse, targeting different aspects of EV fleet modelling. However, they are all connected by the central theme of integrating EVs into transportation and power systems in an efficient, CO₂-minimizing manner.

In short, the identified research gaps are:
1. Early EV fleet studies generally end with the recommendation that EV charging power should be limited but few studies considered the optimal way of dynamically allocating a limited power resource to a group of connected EVs. Publication I targets this research gap.
2. Early EV fleet studies generally assume that EV charging station are abundant, but EVs most likely need to queue for a limited number of stations. Publication II targets this research gap.
3. EV fleet studies generally assume favourable outdoor temperature conditions for the vehicles, which results in over-estimating their efficiency and utility. Publication V targets this research gap.

In the following, we report how different aspects of EV fleet research have been studied in the literature and explain how the approaches taken in this thesis are similar or different.

### 3.2 Traffic generating models

EVs have not yet reached mainstream popularity and so it is not currently possible to conduct a large survey targeting EVs; there simply are not enough EVs on the road. As such, the potential impacts of large EV fleets is generally studied based on travel patterns of conventional ICEVs \([43,44,48,65,83,96–98]\), assuming that each vehicle represents one motorist \([43]\). This is a reasonable first-
order approximation, although it does not account for range anxiety for BEVs and the rebound effect.

Range anxiety for BEVs can be simulated by cancelling planned trip sequences based on the energy level of the battery [45,65]. In Publications I and II, all vehicle agents are assumed PHEVs, to avoid having to include range anxiety. In Publication V, vehicle agents are assumed BEVs and range anxiety is modelled by cancelling tours (trip sequences) that would leave the driver stranded. This is the same approach as used in Ref. [45] with zero minimum range margin.

Rebound effect is not modelled in this thesis for sake of simplicity. Its implications are however discussed in Section 6.2.

3.2.1 Agent-based vs. stochastic traffic models

There are numerous modelling approaches to study EV fleets, but they can be roughly divided in two major categories [80,99]: agent-based [100,101] and stochastic models [82,102].

In the former, a vehicle or a small group of vehicles is represented by an individual agent that interacts with other agents in the simulated system based on a series of rules, e.g. “drive to work at 8:15 a.m.”, “connect the vehicle to a charging station whenever possible”. Even with such simple rules, the large-scale behaviour observed in the real world can be replicated, as is seen in Publications I and II. Agent-based models are also known as microscopic models.

Stochastic traffic models, on the other hand, attempt to estimate the observed real-world effects directly from traffic data, without vehicle agents in between. These models typically combine distributions (e.g. total travel distance), with simplifying assumptions (e.g. vehicles may only charge at home) to arrive at the desired large-scale statistics (e.g. charging load during the evening). As a practical example, Dong & Lin (2014) used a stochastic traffic model to estimate what percentage of planned trips can be realized using a BEV, with different range margins [48].

Stochastic simulations are often faster than agent-based simulations, as there are less parameters and interactions to consider. Furthermore, they are often supported more directly by empirical data, as it is generally easier to obtain large-scale data such as the number of vehicles on a certain parking lot, than small-scale data, such as the driving schedule of an individual person. However, stochastic models cannot yield detailed insight on the vehicle level and cannot model complex vehicle-vehicle interactions as well as agent-based simulations. Depending on the type of survey data available, stochastic models may also not be able to produce spatial vehicle location information, which makes them rather unsuitable for electric power flow studies. Meanwhile, agent-based models can produce such information relatively easily [80].

The authors wished to achieve a deep understanding of EV fleets and study the vehicles closer to how they would appear in the real world; as individuals pursuing their own interests. Thus, agent-based simulation is selected as the simulation paradigm for all three main publications.
3.2.2 Agent-based vehicle traffic-generating models

In this section, we cover some agent-based EV fleet models that are encountered in the literature. For clarity, we are only interested in traffic models that generate EV traffic and describe its flow. Thus we exclude “pure” traffic flow models such as the intelligent driver model [103], Nagel-Schreckenberg traffic flow model [104] and Krauss traffic flow model [105]. Such models are used to evolve the location and velocity of individual vehicles on the road when the direction (i.e. reason for travelling) is already given. However, this is not sufficient for our purposes, as EV movement is not the end goal, but rather an intermediary stage to generate realistic power demand.

Simple travel survey- or GPS-data following models

There are numerous EV traffic models in the literature that do not use an existing vehicle traffic generator, but instead develop a simple agent-based traffic models that are based directly on a travel survey or empirical (e.g. GPS-based) data [43,97]. Such models are tailored to the research question at hand, so any unneeded computation can be minimized. Consequently, they can be very rapid to compute. Meanwhile, extensive traffic simulator suites such as MATSim and SUMO (discussed in the following sections) tend to have a large amount of unnecessary computation due to their complexity and all-inclusiveness.

Typically, these models read the collected travel survey data (travel diaries filled by the respondents) or GPS data and convert them directly to travel schedules. Agents (vehicles) in the simulation then attempt to travel according to these travel schedules. In the case of ICEVs and PHEVs, it is often assumed that the vehicle can always execute the travel plan in the schedule [97]. BEVs, on the other hand, may not always be able to do this. If the BEV would run out of energy during a trip, that trip or tour (a sequence of trips that starts and ends at home) may be cancelled [45,65]. An alternative to this is to modify the behaviour model of the EV based on its SOC [70]. The former approach basically assumes that the driver knows beforehand that the trip or tour is not feasible. Publication V uses a simple travel survey-following model with tour-cancelling.

Some authors, e.g. Wu et al. (2015) argue that GPS data should be used in place of travel survey data whenever possible. This is because travel surveys usually cover only a single day per respondent and they rely on self-reporting. Thus, daily travel distance variation is ignored. In Finland, vehicle GPS data is not easily available, and therefore the current thesis uses travel survey data instead.

MATSim

MATSim (Multi-Agent Transport Simulation) is a travel demand simulator for large scenarios of up to millions of agents in a road network of millions of links [80]. Each agent (vehicle owner) attempts to execute their daily plan of trips and activities. This results in traffic on the road network, and possibly traffic jams. Agents try to maximize their utility, which includes earning money (working), performing activities and spending less time in traffic, by replanning their day based on a co-evolutionary algorithm. The combination of all the agent’s utility is the utility function. Utility function is minimized by varying parameters including routes, working time and car type. Energy consumption can also
be included in the utility function. The evolutionary optimization algorithm eventually finds an equilibrium, which is called the relaxed demand. This equilibrium is then analysed [80].

MATSim has been used in the EV context by e.g. Galus et al. (2013) [40], Waraich et al. (2013) [80] and Vayá & Andersson (2014) [106].

**Simulation of Urban Mobility (SUMO)**

SUMO is free and open source traffic simulation package implemented in C++ and available since 2001 [107]. It is meant for city-scale traffic simulation and has a relatively high level of detail, modelling explicitly even traffic lights. SUMO is intermodal and supports road vehicles, public transport and pedestrians.

Even though the model is intended to use externally generated traffic demand, it can generate traffic demand by itself, from e.g. population statistics using a simple activity-based traffic model. This activity model includes work, school and leisure activities and three different travel means: feet/bike, bus and car.

Examples of SUMO applications in the EV field include Hess et al. (2012) [70] and Maia et al. (2011) [108] and Macedo et al. (2013) [109].

**Traffic generating model in this thesis**

Despite having access to existing agent-based EV fleet simulators, this thesis takes a different route and implements its own agent-based traffic generating model. The reasons for building the model from the ground up are not only to develop the problem-solving and programming expertise in our research group, but also to achieve a deeper understanding of the EV fleet by starting from the basic assumptions. The EV fleet simulator is explained in detail in section 4.3.1.

3.3 Energy consumption and battery modelling

3.3.1 Energy consumption models

The simplest model for EV energy consumption in transit is the linear depletion model, which assumes that energy consumption is directly proportional to the travelled distance. This approach is computationally fast and reasonably accurate, even if it ignores e.g. elevation differences, outdoor temperature and changes in the cargo. Linear depletion model is discussed in more detail in its own section below (Section 3.3.3).

In PHEVs, which incorporate both an electric motor and an ICE, some further simplifications can be made. The possible small fuel consumption in CD mode is often ignored [43,98,110]. Similarly, in the CS mode, net consumption of electricity can be ignored [54]. It is generally assumed that if the trip distance is long enough for the CD range to deplete, the PHEV will remain in CS mode until next recharge [44,54].

More advanced energy consumption models take into account vehicle speed, acceleration, rolling resistance, aerodynamic drag, elevation, and the rotational acceleration of the electric motor [108,111]. Depending on the focus, they might also take into account power “secondary” power consuming operations such as HVAC and battery thermal management (BTM) [65]. These models can capture
more realistically the energy demand of the vehicle and energy regeneration during regenerative braking. However, they are also more computationally demanding.

Publications I and II assume the linear depletion model for simplicity, while Publication V is slightly more advanced, using a mean velocity-dependent power consumption with secondary loads of HVAC and BTM [65].

3.3.2 Battery chemistry

Simple linear consumption models do not typically specify the battery chemistry, as the abstraction level of the vehicle is already very high. This is also done in Publications I and II.

For studies with a more detailed battery model, the most common battery chemistry encountered in EV fleet literature is the Lithium ion battery [65]. Publication V, assumes Lithium manganese chemistry for the EV batteries, which is found in e.g. Nissan Leaf and Chevrolet Volt [112].

3.3.3 Linear consumption and EV battery model (Publications I and II)

By far, the most common battery modelling approach encountered in the literature is the simple linear depletion and charging model [43,44,70,80,97,113], or simply the linear model. The linear model assumes that the SOC of the battery is increased and decreased at a constant rate during charging and discharging. There is typically some effectiveness constant of 90–95% to account for energy losses during charging [14,71,114]. Basically, the linear model is a kilowatt-hour counter with some efficiency factors for energy going in and out. Publications I and II use the linear model.

The linear model is extremely popular for EV fleet studies because it is computationally fast, very easy to implement, and is a relatively good approximation of a battery near room temperature, when charging power is modest and when the operational SOC range is restricted to avoid regions where battery behaviour is nonlinear, e.g. so that the usable range is 65% [110] or 75% [114].

One of the linear model’s limitations is that it ignores battery voltage. As a result, it is too simple to accurately describe battery behaviour at the SOC extremes (less than 20% and more than 80%). For example, when charging a real battery, the battery’s voltage increases in tandem with its SOC. Because a high voltage will damage the battery, charging current must be decreased after exceeding the SOC of around 80%. This results in a reduction of SOC increase per unit time, making the process non-linear. Nevertheless, studies can sidestep this problem by defining that their SOC of 0% refers to the lowest energy level in the battery’s operational range and that SOC of 100% refers to the highest energy level in the operational range. Some authors have acknowledged the need in this field of research to switch to a more CCCV model [40], but the linear model still prevails in large-scale EV fleet research due to its computational advantages.

The final limitation of the linear model, the ignoring of battery temperature, cannot be as easily sidestepped, and it makes the linear model nearly unusable at cold temperatures. Cold temperature can reduce the operational range of an
EV by as much as 50% [115,116]. The reasons for this are covered in the next section.

### 3.3.4 Advanced EV battery models (Publications IV and V)

Various advanced battery models for a range of different chemistries are readily available in the literature. They are typically based on electrochemical, mathematical or equivalent circuits (EC) [51,117]. Advanced battery models achieve a higher level of accuracy due to less abstraction and higher number of input parameters. Combining such a detailed battery model with an EV fleet simulator is certainly possible, but in practice, these models are often too computationally demanding for use in large simulations (hundreds of vehicles and more) [111]. As a result, ideal EV battery models are those that find a good compromise between level of detail and computational difficulty. In Publication IV, we attempt to create such battery model.

EC battery models mimic the behaviour of the battery via electric circuit components such as voltage source, resistors and capacitors. They provide a good trade-off between performance, complexity and usability, although their parameterization can become complicated [51]. The most simple EC model in terms of number of components, known as the IR model, contains only a voltage source and a resistor [118]. Here the resistor represents the combined resistance of contacts, electrodes and the electrolyte [51]. It is common to see the voltage source output dependent on SOC, using e.g. linear interpolation on a look-up table [51]. IR model is a rather popular choice for battery model in the literature due to its simplicity [118].

More advanced EC models add one or two RC-elements, which are resistors and capacitors connected in parallel [51,119]. These elements characterize the transient response of the battery cell electrodes. Basically, they introduce a transition period into the change in voltage as a response to change in current. The identification of parameters in advanced EC models is based on techniques such as impedance spectroscopy and current pulse test cycles [51]. Parameters can then be optimized using a numerical optimization method that minimizes the squared error between model output and measurement [51].

Note that all the aforementioned EC elements can be made current-dependent [117] and SOC-dependent [51], which increases the complexity and accuracy of the overall model. This approach is taken in Publication IV.

SOC is possibly the most important single parameter characterizing the battery. Therefore, it is essential that the battery model implements a suitable SOC tracking method. The most popular SOC tracking method by far is coulomb counting or ampere hour counting, which keeps a record of the amount of ampere-hours (the product of current and time) charged into and discharged out of the battery [51,111,120]. Similarly to the linear battery model, a coulomb counter often uses an efficiency factor for both charging and discharging. More advanced SOC tracking methods include Kalman filters and fuzzy logic [120–122]. Publication IV uses a coulomb counter for SOC tracking.

If the simulated time period for the EV fleet is only a few days, advanced battery models can be simplified by excluding self-discharge and ageing effects.
Temperature
dependency of charging and power consumption, especially low
temperature effects, have often been overlooked in EV fleet research, even if it
is acknowledged that ambient temperature plays a major role in EV perfor-
mance [6,58,65].

The authors were able to locate only a handful of studies that consider how
ambient temperature affects EV utility, charging and range [45,58,65,123]. In a
simulation study, Neubauer & Wood (2014) found that climate extremes pose
challenges for BEVs, due to inefficient cabin heating systems and high on-road
battery temperature, along with battery degradation [65]. In another simulation
study, Farrington and Rug and (2000) claim that air conditioning (HVAC) is the
greatest single largest auxiliary load of an EV by nearly an order of magnitude and that
conventional HVAC can reduce EV range by almost 40% [123]. An empirical
study by Kupiainen (2013) found that EV power consumption increases in win-
ter conditions and that this can be reduced with cabin preheating and lower
HVAC minimum cabin temperature [58].

Publication IV uses charging and discharging data in a wide range of ambient
temperatures (−10°C to +50°C) to build a more complex, highly temperature-
dependent battery model, which is then applied in Publication V.

3.4 Vehicle thermal model

Highly advanced EV thermal models are available in the literature [124–127],
but these models are typically intended for simulating singular vehicles and not
entire EV fleets. Moreover, EV thermal balance calculations increase the com-
plexity of the overall simulation and the computational load. For this reason, EV
thermal balance is often considered beyond the scope of EV fleet studies.

Certain authors, most notably Neubauer & Wood, have developed EV thermal
models with a high level of abstraction to make them computationally feasible
for fleet-scale studies [65]. Publication V uses this EV thermal model, which is
described in detail in section 4.4.2.

3.5 Charging

EV charging has been studied extensively in the literature. Early studies inves-
tigated the impact of EV charging on power consumption profiles and on power
production portfolios, but after researchers acknowledged the limitations in
power distribution capacity, studies became more focused on the distribution
system [40].

It is generally understood that uncontrolled charging will lead to many EVs
charging simultaneously, mainly due to synchronized working hours, thus in-
creasing peak electricity demand and electricity price. As a result, research has
mainly focused on coordinating the charging of EVs so that they do not overload
the transmission or distribution grid [128,129]. These studies implicitly assume
that expanding transmission and distribution capacity is not an economically
attractive option. They typically end with the conclusion that EV charging
should be controlled by either limiting the charging power or by delaying the charging of some vehicles to keep the total charging power manageable.

Besides minimizing load on transmission and distribution grid, there are also other objective functions for optimizing the charging of an EV fleet. Some encountered objectives include:

- Minimizing peak load [130]
- Minimizing total cost of electricity for charging [33,130]
- Maximizing utilization of low-carbon energy production [79,130,131]

Research shows that any of these objectives can be reached by adjusting the charging of individual EVs. Some of the objectives can be mutually conflicting, e.g. wind power generation peak may occur when there is already a large base demand for electricity. In this case, the power distribution system would be strained more, not less. Thus, it may not be possible to achieve all the objectives simultaneously.

In the current thesis, the objectives discussed above are not explicitly included in the simulation. In Publication I, we assume the total charging load at each charging location is limited and thus certain EVs may not charge even if they are grid-connected. In Publication II and V, there are no large-scale objectives that affect the timing of charging. Instead, EVs charge whenever they are able.

### 3.5.1 Centralized vs. decentralized charging control

EV fleet charging studies can also be categorized based on the technical solution. These solutions can be roughly divided into decentralized and centralized ones [132].

Decentralized charging control is a market-driven solution, where EV drivers would determine beforehand how much they are willing to pay for charging their vehicles during some time window, e.g. 24 hours. Some drivers may be willing to pay a higher amount to ensure that their vehicles are charged as quickly as possible, while others may be willing to compromise if money is saved by doing so [132]. Because peak demand electricity is more expensive, this would move the charging window of some vehicles away from peak demand hours.

Centralized charging control uses centralized infrastructure to collect information (e.g. current SOC, departure time) from every EV in some region and optimizes their charging for given objective function, e.g. to minimize overall cost of charging. Because the size of the optimization problem increases with the number of EVs, a decentralized solution could be more suitable for very large EV fleets [133].

