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Master Thesis

The impact of rural road characteristics on the energy consumption of an automated bus operation

Submitted by

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Affidavit

I hereby declare that I have authored this master thesis independently, and that I have not used any assistance other than that which is permitted. The work contained herein is my own except where explicitly stated otherwise. All ideas taken in wording or in basic content from unpublished sources or from published literature are duly identified and cited, and the precise references included.

I further declare that this master thesis has not been submitted, in whole or in part, in the same or a similar form, to any other educational institution as part of the requirements for an academic degree.

I hereby confirm that I am familiar with the standards of Scientific Integrity and with the guidelines of Good Scientific Practice, and that this work fully complies with these standards and guidelines.

Vienna, December 2021 Sophie WEGSCHEIDER *(manu propria)*

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Abstract

A combination of electric-automated technologies has been hailed as a greener alternative to a traditional internal combustion engine and a solution to the increasing energy demand by the transport sector. Whilst many automated electric vehicles (AEVs) have been deployed in pilot projects over the last decade, their energy consumption has not been empirically tested, especially in rural areas where terrains are more challenging than typical urban road geometries. Since the specified energy consumption by manufacturers can often underestimate vehicles' actual energy consumption, field data is necessary to analyse how much energy is spent in real-world scenarios. Utilising data collected from the Digibus project, an automated electric shuttle service deployed in the municipality Koppl, this master thesis aims to examine the energy consumption of an automated bus service in a peripheral terrain with up to 8 % slope. A digital elevation model was calculated and a panel regression analysis was employed to explore the impact of rural road characteristics on the vehicle's energy consumption. The results confirm a correlation between energy consumption and road gradient and indicate that steep uphill slopes cause a significantly higher energy consumption than flat terrains. However, they also illustrate how significantly less energy is spent on downhill slopes compared to flat terrains. These findings imply that the counteracting effects will likely balance each other out leading to a similar average energy consumption compared to urban areas. The energy consumption of the AEV was also evaluated against traditional internal combustion engines of comparable size and was found to perform more energy-efficiently in all tested scenarios. Although there is still a lot of research and advancement of technology necessary for a big roll-out of AEVs, this thesis shows how much potential they have to reduce energy consumption within transport in both urban and rural scenarios.

Kurzfassung

Elektrische automatisierte Fahrzeuge (AEVs) werden als umweltfreundlichere Alternative zu herkömmlichen Verbrennungsmotoren und als Lösung für den steigenden Energiebedarf des Verkehrssektors gepriesen. Obwohl in den letzten Jahren viele Pilotprojekte mit automatisierten Elektrofahrzeugen durchgeführt wurden, wurde ihr Energieverbrauch nicht empirisch getestet, insbesondere in ländlichen Gebieten, wo das Gelände schwieriger ist als in typischen urbanen Gebieten. Anhand von Daten, die im Rahmen des Digibus-Projekts, einem automatisierten elektrischen Shuttleservice im ländlichen Koppl, gesammelt wurden, soll in dieser Masterarbeit der Energieverbrauch eines automatisierten Busdienstes in einem Gelände mit bis zu 8 % Steigung untersucht werden. Es wurde ein digitales Höhenmodell berechnet und eine Panel-Regressionsanalyse verwendet, um die Auswirkungen von ländlichen Straßenmerkmalen auf den Energieverbrauch des Fahrzeugs zu untersuchen. Die Ergebnisse bestätigen eine Korrelation zwischen Energieverbrauch und Straßenneigung und zeigen, dass steile Steigungen einen deutlich höheren Energieverbrauch verursachen als flaches Terrain. Sie verdeutlichen aber auch, dass auf Gefällestrecken deutlich weniger Energie verbraucht wird als in flachem Gelände. Diese Ergebnisse deuten darauf hin, dass sich die gegenläufigen Effekte wahrscheinlich ausgleichen, was zu einem ähnlichen durchschnittlichen Energieverbrauch im Vergleich zu städtischen Gebieten führt. Der Energieverbrauch von AEVs wurde auch mit dem herkömmlicher Verbrennungsmotoren vergleichbarer Größe verglichen, wobei sich herausstellte, dass der Minibus in jedem getesteten Szenario energieeffizienter ist. Obwohl noch viel Forschung und technologischer Fortschritt für eine breite Einführung von automatisierten elektrischen Fahrzeugen notwendig sind, zeigt diese Arbeit, wie viel Potenzial sie haben, den Energieverbrauch im Verkehr sowohl in städtischen als auch in ländlichen Szenarien zu reduzieren.

1. Introduction

Mobility is a key element of today’s life and the demand for mobility services is continuously increasing. However, in the light of growing environmental awareness and the climate crisis, the transport sector is facing huge challenges (Le Boennec et al. 2019; Underwood et al. 2014). Especially regarding energy consumption, transport is responsible for almost a third of the total global energy consumption which, in return, is the cause for greenhouse gas emissions and contributes to global warming. With over 90 % of vehicles driving on oil-based fuels and an increase in demand for mobility due to increasing living standards, emissions are constantly rising with the biggest growth in energy consumption compared to any other sector (International Energy Agency 2020). Moreover, higher living standards go along with an increase in individual mobility which only enhances the negative effects of transport (Conti et al. 2016; Khalili et al. 2019).

As an answer to these pressing issues, electrification and automation of transport have been praised for providing the solutions (Lee and Kockelman 2019). Electric vehicles are proven to be more energy-efficient than internal combustion engines (ICEs), they reduce oil dependency and can reduce emissions by 40 to 70 % depending on the electricity mix and location (Albatayneh et al. 2020). They also shift carbon emissions from the tail pipe towards electric generators which leads to fewer local emissions which affect people’s health, especially in dense urban areas (Schmidt et al. 2021). In these settings, electric vehicles have turned out to be particularly efficient due to their ability to regenerate energy while braking giving them a huge advantage over ICEs (Chen et al. 2021). Automation of vehicles, on the other hand, is predicted to make transport safer as most traffic accidents are caused by human error, as well as less congested due to the vehicles’ ability to communicate with other vehicles and road infrastructure leading to more ecological routing. Smoother driving cycles lead to a reduction of energy consumption and public transport can be more adaptable as automated vehicles can serve routes that are economically and ecologically not feasible in (non-autonomous) public transport due to savings in operating and personnel costs (Riener et al. 2020; Underwood et al. 2014).

In the light of these positive changes that both technologies are hoped to achieve, automated electric vehicles (AEVs) for public transport have emerged on the market. Over the last decade, small manufacturers have brought out automated electric shuttle buses that hold approximately 12 passengers and can drive up to 20 km/h (Antonialli 2019). Multiple pilot projects have been implemented in which their technology and automation level have been tested as well as people’s willingness to use AEVs. The automated electric buses have also served as a basis for a discourse on harmonisation and standardization of data in order to prepare stakeholders for the roll-out of automated vehicles (AustriaTech - Gesellschaft des Bundes für technologiepolitische Maßnahmen GmbH 2020). The shuttle buses have operated in various countries all over the world and projects have been situated mostly in closed areas like airports or hospitals and in urban settings (Cregger et al. 2018; Hagenzieker et al. 2021). Nonetheless, although the combination of automation and electrification is praised to lead to a reduction in energy consumption which is one of the most important problems within transport, the real-world energy consumption of the shuttle buses has not been the focus of research so far.

Additionally, most pilots have been done in urban scenarios rather than rural areas where road conditions and gradients can be quite varied compared to well-maintained urban roads that are typically relatively flat (European Road Safety Observatory 2006). Since steep slopes cause higher energy consumption, these terrains can be challenging and cause the vehicle's battery to drain faster than in flat areas (Liu et al. 2017). However, especially in rural areas where public transport can be sparse or non-existent, there is a big potential for automated electric shuttles to make the public transport system more attractive. Especially the last mile problem, which refers to travellers finding it difficult to reach their final destination from a transportation hub like a railway station, could be solved by AEVs in rural areas (Qin et al. 2018; Riener et al. 2020).

Since the real-world energy consumption of AEVs that are currently on the market has not been investigated in-depth by current research, this master thesis aims to fill this gap. It provides an approach to estimate the energy consumption of an automated electric vehicle in operation with a special focus on rural and hilly environments. It also puts the estimated energy consumption into context by comparing it with an internal combustion engine and evaluating in which conditions they perform better or worse. The goal is to identify scenarios where AEVs are more energy-efficient and scenarios where ICEs might be favourable. Thereby, the following research questions are addressed:

(1) What is the impact of rural road characteristics on the energy consumption of an automated electric bus operation?
(2) How does the energy consumption of an electric autonomous vehicle compare to a traditional combustion engine?

The findings of this thesis contribute to the understanding of the current technology of AEVs and their energy consumption as well as the potential for further developments within this field. They serve as a foundation for a data-based discourse over the deployment of automated electric shuttle buses in rural areas.

2. Literature Review

This chapter gives a summary on the main findings of the literature review that has been conducted on the topic of autonomous electric vehicles and their potential in rural areas. The aim is to lay the foundation in order to give context for the quantitative analysis of this thesis that will be explained in the next chapters.

The chapter is divided into four parts, starting with the current developments and trends within the transport sector and its role in global energy consumption. Following, an overview is given on the electrification of transport which is seen as a great chance to achieve the goal of reducing emissions drastically within the next decade. The third sub-chapter focuses on the estimation of energy consumption by electric vehicles in current literature. After that, the automation of transport is presented, giving an understanding of why automobile manufacturers are putting so much effort into developing automated vehicles at the moment. Lastly, everything is tied together by explaining the potential of automated electric vehicles while research gaps are identified and explained.

2.1. Effects of Global Transport

Mobility of people as well as goods has played a key role in society and economic activities over the last decades and keeps being the basis for many processes the modern world is heavily relying upon. Even as the socio-cultural standards of success are changing and not defined by the ownership or use of a car anymore, comfort while travelling and autonomy remain very important (Le Boennec et al. 2019).

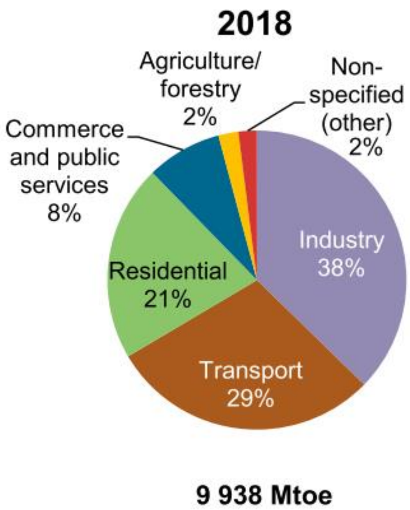

Figure 2.1-1 Worldwide total final consumption of energy divided by sectors (International Energy Agency 2020)

Looking at the global energy demand by sectors, the transport sector accounts for almost 30 % of total final consumption of energy worldwide (see Figure 2.1-1). Donev et al. define the total final consumption as “the aggregate of all of the end use energy that is used for providing various energy services”. Therefore, this percentage includes most dominantly running cars and other vehicles burning fuel, but also the production of vehicles, the creation of roads, airports, sea ports and pipelines (Donev et al. 2021).

For other sectors like industry or the residential sector, the share of energy use has been quite stable over the last 50 years. However, transport has recorded the biggest growth in the timespan since 1971 (International Energy Agency 2020) and is continuing to grow as economic growth raises standards of living and demand for personal transportation (Conti et al. 2016).

Globally, passenger travel has increased by 74 % in the span from 2000 until 2015 while the motorisation rate has increased by 27 %. Especially in urban regions, the global demand for passenger mobility is estimated to double by 2050 (Nemoto et al. 2021), as 55% of the world’s population is currently living in urban areas and this number is estimated to rise to 68% (Antonialli 2019).

Since the transport sector is one of the most energy-intensive sectors in the world, this also makes it one of the major contributors to the earth’s rising greenhouse gas emissions (Albatayneh et al. 2020). With over 92 % of the energy for transport provided by oil, 3 % by natural gas and only 1 % by electricity and 4 % by other fuels, there is a lot of potential for change. However, major suppliers of fossil fuels do not expect huge changes of fossil-fuel demand over the next years, as there is such high dependence on them (Khalili et al. 2019). Especially in developing countries, the transportation energy demand is growing fast, therefore, it becomes even more pressing to reduce emissions in order to combat climate change (Albatayneh et al. 2020).

As the effects of climate change are more and more evident, the European Commission has published a white paper addressing the need for the transport system to become more sustainable. One of the big goals is for the transport sector to reduce greenhouse gases by at least 60 % until 2050, with respect to 1990. As transport is responsible for almost a quarter of Europe’s greenhouse gases and seen as the main cause of air pollution in cities, three key levers have been defined in order to steer transport toward low carbon emissions:

- Higher efficiency of the transport system
- Low-emission alternative energy for transport
- Low- and zero emission vehicles (European Commission 2016).