In Publication I, PHEV charging is centralized at each location (parking area) and vehicles are dynamically allocated charging power based on power allocation functions. The overall objective is to maximize the distance driven in CD mode.
3.5.2 Location

In most studies, home charging is considered the basic charging scheme [43,54,73,96,134,135], while assuming that the vehicle is fully charged when leaving home [44] and upon arrival, either plugged in for charging or placed in a charging queue [54,97]. The current thesis uses these assumptions, as well. Some authors, e.g. Wu et al. (2015) and Dong & Lin (2012), have used a benefit and cost analysis based on price of fuel and electricity along with a “hassle” cost to determine if a PHEV is connected to charge or not [43,44].

Alternative charging schemes typically include workplace [43], or “public” locations as additional places to charge. In some cases, home charging is disallowed, which would represent drivers that either have no charging opportunity at home or live in an area with an extensive public charging infrastructure [44]. Workplace charging is often considered the second-most important form of EV charging, as vehicles occupy their workplace parking lot for around 8–9 hours per work day. Also because of this, a number of EV fleet studies focus entirely on workplace fleets [97].

3.5.3 Power allocation

As discussed above, most studies on coordinated EV charging conclude that EV charging must be constrained. However, not many early studies considered how individual EVs should dynamically charge under such constraints. Instead, they focus on the aggregate EV load management.

If there are vehicles connected for charging at the same time at the same location and their overall charging power is constrained so that all vehicles are not allowed to charge at full rate simultaneously, the available power must be allocated among the vehicles [14,82,136,137]. However, some vehicles may benefit more from the charging power than others, so the optimal allocation is not necessarily equal. This gives rise to the problem of optimal power allocation: how should the limited power be allocated to the connected EVs to maximize some utility function?

Optimal power allocation requires a power allocation function or algorithm. As inputs, some authors have used e.g. target SOC, remaining parking time and electricity price [82,136,137]. Objectives have ranged from maximizing the average SOC to maximizing the value an EV owner places on the electricity they receive.

Publication I begins with the assumption that the total charging power available to the EVs in a certain location is constrained. As one of the goals of electrification of transportation is to reduce CO₂ emissions, we aim to maximize the e-mileage of a fleet of PHEVs, i.e. the total distance driven in electric-only mode. For input parameters which are based on predicting future events, e.g. remaining parking time, a prediction error is included.

3.5.4 Infrastructure

As noted in Section 2.2.5, there are many types of EV charging stations, differentiated by the maximum current supported, and the number of phases used.
For simplicity, this thesis assumes that charging stations are of the same type at each location where charging is supported. Basically, if there is more than one charging station at a location, then those stations are all assumed identical in terms of their features. This approach is relatively common in charging infrastructure-related studies [14,136].

**Charging station placement**

Optimal location and sizing of EV charging stations is a well-studied problem. These studies generally optimize an objective function under budget constraints. Examples include social welfare and the number of cancelled trips due to battery depleting. If there is no budget constraint, the objective is usually to minimize the total cost [138–141]. Such objective functions often end up complex and computationally demanding, and therefore, the optimization routine might rely on heuristic methods [138,141–145]. These publications often include case studies for a specific city [69,138,141,146].

In the current thesis, Publications I and II assume that EV charging stations are placed at home and workplace and that vehicles are only charged at these locations, except in special cases. Instead of studying the optimal charging station placement in the city, we focus on the optimal utilization of abundant charging stations under total power constraints (Publication I), the differences between several low-level charging infrastructure parameters (Publication II), and the performance of EVs using charging stations at extreme temperatures (Publication V).

**Charging station availability**

Many articles, including Publication I, assume that charging stations are abundantly available, so that all vehicles arriving to a location with EV charging supported can plug in immediately [43,134]. This scenario may be too optimistic in the near future as the number of EVs increases, because each charging station has associated installation, operation and maintenance costs. It is more likely that some vehicles will occupy a limited number of charging stations, while others are simply idle and unable to charge. Moreover, even if a vehicle becomes fully charged, it tends to occupy the same charging bay even after charging operation is finished [147]. As a result, the total charging of a large fleet of EVs not parked at home may be exaggerated [27].

While both Publications I and V assume that charging stations are abundant, Publication II assumes that there are not enough charging stations for all vehicles to charge simultaneously, thus necessitating a queuing system. In Publication II, each station’s connector cables and each vehicle are modelled explicitly. This allows detailed study of the impact of charging infrastructure on e-mileage. Note that even if the number of charging stations is limited, the same station can charge multiple parked vehicles in its vicinity if the connector cable is simply switched from one vehicle to another.

Some other authors have also identified this problem of occupied charging stations. Xi et al. optimized the location and size of charging stations for a fleet of BEVs. They used two objectives in their analysis: maximizing the number of EVs that charge and the amount of battery energy recharged. Here, the vehicle
charges if and only if the vehicle can connect to an unoccupied charging station immediately upon arrival. Furthermore, a charging EV occupies the station for the entire duration of the visit [148]. By contrast, in Publication II, a vehicle that arrives to a location with no vacant charging stations may still charge later if a cable becomes available due to a nearby vehicle disconnecting.

Hess et al. applied SUMO to optimize the locations of 30 charging plugs and up to 6 charging stations that house them in Vienna, using genetic algorithms. Their objective was to minimize the average trip time, which includes both queuing and charging. All the vehicles in the study were BEVs that alter their behaviour according to the remaining energy in the battery [70].

Qin & Zhang minimized the queuing time for charging for 100 charging stations in an “open” road network where EVs may enter and leave the system. Here the EVs communicate with the charging stations in order to locate the best one for charging (the one with shortest waiting time, which comprises of queuing time and charging time) [149].

Berndt et al. (2015) used a charging queue to determine if an arriving vehicle is connected to a charging station upon arrival, or if it is placed in a first-in-first-out queue. In this simple approach, the queue has no maximum length [97].

Dong & Lin (2012) did not explicitly model EV charging stations. Instead, they focused on modelling station availability, which they determined by drawing from a Bernoulli distribution at each stop [44].

Publication II considers only the charging infrastructure of workplaces, because the commute between home and work is such a major contributor to weekday travel and because vehicles are parked at work for an extended duration (around 8 hours). This approach is supported by the findings of Xi et al. (2013) [147], who note that the amount of EV energy recharged is maximized when most of the charging stations are built at workplaces.
4. Research method

4.1 Overview

The main research method of this thesis is agent-based computer simulation, which is applied to the city of Helsinki, Finland. Computer simulation is selected over empirical experiments for several practical reasons. Foremost, EVs are currently not an established private transportation solution, so it is not yet possible to study the behaviour of large EV fleets in real life. Second, even though the technology already exists, it would not be economically feasible to conduct real-world experiments with hundreds of rented or leased EVs. Third, transportation patterns using ordinary ICEVs are already well-studied all over the world, and thus it would be a reasonable first-order approximation to assume that these patterns remain similar when the ICEV is replaced by an EV.

Computer simulations are conducted in MATLAB, a numerical computing environment for studying a range of engineering problems [150], which is often encountered in also EV-related studies [111,114,151,152]. MATLAB is commonly used to study novel problems due to its ease of use and active community that provides assistance and custom functions to extend the features of the core program. The downside of MATLAB is that it uses a high-level programming language and is thus not sufficiently fast for solving large, computationally demanding problems requiring thousands of lines of code. For the purposes of this thesis, however, the computation time using MATLAB is sufficiently low to warrant its use in all the main publications.

Input data for the agent-based simulation is based on Helsinki population statistics [153] (Publications I and II) and a travel survey conducted on a national level in Finland [154] (Publications II and V). The author did not have access to a more detailed, GPS-based travel dataset for Helsinki.

Vehicle type varies between publications. In Publications I and II, we consider only PHEVs, as we originally expected PHEVs to be an intermediary stage between ICEVs and BEVs, and because PHEVs would allow us to neglect range anxiety. In Publication V, however, we switch from PHEVs to BEVs, because PHEVs, which incorporate a heat engine, would not suffer from cold temperature to the same extent as BEVs.

EV fleet simulator also varies between publications. In Publications I and II, the agent-based fleet simulator is stochastic, containing random elements, and records the actual geographical location of the vehicles when they are parked.
Meanwhile, in Publication V, vehicle movement is based directly on travel survey data, but the geographical location of the vehicles is lost, as it is not included in the travel survey data. When Publications I and II were written, the geographical location data on the vehicles was expected to play a large role in later research. However, this was not realized, and thus it made sense to reduce model complexity by directly using the travel survey data in the final publication.

The fleet simulator consists of several submodels. All the elements are simulated as collections of variables, which are evolved according to the rules set in the beginning of the simulation. The values of these variables are modified by the fleet simulator during each time step. After the status of all vehicles is updated, data of interest are recorded, e.g. the SOC of the entire fleet. The simulation then moves forward to the next time step.

In all the articles included in this thesis, the power grid is not modelled explicitly. Instead, it is simply assumed to be an infinite energy storage that can be accessed at certain locations with certain maximum power. In Publication I, we assume that the total charging power at each location is limited. Here the grid has been reinforced according to EV load so that locations with a lot of EV traffic have a higher charging power.

For simplicity, in Publications II and V, the power grid is assumed sufficiently strong as to not have any bottlenecks that might cause charging power to become limited.

A comparison of the three main publications is shown in Table 2.
Table 2. Comparison of the three main publications.

<table>
<thead>
<tr>
<th></th>
<th>Publication I</th>
<th>Publication II</th>
<th>Publication V</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focus</td>
<td>Limited charging power allocation</td>
<td>Charging infrastructure</td>
<td>Temperature</td>
</tr>
<tr>
<td>Goal</td>
<td>Maximize e-mileage</td>
<td>Maximize e-mileage</td>
<td>Maximize efficiency (km/kWh), fleet utility and charging power (kW)</td>
</tr>
<tr>
<td>Vehicle type</td>
<td>PHEV</td>
<td>PHEV</td>
<td>BEV</td>
</tr>
<tr>
<td>Battery model</td>
<td>Simple kWh-counter</td>
<td>Simple kWh-counter</td>
<td>ANN-empirical hybrid model</td>
</tr>
<tr>
<td>Vehicle behaviour model</td>
<td>Attraction &amp; saturation model</td>
<td>Attraction &amp; saturation model (updated)</td>
<td>Finnish travel survey data</td>
</tr>
<tr>
<td>Spatial location of vehicles known</td>
<td>✓</td>
<td>✓</td>
<td>-</td>
</tr>
<tr>
<td>EV fleet size</td>
<td>10,000</td>
<td>1,000</td>
<td>212</td>
</tr>
<tr>
<td>Locations where charging is possible</td>
<td>Home, workplace</td>
<td>Home, workplace</td>
<td>Home (and workplace in special cases)</td>
</tr>
<tr>
<td>Queuing for charging</td>
<td>-</td>
<td>✓</td>
<td>-</td>
</tr>
<tr>
<td>Queuing for charging (only at workplace)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Max charging power in base scenario</td>
<td>7.4 kW</td>
<td>3.7 kW</td>
<td>3.6 kW</td>
</tr>
<tr>
<td>Max charging power is varied</td>
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<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Vehicles attempt full charge</td>
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<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Vehicles communicate with a central charging authority</td>
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<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Initial SOC</td>
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<td>100%</td>
<td>Near equilibrium</td>
</tr>
<tr>
<td>Time step</td>
<td>300 s</td>
<td>300 s</td>
<td>20 s</td>
</tr>
<tr>
<td>Vehicle thermal model</td>
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<td>-</td>
<td>✓</td>
</tr>
<tr>
<td>Battery thermal management system (BTM)</td>
<td>-</td>
<td>-</td>
<td>✓</td>
</tr>
<tr>
<td>Heating, ventilation and air conditioning system (HVAC)</td>
<td>-</td>
<td>-</td>
<td>✓</td>
</tr>
</tbody>
</table>

4.2 Determining impact

In order to compare different power allocation strategies in Publication I, to measure the effect of different charging infrastructure in Publication II and to measure the effect of ambient temperature in Publication V, we must select some relevant simulation output that is dependent on these three inputs. In Publications I and II, we use the total distance driven using electricity only during the simulated period (e-mileage) as this metric. In Publication V, several different metrics are used.

4.2.1 E-mileage (Publications I and II)

E-mileage is a convenient metric, because it is a singular macro-scale value which reflects the overall “benefit” gained from the EV fleet due to the use of
electricity instead of gasoline. The larger the e-mileage, the more electricity is used to provide transport service to the vehicle owners, and the less gasoline is consumed by the vehicle fleet, implying a likely decrease in CO₂ emissions. Therefore, it is in our interest to maximize e-mileage. E-mileage has been chosen as a metric by other authors, as well [114,142]. It should be noted that, because electricity production has CO₂ emissions of its own, it is assumed here that, a unit distance driven using electricity produces less CO₂ emissions than unit distance driven using gasoline on average.

In Publication I, e-mileage with a smart power allocation strategy is compared to the e-mileage with the equal allocation strategy. However, comparing two large numeric values in absolute terms is not very descriptive. Instead, it is more convenient to compare the relative e-mileage increase (REMI) that results from switching the equal allocation strategy to a smarter alternative. REMI is used as a metric to rank different allocation strategies in Publication I. A negative REMI indicates that the new, smart strategy performs worse than equal allocation, while a strategy with a positive REMI outperforms equal allocation. Thus, the higher the REMI, the better the strategy used.

4.2.2 Metrics used in Publication V

In Publication V, four different metrics are used instead of only e-mileage. This is done because the more advanced battery and vehicle models allow more precise study of the fleet’s behaviour.

*Utility*

In Publication V, the vehicle fleet consists of BEVs instead of PHEVs, so the ICE cannot be used to extend the range of a vehicle when the traction battery is fully discharged. Because the driver of the vehicle wants to avoid being stranded on the road with a depleted battery, they must know beforehand if all the planned travel can be realized before the battery runs out. In this article, this problem is solved using the concept of a *tour*. The tours are then used to define the utility of the fleet. We define the utility of the EV fleet as the ratio of distance driven by the fleet divided by total distance planned to be driven in the travel schedule. A utility of 100% then means that all planned travel can be realized.

A tour is a sequence of trips that begins and ends at the driver’s home. EV agents attempt to act out each tour in their travel plan with no delays. If the whole tour cannot be performed for any reason, the simulation is “rewound” back to the time step before that tour begins and that tour is removed from the driver’s travel schedule [45]. Failed tours then lower the utility of the EV fleet.

There are two ways for a tour to fail, a power-based failure and battery temperature-based failure. In the former, the battery cannot deliver sufficient power to reach desired vehicle speed. These failures occur more frequently at lower battery temperatures, as a higher internal resistance reduces the output voltage during discharging. The use of HVAC and BTM during driving also increases the likelihood of trip failure, because they act as secondary loads to the battery.
Battery temperature-based trip failure occurs if the battery overheats (battery temperature exceeds +60°C [6,66]. In practice, battery overheating occurs only when the battery thermal management system (BTMS) is offline, as normally BTM maintains battery at a temperature less than +20°C [65].

*State of charge (SOC)*

A high SOC is desirable for the EV driver, as higher remaining range lowers range anxiety. Lower range anxiety makes travelling with the EV more likely, which is beneficial when the energy-efficient EV is used to replace inefficient gasoline-powered transportation. Based on this, it is desirable to maximize SOC during charging. However, one should note that a high SOC also limits the ability of the EV to absorb excess energy production during e.g. periods of high renewable power generation.

*Charging power and charging time*

A higher charging power, or shorter charging time, is naturally beneficial for the EV driver, because time is a generally valuable resource. It is also at least partially desirable for the charging station owner and those queuing for charging, as the charging pole can serve a higher number of customers in the same time period.

Because charging power is not constant during charging, it would be tempting to simply calculate the mean charging power $P_{\text{mean}}$. The problem with using mean charging power is that it places equal importance to time periods near full SOC and to time periods near small SOC. Time periods near full SOC are generally less efficient in terms of charging, as the amount of energy per unit time slows down approximately exponentially as SOC increases. For this reason, we use *self-weighted mean charging power* (SWMCP) $P_{\text{SWM}}$ instead of just mean charging power. In SWMCP, each time step is weighted by the charging power during that time step. In mathematical terms:

\[
P_{\text{mean}} = \frac{\sum_{t_{\text{start}}}^{t_{\text{end}}} P(t)}{t_{\text{end}} - t_{\text{start}} + 1}
\]

\[
P_{\text{SWM}} = \frac{\sum_{t_{\text{start}}}^{t_{\text{end}}} P(t) \cdot P(t)}{\sum_{t_{\text{start}}}^{t_{\text{end}}} P(t)}
\]

where $t_{\text{start}}$ and $t_{\text{end}}$ are the time steps during which the particular charging process begins and ends, respectively. As is evident from Eq. (2), SWMCP gives more weight on time steps with higher charging power. Note that we do not include battery thermal management load and cabin preconditioning loads in the SWMCP because they do not charge the battery.

*Efficiency*

Efficiency is defined in Publication V as the distance travelled (in kilometres) per unit electricity consumed (in kilowatt-hours). High efficiency is desirable, as it reduced energy demand, thus lowering energy costs.


4.3 Fleet movement model

In order to study the charging of vehicles, the simulated vehicles must first consume electricity. An intuitive and practical way of performing this is to simulate the movement of the vehicles in a road network.

In Publications I and II, vehicle trips are generated using an attraction-saturation trip generator developed in our research group for studying the spatial movement of an EV fleet. The trip generator is tuned by requiring that the resulting large-scale PHEV behaviour must be similar to the experimentally observed ICEV behaviour in the Finnish Travel Survey [154].

In Publication V, the movement of individual vehicles is based on actual measured travel schedules from the same travel survey, although detailed spatial information is no longer available with this approach. These two different fleet modelling approaches are described in the following. Regardless of the approach, the simulation period is selected as 24 hours, starting at midnight.

4.3.1 Attraction-saturation trip generator (Publications I and II)

This trip generator is used in Publication I and Publication II to produce movement, and therefore electricity consumption, for the simulated vehicle fleet. In simple terms, the generator relocates vehicles by attracting them towards certain locations at certain times. Because it would not be realistic for the vehicles to be in constant motion, they are kept in place by a saturation mechanism that only allows departure if a certain location-dependent time is spent parked.

The road network in which the vehicle movement takes place is shown in Figure 7. This network consists of four different types of nodes: home, workplace, shopping and leisure. Different types of nodes have different attraction and saturation functions, see Figure 8. The saturation functions are based on expected behaviour: vehicles typically park for 0–2 hours at shopping and leisure nodes and 4–12 hours at home and workplace nodes. The same holds for the attraction functions: around noon the drivers are mostly at work, in the night they are at home, and in the late afternoon or early evening they are spending time at shopping or leisure locations.

Each vehicle $v \in V$ has a saturation factor $s_v \in [0,1]$ obtained from some distribution, and each location has an increasing saturation function $S: [0,24] \to [0,1]$. Let the time (in hours) spent by vehicle $v$ at its current location since arrival be $t_{parked,v}$. When $S(t_{parked,v}) \geq s_v$, the departure of vehicle $v$ is triggered and the driver will decide the next destination. When vehicle $v$ arrives to its destination, it is given a new saturation factor $s_v$, which is used to trigger the start of the next trip.

Let us now assume that vehicle $v$ is departing from node $m$ at time $t$. The next destination of this vehicle is determined by comparing the attraction values of, and distances to, the possible destinations. Each destination candidate $n \in \{N \setminus m\}$ has a time-dependent attraction function $A_n: [0,24] \to [0,\infty]$ and a distance to the vehicle’s current location $d_{n,m}$ via the road network, calculated using Dijkstra’s algorithm [155], the same algorithm as used e.g. in SUMO [107]. From these, a fitness value $f_v(t) = A_n(t)/d_{n,m}$ is calculated for each destination
candidate. In other words, a location’s fitness is directly proportional to its attraction and inversely proportional to its distance. The destination is then selected among the candidates using fitness proportionate selection [156].

The method above is used for all nodes in the road network except for home and workplace nodes, because it is not typical for a driver to have several homes and several workplaces. Instead, each vehicle is given a single home node and single workplace node. The vehicles always see the attraction of other home and workplace nodes as zero. The assignment of home and workplace nodes is semi-random; there is no correlation between the location of the two, but the total number of vehicles assigned to each home and workplace node are proportional to actual population statistics in Helsinki [153].

Saturation factors $s_v$ are generated using the following random process:

$$s_v \leftarrow 0.5 + 0.2 \cdot r_{normal} \quad (3)$$

where $r_{normal}$ is a random number from a normal distribution. If $s_v$ is not between 0 and 1, the process in Eq. (3) is simply repeated.

![Figure 7. Node network used in Publication I. Reprinted with permission from Publication I. Copyright 2013 Wiley.](image-url)
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![Graph](image)

**Figure 8.** Control functions used in Publication I. Reprinted with permission from Publication I. Copyright 2013 Wiley.

*Improvements in Publication II*

For Publication II, the fleet simulator was upgraded in three ways. First, the saturation and attraction functions were modified to achieve a better match with the experimentally measured activity distribution shown in Figure 11a. The modified control functions are shown in Figure 10.

The second modification was to add artificial workplace node “tails” to the original network to account for long-distance commuting originating from Helsinki, see

Figure 9. These workplaces were then assigned to the vehicles in such a way that the resulting commute distance distribution would resemble the experimentally measured commute distance distribution in Ref. [154].

The final modification is the queuing system for a limited number of charging stations described in Section 4.7.2.
Figure 9. Node network used in Publication II. Reprinted with permission from Publication II. Copyright 2015 Oxford University Press.
Figure 10. Control functions used in Publication II. Reproduction of a picture presented at the 2nd International Workshop on the Integration of Solar Power into Power Systems and published in the workshop’s proceedings.

4.3.2 Travel schedule based on travel survey data (Publication V)

In Publication V, the stochastic model is replaced by a travel schedule obtained from the Finnish national travel survey [154]. In this survey, the respondents filled out a travel diary for one specific day. For the most generalizable results, we used a subset of the data where this day was a workday. To maintain focus on EVs in urban environment, we further selected only the respondents that travelled by car and had their home in Helsinki. Finally, to capture the “equilibrium” behaviour in which the SOC at the end of the day is close to that in the beginning of the day, we down-selected respondents that start and end their day at home. This process resulted in driving data for 212 cars. This raw data was converted to arrays where the location and speed of each vehicle is stored for every minute of the simulated day.

A downside in the use of the travel survey data is that the exact location of the vehicles is unavailable to the researcher due to privacy concerns. Therefore, the simulated vehicle fleet in Publication V has no geographical location, but instead a location type (home, workplace, or other).

Figure 11 visualizes the data obtained from the travel survey. Around half of the fleet is parked at work at noon and almost 30% of the fleet is parked at home at all hours. Distinct commuting peaks are seen during morning and evening commuting hours (near 9 am and 5 pm), while traffic is at its lowest during the night. Almost all vehicles that commute work a normal day shift from around 9
am to 5 pm. These observations are consistent with common sense and other travel studies [40,157–160].

![Figure 11](image)

**Figure 11.** (a) Node type occupation of all cars; (b) location of individual cars. Colour coding is the same as in (a), except for black, indicating travel. The total number of cars is 212. Reprinted with permission from Publication V. Copyright 2016 Elsevier.

### 4.4 Vehicle model

In all the articles, the vehicle is represented as a collection of variables which describe the state of the vehicle, such as location and battery SOC. Publication I and Publication II utilize an elementary vehicle model which ignores advanced considerations such as battery voltage limitations, speed-dependent power losses and heat generation and flow in the vehicle. In Publication V, the vehicle model is significantly more detailed and contains an advanced battery model and a thermal model for the vehicle.

The battery model is such an important element of the vehicle model that it warrants its own section. Therefore, battery models are discussed separately in Section 4.5.

#### 4.4.1 Simple vehicle model (Publications I and II)

In Publication I and Publication II, the vehicle fleet consists of identical PHEVs with different home and workplace locations. The electricity consumption of each vehicle is 0.2 kWh/km [161]. The maximum charging power supported by the vehicle battery is such that the battery can be fully charged from fully discharged state in exactly 1 hour, provided that the maximum power of the EV charging station is not exceeded. Battery capacity of the fleet is varied between 1–10 kWh in Publication I and between 1–40 kWh in Publication II. From the above it follows that the maximum supported charging power for a 40-kWh battery is 40 kW. However, if e.g. the charging station limits the maximum charging power to 7.4 kW (as is the case in Publication I), the potential for high charging power is not realized.

All vehicles are assumed to travel at constant speed of 60 km/h. The speed does not affect the energy drawn from the battery during the trip, but does affect the time spent in transit. All vehicles are fully charged at home in the beginning.
4.4.2 Advanced vehicle model (Publication V)

The vehicle used in Publication V is a BEV with a 120 km range, corresponding to an efficient mid-sized sedan [65].

The vehicle performs four basic operations: propulsion, charging, HVAC and BTM, all of which consume power either from the grid or from the vehicle’s battery. Power consumption during a single trip is determined by the average speed of the vehicle, see Figure 12. Charging is always performed at maximum power allowed, as limited by the battery’s cutoff voltage of 420 V. Charging only occurs when the vehicle is parked at a location with access to charging. This is called the standby state. HVAC and BTM, the secondary operations, are performed as needed, and described in more detail in Section “BTM and HVAC” below.

The total power draw from the battery during driving $P_{\text{total}}$ is:

$$P_{\text{total}} = P_{\text{propulsion}} + P_{\text{HVAC}} + P_{\text{BTMS}}$$

(4)

Where $P_{\text{propulsion}}$, $P_{\text{HVAC}}$ and $P_{\text{BTMS}}$ are the power draws due to propulsion, HVAC and BTMS operation, respectively. $P_{\text{total}}$ is used to calculate the discharging current as explained in Section 4.5.2.

![Figure 12. Power consumption model used in Publication V, calculated from Ref. [65].](image)

**Thermal model**

The vehicle thermal model is based on the lumped capacitance model developed by Neubauer & Wood [65]. In this model, battery temperature $T_b$ and cabin temperature $T_c$ (both in °C) are updated as follows:

$$\frac{dT_c}{dt} = \frac{1}{M_c} \left[ K_{ac}(T_a - T_c) + K_{bc}(T_b - T_c) - K_{ce}(T_c - T_e) + q'_{\text{HVAC}} \right]$$

(5)

$$\frac{dT_b}{dt} = \frac{1}{M_b} \left[ K_{ab}(T_a - T_b) + K_{bc}(T_b - T_c) + q_{\text{int}} + (1 - \eta_{\text{inv+EM}}) |P_{\text{propulsion}}| + q'_{\text{BTMS}} \right]$$

(6)

Here $T_a$ is the ambient temperature (in °C), $M_i$ is the heat capacity of element $i$ (in J/K), $K_{ij}$ is the heat transfer coefficient between elements $i$ and $j$ (in W/K),
Research method

$q_{HVAC}$ is the actual heat flow due to HVAC operation (in W), $q_{BTMS}$ is the actual heat flow due to BTMS operation and $\eta_{INV+EM}$ is the combined efficiency of the inverter and electric motor. $q_{int}$ is the internal heating of the battery pack (in W), explained in Section 4.5.2. The values of these parameters and as well as other parameters in this section are shown in Table A1.

The evolution of $T_c$ and $T_b$ is obtained from Eqs. (5) and (6) using the explicit Euler method [162]:

\[
T_{c,t+1} = T_{c,t} + \frac{\Delta t}{M_c} [K_{ac}(T_{a,t} - T_{c,t}) + K_{bc}(T_{b,t} - T_{c,t}) - K_{cc}(T_{c,t} - T_{e,t}) + q_{HVAC}]
\]

\[
T_{b,t+1} = T_{b,t} + \frac{\Delta t}{M_b} [K_{ab}(T_{a,t} - T_{b,t}) + K_{bc}(T_{b,t} - T_{c,t}) + q_{int} + (1 - \eta_{INV+EM})|P_{propulsion}| + q_{BTMS}]
\]

In order to start the simulation as close to a steady state, or thermal equilibrium, as possible, we assume that the initial cabin temperature $T_c$ is equal to the ambient temperature. The initial battery temperature $T_b$ is more complex, as it depends on whether BTM is enabled or not. The logic for determining the initial value of $T_b$ is shown in Table 3. For example, if BTM is enabled and the ambient temperature is below the lower limit $T_{b,standby,low}$ for the battery, the BTM maintains the battery temperature at $T_{b,standby,low}$ and this is used as the initial value for $T_b$.

Table 3. Determining the initial value for battery temperature $T_b$. Reproduced with permission from Publication V. Copyright 2016 Elsevier.

<table>
<thead>
<tr>
<th>BTM on standby</th>
<th>Ambient temperature condition</th>
<th>Initial value of $T_b$</th>
</tr>
</thead>
<tbody>
<tr>
<td>enabled</td>
<td>$T_{b,standby,high} \leq T_a$</td>
<td>$T_{b,standby,high}$</td>
</tr>
<tr>
<td>enabled</td>
<td>$T_{b,standby,low} \leq T_a &lt; T_{b,standby,high}$</td>
<td>$T_a$</td>
</tr>
<tr>
<td>enabled</td>
<td>$T_a \leq T_{b,standby,low}$</td>
<td>$T_{b,standby,low}$</td>
</tr>
<tr>
<td>disabled</td>
<td>$T_a \leq T_{b,standby,low}$</td>
<td>N/A</td>
</tr>
</tbody>
</table>

**BTM and HVAC**

BTM and HVAC are considered secondary operations, which are only performed if there is power left over after performing the primary operation, which is either propulsion (during driving) or charging (during parking). This leftover power is allocated equally to BTM and HVAC.

For example, if the vehicle is charging and it is possible to use all the available charging power from the charging station to increase the SOC of the battery, BTM and HVAC operations are not performed. If this power cannot be completely used e.g. due to a high battery voltage limiting the charging current, the leftover power is divided evenly between BTM and HVAC.

Both BTM and HVAC can be disabled individually under two different states: standby and driving. For example, one can construct a scenario where only BTM is enabled during standby and only HVAC is enabled during driving. This allows
us to investigate the benefits of these secondary operations under different circumstances.

Standby HVAC is a special case, as it can only be performed in the form of preconditioning. This means that instead of always maintaining the cabin temperature between the set limits, cabin temperature is adjusted a certain amount of time before departure. This approach is taken because maintaining the cabin at +16°C in a cold environment of −10°C when the vehicle is not used for the next 6 hours would be highly wasteful.

In the following, we list the equations which are used to calculate the desired heat flow of the secondary operations under different scenarios. The desired heat flow is the heat flow that would occur if the operation is given all the power it requests. Because some power can be used by the primary operations, the actual heat flow may differ from the desired heat flow.

If BTM on standby is enabled and the vehicle is parked, the desired heat flow due to BTM operation \( q_{BTM} \) is given by:

\[
q_{BTM} = \begin{cases} 
- \min(M_b(T_b - T_{b,standby,high})/\Delta t, P_{BTM,cool}), & T_b > T_{b,standby,high} \\
\min(-M_b(T_b - T_{b,standby,low})/\Delta t, P_{BTM,heat}), & T_b < T_{b,standby,low} \\
0, & \text{otherwise}
\end{cases}
\]  

(9)

If BTM during driving is enabled and the vehicle is moving, the following equation is used instead:

\[
q_{BTM} = \begin{cases} 
- \min(M_b(T_b - T_{b,keyon,high})/\Delta t, P_{BTM,cool}), & T_b > T_{b,keyon,high} \\
0, & \text{otherwise}
\end{cases}
\] 

(10)

If BTM on standby is disabled, then \( q_{BTM} = 0 \) when the vehicle is parked, and similarly, if BTM on key-on is disabled, then \( q_{BTM} = 0 \) when the vehicle is being driven.

As for the HVAC system, when i) the vehicle is being driven and HVAC during driving is enabled; or ii) vehicle is parked and being pre-conditioned; the desired heat flow due to cabin HVAC system operation \( q_{HVAC} \) is given by the equation:

\[
q_{HVAC} = \begin{cases} 
- \min(M_c(T_c - T_{c,high})/\Delta t, P_{HVAC,cool}), & T_c > T_{c,high} \\
\min(-M_c(T_c - T_{c,low})/\Delta t, P_{HVAC,heat}), & T_c < T_{c,low} \\
0, & \text{otherwise}
\end{cases}
\] 

(11)

If HVAC during driving is disabled and the vehicle is being driven, then \( q_{HVAC} = 0 \). Similarly, if the vehicle is parked and not being pre-conditioned, \( q_{HVAC} = 0 \).

When the desired heat flows are known, the desired power draws \( P_{BTM} \) and \( P_{HVAC} \) are calculated using:

\[
P_{BTM} = \begin{cases} 
|q_{BTM}|/COP_{BTM,cool}, & q_{BTM} < 0 \\
|q_{BTM}|/COP_{BTM,heat}, & q_{BTM} \geq 0
\end{cases}
\]  

(12)
\[ P_{HVAC} = \begin{cases} |q_{HVAC}|/COP_{HVAC,cool} & q_{HVAC} < 0 \\ |q_{HVAC}|/COP_{HVAC,heat} & q_{HVAC} \geq 0 \end{cases} \tag{13} \]

## 4.5 Battery models

Two different battery models are used in this dissertation. In Publication I and II, the battery model is a simple linear “kilowatt-hour counter”. The second model developed in Publication IV and used in Publication V, is a more advanced hybrid model with special consideration for voltage and self-heating during operation.

For simplicity, regenerative braking is not explicitly modelled in this thesis. Instead, it is assumed that the effect of regenerative braking is already included in the power consumption.

### 4.5.1 Linear EV battery model (Publications I and II)

In Publications I and II, charging is handled as follows: when the vehicle is grid-connected, the energy transferred to the battery from the grid \( \Delta E_{\text{char}} \) (in kWh) is given by:

\[ \Delta E_{\text{char}} = \min(\eta P_{\text{socket}} \Delta t, \quad Q(1 - \text{SOC}), \quad P_b \Delta t, \quad \eta P_{\text{draw}} \Delta t) \tag{14} \]

where \( \eta \) is the charging efficiency of 90\% [82,114], \( P_{\text{socket}} \) is the maximum power limitation of the EV charging station (in kW), \( Q \) is the battery capacity (kWh), \( P_b \) is the maximum power limitation of the battery (in kW), assumed equal to the C-rate of 1C, and \( P_{\text{draw}} \) is the attempted power draw from the socket (in kW). In Publication I, \( P_{\text{draw}} \) is determined by the power allocation function. In Publication II, no power allocation takes place and \( P_{\text{draw}} = \infty \). Also in Publication II, \( P_b = \infty \), because charging power is limited by \( P_{\text{socket}} \) instead.