However, not only is the European Union taking steps, but many countries are participating in an energy transition (Huang and Zhai 2021; Nam and Jin 2021) as the target of the Paris Agreement to keep temperature rise well below 2 degrees Celsius is getting harder to achieve (United Nations Framework Convention on Climate Change 2015). The main focus is the decarbonisation of electricity and heat generation as well as the transport sector since they together accounted for two thirds of the global CO_2 emissions in 2017 and almost the entire global growth in emissions since 2010. Especially the road transportation with mostly passenger travel is responsible for three quarters of the total transportation emissions (Yuan and Li 2021; Yuan et al. 2021).

Similarly to the European Union, the major solutions to reducing emissions worldwide are, firstly, lowering primary energy intensity by improving energy efficiency as well as, secondly, electrification based on renewable energy. Implementing these solutions has the potential of reducing carbon emissions by more than 30 % (Nam and Jin 2021).

The main strategy for transport at the moment is alternative fuel penetration, especially with electricity, but also including hydrogen and renewable fuels like synthetic fuels. Moreover, technological efficiency will play a role as well as demand-side solutions (Khalili et al. 2019) that involve end users and, thus, lifestyle and behavioural change (Creutzig et al. 2016). In this regard, the focus on public transport is also seen as a major factor in order to reduce individual ownership of private vehicles and, hence, to reduce emissions (Pamuła and Pamuła 2020). An attractive public transport system can lead to a sustainable change in mobility behaviour as individual mobility can be replaced by public mobility in many cases. This then leads to fewer local emissions and less noise pollution as well as a significant decrease in energy consumption. Furthermore, far less sealed land is required for parking private vehicles, while parking time accounts for an average of 23 out of 24 hours or 96% of a day (Riener et al. 2020).

Achieving a decrease in private vehicles is especially difficult in rural areas where mobility is a central prerequisite to participating in social life or having access to jobs and services for health care. Access to mobility and its maintenance in rural areas are decisive factors for the quality of life and contribute to these regions remaining attractive places to live in the future (Berg and Ihlström 2019). Public transport often is not able to ensure coordination between the means of transport at transfer points, e.g. when changing bus lines or between train and bus, so people opt for private vehicles instead. Therefore, there is a need for solutions for public transport to become more ecologically friendly and economically attractive in less densely populated areas in the future (Riener et al. 2020).

2.2. Electrification of Transport

There are different sectors and areas in society with the possibility to lower emissions and achieve carbon neutrality (Huang and Zhai 2021), however, the largest potential is seen by improving transport, particularly via electrification (Creutzig et al. 2016). The environmental effects of global transport as well as concerns about energy security are the main reasons for trying to reduce energy consumption by vehicles while still keeping all processes that involve mobility intact. The electrification of transport seems to be one of the most effective solutions (Pollák et al. 2021).

Electric vehicles (EVs) can be broadly defined as road vehicles whose propulsion involves electricity or as “vehicles with motors that are powered by electricity rather than liquid fuels” (Foley et al. 2020).

Electromobility dates back to the 19th century when Thomas Davenport built the first electric car that included a non-rechargeable battery. After that, a lot of research went into inventing the first lead-acid batteries that could be recharged. The entry of electric vehicles to the market shaped and altered the transport ecosystem including old and new players and brands (Schmidt et al. 2021). With the development of new battery technologies, electric vehicles became a commercially available product since the late 2000s and, regarding technology, development has not stopped. Tesla, Nissan and BMW have all come out with EV models that offer the possibility of charging the battery to 80% in only 30 minutes (Wang 2016). In general, the whole automobile industry is pursuing strategies to move e-mobility further, Volkswagen shared their "e-offensive" and Hyundai included electromobility into their "Strategy 2025" while Toyota published an electrification strategy for sustainable mobility (Volkswagen AG 2021; Hyundai Motor Company 2019; Toyota UK Magazine 2017).

Table 2.2-1 Different types of Electric Vehicles with their acronym and description (based on (Harrison et al. 2018))

Acronym	Term	Description
BEV	Battery Electric Vehicle	A vehicle with an electric powertrain fully powered by an internal battery charged from an external source.
PHEV	Plug-In Hybrid Electric Vehicle	A vehicle with a combustion engine as well as an electric powertrain which is powered by an external source.
HEV	Hybrid Electric Vehicle	A vehicle with an electric powertrain which is powered by a conventionally fuelled combustion engine.
FCV	Fuel Cell Electric Vehicle	A vehicle with an electric powertrain powered by a hydrogen fuel cell.

Annual sales of electric vehicles (EVs) have been steadily rising since 2011, with a global sale of 2.1 million in 2019. This increase can be explained by the continued improvement in the cost and performance of commercial EVs, environmental awareness an increased EV options available to consumers (Ahmed et al. 2021). These options include mostly four types of EVs (shown in Table 2.2-1) which are battery EVs, hybrid EVs, plug-in hybrid EVs and fuel-cell EVs (Chen et al. 2021). When talking about EVs, however, people usually refer to battery electric vehicles (BEVs) as they are solely powered by electricity and do not rely on any other fuel.

One of the strongest arguments in favour of electric mobility is how it shifts carbon emissions from the tail pipe towards electric generators. Therefore, EVs make an especially big difference if the carbon intensity of the generation mix is low. As the share of renewable energy within the electricity mix is growing, carbon emissions are decreasing, however, not only $C0_2$, but also many other pollutants like nitrogen oxide or particulate matter (Schmidt et al. 2021).

The difference between a conventional internal combustion engine (ICE) and an electric vehicle is that there are no emissions during the usage of EVs. The well-to-wheel analysis helps explain this as it monitors energy consumption and emission production from production of energy to its final consumption and is divided into two parts. The first phase, well-to-tank, includes energy and emissions that are consumed and produced during energy production, while the second phase, tank-to-wheel comprises energy consumption and emission production during vehicle operation (Petro and Konečný 2017). Generally, it is important to always clarify the scope of the measurement method when describing energy consumption. For EVs, the tank-to-wheel scope corresponds to a plug-to-wheel scope as it refers to the timeframe after plugging the vehicle to the alternating current (AC) electric grid. It then covers the energy consumption of the energy that is stored within the battery for powering both the drivetrain and auxiliaries (Cauwer et al. 2015a).

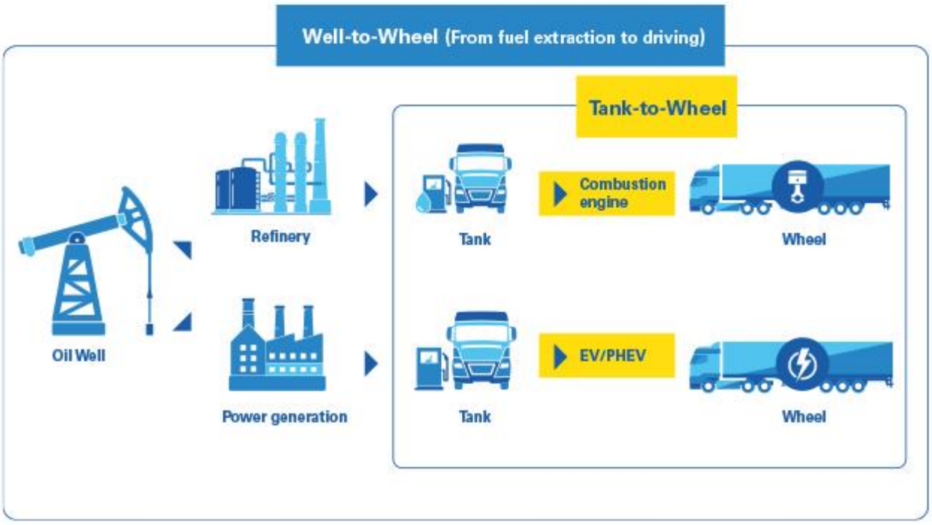

Figure 2.2-1 Well-to-wheel approach for ICEs as well as EVs/PHEVs (IRU International Road Transport Union 2018)

Within the well-to-wheel approach it becomes clear how EVs have a major advantage over ICEs regarding emission production as they cause fewer local emissions and improve public health (Yuan et al. 2021). Moreover, there has been a lot of debate whether EVs cause decreased emissions overall, as electricity generation involves using fossil fuels (well-to-tank). Some question if the diffusion of EVs can mitigate climate change as long as electricity is not fully decarbonized. However, in 2020 Knobloch et al. have calculated that already under current carbon intensities of electricity generation electric cars are less emission intensive than fossil-fuel-based alternatives in 53 world regions, representing 95% of the global transport. One of the few exceptions is Poland where coal remains the main energy source. These findings show that already, EVs can mitigate climate change under the current conditions and there is a big potential to reduce emissions even more while decarbonising the electricity grid (Knobloch et al. 2020).

When examining energy loss along the well-to-wheel chain, EVs perform very well regarding energy efficiency (Cauwer et al. 2015a; Zuccari et al. 2019; Albatayneh et al. 2020). EV motors are more efficient than internal combustion engines with the ratio between wheel power to total energy in ICEs and BEVs being in the range of 15-24 % and 60-70 % respectively (Xie et al. 2020). However, in a well-to-wheel approach, the energy source plays a vital role. Values of energy efficiency for EVs can drop significantly when renewable energy sources are used, from around 40 to 70 % depending on the energy source and its location (Albatayneh et al. 2020).

Other benefits of opting for EVs are the improvement of energy security through reducing the dependency on fossil fuels as well as their lower operational costs (Yuan et al. 2021). However, the global market share is still incredibly low with only around 1 % and in some countries even less than that (Foley et al. 2020). The reason for this are high purchase prices, a limited driving range which can cause so called “range anxiety” and longer charging time compared to conventional vehicles (Ajanovic and Haas 2018). Schmidt et al. point out that the prerequisite for using an electric vehicle is having infrastructure available for them to recharge their batteries. Therefore, they emphasise how poor availability of dedicated infrastructures and low user awareness are the main issues that need to be addressed (Schmidt et al. 2021).

2.3. Estimation of EV Energy Consumption

For estimating energy consumption of EVs, the scope in current literature is usually a plug-to-wheel framework (Chen et al. 2021). The following figure describes the energy flow starting from the energy stored within the battery powering the generator until reaching the propulsion of the wheels through the transmission system:

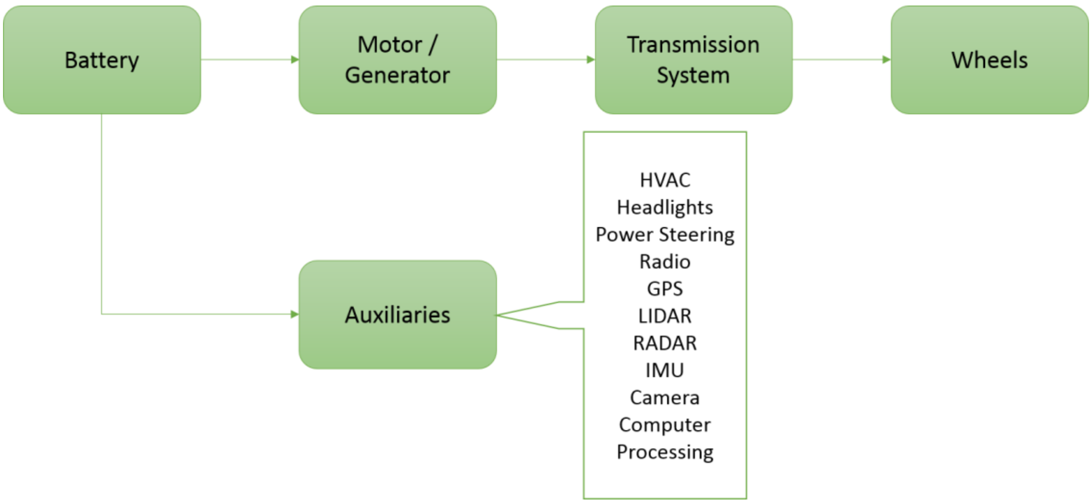

Figure 2.3-1 Energy consumption within an EV including auxiliaries (based on (Zhang and Yao 2019; Baxter et al.))

When only considering the energy flow within the vehicle, energy consumption of electric vehicles is the sum of:

- Energy that is required to move the vehicle (hence, to propel the wheels)
- Energy losses along the powertrain
- Energy that is needed to operate the auxiliary systems

(Miri et al. 2021). The auxiliary systems include air conditioning and heating, often called HVAC, which can cause the battery to drain very quickly in very hot or cold weather. For automated vehicles, the auxiliaries also comprise the different sensors and cameras to detect obstacles and their environment as well as the computer that processes all the data and steers the vehicle (Baxter et al.).