Discharging, on the other hand, is handled as follows: when the vehicle is being driven, energy removed from the battery during the trip is equal to:

\[ \Delta E_{\text{disc}} = \min(Q \text{ SOC}, \quad d \cdot k) \tag{15} \]

where \( d \) is the distance driven during the trip (in km) and \( k \) is the mean electricity consumption, assumed 0.2 kWh/km [161]. Because the simulated vehicles in Publications I and II are all PHEVs, if the battery is depleted during driving, the remaining required power is produced by the ICE. We assume that the ICE does not participate in providing traction power in CD mode [128].

In Publications I and II, the battery is assumed fully charged (SOC is 100\%) at the beginning of the simulated day.
4.5.2 ANN-empirical hybrid (Publication V)

This hybrid model is developed in Publication IV for use in Publication V. It is based on measurements on a Lithium manganese cell and consists of three elements:

1. Empirical voltage model that yields the voltage of the battery as a function of SOC, current and battery temperature
2. Artificial neural network (ANN) internal heating model that yields heating rate (in °C/s) as a function of SOC, current and battery temperature.
3. SOC tracking model (ampere-hour counter) that yields SOC as a function of previous SOC, current and coulombic efficiency.

These three elements are shown in Figure 13 and described in the following subsections. Figure 14 shows how these different parts are connected to each other in order to simulate a battery cell: the user first defines the initial state of the battery and the ambient temperature, after which the battery’s state evolves according to the user-defined power flow into and out of the battery. The CCCV current control automatically adjusts the current so that the minimum and maximum voltage are not violated. Note that this control may result in lower power output or input than desired by the user.

The collection of measurement data and refinement of the data for use model training is described in the Appendix section titled “Hybrid battery model: Data collection and training”. The model is applicable in the battery temperature range [−10°C, +50°C] and C-rate range [−1.86, +1.86], as the measurements were performed under these conditions.

![Figure 13. Composition of the ANN-empirical hybrid battery model. Reproduced with permission from Publication IV. Copyright 2016 Wiley.](image_url)
Figure 14. Operation of the hybrid battery model. Empirical voltage model is represented by the element $f_v$, artificial neural network is represented by the element with five nodes and the SOC tracking model by the element “SOC update”. Reproduced with permission from Publication IV. Copyright 2016 Wiley.

**Empirical voltage model**

The empirical voltage model is based on the well-known relation:

$$ V = V_{OC} - I \, R_{\text{eff}} $$

where $V$ is the voltage (in V), $I$ is the current (in A) and $V_{OC}$ and $R_{\text{eff}}$ are the open circuit voltage (OCV) (in V) and the internal resistance (in $\Omega$), respectively. Both $V_{OC}$ and $R_{\text{eff}}$ are dependent on current, battery cell temperature $T_{\text{cell}}$ (in °C) and state-of-charge SOC, and given by:

$$ V_{OC} = x_{15} - \exp[x_{16}(SOC - x_{17})] + x_{18}SOC + x_{19}(SOC - x_{20})^2 + x_{11}T_{\text{cell}} $$

(17)

$$ R_{\text{eff}} = \{\exp[(T_{\text{cell}} - x_1)x_2] + x_3 + x_4 \} \{\exp[x_6(SOC - x_7)] + x_8SOC + x_9 + x_{10}I \} x_5 + x_{12} + x_{14}I $$

(18)

Where the set of model parameters $X = \{x_i\}, \; i \in \{1,2,\ldots,20\}$ is obtained by least squares fitting (LSQ) to the measured data.

The form of relations in Eqs. (17) and (18) is based on a manual process of increasingly advanced educated guesses where terms are gradually added to the original relation to increase its complexity and thereby improve its ability to fit to the measured data points. The first part of Eq. (17) is similar to the OCV relation in Ref. [163], but accuracy was found to improve if a small temperature-dependency was added through the term $(x_{11}T_{\text{cell}} + x_{13}T_{\text{cell}}^2)$. With the LSQ optimized values of $x_{11}$ and $x_{13}$, this term causes a slight increase in OCV at low temperature near zero current, but this is tolerable, because the battery model should be used with higher currents.

In Eq. (18), the effective resistance depends exponentially on cell temperature, approximating the Arrhenius relation. The exponential dependency on SOC reflects the experimentally observed, but not clearly understood, increase in resistance when SOC approaches 0 and 1 [163–165]. The remaining terms in the are small empirical corrections which were found to improve overall accuracy.
Although 20 is a large number of model parameters, the voltage behaviour of a Li-ion battery in the battery temperature range \([-10^\circ C, +70^\circ C]\) displays such variety that a different parameter set \(X\) is used for each of the following cases:

1. Charging at low battery temperature (CL)
2. Charging at high battery temperature (CH)
3. Discharging at low battery temperature (DL)
4. Discharging at high battery temperature (DH)

This division leads to four different voltage quarter-models. The parameters for each quarter-model are shown in Table A3. For the discharging quarter-models DL and DH, some parameters, e.g. \(x_{29}\) and \(x_{29}\), were found to have a negligible effect on the performance, and were set to zero post-optimization to simplify computation.

The four quarter-models are combined into two half-models for charging and discharging, see Figure 13. To describe this process, let \(V_M, M \in \{CH, CL, DH, DL\}\) be the voltage outputs of the quarter-models and \(V_C\) and \(V_D\) be the voltage output of the charging half-model and discharging half-model, respectively. The following relation is then used to form the half-models:

\[
V_C = w_{CH}V_{CH} + w_{CL}V_{CL}, \quad V_D = w_{DH}V_{DH} + w_{DL}V_{DL}
\]

(19)

where \(V_M, M \in \{CH, CL, DH, DL\}\) are the voltage outputs of the quarter-models and \(w_M, M \in \{CH, CL, DH, DL\}\) are dimensionless weights calculated using:

\[
\begin{align*}
w_{CL} &= \Gamma(w_1, w_{s,C}) + L(w_1, w_{s,C}) \arctan[(T_{cell} - w_1) w_{s,C}] \\
w_{CH} &= 1 - w_{CL} \\
w_{DL} &= \Gamma(w_2, w_{s,D}) + L(w_2, w_{s,D}) \arctan[(T_{cell} - w_2) w_{s,D}] \\
w_{DH} &= 1 - w_{DL}
\end{align*}
\]

(20)

Here \(w_{s,C} = -0.4\) and \(w_{s,D} = -0.3\) are parameters that govern the size of the “transition region” between low battery temperature and high battery temperature quarter-models. These values were selected by hand so that the transition from low to high temperature is continuous and smooth, without overly sacrificing accuracy. Parameters \(w_1 = 16.16\) and \(w_2 = 25.51\) determine the location of the centre of the transition region and were optimized with MATLAB by minimizing the mean squared error (MSE) between predicted and measured voltage. \(\Gamma\) and \(L\) are scaling functions for ensuring that relative weights of the low-temperature submodels are unity at \(-10^\circ C\) and that relative weights of the high-temperature submodels are unity at \(+70^\circ C\). This essentially leads to low-temperature submodels dominating the low-temperature region and high-temperature submodels dominating the high-temperature region. They are calculated using the following relations:

\[
\Gamma(w, w_s) = \left(1 - \frac{\arctan[w_s(-10^\circ C - w)]}{\arctan[w_s(70^\circ C - w)]}\right)^{-1}
\]

(21)
\[ L(w, w_s) = \frac{-\Gamma(w, w_s)}{\arctan[w_s(70^\circ C - w)]} \]  \hspace{1cm} (22)

For visual reference, the transition between high- and low-temperature models is shown in Figure 15.

**Figure 15.** Relative weights of submodels CL (charging at low battery temperature) and CH (charging at high battery temperature) and DL (discharging at low battery temperature) and DH (discharging at high battery temperature). Reprinted with permission from Publication IV. Copyright 2016 Wiley.

*Artificial neural network internal heating model*

The optimal architecture for the ANN used here was determined by trial-and-error [166] by training the ANN with a small dataset and calculating the MSE between simulated and measured heating rate. We used the default MATLAB neural network training algorithm, Levenberg-Marquardt, with early stopping technique. The resulting architecture has two hidden layers with 4 nodes in the first hidden layer and 3 nodes in the second, see Figure 16.

After selecting the architecture, the network was trained with the full training dataset. This results in a set of parameters (Table A4) that fully characterizes the ANN, which yields heating rate (\(^{\circ}\text{C/s}\)) as a function of SOC, current (A) and battery temperature (\(^{\circ}\text{C}\)).

**Figure 16.** Artificial neural network architecture for predicting heating rate. Reproduced with permission from Publication IV. Copyright 2016 Wiley.

*State of charge tracking model*

The SOC of the battery is updated as follows:
Research method

\[
SOC(t + \Delta t) = \begin{cases} 
SOC(t) - I \Delta t / (\eta_{\text{Coul, disc}} Q), & I \geq 0 \\
SOC(t) - \eta_{\text{Coul, char}} I \Delta t / Q, & I < 0 
\end{cases}
\]

(23)

where \(\eta_{\text{Coul, disc}}\) and \(\eta_{\text{Coul, char}}\) are the coulombic efficiencies of discharging and charging, respectively, \(I\) is the current (in A), positive for discharging and negative for charging, and \(Q\) is the cell capacity of 2.691 Ah.

The coulombic efficiency for both charging and discharging was determined by minimizing the MSE between measured and simulated voltage for all charging and discharging scenarios, see Figure 17. We find that the minimum voltage MSE for charging is reached with a coulombic efficiency greater than 1, which is physically unacceptable, so this value is not used for charging. Instead, for simplicity, we choose the same coulombic efficiency of \(\eta_{\text{Coul, disc}} = \eta_{\text{Coul, char}} = 97\%\) for both charging and discharging.

![Figure 17. Voltage mean squared error vs. coulombic efficiency under different types of scenarios. Reproduced with permission from Publication IV. Copyright 2016 Wiley.](image)

**Charging and discharging**

In the simulation program, the hybrid battery model is charged with given power \(P > 0\) by solving for the current \(I\) that yields voltage \(V\) such that \(P = |I \cdot V|\). Discharging at power \(P > 0\) is handled in the same manner. In both cases, battery SOC is updated using Eq. (23). If the high cutoff voltage limitation of 4.2 V would be violated when charging a cell, absolute charging current is reduced so that voltage is maintained at 4.2 V. This indicates a shift to the CV phase of CCCV battery charging. This CV phase continues until absolute current reaches the saturation value of 0.5 A. If the low cutoff voltage limitation of 2.5 V would be violated during discharging a cell, absolute discharging current is similarly reduced to maintain voltage at 2.5 V.

**Application in Publication V**

The battery pack model used in Publication V is based on this hybrid model for a Lithium-ion cell. The cell model is scaled up to form the battery pack in the EV by simply multiplying the output voltage and reducing the absolute input
current to maintain the same C-rate between the large battery pack and the small cell.

Thus, the voltage of the battery pack \( V \) at a certain current \( I \), battery temperature \( T_b \) and SOC is given by:

\[
V(I, T_b, SOC) = N_{\text{series}} \cdot V_{\text{cell}}(I \cdot Q_{\text{cell}} / Q_{\text{pack}}, T_b, SOC)
\] (24)

where \( V_{\text{cell}} \) is the hybrid model voltage output (in V), \( N_{\text{series}} \) is the number of cells in series (100 units [65]) and \( Q_{\text{cell}} \) and \( Q_{\text{pack}} \) are the ampere-hour capacities of the cell (2.691 Ah) and the battery pack (60.6 Ah [65]), respectively. The minimum voltage, or discharging cut-off voltage, of the battery pack is then equal to \( V_{\text{min}} = 2.5 \cdot V \cdot N_{\text{series}} = 250 \) V and the maximum voltage (charging cut-off voltage) is equal to \( V_{\text{max}} = 4.2 \cdot V \cdot N_{\text{series}} = 420 \) V.

The internal heating of the battery pack \( q_{\text{int}} \) (in W) is obtained by multiplying the heating rate given by the hybrid heating model \( p_{\text{heat}} \) (in °C/s) with the battery’s thermal mass \( m_b \) (in J/K):

\[
q_{\text{int}}(I, T_b, SOC) = m_b \cdot p_{\text{heat}}(I \cdot Q_{\text{cell}} / Q_{\text{pack}}, T_b, SOC)
\] (25)

In Publication V, the initial SOC at the beginning of the simulated period \( SOC(t = 0) \), is chosen to be close to the “equilibrium” value, i.e. the initial SOC that the vehicle would have after experiencing a long sequence of identical days. However, in Figure 37 we observe that the SOC of the fleet reaches equilibrium in only a few days. We use this notion to obtain the initial SOC by simulating two consecutive workdays and calculating results based only on the data from the second day.

4.6 Charging strategies (Publication I)

In this section, we describe the different charging strategies which allocate limited charging power to a group of grid-connected vehicles. The main goal in Publication I is to test different smart charging strategies that aim to maximize the total e-mileage of the vehicle fleet, and see how they compare against the ‘dumb’ equal allocation strategy.

The allocation methods, denoted by \( Z \) with a subscript specific to the strategy, operate by calculating “weight” values for each vehicle and apportioning the total power to the vehicles based on relative weight values. In more detail, this is performed as follows: let \( V_n \) be the set of vehicles that are connected to the power grid at node \( n \). Let \( X_v \) be those parameters of vehicle \( v \in V_n \) that affect the power allocation process (e.g. SOC and remaining parking time). Finally, let \( Z(X_v) \in \mathbb{R} \) be the output of the allocation function \( Z \) given \( X_v \). The power vehicle \( v \) may charge with \( P_{\text{draw,v}} \) is then given by:

\[
P_{\text{draw,v}} = \frac{Z(X_v)}{\sum_{v \in V_n} Z(X_v)} P_{\text{total,n}}
\] (26)
where $P_{\text{total,n}}$ is the total charging power available at node $n$. It can be easily verified that the combined charging power of all vehicles at this node is $P_{\text{total,n}}$ at maximum, so the total charging power limitation is not violated. Note that $X_p$ may include evolving variables such as SOC and remaining parking time, and therefore the charging power of a single vehicle may be time-dependent even if the number of connected vehicles stays constant.

An intuitive way of allocating power to vehicles is to divide it equally among all vehicles. In this case, $Z$ is simply a nonzero constant, e.g. 1. We wish to find out if strategies smarter than equal allocation can yield significant gains in terms of total e-mileage. An example of such a smart strategy would be $Z_\text{A} = 1 - \text{SOC}$, which favours, i.e. allocates more power to, vehicles that have a low SOC.

### 4.6.1 Predictive charging strategies

The above example strategy does not utilize possible knowledge of future behaviour of the vehicle, and therefore its potential is limited. If reliable predictions about future behaviour are available, these should be used to achieve higher gains in e-mileage. In Publication I, we use two different predicted parameters: the remaining parking time at current location and the distance driven before the next grid connection (next free distance, NFD). Exact predictions are easily obtained by running the trip generation algorithm once and recording the vehicle movement. This can be done because in the attraction-saturation model, the movement of vehicles is independent of SOC.

Two advanced charging strategies that utilize knowledge of the future are tested in Publication I. The first one accounts for the remaining parking time only, and the second considers both parking time and NFD. Their equations are as follows:

$$Z_B = \frac{Q_{\text{max}} - Q \text{SOC}}{w t_{\text{park}} + \bar{t}_{\text{park}}(1 - w) + 1} \quad (27)$$

$$Z_C = \exp\left(w_1 Q \text{SOC} + w_2 (\text{NFD} k - Q \text{SOC}) - w_3 \bar{P} t_{\text{park}} \right) \quad (28)$$

In Eq. (27), $Q_{\text{max}}$ is the maximum battery capacity (in kWh) among all vehicle batteries at the current node, $Q$ is the battery capacity of the vehicle (in kWh), $t_{\text{park}}$ is the remaining parking time of the vehicle (in time steps) and $\bar{t}_{\text{park}}$ is the mean remaining parking time for the current activity (e.g. working) among all vehicles in the simulation (in time steps), see Eq. (30) below. $w \in [0,1]$ is a dimensionless weight parameter that determines the relative emphasis between predicted and mean values. Note that because the vehicles are assumed identical, $Q_{\text{max}}$ is equal to any vehicle’s battery capacity.

In Eq. (28), NFD is next free distance (in km), see Eq. (31) below, $k$ is the electricity consumption (in kWh/km), $\bar{P}$ is a reference power of 12 kW, and the $w$:s are weight factors (in kWh$^{-1}$). The reference power value of 12 kW is selected for convenience, because $t_{\text{park}}$ is given in time steps (each with length of 300 seconds), and thus their product is exactly 1 kWh. In Eq. (29), the weight parameters $w_1$, $w_2$ and $w_3$ all have the dimension kWh$^{-1}$.
When predictions of future behaviour are involved, it is proper to also consider the effect of possible prediction errors on the results. To incorporate errors into our exact predictions, a Gaussian error term is added to both parking time and NFD.

Remaining parking times \( t_{park} \) and \( \bar{t}_{park} \) (in time steps) are calculated using:

\[
\begin{align*}
  t_{park} &= \max(t_D - t + \delta_{park} \tau, 0) \\
  \bar{t}_{park} &= \max(t_D - t, 0)
\end{align*}
\]

where \( t_D \) is the exactly known departure time step and \( \bar{t}_D \) is the mean of the exactly known departure time steps from workplaces among all vehicles in the simulation. \( \delta_{park} \) is an error scaling parameter (in time steps) which multiplies a normally distributed random number \( \tau \) with mean of 0 and standard deviation of 1. For example, a one-hour prediction error (\( \delta_{park} = 1 \) h/300 s = 12) would then mean that around 68% of the EVs depart within ±1h from the predicted time value.

Similarly to Eq. (30), the NFD is calculated using:

\[
NFD = \max(NFD_{exact} + \delta_{NFD} \tau, 0)
\]

where \( NFD_{exact} \) is the exactly known NFD (in km) and \( \delta_{NFD} \) is the error parameter for NFD (in km).

An overview of all the charging strategies used in Publication I is shown in Table 4.

<table>
<thead>
<tr>
<th>Allocation function</th>
<th>Parameters</th>
<th>Uses predictions</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Z_0 = \exp(w \text{SOC}) )</td>
<td>SOC</td>
<td>-</td>
<td>Favours either low SOC or high SOC, depending on ( w )</td>
</tr>
<tr>
<td>( Z_A = 1 - \text{SOC} )</td>
<td>SOC</td>
<td>-</td>
<td>Favours low SOC.</td>
</tr>
<tr>
<td>( Z_B = \frac{Q_{max} - Q_{SOC}}{w\bar{t}<em>{park} + \bar{t}</em>{park}(1 - w) + 1} )</td>
<td>SOC, remaining parking time</td>
<td>If and only if ( w \neq 0 )</td>
<td>Favours low SOC and short remaining parking time</td>
</tr>
<tr>
<td>( Z_C = \exp(w_1 Q_{SOC} + w_2 (NFD k - Q_{SOC}) - w_3 \bar{t}_{park}) )</td>
<td>SOC, remaining parking time, NFD</td>
<td>✓</td>
<td>Favours either low or high SOC, depending on ( w_1 ). Favours either short or long NFD, depending on ( w_2 ). Favours either short or long remaining parking time, depending on ( w_3 ).</td>
</tr>
</tbody>
</table>

### 4.7 Charging infrastructure and power system

In this section, we describe the infrastructure used for charging the EV fleet. In Publication I and Publication V, the infrastructure is very simple, while Publication II uses a more detailed model. Regardless of the level of detail, it is assumed that infrastructure investments are subsidized by the local government. Consequently, problems related to the commercialization of EV charging can be
ignored [167]. Similar assumptions have also been made by e.g. Wang et al. (2013) [69], Sathaye & Kelley (2013) [168] and He et al. (2013) [169].

4.7.1 Simple infrastructure model (Publications I and V)

Publications I and V use a simple infrastructure model in which EV charging is limited by the maximum power of the charging station (7.4 kW in Publication I, 3.6 kW in Publication V). This maximum power may depend on the type of the location, e.g. if maximum charging power at some location is set to zero, this location does not provide charging service. In both publications, charging is possible at home. In Publication I, workplace charging is possible in the base scenario, but in Publication V, this is allowed only in special cases. In both publications, each location that supports charging has enough charging stations so that no queuing is required.

Publication I further restricts charging by imposing a limit on total charging power at certain locations; the available charging power for workplace nodes is limited to 0.1 kW per assigned vehicle. This means that if there are 10 vehicles in the fleet that have node \( n \) set as their workplace node, the total charging power at node \( n \) is limited to 1 kW. If the total power were not restricted, the allocation methods described in Section 4.6 would be irrelevant. On the other hand, if no power is available, allocation is impossible. We found that 0.1 kW provided sufficiently scarce power to allow smart charging strategies to distinguish themselves.

In Publication V, the total charging power is unlimited at every location, but each charging station imposes a maximum charging power limit of 3.6 kW for a single vehicle in the base scenario.

4.7.2 Advanced infrastructure model (Publication II)

Publication II focuses on the impact of charging infrastructure and therefore, the level of detail is greater than in Publications I and V. This advanced infrastructure model accounts for the fact that parking slots are occasionally physically occupied by fully charge vehicles, which may prevent the charging of other vehicles with depleted batteries.

Overview

Each vehicle is assumed to have a dedicated charging station at home, operating at 3.7 kW. For workplaces, the charging infrastructure is defined by the following charging infrastructure parameters:

1. number of charging poles at each node (poles)
2. number of parking slots around each pole (slots per pole)
3. number of charging cables connected to each pole (cables per pole)
4. maximum power of a single charging cable (cable max power)
5. amount of time it takes to switch one charging cable from one vehicle to another (cable switching delay)
6. battery capacity
Note that this selection of parameters implies that each charging pole in the simulation is identical with respect to the number of slots, number of cables and switching delay. Moreover, each cable has identical maximum charging power. This approach allows for a simple setup procedure and more straightforward interpretation of results. Similar symmetry assumptions have been made by other authors [147,149]. The infrastructure parameters are listed in Table 5 along with their ideal values and their effect on the total e-mileage. They are further discussed in a separate subsection below, except for battery capacity.

When a vehicle arrives to a workplace node, it attempts to park at the pole that has the shortest queue (the lowest number of vehicles that will be charged before that vehicle). If the shortest queue is tied between two or more poles, the pole with the lowest identification number is chosen. If all the slots near every pole are full, the vehicle parks into a conventional parking slot for ICEVs, and cannot be charged unless moved.

The charging queue for each charging pole is generated using the above rules, i.e. in the order of arrival to the parking slots around the pole in question.

**Table 5.** Infrastructure parameters in Publication II and how they improve the total e-mileage of an EV fleet.

<table>
<thead>
<tr>
<th>Infrastructure parameter name (shorthand)</th>
<th>Base scenario value</th>
<th>Ideal value</th>
<th>How it improves e-mileage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery capacity (Battery capacity)</td>
<td>5 kWh</td>
<td>Large</td>
<td>More distance is covered before switching to ICE propulsion/charge-sustaining mode.</td>
</tr>
<tr>
<td>Number of poles (Poles)</td>
<td>20 in total</td>
<td>High</td>
<td>Queues are shorter and less vehicles are parked in slots with no access to charging.</td>
</tr>
<tr>
<td>Number of charging cables per charging pole (Cables per pole)</td>
<td>1</td>
<td>Number of slots per pole</td>
<td>One pole can charge more vehicles simultaneously. Less need for switching cables between cars.</td>
</tr>
<tr>
<td>Number of parking slots per pole (Slots per pole)</td>
<td>4</td>
<td>High</td>
<td>One pole can charge more vehicles without need to move any vehicles. Less cars are parked in slots with no access to charging.</td>
</tr>
<tr>
<td>Maximum power of charging cable (Cable max power)</td>
<td>3.7 kW</td>
<td>High</td>
<td>Individual vehicles are charged more rapidly, allowing the next vehicle in queue to begin charging sooner.</td>
</tr>
<tr>
<td>Charging cable switching delay (Cable switching delay)</td>
<td>15 min</td>
<td>0</td>
<td>Less downtime for cables; next vehicle in queue begins charging sooner.</td>
</tr>
</tbody>
</table>

**Charging infrastructure parameters in detail**

The charging pole is the central charging infrastructure element in our model and represents a charging access point that can charge one or more EVs simultaneously. Each charging pole has an associated area of service, which consists of one or more parking slots in its vicinity, see Figure 18. A charging pole can only be used to charge a vehicle located its own area of service and each parking slot only belongs to one area of service, i.e. each parking slot is only associated with a single charging pole.
As mentioned previously, every vehicle has a dedicated charging pole at home [136], but at workplaces the poles are more scarce. We assume that the limited number of workplace charging poles are distributed in a smart way such that their numbers reflect actual demand for charging. We therefore require that the number of charging poles at workplace node $n$ ($N_{\text{pole},n}$) is proportional to the number of vehicles assigned to that node:

$$N_{\text{pole},n} \approx \frac{N_{\text{vehicle},n}}{\sum_{n \in W} N_{\text{vehicle},n}} \cdot N_{\text{pole, total}}$$  (32)

where $N_{\text{vehicle},n}$ is the number of vehicles that have node $n$ set as their workplace, $N_{\text{pole, total}}$ is the total number of charging poles at all workplaces (one of the charging infrastructure parameters) and $W$ is the set of workplace nodes. Because the number of charging poles must be an integer at every location, the relation in (32) is approximate, and may not hold due to rounding errors. If the sum of the number of charging poles over all workplace nodes does not match the predetermined total number of workplace charging poles ($\sum_{n \in W} N_{\text{pole},n} \neq N_{\text{pole, total}}$), then values $N_{\text{pole},n}$ are slightly adjusted to ensure that the two values match.

More than one vehicle may charge simultaneously at the same pole if there are enough charging cables integrated into the pole. A charging cable can essentially be considered a charging station (or electric vehicle supply equipment) which may charge one vehicle at a time with a certain maximum power. The maximum number of vehicles that can charge at the same time at a specific pole is given by $N_{\text{ simult}} = \min(N_{\text{slot}}, N_{\text{cable}})$, where $N_{\text{slot}}$ is the number of slots in the pole’s area of service and $N_{\text{cable}}$ is the number of charging cables. This means that increasing the number of charging cables beyond $N_{\text{slot}}$ yields no additional benefit. However, increasing the number of slots past $N_{\text{cable}}$ does provide benefit. This is because fully charged vehicles continue to occupy their parking slot until the vehicle is moved. If all the parking slots in the area of service of some pole are occupied and the vehicles are fully charged, that pole is effectively out of service. Thus, having more parking slots makes the pole less likely to be out of service.

A vehicle that is fully charged cannot be moved away from the parking slot in the base scenario, unless the driver departs from the node. In selected special cases, we consider the possibility of physically moving fully charged vehicles to make room for depleted vehicles, even if that were economically unfeasible.
A charging cable that is connected to a fully charged vehicle provides no value, and therefore we allow some entity to switch the charging cable from a fully charged vehicle to a depleted vehicle located in the same area of service, after a certain delay. This delay is given by the parameter cable switching delay, which reflects the time it takes for the entity to disconnect the fully charged vehicle and connect the depleted vehicle. However, if a new vehicle arrives to the area of service, the switching delay is set to zero, because the driver of the arrived vehicle is present and can perform the switch themselves.

It should be noted that, although Publication II assumes that the entity that performs the cable switch is human, this does not necessarily have to be the case. The entity can also be e.g. an intermediary “switchboard” acting between the EV charging station and the EVs. In this case, when a vehicle becomes fully charged, the switchboard would automatically relay power from the station to another vehicle without need to unplug any charging cables.

The maximum charging power a connected vehicle can charge with is determined by the maximum power supported by the cable (cable max power). The maximum charging power for the entire pole ($P_{pole}$) is then determined by the number of cables and their maximum power: $P_{pole} = N_{cable} \cdot P_{cable}$. 
5. Results

5.1 Results to research question #1: Limited power allocation (Publication I)

This section will cover the results pertaining to research question 1. First, we discuss power allocation without any predictions about future trips made by the vehicles. We then move on to allocation strategies that utilize predicted travel information. Finally, we discuss the effect of prediction errors.

5.1.1 No knowledge on future trips

Figure 19 shows the relative increase in e-mileage with allocation strategy $Z_0$ (see Table 4) compared to equal allocation strategy (relative e-mileage increase, REMI), with different values of SOC weight parameter $w$ and different fleet battery capacities. We observe a change in the optimal value of $w$ as battery capacity changes: for very small batteries (less than 2 kWh), REMI is positive with positive values of $w$. For larger batteries (2–8 kWh), REMI is positive with negative values of $w$. Finally, for batteries larger than 8 kWh, REMI is nearly zero, implying that there is little improvement over the simple equal power allocation strategy.

The change can be explained by the fact that a small battery (e.g. 2 kWh) is more likely to be fully discharged during the next trip than a larger (6 kWh) battery, and because a battery with a low SOC is more likely to have just arrived at the node, having a longer remaining parking time and thus lower priority. Small batteries with high SOC should therefore be fully recharged rapidly. Larger batteries don’t have as high priority, because we may recharge the battery too much, i.e. the excess energy is not utilized. Therefore, with larger batteries, it is sensible to favour low SOC when allocating power.

However, as predictions are not utilized here, the effectiveness of this charging strategy is limited to only around 1% REMI.
5.1.2 Knowledge on future trips

The REMI using strategies $Z_B$ and $Z_C$ from Eqs. (27) and (28) is shown in Figure 20. For comparison, the figure also shows the REMI from a non-predicting strategy $Z_A = 1 - \text{SOC}$. We observe that, with complete knowledge of the travel pattern, strategy $Z_B$ yields a REMI of around 3.5% at most. The more sophisticated strategy $Z_C$ yields a REMI of up to 5.5%. However, with both strategies, the gains are heavily dependent on battery capacity. With a very small battery (1 kWh), the charging controller manages to recharge all batteries even with a bad strategy, and with large batteries (larger than 8 kWh), the vehicles manage to finish their travel in electric-only mode regardless of allocation strategy. In the area between these extremes (1.5–5 kWh), the battery capacity is suitable for effective smart power allocation.

It should be noted that although the REMI of 5.5% sounds modest, no strategy can increase the e-mileage by more than 11%. This is observed by removing the total power limitation at each workplace (“Upper limit” in Figure 20).
Results

Figure 20. Relative increase in e-mileage with 10,000 vehicles with different allocation strategies $Z_i$, fleet battery capacities and perfect predictions. Strategy $Z_A = 1 - S0C$. In strategy $Z_B$ (Eq. (27)), $w = 1$. In strategy $Z_C$ (Eq. (28)), $w_2 = 0$, $w_3 = 1$, and $w_1$ is optimized to the integer value that yields the highest e-mileage for the current capacity. Reprinted with permission from Publication I. Copyright 2013 Wiley.

Figure 21 shows REMI with strategy $Z_C$ (Eq. (28)). We see that REMI is positive with positive NFD prediction coefficients $w_2$ and that REMI decreases when $w_2$ decreases below zero. We gather that a smart allocation strategy should, in general, favour vehicles that will travel longer distances after departure, which is very intuitive.

If the prediction for remaining parking time is not used at all ($w_3 = 0$), the maximum REMI obtainable is around 1%. However, if this prediction information is combined with a prediction for the NFD, a REMI of 5% can be obtained with proper weight values. If only the remaining parking time prediction is used and NFD is ignored ($w_2 = 0$), the maximum REMI is slightly less, around 4.5%. This indicates best results are achieved when both predictions are used with a good choice of weight factors. Moreover, information on the parking time seems to have higher potential for increasing e-mileage than information on NFD.

Although not shown in the figure for readability, negative weight values for remaining parking time prediction $\sigma_3$ turned out to decrease REMI. This suggests that a smart allocation strategy should favour vehicles that have a short remaining parking time.
5.1.3 Effect of prediction accuracy

Figure 21 shows the effect that inaccuracies in the predicted parameters have on the REMI when using the allocation strategy $Z_p$ from Eq. (27). Here the horizontal axis displays the value of $w$. If $w = 0$, only the mean remaining parking time is used in the power allocation. If $w = 1$, the allocation strategy relies only on the predicted remaining parking time.

The figure shows that when only the average value of remaining parking time is used ($w = 0$), REMI is not dependent on the prediction accuracy. When the weight of prediction is increased ($0 < w < 1$) and there is no prediction error, REMI increases monotonically towards its maximum value at $w = 1$. This is because the charging controller can then effectively allocate more power to the vehicles that need it the most. However, when the prediction error increases, the controller is no longer able to allocate resources optimally and REMI decreases.

High prediction error in remaining parking time can be compensated by using a linear combination of the mean parking time and the error-contaminated predicted parking time. This is indicated by the local optima seen in REMI at values $0 < w < 1$ when the error is 4–8 h.

We also observe that a high prediction error (higher than 8 h) completely negates the REMI that could be gained from the prediction. If the error is very large, use of the prediction makes the e-mileage worse.

As seen in Figure 20, REMI is small when the battery capacity is large: with 10 kWh fleet battery capacity (right-hand side subfigure), REMI is very modest compared to REMI with 2 kWh fleet battery capacity (left-hand side subfigure). The highest REMI was obtained at a battery capacity of around 2 kWh.
Figure 22. Effect of parking time prediction on the e-mileage with different prediction errors (in hours) and fleet battery capacities. The horizontal axis depicts the linear combination of observed average parking time and the prediction of the parking time individually (0 = average, 1 = prediction). Smart control strategy $Z_p$ (Equation 27) is used. Reprinted with permission from Publication I. Copyright 2013 Wiley.

5.2 Results to research question #2: Effect of charging infrastructure on e-mileage (Publication II)

The effect of charging infrastructure is studied here using a pairwise comparison of different infrastructure parameters. The parameter that increases e-mileage the most with a similar resource investment is considered an infrastructure “bottleneck”. These bottlenecks are shown in Table 6. We assume that parameters identified as bottlenecks most often are the most critical parameters in the charging infrastructure.

5.2.1 Fleet battery capacity

In this section, improvements to fleet battery capacity are compared against the increasing the number of vehicle slots per charging pole, upgrading the maximum charging power of a charging cable and the increasing number of workplace charging poles. It turns out that battery capacity is the bottleneck in each comparison scenario.