Mamala et al. describe how all components that have an impact on energy consumption can be summarized in one word with the acronym CARE, Chauffeur, Automobile, Road, and Environment. Chauffeur stands for the driver and their driving style. Aggressive driving, which can be roughly defined by more intense acceleration and deceleration phases, is often the reason for higher energy consumption compared to a smooth driving style. The vehicle or automobile itself also plays a role, therefore, vehicle parameters like its weight, construction properties and coefficient of drag have an impact. The vehicle’s technology also falls under this category including the state of the battery (age, type, capacity) and the included auxiliaries (navigation system, heating, air conditioning, driver assistance etc.) (Sweeting et al. 2011; Mamala et al. 2021; Li et al. 2016).

In a study by Li et al., the remaining components are not called road and environment, but rather artificial environment and natural environment. Artificial environment factors include road conditions and surface, degree of urbanization and traffic (congestion, traffic lights etc.). Environmental environment factors comprise topography with gradient and altitude profile as well as all weather related factors as cold weather, for example, noticeably reduces battery capacity (Li et al. 2016).

Energy consumption, particularly of electric vehicles, has been the focus of a lot of research over the course of the last ten years. Chen et al. reviewed the state of the art of EV energy consumption models and classified approaches based on modeling scale (microscopic vs. macroscopic) and methodology. They split methodologies of existing models into rule-based and data-driven models. Rule-based models follow a white-box approach that is based on fundamental laws of physics and mimic the dynamic and interactions of various vehicle and powertrain components to calculate energy consumption (Chen et al. 2021). Physical models are usually based on Newton’s second law where the tractive effort of an EV is expressed as the sum of rolling resistance, grading resistance, inertial force and aerodynamic drag respectively (Zhang and Yao 2019).

$$F_{total} = F_{accel} + F_{grade} + F_{roll} + F_{aero} \text{ (Faris et al., 2011)} \quad (1)$$

Such a model is called a vehicle longitudinal dynamics model. For accelerating a vehicle against external resistances (air drag, rolling and grade resistance), the electric motor provides a tractive effort. This tractive power for moving the vehicle comes from the motor which is connected to the battery. The energy consumption of these models, therefore, only includes the forces that are acting upon the moving vehicle, but not auxiliaries or energy losses along the powertrain (Graser et al. 2015).

Data-driven models, on the other hand, take on a black-box approach where users do not need to understand the physical process of electricity generation and consumption, but rely on the exploration of the statistical relationship between inputs and outputs of energy. The most widely used statistical method is multivariate linear regression, but some studies have also implemented machine learning techniques like neural networks (Chen et al. 2021). Wang argues that “using real-world driving measurements can result in more realistic values for energy consumption”, but access to real-world data is not always given and they often cannot reflect changes of vehicle parameters and environmental conditions (Wang 2016). The advantage of data-driven methodologies is that they describe correlations between certain input parameters and the vehicle’s energy consumption and are able to capture complex relations between parameters and energy consumption. However, the quality depends on the available data and its accuracy. Some studies actually use a combination of physics-based and data-driven methods where the model structure is based on underlying physics even though a data-driven approach is used (Beckers et al. 2019). Cauwer et al. take the physical formula in order to extract a simplified regression model which contains a speed-squared-dependent term describing aerodynamic losses, a height-dependent term for potential energy, but also adds an independent variable to account for ambient temperature (Cauwer et al. 2015b).

Energy consumption models can also be classified by modeling scale which is defined by the temporal resolution of the data. Microscopic-scale models can estimate energy consumption of EVs at high frequency, typically 1 Hz. This means that the data would exist on a second-by-second level and can be used to determine energy consumption during different traffic scenarios and evaluate energy implications of EVs in traffic simulation. As a counterpart, macroscale models explore the relationship between energy consumption and driving characteristics at an aggregated spatial or temporal span. They are usually applied for planning of charging infrastructure or energy portfolio prediction. Figure 2.3-2 shows how the majority of models since 2011 have been macro-scale models, however, there has been a huge increase in research overall and micro-scale models have been implemented more and more (Chen et al. 2021).

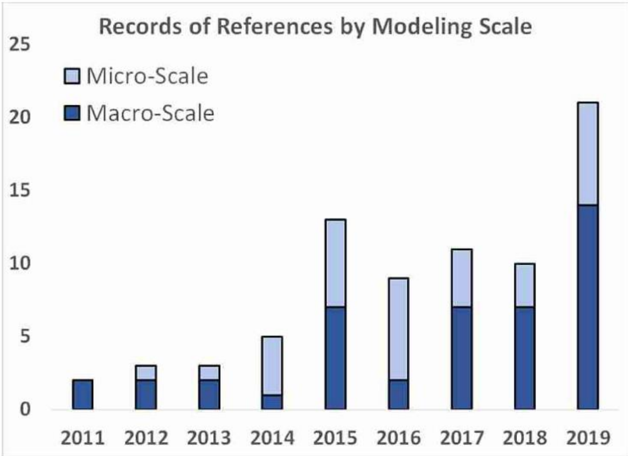

Figure 2.3-2 Number of research papers for microscale and macroscale EV energy consumption estimation model from 2011 until 2019 (Chen et al. 2021)

An example of a macro-scale model is how Wang et al. calculated energy consumption of electric buses on the basis of data per trip driven by public buses. This was done by taking the difference between the State of Charge in the beginning of the trip and the end and the distance that the bus travelled. This resulted in average energy consumption per kilometer for each trip as the target variable to be explained. Average speed and acceleration as well as standard deviations were then taken into account to check for causalities (Wang et al. 2020). Qi et al. also investigated energy consumption per trip by 50 test vehicles and focused on the influence of distance, initial SoC, temperature and speed (Qi et al. 2018). Braun et al. estimated energy consumption per segment of a route and also used speed distribution, speed and acceleration means and the occurrence and duration of stops (Braun and Rid 2017). Liu et al. combined large-scale GPS data and terrain data to reveal the contribution of road gradient on energy expenditure. With a polling frequency with a 60 seconds interval, the information on actual driving patterns and changes in SoC was not detailed enough, therefore, energy consumption per trip in kilowatt-hours per kilometre was used as the energy efficiency measure (Liu et al. 2017).

In micro-scale models, on the other hand, energy consumption is usually determined on real time by installing an instant power measurement system. This allows to track how much power the vehicle is demanding at each point in time. For instant power measurement, both current and voltage of the batteries are required (Flores et al. 2015). Yao et al. used a regression model with speed, acceleration as well as the initial State of Charge to determine energy consumption per second (Yao et al. 2013a). Microscopic-scale models are often used in applications related to optimizing real-time vehicle control, called eco-driving, particularly to reduce congestion on corridors or signalized intersections (Chen et al. 2021).

Micro-scale and macro-scale models serve different purposes in research, depending on the focus of the study and the relationship that wants to be focused on. However, the decision on a model always lies in the data that is available (Chen et al. 2021).

2.4. Automation of Transport

Stocker and Shaheen broadly define automated vehicles (AVs) as "vehicles used to move passengers or freight with some level of automation that aims to assist or replace human control" (2017). Chmielewski, on the other hand, describes self-driving vehicles as vehicles capable of navigating roadways and interpreting traffic-control devices without a driver actively operating any of the control systems (Chmielewski 2019). Controlled, fixed-guideway systems like trains or airport people movers are examples of AV systems already in operation today. Currently, AVs are being developed for use on public roadways and most major automobile manufacturers and lots of technology companies are trying to bring automated vehicles to the market as soon as possible (Stocker and Shaheen 2017).

Table 2.4-1 Explanation of the six SAE Levels from No Automation at Level 0 to Full Automation at Level 5 (based on (Yeong et al. 2021))

SAE Level 0	SAE Level 1	SAE Level 2	SAE Level 3	SAE Level 4	SAE Level 5
No Automation	**Driver Assistance**	**Partial Automation**	**Conditional Automation**	**High Automation**	**Full Automation**
The human driver performs all tasks related to driving.	The vehicle features a single automated system for driver assistance with the anticipation that the human driver performs all remaining driving aspects.	The vehicle can perform steering and acceleration or deceleration, but the human driver is required to monitor the driving environment and can take control at any time.	The vehicle can detect obstacles and perform most driving tasks. Human override is still required.	The vehicle can perform all aspects of dynamic driving under specific scenarios. Georeferencing is required. Human override is still an option.	The vehicle performs all driving tasks under all conditions and scenarios without human intervention.
Human drivers monitor the driving environment			**The automated system monitors the driving environment**		

As a framework needed to be put into place in order to have a common understanding of how automated a vehicle actually is, the SAE International, previously known as the Society of Automotive Engineers (SAE) put out a standard defining the different levels of driving automation for consumers (see Table 2.4-1). The J3016 "Levels of Driving Automation" standard comprises six distinct levels of driving automation starting with the driver having full control of the vehicle at SAE level 0. On the other side, at SAE level 5, vehicles control all aspects of the dynamic driving tasks without human intervention (Yeong et al. 2021).

Automation Levels 0 through 4 will require a driver to be present in the vehicle in order to step in in case of an incident that the automated system cannot handle, only when Full Automation is achieved in Level 5 does the vehicle drive completely on its own. However, vehicles at SAE Level 3 and 4 already change the experience of driving significantly since the driver is relieved of the task of constantly monitoring the environment (Lutin 2018).

With multiple benefits of automation, safety is usually the first that is mentioned. It is claimed that by automatization of the vehicle fleet an improvement of 90 % or more regarding traffic fatalities and injuries can be achieved. Equity and accessibility are also big factors as automated vehicles can improve access to vehicle mobility for seniors, disabled people as well as low-income groups. AVs could significantly change the quality of life for elderly people or people with severe disabilities who otherwise face challenges in using today's modes of transport. Since AVs are likely to be small, light, energy efficient and suited for alternative power sources, they would also benefit the environment. Furthermore, the use of AVs can mitigate congestion which creates higher fuel and energy consumption and local emissions. Congestion is usually caused by capacity bottlenecks, traffic incidents, poor signal timing and construction, and can be reduced by the vehicle automatically adapting its speed, choosing different routes and having fewer accidents (Ticoll 2015).

Even though there are great advantages of AVs, there are complex issues regarding legal aspects, liability, privacy, licensing, security and insurance regulation that need to be solved (Antonialli 2019). Moreover, a big concern is how self-driving vehicles will affect energy consumption. This question is hard to answer since their implementation could either result in a reduction or an increase of energy consumption. On the one hand, automation leads to smoother driving cycles which would lower energy consumption, on the other hand, users might be less reluctant to travel farther distances or to make additional trips which would have the opposite effect. Another reason for higher energy consumption of AVs is seen in their computer and sensor power demands (Lee and Kockelman 2019).

Autonomous vehicles have a large number of sensors or cameras that work, for example, with ultrasound, laser scanners or radar technology. Thus, the environment is continuously captured which makes orientation in road traffic possible. A wiring architecture connects all sensors to the power sources and enables communication, while on-board computer processors analyse the generated data and convert it into commands that allow the vehicle to drive without a driver (Baxter et al.).

A large component group is the sensor system which is crucial for operating an automated vehicle. Different sensor systems are usually implemented. Ultrasonic sensors guarantee near-field monitoring by transmitting sound waves above the range of human hearing which are reflected by obstacles. Radar sensors work similarly. They cover their detection range with electromagnetic waves and primarily cover the area in front and behind the vehicle. Radar sensors are especially important for capturing moving objects like other vehicles. Other sensors that are needed for object detection next to the roadway are Lidar sensors. Lidar (Light detection and ranging) stands for a method based on light waves, typically infrared laser beams. They emit several laser beams which form independent transmission channels due to slightly different wavelengths and phase lengths. By evaluating the back radiation, distances and relative speeds as well as contours of objects can be determined. On the basis of this sensor data, algorithms can calculate very precise spatial models of the vehicle's surroundings. The sensors are complemented with optic cameras that detect the lanes, traffic signs and obstacles (Büro autoBus et al. 2018; U.S. Energy Information Administration 2017).

In order to handle data errors that are inevitable, different sensors need to be in place at all times to be able to correct the data and to provide maximum safety (Yeong et al. 2021). The higher the SAE automation level of a vehicle, the more necessary redundant data becomes. If the vehicle would suddenly lose the power line to a set of sensors or the computer processor, the system would need to have enough redundancy to safely bring the vehicle to a stop without causing danger (Baxter et al.). Individual sensors do not present large loads to the energy consumption, however, the power drawn by a multitude of sensors and processing of the huge amount of captured data can be significant (Baxter et al.). The sensors and computer deliver better performance, higher efficiency as well as an improved and smoother driving experience, however, these systems need additional energy. Lee and Kockelman estimate an increase in energy consumption from 4 % to as much as 15 % produced by the sensor systems and computers used in automated vehicles (Lee and Kockelman 2019).