Number of vehicle slots per charging pole

Figure 23 shows that battery capacity has a major effect on e-mileage while increasing the number of vehicle slots for each charging pole increases e-mileage by a relatively minuscule amount. This is expected, as a non-empty battery is guaranteed to be used every time the vehicle travels, but the use of public charging infrastructure is only possible when there is a vehicle slot, charging cable, and some charging power available.

However, even if the effect of slots is relatively small, the effect of slots is still significant, around 11% at 8 slots per pole, with small fleet battery capacities, as
is evident from Figure 24. With higher-capacity batteries, longer distances can be travelled without charging, and consequently, the total e-mileage is less influenced by the public charging infrastructure.

**Figure 23.** E-mileage as a function of slots per pole and battery capacity. Reprinted with permission from Publication II. Copyright 2015 Oxford University Press.

**Figure 24.** Relative increase in e-mileage when increasing the number of slots per pole from 1, for different battery capacities. Reprinted with permission from Publication II. Copyright 2015 Oxford University Press.

*Maximum charging power of charging cable*

Figure 25 shows a relationship similar to Figure 23; the effect of battery capacity is sufficiently strong that maximum charging power of the cable has a relatively small effect. With a wide range of fleet battery capacities, increasing maximum charging power does not improve total e-mileage at all. Therefore, the charging power of 3.7 kW from our base assumption is seemingly sufficient for workplace charging.
Figure 25. E-mileage as a function of maximum power of charging cable and battery capacity. Reprinted with permission from Publication II. Copyright 2015 Oxford University Press.

Number of workplace charging poles

Figure 26 shows that, once again, the battery capacity has an immense effect on e-mileage and that its counterpart, number of charging poles at workplace, has a relatively small effect. Workplace charging infrastructure improves the e-mileage by around 10%-units (0 to 100 poles), but battery capacity has the potential to improve e-mileage all the way to 100%.

With very small (less than 1 kWh) and large (higher than 15 kWh) fleet battery capacities, workplace charging infrastructure has only a small impact on e-mileage. This result is similar to the one in Publication I (Section 5.1.2), where it was noted that smart power allocation strategies have little effect with very small and large fleet battery capacities. Apparently, for both smart allocation of power and charging infrastructure, there exists a certain battery capacity region where their effect is noticeable.

Figure 26. E-mileage as a function of battery capacity and number of charging poles at workplace. Reprinted with permission from Publication II. Copyright 2015 Oxford University Press.
5.2.2 Number of vehicle slots per charging pole

In this section, improvements to the number of vehicle slots per charging pole is compared against adding more charging cables to each pole, increasing the maximum power of each charging cable and increasing the number of workplace charging poles. For the first two comparisons, we find that in the most realistic scenarios where moving of fully charged vehicles is not allowed, the number of parking slots per charging pole is the bottleneck. In the final comparison, this statement holds assuming it is more economical to increase the number of parking slots per pole than increasing the number of charging poles themselves.

Number of charging cables per charging pole

Figure 27 shows that e-mileage is increased the most by increasing the number of slots. Apparently, the charging pole can easily charge several vehicles with only a single cable when the cable is switched from one vehicle to the next after each full recharge. Added cables don’t have a significant effect on e-mileage, except when there are many slots (8). Note that the effect of adding more cables saturates at the number of slots, because a cable can only charge a vehicle parked in a nearby vehicle slot. Having more cables than slots would thus not be sensible.

If we add the possibility to move fully charged vehicles away from a slot, making room for another, depleted vehicle, we observe that the number of cables will have a stronger effect on increasing the e-mileage (Figure 28). The charging pole can now utilize extra cables more effectively, because the added cables are not made redundant by slot-occupying fully charged vehicles.

![Figure 27. E-mileage as a function of slots per pole and cables per pole. Moving of fully charged vehicles is not allowed. Reprinted with permission from Publication II. Copyright 2015 Oxford University Press.](image-url)
Figure 28. E-mileage as a function of slots per pole and cables per pole, when moving of fully charged vehicles is allowed. Reprinted with permission from Publication II. Copyright 2015 Oxford University Press.

Maximum charging power of charging cable

Figure 29 shows that the effect of increasing the charging power for the charging cable has little effect on e-mileage, except when the number of slots per pole is very high (over 8). Again, the charging pole has no problem charging the vehicles in its parking slots with the chosen base power of 3.7 kW, so increasing the power is not effective. When the number of parking slots per pole increases, the maximum number of vehicles in the charging queue also increases and at some point, there is not enough time to fully recharge every vehicle in the area of service at 3.6 kW. It is at this point where the charging power becomes the bottleneck. However, this notion is more theoretical than practical, because the shift occurs at 8 parking slots, which could be considered the maximum practical number of parking slots for a single charging pole. Therefore, the number of parking slots is the true bottleneck in this comparison.

We again tested the “impractical” scenario where the moving of fully charged vehicles is allowed. Here the situation is very different; even with only a single parking slot, power has a noticeable effect on e-mileage. When the power is high and vehicles can be moved, the charging pole can perform a rapidly repeating sequence consisting of charging and vehicle switching, serving a higher number of vehicles in total.
Results

Figure 29. E-mileage as a function of maximum power of charging cable and slots per pole. Moving of fully charged vehicles is not allowed. Reprinted with permission from Publication II. Copyright 2015 Oxford University Press.

Figure 30. E-mileage as a function of maximum power of charging cable and slots per pole, when moving of fully charged vehicles is allowed. Reprinted with permission from Publication II. Copyright 2015 Oxford University Press.

Number of workplace charging poles
Figure 31 shows how the e-mileage increases as more charging poles are added to workplaces and more vehicle slots are added to each charging pole. When the level of charging infrastructure at workplaces is low, e-mileage increases almost linearly as more poles are added. However, a much more affordable approach to obtain the same improvement in e-mileage is to increase vehicle slots for each pole. For example, around the same e-mileage is reached with 50 units of four-
slot charging poles and 150 single-slot charging poles. Because increasing vehicle slots is the more effective use of resources, we consider the number of slots the bottleneck in this scenario.

Figure 31. E-mileage as a function of workplace charging poles and slots per pole. Reprinted with permission from Publication II. Copyright 2015 Oxford University Press.

5.2.3 Number of workplace charging poles

In this section, the improvement of increasing the number of workplace charging poles is compared to upgrading the maximum power of each charging cable, reducing the switching delay for the cables and adding more cables to each charging pole.

Maximum charging power of charging cable

Figure 32 shows that the effect of charging power is already saturated at 3.7 kW while the number of charging poles continues to improve e-mileage up to around 150 poles. Although not shown, this 3.7 kW saturation was also observed for battery capacities 2 and 10 kWh. Because 3.7 kW is the charging power of the base scenario, we consider number of charging poles the true bottleneck in this comparison.
Figure 32. E-mileage as a function of maximum power of charging cable and number of charging poles at work. Reprinted with permission from Publication II. Copyright 2015 Oxford University Press.

Charging cable switching delay and number of charging cables per charging pole

Figure 33 shows that cable switching delay has a relatively small effect on e-mileage if the number of workplace charging poles is small (10 or less) or large (200 or higher). If there are only a few charging poles, there will be relatively little charging overall, no matter how fast the charging cable is switched. If, on the other hand, there is an abundance of charging poles, every arriving vehicle can park next to a vacant charging pole and there will be no need to switch the cable. We also observe that the e-mileage improvement saturates already at 1 hour switching delay. This is fortunate, because a 1-hour switching delay is certainly possible to arrange in practice.

However, if switching delay cannot be reduced for some reason, it is possible to compensate a long delay by adding more charging cables to the charging pole, as shown in Figure 34. For example, it is possible to obtain the same e-mileage improvement either by reducing delay from 4 hours to 1 hour, or adding one cable to the charging pole.
5.2.4 Bottleneck identification from a pairwise comparison

Table 6 shows that in a pairwise comparison, battery capacity is always the bottleneck for increasing e-mileage. This means that increasing battery capacity has a higher potential for improving e-mileage than the other parameters studied.

The number of parking slots around a single charging pole (“Slots/pole”) and the number of charging poles are both important charging infrastructure parameters, as both are identified at least 3 times as bottlenecks in a comparison scenario against the other parameters. However, due to the relatively high cost for building and connecting new charging poles, it is likely more efficient to prioritize having more parking slots around a single pole.
In the base scenario, the e-mileage is already in the “saturated region” for cable switching delay (“Sw. delay”) of 15 minutes and cable maximum power (“Power”) of 3.7 kW. Thus, improving either of these infrastructure parameters provides little additional benefit. Consequently, they are not considered bottlenecks for improving the charging of EVs.

Table 6. Pairwise comparison of charging infrastructure parameters. Parameters inside the matrix are the bottlenecks (i.e. improve e-mileage more effectively) in an upgrade comparison test, where two parameters are improved from their base scenario values. Text in italics signifies a result not based on a test, but inference. Reproduced with permission from Publication II. Copyright 2015 Oxford University Press.

<table>
<thead>
<tr>
<th>Poles</th>
<th>Cables/pole</th>
<th>Slots/pole</th>
<th>Power</th>
<th>Sw. delay</th>
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*Increasing slots per pole is likely more economical than increasing the number of poles.
Provided maximum power is around 2 kW or greater (as in base scenario).
Provided switching delay is around 1 h or less (as in base scenario).
Maximum power begins to matter only at unrealistically high number of slots per pole.
Both are relatively ineffective, but it is presumably easier to upgrade the cables than to reduce switching delay.
Charged battery is always used during travel, but the benefits of more cables per pole and shorter switching delay are situational.
Benefit of more cables is limited by the amount of slots, and slots were already identified as the bottleneck in a comparison against increased maximum power.
The effect of reducing switching delay saturates early, at around 60 minutes, so further reduction is not economical.

5.3 Results to research question #3: Effect of temperature on EV performance (Publication V)

5.3.1 Effect of temperature on secondary operation energy consumption

Figure 35 shows the mean hourly energy consumption of HVAC and BTM systems, i.e. total energy consumption of these systems during each hour divided by the number of simulated vehicles. At cold ambient temperature (−10°C), there is no observable cabin cooling and only a small amount of battery cooling during the main commuting hours. Most of the secondary operation energy is spent to heat the battery, followed by cabin heating. When the ambient temperature is approximately equal to room temperature, secondary operation load is at its minimum and we observe only battery cooling loads. This is sensible, as the optimal battery temperature and comfortable cabin temperature are both approximately equal to room temperature. At warm ambient temperature (+40°C) we observe no battery heating or cabin heating, because the vehicle is kept warm by the passive heat flow from ambient air to the vehicle. Most of the
Results

Secondary operation energy is spent to cool the battery, followed by cabin cooling. The shape of the battery heating and cooling at –10°C and at +40°C reflects the vehicle movement observed in Figure 11a.

![Mean secondary energy consumption over the simulated day at different ambient temperatures.](image)

**Figure 35.** Mean secondary energy consumption over the simulated day at different ambient temperatures. Reprinted with permission from Publication V. Copyright 2016 Elsevier.

### 5.3.2 Effect of temperature and standby operations on SOC

Looking at the median SOC of vehicles from Figure 36 we see that SOC versus time at –10°C ambient temperature deviates noticeably (up to around 3%-units) from the SOC at room temperature and above when there is no BTM on standby. Without standby BTM, the passive heat flux between battery and ambient air cools the battery. This increases internal resistance, and consequently, the voltage of the battery during charging, as seen from the number of vehicles with their batteries within 2% of their maximum voltage of 420 V. Because the final stage of CCCV charging is limited by voltage, less power is transferred to the battery. This causes the lower SOC at cold ambient temperature.
Results

Figure 36. Effect of secondary standby operations on charging the EV fleet at different ambient temperatures. In the lowermost figures, "near" means "within 2% of". Reprinted with permission from Publication V. Copyright 2016 Elsevier.

If secondary standby operations are enabled, additional power is consumed from the grid to maintain battery temperature between +10°C and +30°C. Consequently, a “baseload” consumption of around 30 kW appears over the whole day at −10°C. It seems that, at low ambient temperature, there is a trade-off between 1) maintaining the highest possible fleet SOC; and 2) having a low baseline EV consumption.

Figure 37 shows a more detailed breakdown of the fleet’s SOC at −10°C ambient temperature in 30-minute intervals. The median SOC of the fleet is clearly reduced when standby operations are disabled, by around 3-6%-units depending on the time of day. Although not shown here, this same comparison was also made for saturation currents of 0.2 A and 1.0 A. In both cases, the reduction in median SOC remained at 3-6%-units.
Figure 37. SOC distributions of EV fleet calculated over 30-min intervals at −10°C ambient temperature, with (top subfigure) and without (bottom subfigure) secondary operations. The thick line in bottom subfigure is the median SOC from top subfigure. Reprinted with permission from Publication V. Copyright 2016 Elsevier.

5.3.3 Effect of secondary operations on vehicle fleet utility

In the base scenario, the utility of the fleet is around 85% at and below room temperature of +20°C, as can be seen from Figure 38. At +30°C and above, the utility is slightly lower due to increased cooling load.

Figure 38. Utility of EV fleet under different ambient temperatures, charging infrastructure and secondary operation configurations. Reprinted with permission from Publication V. Copyright 2016 Elsevier.
If secondary standby operations are disabled, at −10°C utility reduces to around 82%, because all BTM and HVAC must now be performed during driving. There is no effect on utility at and above +20°C.

If **all** secondary operations are disabled, there is no effect on utility at +20°C and below, but it drops rapidly to 75% at +40°C, as tours will then fail due to battery overheating.

**Additional 3.6-kilowatt charging stations at workplace**
If charging infrastructure is added to the workplace, the utility of the fleet increases to 89% and above at all ambient temperatures, except in the case where BTM and HVAC are completely disabled. If this is the case, then at +40°C utility is even lower than in the base scenario, because workplace charging heats up the battery further, which increases the risk of overheating during a tour.

At −10°C ambient temperature, highest utility is achieved if all secondary operations are turned off. Even if battery internal resistance is higher at low battery temperature, overall the utility is not reduced because ohmic losses heat up the battery, which compensates for missing BTM. Nevertheless, this minor increase of around 1%-unit comes at a significant cost to driver safety and comfort.

**Additional 20-kilowatt fast charging stations at every location**
In a theoretical scenario where 20 kW would be installed at every location, the utility profile is similar to the previous case, but the overall utility is again higher; above 90%. Interestingly, this excessively costly solution would not bring much additional benefit compared to the more economical solution of adding 3.6 kW charging stations only at workplaces.

**5.3.4 Effect of temperature and standby operations on charging**
From Figure 39 we see that low ambient temperature increases the time spent in charging; when no standby secondary operations are performed, the median charging time increases by 70% when moving from room temperature to 0°C (65 min to 110 min). After reaching −10°C, charging time increases by further 88%-units. The reason for the increase in charging time is the lengthened CV phase due to higher internal resistance. At warm ambient temperatures (+30°C and +40°C), there is also an increase of 15–31%, caused by increased drivetime HVAC and BTMS consumption.
Preconditioning and BTM on standby significantly reduce charging time at low ambient temperatures; the median charging time at $-10^\circ$C ambient temperature is reduced by 28% (from 167 min to 120 min). At $0^\circ$C, this reduction is still over 10% (110 min to 97 min), but at $+10^\circ$C, there is only around 1% improvement. Because the two leftmost figures are similar, most of the improvement in the charging time seems to be due to BTM.

**Self-weighted mean charging power (SWMCP)**

The impact of temperature on the charging time is major, but the use of charging time as a sole metric may be misleading. This is because charging becomes less and less effective in terms of ampere-hours deposited per unit of time, due to the exponential decay of the charging current in the final phase of charging to maintain constant voltage. For this reason, we plotted the SWMCP (see Section 4.2.2) in Figure 40. This figure shows that in the base scenario (preconditioning and BTM on standby are enabled), median SWMCP decreases 15% (3.45 kW to 2.93 kW) when ambient temperature drops from $+20^\circ$C to $-10^\circ$C. If standby operations (both BTM and preconditioning) are disabled, we see almost no change in the median SWMCP, but the “low-power tail” of the distribution is longer. Moreover, if only BTM is operating during standby, the low-power tail is shorter than in the base scenario. BTM on standby thus improves charging for certain vehicles, but the impact on the median SWMCP is minimal. The use of preconditioning may slightly reduce SWMCP for some vehicles, as it is a load that competes with battery charging on the power coming from the EV charging station. It again should be noted that preconditioning and BTM are not included in the SWMCP.
5.3.5 Effect of temperature, battery thermal management system and cabin preconditioning on efficiency

Figure 41 shows that the median driving efficiency is maximized when the ambient temperature is close to the optimal battery and cabin temperature of $+20^\circ$C. This is expected, as less power is used by the HVAC and BTM systems to adjust the temperatures of the cabin and battery, respectively.

Preconditioning together with BTM improves the efficiency of the EV fleet, because the power grid now provides some of the energy required to reach desired battery and cabin temperatures during the trip. If cabin preconditioning and standby BTM are enabled, the median efficiency increases by 8% at $-10^\circ$C.
and by 9% at +40°C, compared to the median efficiency at these ambient temperatures without any secondary standby operations.

In all secondary standby configurations, efficiency is lowest at +40°C ambient temperature. While this may seem surprising, it is explained by the fact that, during use, the EV battery's temperature will increase “naturally” due to resistive heating within the battery. The colder the battery, the higher the resistance, and thus, the more the battery heats up. This negative feedback system reduces the need to heat the battery at low temperature. When one wishes to cool the battery, however, resistive heating no longer works in one’s favour.
6. Discussion

In this section, the theoretical and practical implications of the results are discussed and these are compared against results obtained by other researchers. The validity of the findings is then considered by introducing some complementary assumptions and discussing how they could affect the results.