2.5. Automated Electric Shuttles for Public Transport

When picturing future scenarios for transport development, automation and electrification are often seen as a combination rather than separate developments. Lee and Kockelman argue that increased adoption of automated vehicles is likely to inspire greater adoption of electric and hybrid powertrains. Especially due to empty-driving capabilities, EVs would be able to self-charge without drivers by charging inductively or with a robotic arm. No human would need to be present for refuelling which would be specifically valuable for shared AVs as travellers would not have to worry about the range being sufficient (Lee and Kockelman 2019). Regarding energy consumption, Tate et al. come to the conclusion that an optimized EV powertrain in a fully automated transport system would only require one-third of the energy of an equivalent ICE vehicle (Tate et al. 2018).

Underwood et al. identify four major problems with current transportation technology which are:

(1) Oil dependence in transportation
(2) Fatalities and injuries from road accidents
(3) Congested roadways
(4) Underutilisation of public transport.

They also emphasise how automated electric vehicles have the potential to solve all of these issues as electrification of transport leads to higher energy efficiency and safety and less dependence on oil.

Fatalities and injuries are predicted to drastically decrease with self-driving vehicles as most accidents are caused by human error. Furthermore, automation is also likely to reduce congestion and public transport is presumed to be much more adaptable when automated vehicles are used (Underwood et al. 2014).

In regard to public transport, the implementation of automated buses for public transport offers a lot of benefits. Due to reduced driver costs, bus fares could be lowered. They can also increase the capacity utilization of the existing road network and enhance traffic efficiency (Guo et al. 2021). Therefore, they can serve routes in public transport that are economically and ecologically not feasible in (non-autonomous) public transport due to savings in operating and personnel costs. They also might be a solution for the last mile problem which refers to the problems of travellers finding it difficult to reach their final destination from a transportation hub like a railway station or bus stop (Riener et al. 2020; Qin et al. 2018).

Even though automation is still in its early stages and a big roll-out of automated electric vehicles is not likely to happen any time soon, automated electric shuttles have increasingly been deployed and continuously tested for a few years now. Pilot projects have been launched in different countries like the United States, China, Germany, Austria and South Korea in order to test automated vehicles and integrate them into existing public transport (Hagenzieker et al. 2021). Especially Europe has been on the forefront of testing autonomous vehicles with programs like CityMobil2 funding demonstrations and showcases of small automated shuttle buses in cities (National Center for Transit Research 2016). Moreover, the majority of experimentations have been done in Europe and the continent holds almost half of all manufacturers that specialize in automated electric shuttle buses for collective transport. Navya and EasyMile are two French companies that have been dominating the field since their founding in 2015 and 2014 respectively. Their concept is similar as they both provide autonomous minibuses that are powered by electricity, reach a top speed of 20 km/h and hold around 12 people (Antonialli 2019).

Most pilots have been deployed in urban areas in order to overcome mobility gaps, improve transport accessibility, flexibility and sustainability (Nemoto et al. 2021). More than half of all projects focused on testing the vehicles in closed and controlled areas like university campuses, parks, hospitals, resorts and airports. The remaining projects examined the shuttles among mixed traffic where the routes were mostly pre-determined for city centres and areas with a slow-speed circulation of regular vehicles (Antonialli 2019). The main research purpose of pilot projects has been to investigate user attitudes and willingness to use future autonomous services. However, public acceptance is difficult to test due to selection bias as those who choose to ride the automated shuttles might not reflect the general public's opinion. Also, since there is an on-board operator present, this might change people's feeling of security as well and might not represent their willingness to use an unaccompanied AV (Feys et al. 2020; Cregger et al. 2018).

Rural settings and roads are quite different than urban roads and have different factors that need to be taken into account. In urban areas, high density both of traffic and other functions are being served by the road, traffic needs to be integrated into residential space and the roads are catering to the needs of a wide range of road users using different modes (European Road Safety Observatory 2006). Rural roads are often defined as two-lane roads that are not set in an urban area which contains 50.000 or more inhabitants within densely settled territory. Another method of defining rural roads is using traffic volume, specifically the average annual daily traffic level and setting a certain amount as a threshold (Cannon et al. 2009; Bhandari 2013). Rural road standards and characteristics can be very different depending on the country as well as definition of rural roads (European Road Safety Observatory 2006), however, in this context, the difference to urban traffic is of utmost importance. Urban environments present their own challenges with uncertainties and disruptions that can change traffic flow (like temporary lane blockages and road closures) as well as congestion, traffic signs and unsignalized intersections (Xie et al. 2014). Rural roads, on the other hand, are much more diverse, speed limits can be much higher and road grade, curvature and surface vary a lot. Single carriageways and two-lane roads are the cause of most fatal accidents and account for the majority of fatal and serious crashes. The risk of fatalities can be up to six times higher on two-lane rural roads than on motorways, and decrease as traffic flows increase (EuroRAP 2011; European Road Safety Observatory 2006).

Since most experiments of automated electric vehicles for public transport are taking place in urban settings or closed traffic environments, exploring how they would perform in a rural setting is crucial for future implementation of AEVs in different scenarios. Moreover, case studies show how much potential autonomous electric vehicles have and test people’s willingness to use them, but do not focus on energy consumption with real life data. Therefore, there is a lack of evidence how sustainable the deployment of AEVs can be with current technological standards. This master thesis aims to fill this gap and provide an approach to estimating the energy consumption of an automated electric vehicle in operation. The goal is to answer the following research questions:

(1) What is the impact of rural road characteristics on the energy consumption of an automated electric bus operation?
(2) How does the energy consumption of an electric autonomous vehicle compare to a traditional combustion engine?

3. Methodology

The methodology is structured in three chapters including data collection, data processing and data analysis. The following flowchart shows an overview and which steps were taken during each phase until the final regression model was defined.

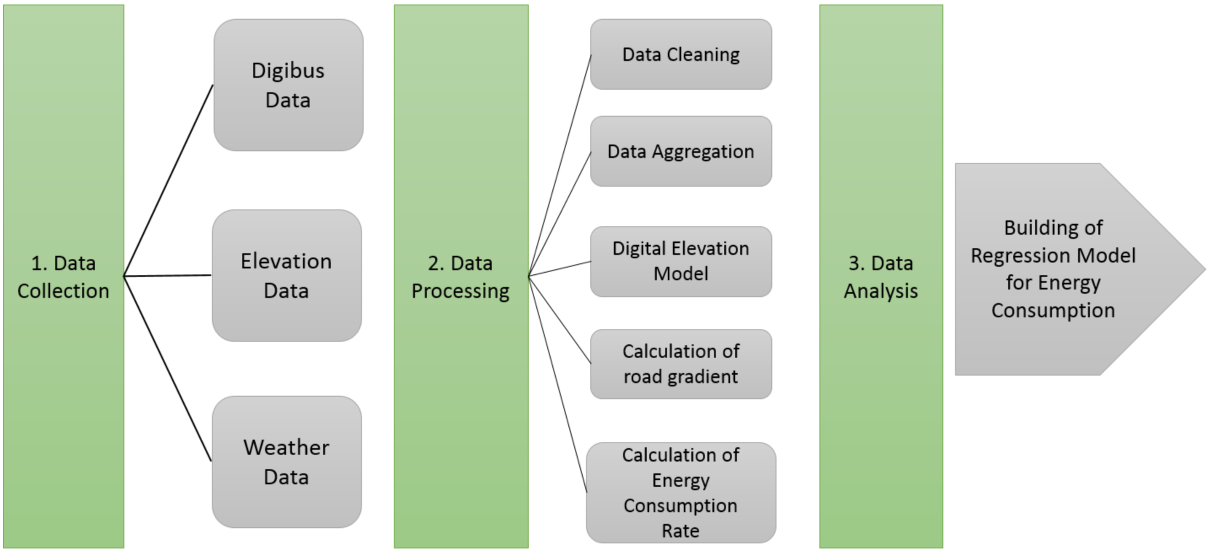

Figure 2.5-1 Overview of the steps undertaken from data collection, processing to analysis

3.1. Data Collection

In order to analyse energy consumption of an automated electric vehicle, quantitative data was collected by a shuttle bus that was implemented during the project Digibus. Furthermore, data on the elevation and road gradient was included since rural areas often have a much more varying slope than urban regions which was provided by the Austrian Institute of Technology (AIT). Additionally, data on the weather conditions from Zentralanstalt für Meteorologie und Geodynamik (ZAMG) was added which signifies whether heating or air conditioning was being used.

3.1.1. Digibus EZ10

This master thesis is based on the data provided by the Austrian flagship project "Digibus Austria" which was funded by the Austrian Research Promotion Agency and the Federal Ministry for Climate Action, Environment, Energy, Mobility, Innovation and Technology. It was running from April 2018 until March 2021 and included the operation of an automated electric vehicle in a real-life environment (Salzburg Research 2021).

Figure 3.1-1 The Digibus shuttle operating in Koppl (Salzburg Research 2021)

A passenger shuttle, referred to as "Digibus" (depicted in Figure 3.1-1) within the framework of the project, was operating in the municipality Koppl near Salzburg from August until October 2020 running five times per weekday. The testing track was approximately 1.3 kilometres long. There was a safety operator present at all times, however, the small bus was operating automatically for most of the time. For every microsecond the shuttle was running, it collected time-stamped data on different factors like its exact location, direction, speed and many more. In total, over 30 variables have been documented by the sensors with more than 863.000 entries.

Within Table 3.1-1, an overview is given regarding the operational characteristics of the shuttle. These include information about the vehicle type as well as the framework that it is operating within. It can hold up to 12 people, however, because of the Covid-19 outbreak, this number was reduced in order to fulfil the governmental requirements and to ensure safety. Since the legislation does not allow for automated vehicles to be unaccompanied by a driver, a safety operator was present during testing, however, the vehicle does not have a driving wheel, only a joy stick for driving manually.

Table 3.1-1 Characteristics for the EZ10 Shuttle provided by EasyMile (Diary Ali 2020; Transport Canada Innovation Centre 2021; U.S. Department of Transportation 2019; Salzburg Research 2021)

Operational Characteristics of the Digibus	
Trademark	EasyMile EZ10 Generation 3
Type of vehicle	Electric Automated Shuttle
Vehicle Driving Automation	SAE Level 4 – High Automation
Passenger Capacity	12 people (6 seats + 6 standing), 900 kg maximum
Accessibility	Equipped with built-in automated electric ramp
Driving modes	Two driving modes: automated mode (under normal conditions) & manual mode (operator is driving)

After looking at the operational characteristics, Table 3.1-2 shows the technical aspects of the vehicle and under which conditions it can operate. For the purpose of exploring factors resulting in energy consumption of the vehicle, especially battery capacity and engine power are of great importance. It also has to be mentioned that the four lithium-iron phosphate batteries are used to power the main motors and the steering motor as well as the Programmable Logic Controller (PLC), but also to recharge a 12 V battery that is used to power the accessories of the vehicle. This smaller battery is, therefore, powering the lights, the bell, the monitors and the computers.

Table 3.1-2 Technical Specifications for the EZ10 Shuttle provided by EasyMile (Diary Ali 2020; Transport Canada Innovation Centre 2021; U.S. Department of Transportation 2019; Salzburg Research 2021)

Technical Specifications of the Digibus	
Length / Width / Height	4,050 m / 1,892 m / 2,871 m
Frontal area	4,7 m^2
Gross Vehicle Weight (fully loaded)	3.130 kg
Net Vehicle Weight	2.130 kg
Battery Capacity	30,72 kWh (four 48 V lithium-iron phosphate batteries with 7,68 kWh each)
Traction and Engine Power	Two independent asynchronous electric motors with 8 kW nominal power each
Maximum Speed	Up to 40 km/h, but electronically limited to 20 km/h
Vehicle Range	Up to 16 hours
Charging Time	6 hours
Temperature conditions	Operating from -15 to 45 °C
Maximum slope	15 %
Sensors	GPS, Radar, Lidar, Camera, IMU, Odometry

Since the EZ10 shuttle has to know its position at all times, the vehicle's software is designed to locate it with centimetre-level precision. It merges different types of data that the sensors (see Figure 3.1-2) are capturing during operation (San Joaquin Regional Transit District 2019).

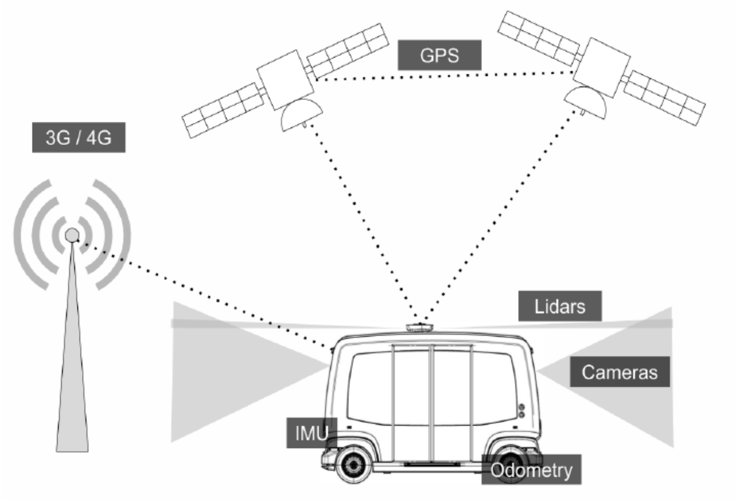

Figure 3.1-2 The multiple ways of localisation and obstacle detection sensors of the EZ10 vehicle including Cameras, Lidars, Odometry and IMU (San Joaquin Regional Transit District 2019)

3.1.2. Data on Elevation and Weather

The Digibus captured most variables of interest that would affect energy consumption of an AEV in a rural environment, however, it did not cover the road gradient at each point. As the influence of the slope on energy consumption is a major concern of implementing electric vehicles in rural areas, elevation data was added in order to calculate the slope during data processing.

An elevation model was provided by the AIT which was provided especially for the Digibus operation. This model was made availabe in vector form and includes 7.380 points with their longitude and latitude as well as the elevation at each location.

Furthermore, even though the data captured by the EZ10 included temperature within the vehicle as well as temperature outside, this data was examined and relatively inconsistent. Therefore, weather data by Zentralanstalt für Meteorologie und Geodynamik (ZAMG) was taken into account. By adding this data set, not only accurate outside temperature could be included, but also information on precipitation, wind speed and snow fall. There is no weather station exactly located in the municipality Koppl, but the next station Salzburg-Freisaal is only 12 kilometers away.

3.2. Data Processing

After collecting data from various sources, the raw data had to be joined together and adapted in certain ways. The programs used for data processing were mostly FME, QGIS and R. The software FME was mostly used to join all the data sets together and to filter out the entries that had to be removed. Elevation data was handled in QGIS, whereas indexing and aggregation was done in R.

3.2.1. Data Cleaning and Aggregation

One of the most important parts of data processing was removing certain data entries that had to be excluded from the final model. The overall goal was to keep as much data as possible, however, cleaning the data was crucial in order for the final model to not be distorted in any way. A combination of FME and QGIS was used for this step. FME was applied for filtering entries that were to be omitted, whereas the geographical information system allowed to check the location of the points and visualize any errors.

Inspired by Liu et al., rules were applied for the process of data cleaning and served as a guideline, or threshold in some cases, to omit data where necessary (Liu et al. 2017):

1. Data entries that were calculated via a simulation and were identified as not being data captured by the shuttle in real life
2. Dates with greater than 10 % poorly map-matched GPS points (where location sensors did not function properly and the distance between the route in Koppl and the recorded points was greater than 10 meters) (see Figure 3.2-1 for examples)
3. Data entries where no other attributes were recorded other than location and time
4. Data entries that defined the mode of driving as null when it should either be “automated” or “manual”
5. Date where battery State of Charge is given as 0

After cleaning the data based on the rules above, 760.713 data entries remained. Subsequently, the data entries were aggregated from a microsecond-level to a second-by-second level in order to make data handling less difficult. Moreover, acceleration was calculated by taking the difference within vehicle speed between the timestamps that were always one second apart.

Figure 3.2-1 Examples of dates that had to be removed due to sensory issues

3.2.2. Digital Elevation Model and Road Gradient

For the calculation of slope which is a very important feature that needed to be included in the model, the elevation model of the AIT was taken as the basis. The elevation model consists of 7.150 points along the road that the Digibus was operating on and covers the location as well as the elevation at each point. The points are only centimetres apart which makes the model very accurate and ideal for calculating the slope precisely.

As a first step, the vector data points were converted into a raster elevation model in QGIS in order to perform the calculation of the gradient. This also helped visualize the elevation along the route (see Figure 3.2-2). Through the rasterization of the vector data, each pixel within the defined polygon was assigned a certain elevation in metres. For interpolation, the inverse distance weighting method was used. Inverse distance weighing is quite a simple and commonly used interpolation technique which estimates the variable of interest by assigning more weight to closer points. It therefore takes a spatially weighted average of the sample values within a search neighbourhood (Babak and Deutsch 2008).

Since there are over 7.000 points within the vector data, the interpolation is very precise as there is not a lot of distance between the points. For that reason, the pixel values along the route are very accurate as the points are very close together, however, the more you move away from the street the less accurate the raster polygon will be. Nonetheless, this is not concerning as only the elevation along the street is of interest for calculating the slope.

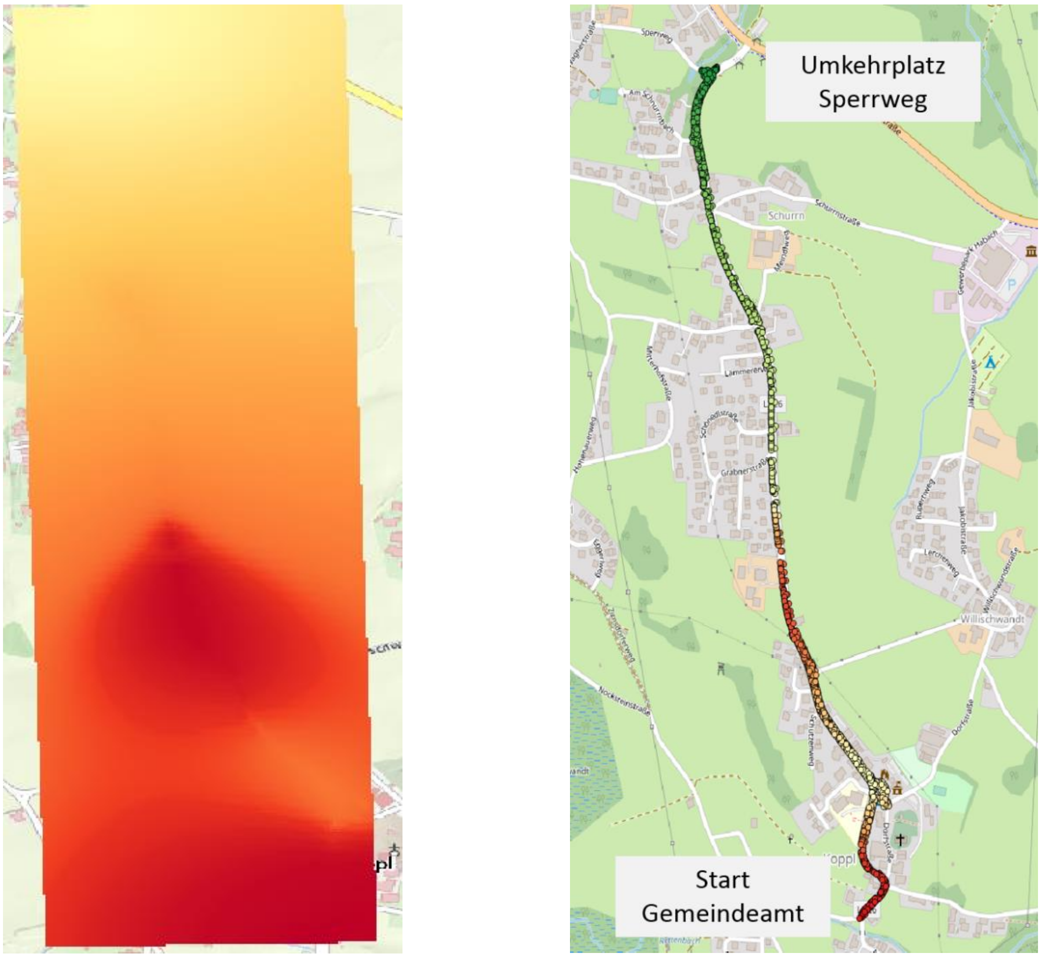

Figure 3.2-2 Elevation raster model, yellow symbolizes a lower elevation, red the highest elevation level (left); Vector data points with their assigned elevation along the route (right) (background layer basemap.at)

After interpolating the elevation along the route, a calculation of slope was done in QGIS based on the elevation raster. The slope was calculated for each pixel expressed in percent. In order to then join the data with the data entries of the vehicle again, the raster values for slope were assigned to the vector points based on their location. The final step was to calculate whether the bus was going uphill or downhill. As the calculated slope is always a positive value, the difference in elevation between the points in time was taken into account. If the difference was negative and the bus was going down, the variable for slope was adapted and the absolute value was converted into a negative value.

3.2.3. Energy Consumption Rate

Different measures can be used to evaluate energy consumption, for example consumption per unit distance (e.g. per kilometre) or consumption per trip (Liu et al. 2017). Within the collected data by the EZ10 shuttle, the information on State of Charge (SoC) was saved for each microsecond of operation. SoC of a battery pack is defined as the percentage of the rated capacity (RC) or nominal capacity.

Differently put, it is the ration between the saved energy in the battery and the total energy that can be saved in the battery (Kularatna 2015).

As State of Charge reflects the level of charge compared to its capacity it can be used as a measure of energy consumption. It is scaled from 100 % which represents a fully charged status, to 0 % which signals an empty battery with no stored energy left (Wang et al. 2020).

Following the calculation of energy consumption by Hao et al., it is assumed that during a discharge period the electric energy changes approximately linearly with the SoC (Hao et al. 2020).

$$\Delta E = k \times \Delta\, SoC \tag{2}$$

Variable k represents the battery capacity, while ΔE is the change in energy measured in kWh and Δ SoC is the change in the State of Charge. SoC is given in the range of 100 until 0 %, hence, k can be estimated as E_0 / 100. As the battery capacity of the EZ10 is 30,72 kWh which is 110592 kWs, the coefficient is 1105,92 and will be multiplied by the change in SoC (Hao et al. 2020). As an example, if the State of Charge is going down from 75 to 72 % during a trip, Δ SoC is 3 % and is multiplied by 1.105,92. The result is 3.317,76 kWs which is the energy that is consumed over the course of the trip.

Figure 3.2-3 Battery State of Charge before and after smoothing (example of the 23rd of September 2020)

Since the State of Charge represents the target variable that wants to be explained by the model and its accuracy strongly affects the results, battery smoothing was done to cancel out noisy data. There were, in total, 62 instances where the SoC had dropped already by one percent, but went back up for a few seconds to go down again later. These spikes caused some problems as the consumption rate was calculated on the basis of duration of each SoC percentage. For that reason, for each timestamp, the difference in SoC was identified and if it was positive, the SoC was changed to the SoC of the moment before. Figure 3.2-3 shows how spikes in the data, where it would go up and soon down again, were smoothed.

Since the variable on energy consumption was calculated on the basis of the amount of time that the same State of Charge was shown in the vehicle data, the variable was not always consistent and there were many outliers. These outliers stemmed from turning the vehicle on and the Digibus adjusting the State of Charge within the first seconds which resulted in a lot of high energy consumption values, specifically when the bus was not moving yet. Moreover, when the vehicle was turned off just after the SoC had changed, it would result in very high values as well. This affected energy consumption values during idling time in the beginning of a trip or the end. Therefore, the upper quartile was taken into account and the outliers were removed from the model.

3.2.4. Identifying Charging Cycles and Distance travelled

In order to identify at which point the vehicle was charging, an index was created in R. The beginning of a new charging cycle was defined as the moment when the difference of the State of Charge between the timestamps following each other was positive, meaning that the battery was filled up again. In order to calculate the distance that the bus has travelled during each charging cycle or usage during a day, the "haversine method" was used to calculate the shortest distance between each point of location. The method assumes a spherical earth, ignoring ellipsoidal effects which were neglected since the data points were so close together (Hijmans et al. 2019).

3.3. Data Analysis

3.3.1. From Linear to Panel Regression

Using regression models, the goal is always to explore causal relationships between different factors. They can be used for policy recommendations, predictions or just statements like "x leads to y". The basic regression model is simple linear regression. Simple linear regression is often avoided in applied econometrics as there can be multiple problems arising from using it. However, it can serve as a starting point to assess the nature of a relationship between variables since the algebra and interpretation are relatively straightforward. Simple linear regression involves only two variables, the explained variable (often y variable) as well as the explaining variable (x variable), also called dependent and independent variable. It uses the ordinary least-squares (OLS) algorithm to fit a linear model and to give estimates that define a fitted value for the explained variable y:

$$y_i = \beta_0 + \beta_i x_i + \varepsilon_i \tag{3}$$

, where y_i is the explained variable, β_0 the intercept and β_1 the coefficient for the explaining variable x_i, and ε_i represents the error term. The error term plays an important role as it holds all variables that influence the explained variable other than x_i. This can be a problem as it is often unknown which other variables have an impact and whether or not they might be correlated with the predictors. If a variable within the error term is influencing not only the dependent variable, but also the independent variables, the coefficients might be biased and the model will be inaccurate. One way of dealing with this problem of biased coefficients due to omitting important predictors is using multiple linear regression which uses multiple independent variables instead of just one. Other explaining variables, therefore, are included in the model rather than in the error term and cannot cause omitted variable bias. This means that a fundamental assumption for OLS regression is to have no unobserved variables that are associated both with the x variables or y variable. However, since there are often unknown variables that might influence the dependent variable or data on some factors is simply not available, other solutions must be found (Wooldridge 2013).