6.1 Implications

6.1.1 Publication I / Research question #1

In Publication I, it was discovered that the equal power allocation strategy is a surprisingly effective way to divide limited charging power between several connected EVs. There are three reasons for this strategy’s unexpected success. First, a PHEV fleet with a very small battery capacity does not benefit from smart power allocation, as they will be able to fully recharge with practically any allocation strategy. Second, a fleet with large battery capacity also does not benefit from smarter power allocation, as they do not exhaust their all-electric range. Therefore, smart power allocation may only be beneficial for medium-sized battery capacities. The third reason is that smart power allocation strategies rely on predictions, which will inevitably contain errors. If these errors are sufficiently large, the equal allocation strategy will perform better (i.e. yields a higher e-mileage than) a smart power allocation strategy.

Because equal power allocation strategy is very easy to implement and does not rely on any predictions, the fact that it is an effective allocation strategy is good news for multiple-charger charging stations that might experience optimal power allocation problems in the future.

Figure 21 shows that a heuristic algorithm should allocate more power to vehicles that have less remaining parking time and longer next free distance. This result is in line with intuition: a vehicle that will soon depart for a long journey will value power more than a vehicle that will remain parked for hours. Galus & Andersson (2008) also assume higher priority (in their words, higher personal value) for vehicles with less remaining parking time in their power allocation heuristics [137].

Su & Chow (2012) claim that their estimation of distribution-based power allocation optimization algorithm provides uniformly higher departure SOC than a heuristic method [170] and the equal allocation method [82]. Indeed, the sim-
ple equal power allocation method cannot compete with such advanced optimization algorithms. Provided that sufficient computational power and communications capacity is available and affordable, we recommend that a more advanced online optimization system is used in place of the simple offline equal power allocation system.

Refs. [137] and [82] both account for electricity price in their power allocation optimization scheme, while we assume that power allocation is not affected by electricity price. PHEV owners are likely to have some individual differences, which would cause them to value a unit of energy differently. Our simplified approach gives more weight to the collective benefit (total e-mileage of fleet) instead of individual preferences (the sum of personal utility). While our method is less computationally demanding and easier to implement, we agree that the market-driven individual approach is more realistic in the long term and recommend that the individual differences are accounted for when possible.

In this publication, it was assumed that drivers would truthfully report their planned travel schedule. However, some people could try to abuse the system [136]; a person that wishes to maximize their personal e-mileage might untruthfully report that they are about to make a long journey with their vehicle soon, and consequently, the system will allocate more power to them. An allocation system that does not rely on truthful behaviour of PHEV drivers would likely lead to more realistic results. On the other hand, the equal allocation strategy fulfils this requirement.

An alternative to driver self-reporting would be to e.g. apply machine learning to historical data based on observations made on individual drivers. This would make it very difficult for a driver to game the allocation system in their benefit, but would also raise concerns about the drivers’ privacy.

6.1.2 Publication II / Research question #2

In Publication II, we found that PHEVs with smaller batteries benefit most from added charging infrastructure (see Figure 24). This is consistent with the finding by Dong & Lin (2012) [44]. The reason is intuitive: a smaller battery is more likely to be fully discharged during driving than a larger battery. The result implies that EVs in the future could be equipped with smaller batteries, reducing vehicle prices and thus increasing demand, provided that a sufficiently large public charging infrastructure is in place.

Another way of interpreting the result is that the same gasoline use reduction can be achieved either by increasing public charging coverage or increasing battery size (see Figure 26). This is also seen in other research: in Ref. [44], a PHEV fleet with all-electric range of 20 miles was found to have around the same gasoline consumption as a PHEV fleet with all-electric range of 10 miles. In a study by Smith et al. (2011) [171], battery size could be reduced by around 40% by providing charging opportunities during the day.

Battery capacity is the most important charging infrastructure parameter, and the second and third most important parameters are the number of parking slots around a single pole and the number of charging poles, see Table 6. It is very economically efficient to use the same charging pole and the same charging
cable to serve multiple vehicles around the pole without moving fully charged vehicles. Thus, we highly recommend placing the charging pole in a “central” location where it can serve as many vehicles as possible, i.e. where it can have the largest area of service. In this sense, the worst place to install an EV charging station would be a corner or a wall, where only one or two vehicles can use it. Unfortunately, this choice is seen quite often at public EV charging stations.

Different charging infrastructure parameters can compensate for one another to achieve the same fleet e-mileage, as is seen in e.g. Figure 31. As money is often the most important constraint for adding charging infrastructure, we should pick the development route with the highest cost-efficiency. For example, in Figure 31 the same fleet e-mileage can be achieved by having 50 units of four-slot charging poles and 150 single-slot charging poles, the former being a much more cost-efficient solution.

Increase in e-mileage saturates after a certain number of charging poles, see Figure 31. This suggests that, all other things being equal, improving EV charging infrastructure is subject to diminishing returns. Diminishing returns are also found by Berndt et al. (2015): increasing the number of charging plugs beyond a certain value does not improve charging time [97]. The practical implication is that, as public charging infrastructure grows, investing in additional infrastructure becomes less and less economically efficient in reducing gasoline consumption. Note that this assumes that the number of EVs, as well as the price of charging stations, is stable. If the EV fleet is growing, or the price of charging stations is decreasing (both of which are likely), it may well be cost-efficient to continue improving public charging infrastructure.

Diminishing results are also encountered when increasing EV battery capacity. This is observed in other PHEV studies, e.g. by Rautiainen (2015) [73]. In Publication II, Figure 23, Figure 25 and Figure 26, we see that the marginal benefit of increasing battery capacity becomes small at around 10-12 kWh. This battery capacity range corresponds well to the battery capacity suggested for a mid-size sedan or mid-size SUV by Kintner-Meyer et al. (2007) [172] and for a 40-mile PHEV by Pesaran et al. (2007) [53], which is a reasonable battery size in U.S., where typical passenger vehicles travel an average of less than 30 miles per day [47]. The battery capacity range also corresponds well to the battery capacities of 2017 PHEV models, which have a mean kWh capacity of 9.6 kWh and median capacity of 8.8 kWh (17 PHEV models from 11 manufacturers listed in Ref. [173]).

### 6.1.3 Publication V / Research question #3

In Publication V, we found that at −10°C ambient temperature, there is a trade-off between having a high fleet SOC and low baseline fleet power consumption, see Figure 36. This is because, for the battery to absorb additional energy at high SOC, its internal resistance must be reduced by heating, which consumes additional power. Thus, if EV owners are known to have high range anxiety and aim to always fully charge their vehicles, we would expect to see higher power consumption at cold ambient temperatures.
The second result from Publication V is that EV fleet utility is highest near +20°C ambient temperature and that standby operations slightly increase the EV fleet’s utility, see Figure 41. The same finding was made in Ref. [65]. However, there is no single secondary load (HVAC and BTM) arrangement that always yields the highest utility at every tested ambient temperature. A simple utility-maximizing solution appears to be disabling secondary loads below +20°C ambient temperature and enabling them above +20°C. At low ambient temperature, secondary loads can, in theory, be disabled, because resistive losses will heat the battery, compensating for lack of BTM. In practice however, without HVAC the cabin windows would frost, which poses a safety risk for the driver and others on the road. Consequently, the cabin should be sufficiently heated, even if it would lead to some planned tours being cancelled due to higher power consumption. At high ambient temperature, on the other hand, the battery easily overheats without BTM. Therefore, to realize more planned trips and achieve higher utility, BTM should be used.

A related result is that the median efficiency (km/kWh) of the EV fleet is maximized when the ambient temperature is near +20°C (see Figure 41), which coincides with optimal battery temperature and comfortable cabin temperature. The more the ambient temperature deviates from this value, the more BTM and HVAC are required. Moreover, cabin preconditioning and BTM have a positive effect of around 8–9% on median EV fleet efficiency at −10°C and +40°C.

Results 2 and 3 support the intuition that the power system should expect increased EV charging power consumption on cold and hot days.

The fourth result is that low ambient temperature (−10°C) significantly reduces the SWMCP of the fleet (15% compared to the base scenario, see Figure 40), i.e. low temperature makes charging less time-efficient, but for some vehicles, standby BTM and cabin preconditioning improve the SWMCP. Even though energy spent on BTM and preconditioning does not directly elevate the battery’s SOC, these secondary loads can improve the battery’s ability to absorb more energy per unit time due to lower internal resistance. For some vehicles, the net effect is higher SWMCP, and for others, the net effect is lower SWMCP. It is likely that the deciding factors for the net effect are the battery’s SOC and temperature during plug-in. From a fleet management perspective, this implies that the use of BTM and preconditioning during parking would have to be decided case-by-case by e.g. an artificial intelligence to make EV charging as time-efficient as possible. Moreover, ambient temperature’s effect on SWMCP should be considered by EV fleet owners looking to minimize their vehicle downtime. For example, it may be economical to pay extra to have access to a heated parking garage.

The final result from Publication V is that having abundant quick (20 kW) charging stations provides little additional EV fleet utility compared to having normal (3.6 kW) charging stations at home and at workplace (see Figure 38), a finding that was also made in Refs. [45,73]. Apparently, the two “lowest hanging fruits” for maximizing EV fleet utility are installing charging stations at home and workplace.
6.2 Reliability and validity

As the research area of EV fleet studies is large and relatively complex, a great many assumptions must be made about e.g. vehicle technology, driver behaviour and future societal development, to arrive at numeric results. These assumptions may have a dramatic effect on our findings, which we discuss in this section. In the same manner, we also discuss the reliability of our input data.

6.2.1 Society-level assumptions

The rebound effect, which here refers to the phenomenon where predicted energy savings from EVs are not realized due to the increase in consumption induced by lower operating costs [174–176], has been excluded from the scope of this thesis. This phenomenon can have a major effect on our results, as the EVs operating cost per unit distance is only a fraction of that of an ICEV.

Telecommuting, which refers to people working remotely from home instead of physically commuting to their workplace, is likely to increase in popularity as more and more jobs are performed with a computer, and as high-speed internet connections become cheaper and more available. It is possible that the workplace of the future has no central physical office, but instead the employees are working in a “virtual office” while being physically spread all over the world. If this is the case, we may severely overestimate the energy consumption due to EV-based commuting and the effectiveness of workplace charging.

Moreover, private car ownership can reduce drastically due to the emergence of Mobility as a Service (MAAS) concepts. Examples of MAAS business models that are likely to reduce car ownership include taxi-like services (e.g. Uber [177]), fully digital car rental (e.g. EkoRent [178]), private car sharing (e.g. Go Now! [179]) and ridesharing (e.g. Lyft [180]) [181]. If private car ownership is no longer a popular lifestyle choice in the future, the results of this thesis must be viewed critically, as many of our findings assume that EVs are used by only a single person.

In all the main publications, we assume that gasoline price and electricity price remain at a such stable “normal” level that people would not cancel trips or plan more trips as a reaction to changes in these prices. For example, if electricity price would increase 100-fold overnight, this would have a major negative effect on the utilization of BEVs.

6.2.2 Driver-level assumptions

Range anxiety, which was defined in Section 2.2.3 and was excluded from the scope of this thesis, affects the true utility of an EV fleet. If the owners of the EVs have high range anxiety, the true utility of an EV fleet can be significantly lower than estimated in Publication V. In Publication I and II, there is no range anxiety, as all EVs were assumed PHEVs with a gasoline tank.

It was assumed that PHEV drivers and BEV drivers would behave similarly to ICEV drivers in the survey data. This assumption is reasonable for PHEV drivers that still need to purchase gasoline and who have no range anxiety, but it may
not hold well for BEV drivers that have very low operational costs and who may have high range anxiety. If BEV drivers are later found to behave very differently to ICEV drivers, the results of Publication V must be viewed critically.

In all the three main publications, we assumed that each EV has its own home charging station. This may not be possible for all drivers due to space limitations in crowded cities [14], or electric safety hazard [182]. If a significant portion of EVs cannot charge at home, we overestimate charging power at home and underestimate charging power at other locations such as workplaces.

It may be that EVs are not plugged in at home upon every arrival, contrary to what is assumed in the publications. This could happen due to short expected parking time, or the driver simply forgetting to plug the vehicle in after growing accustomed to conventional ICEVs. Because of these, we are likely to somewhat overestimate the e-mileage of PHEVs and the utility of BEVs.

6.2.3 EV and charging technology assumptions

For simplicity, we assumed that all vehicles would be identical in each simulation run. It is very unlikely that a large sample of EV owners would all own the same vehicle.

Elevation differences are not included in the simulations. Elevation difference will affect the energy consumption of the EV via increased consumption during uphill climb and increased energy recovery during downhill descent [108]. Consequently, depending on the landscape of the actual area where EVs are employed, we overestimate electricity consumption during some trips and underestimate it on others.

Battery ageing is considered beyond the scope of this thesis, as its effect is negligible in simulations of 1–3 days. Battery ageing can be simulated by e.g. reducing its maximum capacity as a function of ampere-hour throughput [183]. If the results of this thesis would be applied in a real-world scenario, we recommend including some battery ageing model separately. If this is not done, our results overestimate the e-mileage and utility of the EV fleet in the long term.

Advanced battery operations, such as battery cell balancing was excluded from the scope of this thesis. Such operations consume additional electric energy from the battery, and therefore, our results will slightly overestimate the e-mileage and utility of the EV fleet.

In Publications I and II, PHEVs were assumed to consume no gasoline in CD mode. Depending on the design of the vehicle power train, real-world PHEVs may consume gasoline to e.g. help maintain acceleration performance. If such vehicles are used, this thesis underestimates the amount of fuel consumed and overestimates in the amount of electricity consumed.

In Publications I and II, for the PHEVs, increased electricity consumption per distance driven as the vehicle battery becomes larger and larger (due to higher mass) was not explicitly considered. One can argue that larger battery mass can be compensated by having a smaller gasoline tank, which would reduce the vehicle's mass. However, if all other parts of the vehicle remain the same, these publications will slightly overestimate the e-mileage.
In Publication II, we assumed a multiple outputs multiple cables-type charging station (MOMC). Zhang et al. (2016) propose a single output multiple cables (SOMC)-type charging station which would not require manual switching of cables and would have lower cost than the MOMC stations [14]. Even though the downside of SOMC is that such equipment would not be able to charge multiple vehicles at the same time, the SOMC could be a very attractive alternative to the MOMC.

In Publications I and V, we assumed that EVs would not need to queue for charging, while in Publication II, queuing was included. Publications I and V will therefore overestimate e-mileage and EV utility, as some charging sessions would be delayed or removed due to queuing.

The hybrid battery model in Publication V is partly a black box model due to the presence of an ANN element, and may have discontinuities and errors that were not found during extensive testing. An advanced electrochemical battery model such as the one in Ref. [184] can be used to replace the hybrid model to arrive at more reliable and realistic results, at the cost of increased computation time.

6.2.4 Input data reliability

Travel survey data used in Publication V was for one day, and therefore it should not represent all days. It has been shown that there is considerable day-to-day variation [54,185], in terms of trip frequency, trip chaining, departure times and route choices [186]. For PHEV40s (40-mile CD range) assuming uniform daily vehicle miles travelled over time can cause nearly 68% underestimation of expected fuel use [54]. Multi-day surveys capture the day-to-day variation better [43], and these should be used when available. Moreover, travel data from the survey is based on phone interviews and self-reporting, and is thus subject to human errors. GPS-based data collection would be more reliable [27].

The hybrid battery model was trained based on measurements on two Lithium manganese cells. While the resulting model behaves in a very sensible manner, we acknowledge that there is always a risk that both cells could be defective, and thus not fully accurate representatives of a typical Lithium manganese cell. We suggest that results of Publication V are applied with caution, or at minimum tested against results obtained using a different battery model, preferably an electrochemical one.
7. Conclusions

In this thesis, we studied the performance and charging of EV fleets in an urban environment. Research focused on three different research questions that considered optimal charging power allocation, effect of charging infrastructure on e-mileage and effect of extreme temperatures on EV performance and charging, respectively. Using a variety of EV fleet modelling approaches and computer simulation, we obtained answers to these questions. Due to the large scale of the research topic, our results are dependent on a variety of assumptions. These assumptions should be kept in mind when applying the results discussed in the following.

For the first research question, we find that using smart charging power allocation strategies, the relative electric mileage increase compared to the “dumb” equal allocation strategy (REMI) is heavily dependent on the chosen battery capacity for the PHEV fleet. If knowledge of future driver behaviour is not available, REMI is restricted to around 1%. With full knowledge of future trips, i.e. remaining parking time and distance driven until next grid connection, REMI is around 5.5%. Errors in the predictions lead to lower REMI, and even losses in e-mileage compared to equal allocation strategy.

Our simulation results support the intuitive assumptions that e-mileage can be improved by allocating more power to vehicles that will travel longer distances before next grid connection and to vehicles that will depart earlier. The required information on future behaviour would either be given by the driver (e.g. wirelessly from a smart device) or predicted by an external entity (e.g. by applying machine learning to historical data).

For the second research question, we discover that PHEVs with small battery capacity gain the most benefit from added charging infrastructure, and that the same total daily EV fleet e-mileage can be realized by either improving public charging coverage or increasing battery capacity.

Battery capacity seems to be the charging infrastructure parameter with the highest potential, while number of parking slots per charging pole and the number of charging poles are the second and third most important parameters. To realize the highest potential of charging poles, these poles should allow charging from as many parking slots around it as possible, i.e. charging poles should not be placed in a corner.

Increase in e-mileage saturates after a certain public charging coverage is achieved. The same saturation occurs for battery capacity and charging power,
as well. We find that a “normal” charging power of 3.7 kW is sufficient for workplace charging, which is already supported by most installed charging poles in Finland [25].

For the third research question, we find that cold battery temperature makes it more difficult to fully charge the battery. This results in a lower median SOC for the EV fleet at cold ambient temperatures. Batteries can be heated when the vehicle is parked to achieve around 3%-units higher median SOC.

EV fleet utility and median efficiency (km/kWh) are highest near +20°C ambient temperature. The higher the temperature deviation from +20°C, the more energy is consumed by HVAC and BTM processes. This increases energy consumption per unit distance and leads to lower utility. Cabin preconditioning and BTM have a positive effect of around 8–9% on median EV fleet efficiency at −10°C and +40°C.

Cold temperature (−10°C) significantly reduces the rate of EV charging, but EV charging rate should not only be measured using total charging time, as charging gradually becomes less and less effective in terms of energy transferred per unit time as the battery’s SOC increases. Charging rate in terms of SWMCP can be increased for some, but not all, vehicles by using part of the charging station-supplied power to directly heat the battery. Battery heating did not have a major impact on the median SWMCP, as heating is a process that competes with battery charging on the limited power provided by the charging station.

During writing the publications and this thesis, we gathered valuable insight that can be helpful to future researchers in the same field. In general, we consider charging of EV fleets a multi-faceted area of research that should not be overly simplified as has been done multiple times in the past. Instead, care must be taken to have realistic assumptions about the charging infrastructure and appropriate consideration of temperature effects. If these considerations are not included, the results are likely to be misleading.

We recommend careful consideration on how vehicles physically connect for charging. The physical location of the EV charging station is very important, as it will determine how many vehicles can be positioned around it for easy access. EV fleet charging simulations should also consider the actual number of EV charging stations, whether those stations are occupied or not, and what kind of queuing system is in place (if any) for those stations. If instead it is assumed that charging will automatically and immediately occur when a vehicle is parked at a location with a charging station, we will risk severely overestimating the utility of the EV fleet.

We recommend that temperature effects and secondary loads (such as HVAC and BTM) are properly considered when studying EV charging and performance. The EV battery is a complex electrochemical system with strong temperature dependency, and neglecting these will lead to overestimating the charging rate and performance of the EV fleet. Highly detailed battery models (such as electrochemical battery models) and EV fleet models with high computational complexity can be used more easily in the future as high-performance computing becomes more accessible and affordable. These advanced models would be
able to find new charging phenomena that are beyond the reach of more rudimentary models such as the ones used here.

There is currently very little survey data available on EV users, mainly due to as-of-yet low number of EV owners. Consequently, the current study, as many other related studies, rely heavily on ICEV survey data. However, when people switch from ICEV users to EV users, complex effects such as range anxiety and rebound effect are likely to manifest. To capture these effects, EV-specific travel surveys should be performed when there are enough EVs on the road. We recommend that such surveys are conducted using GPS instead of error-prone manual reporting, and multi-day (longitudinal) instead of single-day, to capture variation between different days.

On a more broader perspective, researchers should be prepared for telecommuting, vehicle sharing and mobility-as-a-service solutions, which may heavily transform the landscape of personal transportation. Privately-owned cars are not necessarily the main method of transportation in future cities with little land area to spare for parking. Instead, there may be considerably less emphasis on movement of personnel and more emphasis on the movement of information, along with increased use of efficient integrated public and shared transportation options.
Errata

Publication II: Identifying bottlenecks in charging infrastructure of plug-in hybrid electric vehicles through agent-based traffic simulation
In Table 2, in comparison battery capacity vs. cables/pole, the result is not based on simulation, therefore the text should be in italics.
In Eq. (5), the relationship is proportional instead of an approximation: “≈” should be replaced by “∝”.

Publication V: Effect of extreme temperatures battery charging and performance of electric vehicles
In Nomenclature, the unit of heat flux $q$ should be watts (W).
References


[83] N.S. Pearre, W. Kempton, R.L. Guensler, V. V. Elango, Electric vehicles: How much range is required for a day’s driving?, Transportation Research Part C:


Appendix

Publication V simulation parameters

Table A1. Simulation parameters in Publication V.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Parameter</th>
<th>Value</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of vehicles</td>
<td>212</td>
<td></td>
</tr>
<tr>
<td>$\Delta t$</td>
<td>Time step length</td>
<td>20 s (battery operations), 60 s (vehicle movement)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Initial battery temperature</td>
<td>See Table 3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Initial cabin temperature</td>
<td>Ambient temperature</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Vehicles parked outdoors at ambient temperature</td>
<td>True</td>
<td></td>
</tr>
<tr>
<td>$T_a$</td>
<td>Ambient temperature</td>
<td>20°C / 293.15 K</td>
<td></td>
</tr>
<tr>
<td>$V_{\text{max}}$</td>
<td>Battery pack charging cutoff voltage</td>
<td>420 V</td>
<td></td>
</tr>
<tr>
<td>$V_{\text{min}}$</td>
<td>Battery pack discharging cutoff voltage</td>
<td>250 V</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Initial battery SOC</td>
<td>Near equilibrium, see Section 4.5.2</td>
<td></td>
</tr>
<tr>
<td>$Q$</td>
<td>Consumption model</td>
<td>See Figure 12</td>
<td>[65]</td>
</tr>
<tr>
<td></td>
<td>Battery capacity</td>
<td>60.6 Ah</td>
<td>[65]</td>
</tr>
<tr>
<td>$N_{\text{series}}$</td>
<td>Number of cells in series in a battery pack</td>
<td>100</td>
<td>[65]</td>
</tr>
<tr>
<td>$\eta_{\text{Coul, char}}$</td>
<td>Coulombic charging efficiency</td>
<td>0.9717</td>
<td>[187]</td>
</tr>
<tr>
<td>$\eta_{\text{Coul, disc}}$</td>
<td>Coulombic discharging efficiency</td>
<td>0.9717</td>
<td>[187]</td>
</tr>
<tr>
<td>$M_c$</td>
<td>Thermal mass of vehicle cabin</td>
<td>101 800 J/K</td>
<td>[188]</td>
</tr>
<tr>
<td>$M_b$</td>
<td>Thermal mass of battery</td>
<td>182 000 J/K</td>
<td>[188]</td>
</tr>
<tr>
<td>$K_{ac}$</td>
<td>Heat transfer coefficient between ambient and cabin</td>
<td>See Eq. (33) below</td>
<td>[188]</td>
</tr>
<tr>
<td>$K_{ab}$</td>
<td>Heat transfer coefficient between ambient and battery</td>
<td>4.343 W/K</td>
<td>[188]</td>
</tr>
<tr>
<td>$K_{bc}$</td>
<td>Heat transfer coefficient between battery and cabin</td>
<td>3.468 W/K</td>
<td>[188]</td>
</tr>
<tr>
<td>$P_{\text{BTMS, cool}}$</td>
<td>Battery cooler maximum power</td>
<td>3.54 kW</td>
<td>[65]</td>
</tr>
<tr>
<td>$\text{COP}_{\text{BTMS, cool}}$</td>
<td>Coefficient of performance of battery cooling system</td>
<td>2.5</td>
<td>[65]</td>
</tr>
<tr>
<td>$P_{\text{BTMS, heat}}$</td>
<td>Battery heater maximum power</td>
<td>0.3 kW</td>
<td>[65]</td>
</tr>
<tr>
<td>$\text{COP}_{\text{BTMS, heat}}$</td>
<td>Coefficient of performance of battery heating system</td>
<td>1</td>
<td>[65]</td>
</tr>
<tr>
<td>$T_{b, \text{key on, high}}$</td>
<td>Battery temperature above which battery cooler begins operation when vehicle is being driven</td>
<td>20°C / 293.15 K</td>
<td>[65]</td>
</tr>
</tbody>
</table>
Battery temperature below which battery heater switches on when vehicle is parked

\[ T_{h, \text{standby,low}} = 10°C / 283.15 \text{ K} \]  

Battery temperature above which battery cooler switches on when vehicle is parked

\[ T_{h, \text{standby,high}} = 30°C / 303.15 \text{ K} \]  

BTMS operation at standby

Enabled

BTMS operation during driving

Enabled

Cabin preconditioning interval

10 min prior to departure, until departure

Cabin temperature above which cabin cooler switches on when vehicle is moving or preconditioning is active

\[ T_c, \text{high} = 24°C / 297.15 \text{ K} \]  

Cabin temperature below which cabin heater switches on when vehicle is moving or preconditioning is active

\[ T_c, \text{low} = 16°C / 289.15 \text{ K} \]  

Cabin heater maximum power

4.0 kW

Coefficient of performance of cabin heating system

2.5

Cabin cooler maximum power

4.5 kW

Coefficient of performance of cabin cooling system

2.5

HVAC operation at standby (cabin preconditioning)

Enabled

HVAC operation on during driving

Enabled

Combined inverter and electric motor efficiency

0.9

Charging method

Constant current, constant voltage (CCCV)

Maximum charging power

3.6 kW

Locations with charging allowed

Home

Saturation current during constant voltage phase of charging

0.5 A

\[
\begin{cases} 
1522.6 \text{ W/K}, & \left( |P_{\text{propulsion}}| > 0 \right) \land \left( T_c > T_a \right) \land \left( T_c > 24\, ^\circ\text{C} \right) \\
22.6 \text{ W/K}, & \text{otherwise}
\end{cases}
\]
Hybrid battery model: Data collection and training

A total of 46 measurement sets were obtained for ambient temperatures from -10°C to +50°C and for currents from 0.5 A to 5 A in both charging and discharging, see Table A2. Each of the 46 measurements was performed twice using a set of two Lithium manganese dioxide (Sony US18650VTC5, 2600 mAh) batteries. All measurements were carried out with the constant current constant voltage (CCCV) method. Data sets 3 and 6 in Table A2 were excluded from model training due to measurement failure.

A single measurement set in Table A3 represents either: 1) from a fully charged state to a complete discharge using the CCCV method, including a short rest period after the CC phase, or; 2) a full charging of the battery from a totally discharged state using CCCV but without a rest period. All measurements were conducted in a controlled environment in a weather chamber (Arctest 400). Battery cycling was done with a programmable electronic load (Kikusui PLZ164WA) and a power supply (Agilent N5764A) connected to a data logger (Agilent 34970A data logger with BenchLink Data Logger 3 software). All temperatures were monitored with T-type thermocouples.

To ensure that the SOC is uniform in the dataset, we employed the measurement procedure by Hu et al. [163]: immediately before a charging measurement, the cell is discharged with the CCCV method at +20°C ambient temperature. When the CV phase ends at low temperature, the cell is brought to +20°C and the CV phase is finished at this temperature. This was done to ensure that the cell is fully charged for the next discharging measurement. Similarly, immediately before a discharging measurement, the cell is fully charged at +20°C ambient temperature and when the CV phase ends at a low temperature, the CV phase is finished at +20°C.

To reduce forced convection on the cells caused by the weather chamber fan, the cells are placed inside a cardboard box cover that shields them from direct high-speed airflow. This approach has also been used by e.g. Chacko and Chung [60].

In the ANN architecture we have chosen, SOC is one of the inputs. This poses a problem, because SOC must be known to train the ANN, but SOC cannot be directly measured in practice [191]. Thus, we create the following simple SOC estimator, where coulombic efficiency for charging $\eta_c$ and discharging $\eta_d$ is assumed linearly dependent on both cell temperature $T_{cell}$ and current $I$:

1. Initial capacity $C$ is set to zero: $C(0) = 0$.
2. Battery capacity is calculated iteratively:

$$C(t + \Delta t) = C(t) + \Delta t \cdot \begin{cases} I(t) / \eta_d(t), & I(t) > 0 \\ I(t) \eta_c(t), & I(t) < 0 \end{cases}$$

\forall t = \{0, \Delta t, 2\Delta t, ..., t_{end} - \Delta t\}$

Where $\eta_c = 1 + a_c I - b_c [70°C - T_{cell}]$ and $\eta_d = 1 - a_d I - b_d [70°C - T_{cell}]$

3. SOC is calculated by scaling the capacity $C$ to end capacity.

For charging scenarios:

$$SOC(t) = \frac{|C(t)|}{|C(t_{end})|}, \quad \forall t = \{0, \Delta t, 2\Delta t, ..., t_{end}\}$$

For discharging scenarios:
SOC\( (t) = 1 - \frac{|C(t)|}{|C(t_{end})|}, \quad \forall t = \{0, \Delta t, 2\Delta t, \ldots, t_{end}\} \)

The four parameters \((a_c, a_d, b_c\) and \(b_d)\) are then obtained by requiring that the standard deviation of the estimated battery capacity over all 46 measurement scenarios is minimized. This results in \(a_c = 0 \text{ A}^{-1}, a_d = 0.001121521 \text{ A}^{-1}, b_c = 0.001678467 \text{ K}^{-1}\) and \(b_d = 0 \text{ K}^{-1}\).

The SOC estimator is applied to the measurement data, which contains time series of voltage \(V\) (targeted ANN output), cell temperature \(T_{cell}\) (ANN input) and current \(I\) (ANN input) to arrive at SOC inputs for training the ANN.

**Table A2.** Measurement data sets used for the ANN battery temperature model training, with identification numbers between 1–48.

<table>
<thead>
<tr>
<th>Ambient temperature (°C)</th>
<th>Current (A)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-5</td>
</tr>
<tr>
<td>50</td>
<td>48</td>
</tr>
<tr>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td>30</td>
<td>32</td>
</tr>
<tr>
<td>20</td>
<td>24</td>
</tr>
<tr>
<td>0</td>
<td>16</td>
</tr>
<tr>
<td>-10</td>
<td>8</td>
</tr>
</tbody>
</table>
**Hybrid battery model: Empirical voltage model parameters**

**Table A3.** Empirical voltage model parameters. CH=charging at high battery temperature, CL=charging at low battery temperature, DH=discharging at high battery temperature, DL=discharging at low battery temperature.

<table>
<thead>
<tr>
<th></th>
<th>CH</th>
<th>CL</th>
<th>DH</th>
<th>DL</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-469.9056454</td>
<td>-132.5532666</td>
<td>72.92129425</td>
<td>49.19374567</td>
</tr>
<tr>
<td>2</td>
<td>-0.011934062</td>
<td>0.075313861</td>
<td>-0.136692345</td>
<td>-0.150362614</td>
</tr>
<tr>
<td>3</td>
<td>-0.003341501</td>
<td>-2.958E-05</td>
<td>0</td>
<td>309.234804</td>
</tr>
<tr>
<td>4</td>
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<td>3.086E-06</td>
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<td>-51.52382464</td>
</tr>
<tr>
<td>5</td>
<td>-0.046608755</td>
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<td>-5.180E-07</td>
<td>-0.000397478</td>
</tr>
<tr>
<td>6</td>
<td>-7.78772185</td>
<td>-0.253710145</td>
<td>-25.3902554</td>
<td>-16.31717853</td>
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<tr>
<td>7</td>
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<td>0.311933932</td>
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<tr>
<td>8</td>
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<td>-0.234873037</td>
</tr>
<tr>
<td>9</td>
<td>179.5830414</td>
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<tr>
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<td>-0.013608316</td>
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<td>11</td>
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<tr>
<td>13</td>
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<tr>
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</tr>
<tr>
<td>15</td>
<td>1.703724213</td>
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<td>3.271566001</td>
</tr>
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<td>16</td>
<td>-59.07497574</td>
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<td>-34.28379007</td>
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<td>0</td>
</tr>
<tr>
<td>20</td>
<td>2.485562569</td>
<td>1.886130613</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Hybrid battery model: Artificial neural network heating model parameters

Table A4 shows the neural network parameters as given by MATLAB version R2015a when exporting the network using GENFUNCTION. The following 3 modules are employed to process the inputs: MAPMINMAX, MAPSTD, PROCESSPCA. The transfer function used is $y = \frac{2}{1 + \exp(-2x)} - 1$.

**Table A4.** Neural network parameters for MATLAB implementation.

<table>
<thead>
<tr>
<th>Input</th>
<th>x1_step1_xoffset</th>
<th>x1_step1_gain</th>
<th>x1_step1_ymin</th>
<th>x1_step3_xoffset</th>
<th>x1_step3_gain</th>
<th>x1_step3_ymean</th>
<th>x1_step2_transform</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>2</td>
<td>-1</td>
<td>-0.003292447</td>
<td>1.151051158</td>
<td>0</td>
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</tr>
<tr>
<td>-5</td>
<td>0.199960008</td>
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<td>1.151051158</td>
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<td>0.099983302</td>
<td>2.140424278</td>
</tr>
<tr>
<td>-9.360785465</td>
<td>0.029019286</td>
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<td>-2.493298655</td>
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<td>0.89727993</td>
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<td>6.112797451</td>
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<th>y1_step2_gain</th>
<th>y1_step2_xoffset</th>
<th>y1_step1_ymin</th>
<th>y1_step1_gain</th>
<th>y1_step1_xoffset</th>
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The electric vehicle is not for everybody.

It can only meet the needs of 90 percent of the population.

—Ed Begley Jr.