One solution for estimating a model with unobservable variables is collecting panel data rather than cross-sectional data where data is collected as a whole at a single point in time. Panel data, on the other hand, is two-dimensional where the same individuals are observed repeatedly over different periods in time. Panel regression models are implemented in order to control for unobserved dependency of other independent variables, called unobserved heterogeneity. The most commonly used method is the fixed effects regression model:

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \cdots + \beta_k x_{itk} + a_i + u_{it} \tag{4}$$

, where i is denoting individuals (often households, firms, countries etc.) and t stands for the time period. The error term consists of a_i as the time constant unobserved effect, also called fixed effect or unobservable individual-specific effect, while u_{it} denotes the remainder disturbance. In a fixed effects model, the individual-specific error component captures any unobserved effects that are constant across time, but different among individuals. One way to deal with a_i is to transform the data in a way that it disappears, called within-group estimation. This is done by demeaning the data for each of the individuals and therefore, differencing the time-invariant fixed effects away, whether observed or unobserved. This has many advantages, but also leads to being unable to measure the effect of variables that are time-invariant within individuals (Wooldridge 2013; Baltagi 2005).

Another method of estimating fixed effects is the Least Squares Dummy Variable (LSDV) estimation which creates a dummy variable for each individual, but achieves the same result as the within-estimation. In contrast to the within-group estimation, this makes it possible to measure the effects if one is interested in the individual-specific effects. The dummy variables, or individual error components, can be thought of individual-specific intercept terms which capture any omitted variables that might not be included in the regression. The downside of the LSDV estimation is, however, a loss of degrees of freedom. If there are too many individuals, too many dummies can cause a problem of multicollinearity among the independent variables (Baltagi 2005).

In the case of the Digibus, the shuttle continuously saved its data during operation making the data two-dimensional. Therefore, individuals were selected to be different modes of driving and a panel model was implemented to account for unobservable variables.

3.3.2. Model Building

In current literature, macro-scale or meso-scale models are usually applied when the energy consumption can only be approximated based on the State of Charge given in the data (Wang et al. 2020; Hao et al. 2020; Xie et al. 2020). Micro-scale models, on the other hand, are typically used when the power at each moment in time is captured by ampere and voltage and the energy consumption is much more precise (Badin et al. 2013; Cauwer et al. 2015b; Galvin 2017). Therefore, a macro-scale model was firstly considered by calculating the energy consumption per kilometre for trips, days or charging cycles. However, the Digibus always travelled the same route with the same shares of different road gradients. Also, the driving behaviour was relatively constant due to the automated system. Hence, the variance of energy consumption would mostly be explained by the differences in weather conditions or occurrence of obstacles that cause abrupt stops. For these reasons, a micro-scale model was chosen in order to explore the influence of road gradient. This was possible due to a high temporal resolution of the independent variables the Digibus captured and a high spatial resolution of the elevation data.

Hu et al. and Yao et al. used a categorization of vehicle data by driving mode into Idling, Acceleration, Deceleration and Constant Driving, while Liu et al. and Wang et al. grouped their data into bins for road gradient (Hu et al. 2017; Yao et al. 2013a; Liu et al. 2017; Wang et al. 2017). Since energy consumption and the effect of road gradient wanted to be explored, these ideas were combined and resulted in eight driving conditions for the Digibus shuttle bus (shown in Table 3.3-1). As the within-group estimation of fixed effects would lead to not being able to measure these effects, LSDV estimation was applied. With only eight driving conditions to be estimated, loss of degrees of freedom and multicollinearity were not a big concern.

Especially the effect of road gradient on energy consumption of an AEV has not been explored in current literature on such a detailed level. Therefore, the focus of the driving conditions is on the road gradient which can be much more varied in rural areas than in urban regions and can cause the energy stored within the battery to discharge faster.

Table 3.3-1 Driving Conditions used as individuals in the LSDV panel regression

Driving Conditions	Description
Idling	Vehicle is not moving, speed and acceleration are zero, but the battery power is turned on to supply the auxiliaries
Moving on a flat surface	Vehicle is moving, road gradient is quite flat (- 1 % to 1 %)
Moving uphill on a slightly steep surface	Vehicle is moving uphill, road gradient is 1 % to 3 %
Moving uphill on a steep surface	Vehicle is moving uphill, road gradient is 3 % to 6 %
Moving uphill on very steep surface	Vehicle is moving uphill, road gradient is greater than 6 %
Moving downhill on a slightly steep surface	Vehicle is moving downhill, road gradient is - 3 % to -1 %
Moving downhill on a steep surface	Vehicle is moving downhill, road gradient is - 6 % to -3 %
Moving downhill on a very steep surface	Vehicle is moving downhill, road gradient is smaller than -6 %

However, other driving factors should also be accounted for by the model. Factors that are present in all micro-scale energy consumption models are speed and acceleration as they have a great impact on the energy that is spent and represent driving characteristics. Since the relationship between speed and energy consumption follows the laws of physics and is not linear, instantaneous speed and its higher orders, up to the third order, have been included in various studies as well as combinations of speed and acceleration (Yao et al. 2013b; Yao et al. 2013a; Liu et al. 2018; Galvin 2017; Chen et al. 2021).

Another variable that has been explored by multiple researchers is the initial State of Charge since the current level of energy stored in the battery has an influence on the energy consumption rate and discharging efficiency (Yao et al. 2013a; Qi et al. 2018; Chen et al. 2021). With a higher percentage of SoC, or more remaining energy in the battery, the battery usually drains a bit faster as its energy consumption curve is not perfectly linear (Espedal et al. 2021).

Moreover, ambient temperature has an impact on energy consumption and driving range since battery performance, including its capacity, internal resistance, efficiency and open-circuit, is dependent on temperature (Xie et al. 2020). Ambient temperature affects energy efficiency by influencing the output energy loss as well as auxiliary loading with the use of air conditioning and heating. The climate control system plays a big role in energy consumption of the auxiliaries. The measured amount of energy consumption by the HVAC system varies between studies from 18 to 33 % of energy spent due to heating in winter, as well as 14 or 15 % due to air conditioning in summer (Liu et al. 2018; Doyle and Muneer 2019; Desreveaux et al. 2020).

Since the use of HVAC is important to include in the model, but it is unknown when it was turned on, a factor variable was introduced to take additional energy consumption due to AC and Heating into account. A categorical variable was chosen with the following temperature ranges:

- Temperature lower than 10 ° C
- Temperature between 10 and 18 ° C
- Temperature in the range from 18 to 24 ° C
- Temperature higher than 24 ° C

The temperature bin between 18 and 24 ° C is used as the base category as it roughly presents the range in which neither Heating nor AC is used (Doyle and Muneer 2019; Evtimov et al. 2017).

Other weather conditions like rain or snow change the driving behaviour and cause changes in energy consumption due to the use of auxiliaries (e.g. for window cleaning, seat heating, use of lights) (Evtimov et al. 2017), however, as there was no snow during the time of deployment of the Digibus as well as no rain, the factors were disregarded. The Digibus captured data on the passenger load which would have an effect due to the increased weight of the vehicle, but the data was mostly unreliable which led to the exclusion of this factor. Since the individual-specific effect for the driving conditions would account for any differences, the outcome should not be affected too much.

Figure 3.3-1 shows the final regression model that was used and which variables were taken into account. The dependent variable of the energy consumption rate is given in the unit of Kilowatt-seconds which is important for interpreting the coefficients of the predictor variables.

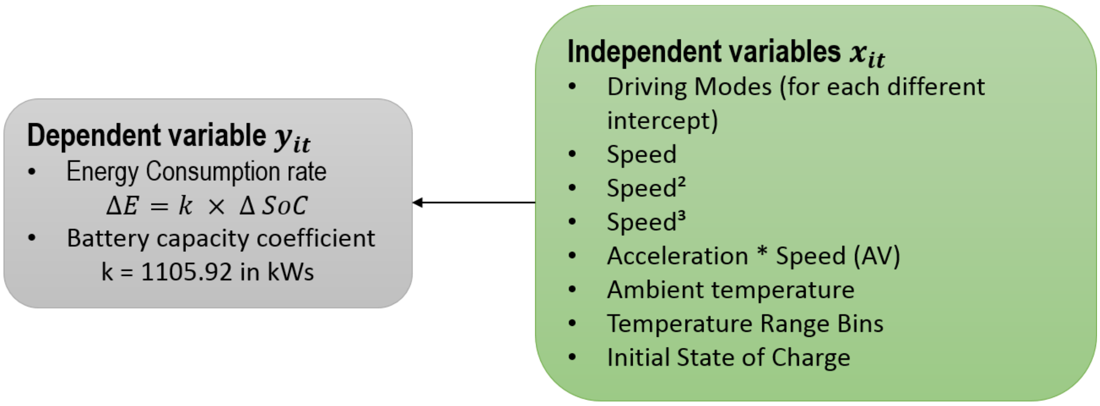

Figure 3.3-1 Final Panel Regression Model with dependent and independent variables

In the end, in addition to the driving condition dummies for the panel regression, seven independent variables were used to explain the AEV's energy consumption, described in Table 3.3-2. The vehicle's speed was used in four different terms, as the correlation between speed and energy consumption follows Newton's second law and is not solely linear. Therefore, a quadratic and cubic term were included as well as an interaction term of acceleration and speed. Temperature range was added in order to control for the use of the HVAC system, while ambient temperature represents the climatic environment that impacts the battery efficiency.

Table 3.3-2 List of explanatory variables of panel regression model with v [m/s], a [m/s²], T [° C] and SoC [%]

Explanatory Variable	Description
v	Instantaneous vehicle speed
v^2	Quadratic speed term
v^3	Cubic speed term
va	Acceleration term (speed * acceleration)
SoC	Initial State of Charge
T	Ambient temperature outside of the vehicle
Temperature Range	Levels: < 10; 10 - 18; 18 - 24 (reference); > 24
Driving Conditions	Levels: Idling (reference); Flat moving; Uphill 1-3 %; Uphill 3-6 %; Uphill > 6 %; Downhill -3- -1 %; Downhill -6- -3 %; Downhill < -6 %

4. Results

The results are structured by first getting an overview of the data and looking at the descriptive statistics and distributions of the key variables. Then, the hypothesis is tested whether the energy consumption of the driving conditions in different road gradient settings is significantly different and whether they are suitable for usage in the panel data regression. Afterwards, the results of the regression are focused on explaining the goodness of fit of the model and the significance of the variables and their coefficients. The next sub-chapter revolves around the different scenarios for deployment of an AEV and how the energy consumption compares to an ICE. Lastly, the limitations of the study are explained and to what extent the results can be interpreted.

4.1. Descriptive Statistics

Table 4.1-1 summarizes the characteristics of the Digibus data which was used for the energy consumption analysis. It describes how many days of operation were taken into account and how much distance the shuttle bus covered. Charging of the battery usually happened only every second day of usage as there were many days with only a few scheduled trips which explains only 24 charging events compared to 41 days of usage. It can also be seen that a third of the time the bus was turned on, it was idling, hence standing in a bus station or momentarily not moving due to an obstacle.

Table 4.1-1 Operational Statistics based on dataset used for the analysis within this study (after data cleaning and processing)

Characteristics of the Digibus deployment in Koppl	
Days of operation	41
Total energy consumption [kWh]	206,5
Total time of usage [hours]	103
▪ **Hours idling**	34
▪ **Hours moving**	69
Distance covered [km]	366,6
Number of trips (each approx. 1,3 km)	282
Number of Charging Cycles	24
Temperature min [° C]	-2,1
Temperature max [° C]	32,8

Since the deployment of the automated electric shuttle bus started in July/August and ended in December 2020, the temperature minimum and maximum show that the bus was in use under various temporal conditions. However, there was no rain as well as no snow during the days of operation. The distribution of temperature can be seen in Figure 4.1-1 where it becomes clear that the most frequent temperature was around 20 to 25 ° C, however, there was a significant amount of time below the optimal temperature range where air conditioning or heating was likely being used.

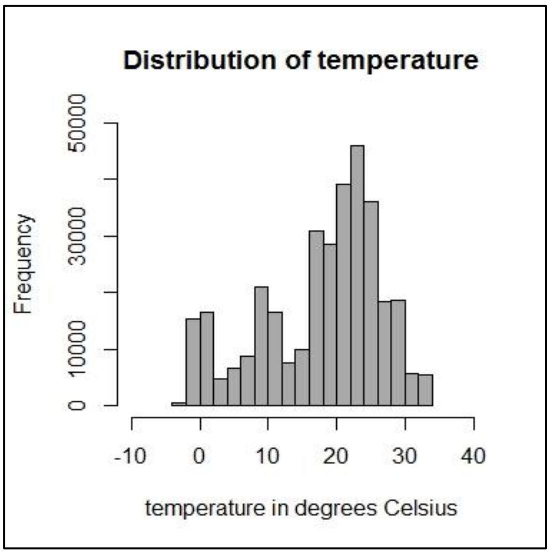

Figure 4.1-1 Distribution of temperature during the whole observed period of operation of the Digibus

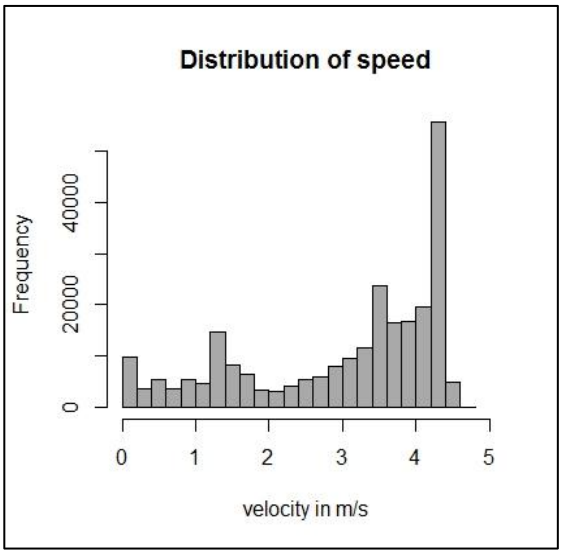

Figure 4.1-2 Distribution of velocity during the observed period while the Digibus was moving

Next to the distribution of temperature over the course of the deployment of the AEV, the distribution of speed is also depicted (Figure 4.1-2). The histogram shows how the most frequent speed was the maximum speed of the vehicle with about 4,5 m/s, which is around 16 km/h. Looking at the variables describing the shuttle's driving behavior in Table 4.1-2, the mean speed while moving (excluding idling time) was about 3 m/s, equivalent to approximately 11 km/h. The maximum absolute value of deceleration is much higher than the maximum acceleration which signifies that the bus made abrupt stops. This can be explained by the vehicle sensing obstacles very late and coming to a sudden halt. Nevertheless, the driving behavior seems very smooth as the mean acceleration and deceleration are both quite low which usually leads to a lower energy consumption.

Table 4.1-2 Descriptive Statistics of explanatory variable and dependent variable while the Digibus was moving

Variable	mean	std. deviation	min	max
Energy consumption rate [kWs]	2,59	1,4	0,37	6,36
Speed [m/s]	2,98	1,36	0	4,71
Acceleration [m/s²]	0,075	0,16	0	1,19
Deceleration [m/s²]	-0,076	0,17	-3,21	0

4.2. Road Gradients and ANOVA

Looking at the elevation profile for one trip from the southern to the northern bus stop in Figure 4.2-1, it becomes clear that there is almost no flat area along the route. In total, the bus was driving only 2 % of its time on flat ground covering 26 m per trip. The automated electric shuttle travelled the longest distance both uphill and downhill within the range of 3 to 6 % of road gradient, and -6 to -3 % respectively. The maximum slope that the Digibus was driving uphill as well as downhill was over 8 %, which is approximately 65 meters difference. Especially close to the bus stop "Sperrweg", the highest road gradients were encountered.

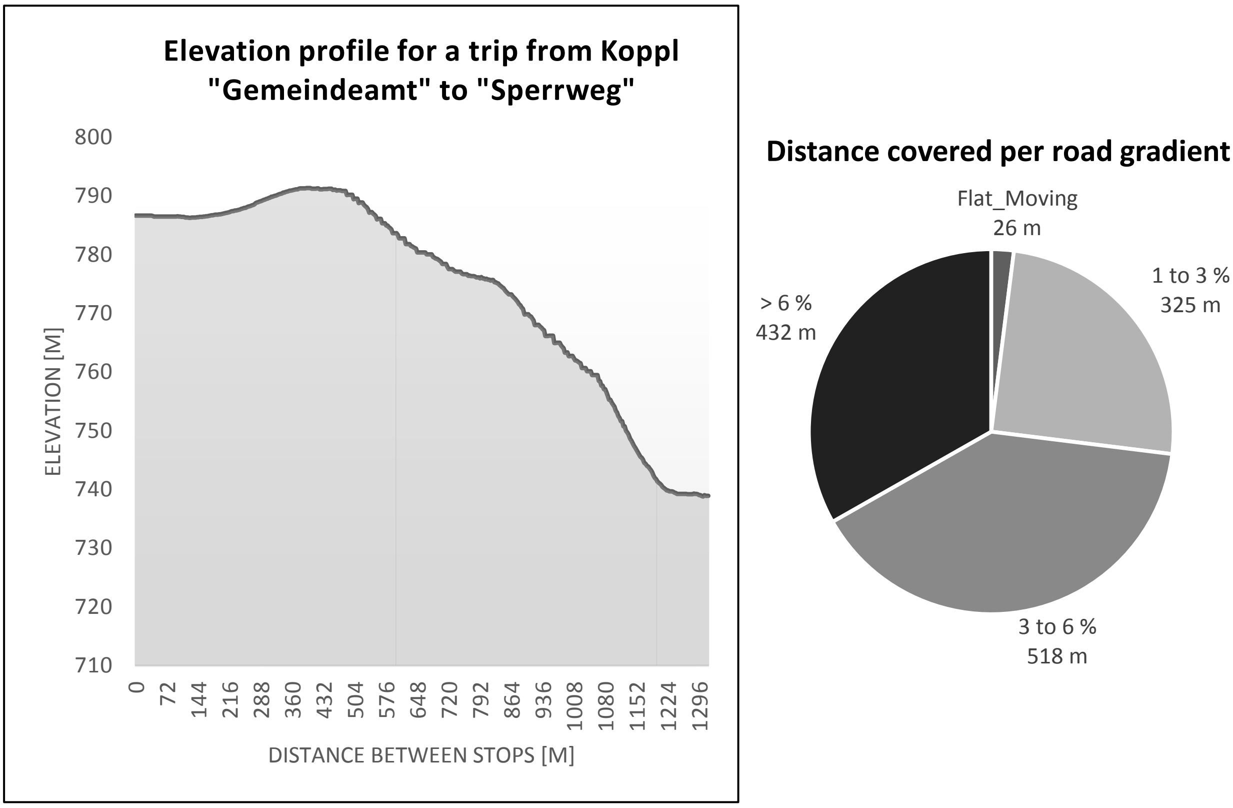

Figure 4.2-1 Elevation profile for one trip from the start "Gemeindeamt" to the northern station "Sperrweg" (left) and the distribution of distance for each road gradient group travelled by the Digibus along the route (right)

Before doing the panel regression, an ANOVA, short for analysis of variance, was performed in order to validate the driving conditions chosen as individuals. ANOVA is a statistical analysis procedure that allows to examine whether the means of different groups differ significantly from each other. The aim is the same as with the t-test, except that with ANOVA more than two groups can be compared at the same time. In the case of the road gradient factors, this method was used to test whether the driving conditions were suitable as individuals used in the panel regression model (Ostertagova and Ostertag 2013).

Afterwards a pairwise comparison with the Tukey HSD test was done which compares the means of values for all combinations. The results confirmed the choice of driving conditions with only the pair "Flat moving" and "Downhill -3 to -1" having a non-significant difference in their mean values. Figure 4.2-2 visualizes the means for each driving conditions with boxplots that include the mean as well as the lower and upper quartiles. The highest mean for energy consumption can be seen when the bus was driving uphill between 3 and 6 % of road gradient. During idling, the bus spent the least amount of energy.

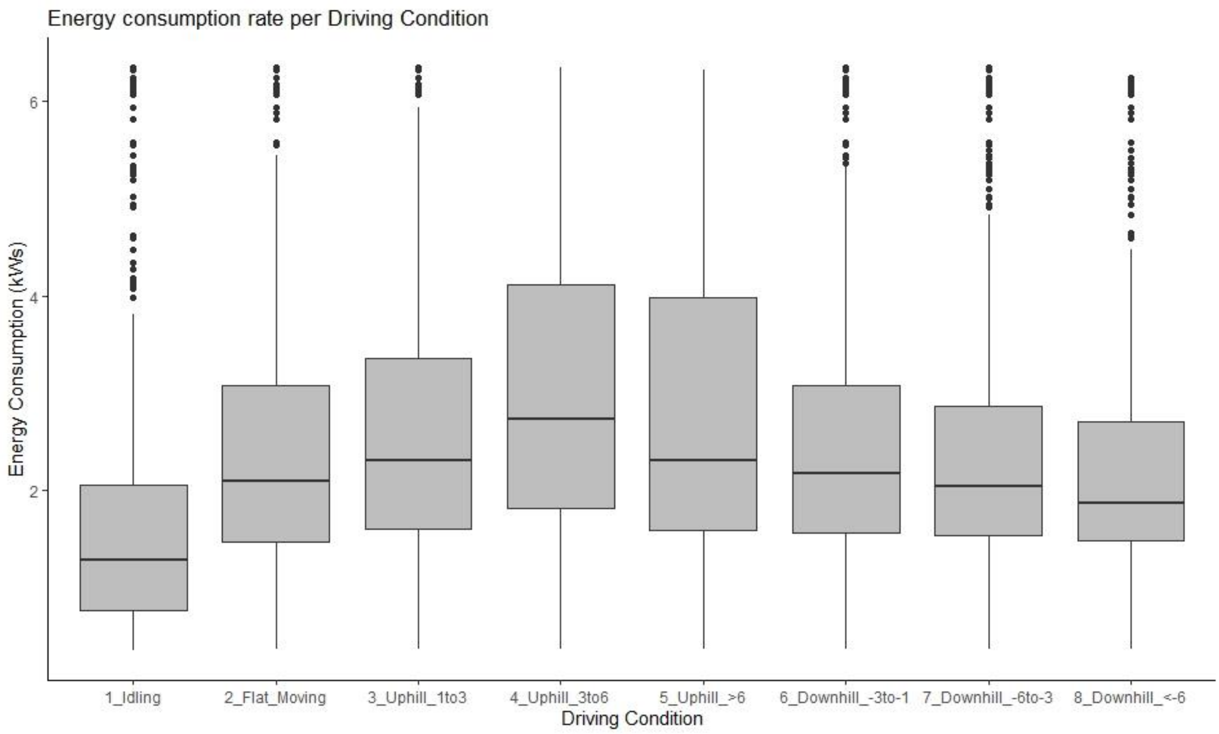

Figure 4.2-2 Boxplot for energy consumption rate per driving condition based on road gradient

4.3. Regression Model

Table 4.3-1 shows the results of the LSDV panel regression model explained in chapter 3.3.2. The coefficient of determination R^2 which serves as a goodness-of-fit measure for regression models is 0,21. R^2 is a key number for estimating the performance of a regression model. It ranges from 0 to 1 and its value increases as the fitting effect improves (Bi et al. 2018). In this case, it means that 21 % of the variance within the variable of energy consumption is explained by the model. The p-values signify that all variables are significant on a 1 % level. Since the dependent variable is the energy consumption rate during one second [kWs], a positive coefficient means that the higher the variable, the higher the energy consumption will be.

As an LSDV panel regression was used, the coefficients for the driving condition can be interpreted as different intercepts (constant variables) and show the effects of road gradient both uphill and downhill. The factor for idling mode is by far the lowest compared to all other driving conditions when the vehicle is moving. The intercept for moving in a flat area is very close to the intercept for driving slightly uphill which indicates that small slopes do not increase energy consumption much. Driving downhill, on the other hand, has a smaller effect on energy consumption compared to driving in a flat area. The coefficients decrease with higher road gradients which can be explained by the use of gravity to keep the vehicle moving. Similarly to Figure 4.2-2, the coefficients for uphill driving confirm that most energy was consumed in the range of 3 to 6 % road gradient. This might be explained by difficult road conditions during certain parts along the route that could cause more energy to be consumed. Another reason could be the driving behavior of the automated vehicle.

Table 4.3-1 Estimated parameters for the proposed model (see chapter 3.3.2), $R^2 = 0,21$

Independent variable	**Coefficient**	**t-value**	**p-value**
Driving Condition (Idling)	0,093	4,479	7,51e-06
Driving Condition (Flat Moving)	0,666	34,538	< 2e-16
Driving Condition (Uphill 1 to 3 %)	0,710	48,312	< 2e-16
Driving Condition (Uphill 3 to 6 %)	1,143	84,286	< 2e-16
Driving Condition (Uphill > 6 %)	1,026	77,229	< 2e-16
Driving Condition (Downhill -3 to -1 %)	0,572	42,126	< 2e-16
Driving Condition (Downhill -6 to -3 %)	0,324	23,811	< 2e-16
Driving Condition (Downhill < -6 %)	0,139	10,188	< 2e-16
Initial State of Charge (SoC)	0,0066	58,920	< 2e-16
Ambient temperature (T)	0,035	43,813	< 2e-16
Temperature Bin < 10 ° C	0,911	61,221	< 2e-16
Temperature Bin 10 to 18 ° C	0,508	63,632	< 2e-16
Temperature Bin > 24 ° C	0,255	35,709	< 2e-16
Instantaneous speed (v)	0,127	6,034	1,60e-09
Speed² (v^2)	0,054	5,060	4,18e-07
Speed³ (v^3)	-0,014	-8,912	< 2e-16
*Acceleration * Speed (av)*	0.0277	5,221	1,78e-07

The results confirm that the relationship between energy consumption and speed is not strictly linear, as both coefficients for speed² and speed³ are significant. In order to show the resulting effect (visualized in Figure 4.3-1), the following formula was used to calculate the estimated energy consumption per kilometer, based on the regression coefficients:

$$EC_{DrivingMode}\left[\frac{kWh}{km}\right] = \left(\left(Intercept_{DrivingCond} + 0{,}127v + 0{,}054v^2 - 0{,}014v^3 + 0{,}035 * 20\right) * \frac{1000}{v}\right)\frac{1}{3600} \qquad (5)$$

, with $EC_{DrivingCond}$ standing for energy consumption per driving condition and v representing the vehicle's speed [m/s]. Evtimov et al. concluded that the minimal energy consumption of auxiliary systems is realized at an external temperature of 20 ° C. Therefore, this was used as the reference temperature in order to only show the effects of speed and road gradient without additional energy consumption due to the HVAC system (Evtimov et al. 2017; Cauwer et al. 2015b). The formula was divided by 3600 to convert energy consumption from kilowatt-seconds to kilowatt-hours, while the term $\frac{1000}{v}$ was introduced to take the time into account that the vehicle needs to travel one kilometer. Initial State of Charge as well as acceleration were left out for simplification in order to focus on the impact of road gradient.

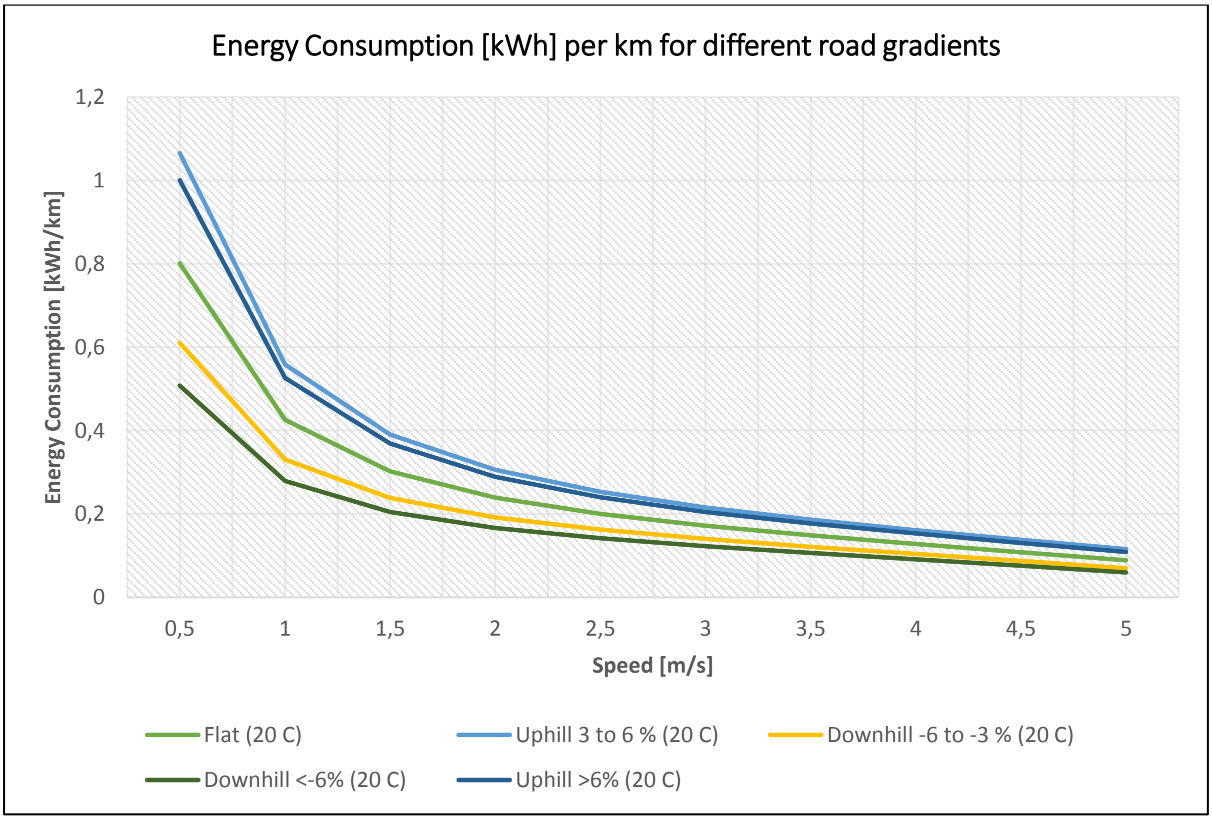

Figure 4.3-1 Energy consumption [kWh] per km for different road gradients assuming constant speed

Due to the non-linear correlation, the energy consumption is high for low speeds while continuously decreasing with higher average speeds. The plot also emphasizes how the road gradient plays a big role during low speeds, but the effect becomes less obvious when the vehicle is driving faster.

Regarding temperature, the highest coefficient was estimated for temperatures below 10 ° C where heating was turned on. For the temperature bin above 24 ° C, the coefficient is the lowest, however, ambient temperature is also included in the model and has a positive correlation with the energy consumption rate which increases the result especially for very high temperatures. The effects of temperature and implicitly, heating and AC, can be seen in Figure 4.3-2. The values are quite similar for 5 ° C, 15 ° C or 25 ° C, with only 20 ° C having a much lower energy consumption rate. The highest rate is estimated for 30 ° C where air conditioning is likely to have a great impact on the overall energy consumption.

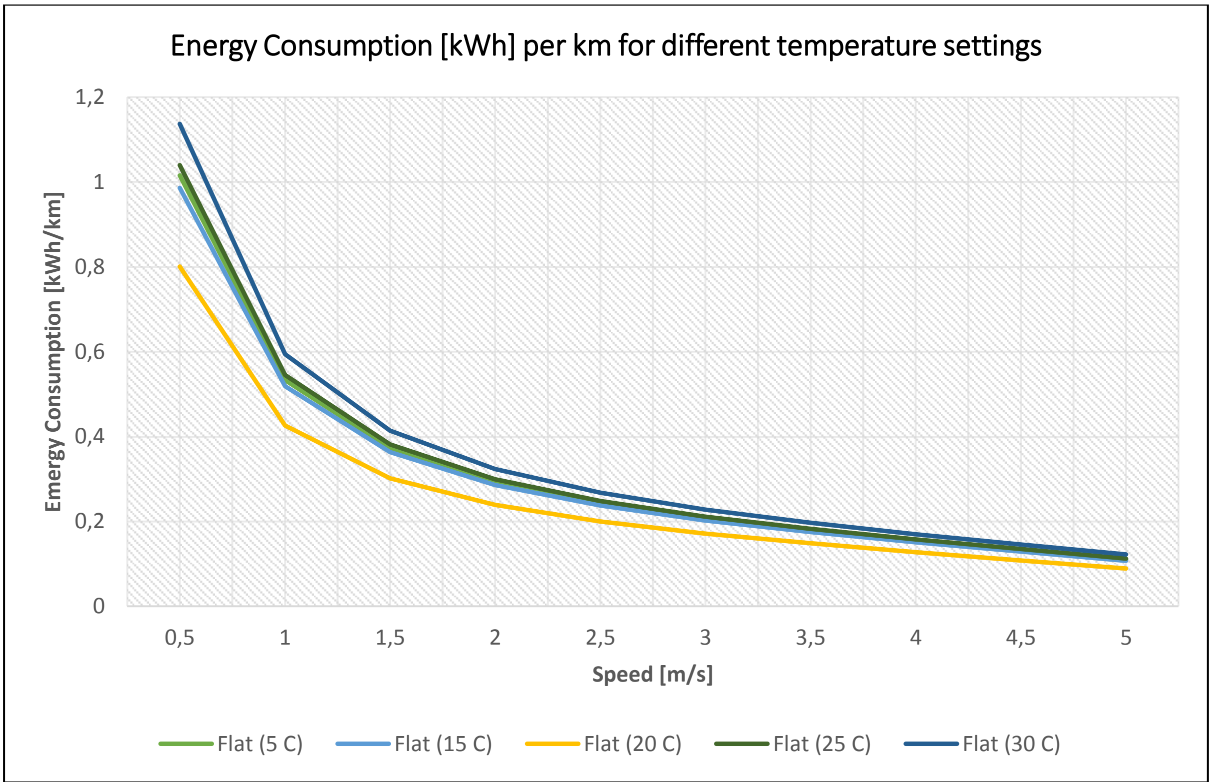

Figure 4.3-2 Energy consumption [kWh/km] for different temperatures from 5 to 30 ° C

4.4. Comparison with Internal Combustion Engines

In order to put the estimated energy consumption of the Digibus into context, the vehicle's energy consumption was evaluated against the energy consumption of an internal combustion engine with similar weight. As the average energy consumption is usually given in kWh/km, the total energy consumption was divided by the total distance travelled (see Table 4.1-1). Therefore, the resulting average energy consumption of 0,32 kWh/km also includes the time that the AEV spent idling (about one third during operation). Provided by the Umweltbundesamt in Austria, average energy consumption values for different ICE vehicle classes were drawn as a basis (Umweltbundesamt 2021):

- Diesel minibus < 3,5 t: 0,87 kWh/km
- Passenger car (Diesel or Gasoline): 0,67 kWh/km
- **Automated electric Digibus: 0,32 kWh/km**
- Electric passenger car 0,174 kWh/km

The average fuel consumption of a minibus in Austria weighing below 3,5 tons is approximately 9 liters per 100 km, which corresponds to 0,87 kWh/km. As reference, the average energy consumption of a passenger car in Austria, diesel or gasoline, and of an electric passenger vehicle in Salzburg was also included (Umweltbundesamt 2021; Statistik Austria 2021). Comparing these average values, the energy consumption of the Digibus is about a third of the energy consumption of an ICE minibus and half of a standard ICE passenger car. However, it is still double the energy consumption of an electric passenger car which is due to the higher weight of the Digibus, but also to the current technology of the AEV.

Table 4.4-1 Energy consumption for different scenarios assuming constant speed (Average speed when moving 3 m/s = 10,8 km/h) as well as average values for ICE passenger vehicles and minibuses

Scenarios (3 m /s)	**Energy Consumption kWh/km**
Digibus Downhill -6 to -3 % (20 ° C)	0,142
Digibus Flat (20 ° C)	0,172
Digibus Uphill 3 to 6 % (20 ° C)	0,216
Digibus Uphill 3 to 6 % (5 ° C)	0,251
Digibus Uphill 3 to 6 % (30 ° C)	0,272
ICE passenger car Austria	0,67
ICE Diesel minibus Austria	0,87

As a next step, a more in-depth ranking was done to estimate the performance for different road gradients compared to an ICE vehicle. For this purpose, formula (5) was again used assuming the shuttle's average speed of 3 m/s or 10,8 km/h (see Table 4.1-2). Since speed was held constant, these values do not include any idling time or acceleration which leads to overall smaller energy consumption values per km (see Table 4.4-1).

The energy consumption of the Digibus for all scenarios with various road gradients is only a fraction of the average energy consumption of an ICE minibus. The lowest value of 0,142 kWh/km is estimated for a downhill slope at the temperature of 20 ° C which is about half of the maximum energy consumption of the Digibus. This was found for an uphill terrain at 30 ° C ambient temperature signifying the usage of air conditioning. Nonetheless, the highest energy consumption of the Digibus is still not even half of the average consumption of an ICE passenger car.

However, a comparison using averages for ICEs has limitations as the average speed of a vehicle in typical traffic would be much higher than 3 m/s or maximum 5 m/s. Therefore, a formula provided by Song et al. was used to focus on energy consumption at low speeds (Song et al. 2013):

$$Fuel\ Consumption = 1{,}56 * 10^2 * v^{-1} + 3{,}54 - 3{,}88 * 10^{-2} * v + 7{,}76 * 10^{-4} * v^2 \qquad (6)$$

The model is based off a gasoline light duty vehicle operating in Beijing which serves as an indication of how well an ICE minibus performs at low speeds. By comparing the energy consumption rates at the speeds from 0,5 to 5 m/s (see Figure 4.4-1), it becomes clear that the internal combustion engine spends much more energy during low speeds than the automated electric shuttle bus. The difference decreases with higher average speed, however, at 5 m/s the energy consumption of the ICE is still several times higher than the energy consumption of the Digibus.

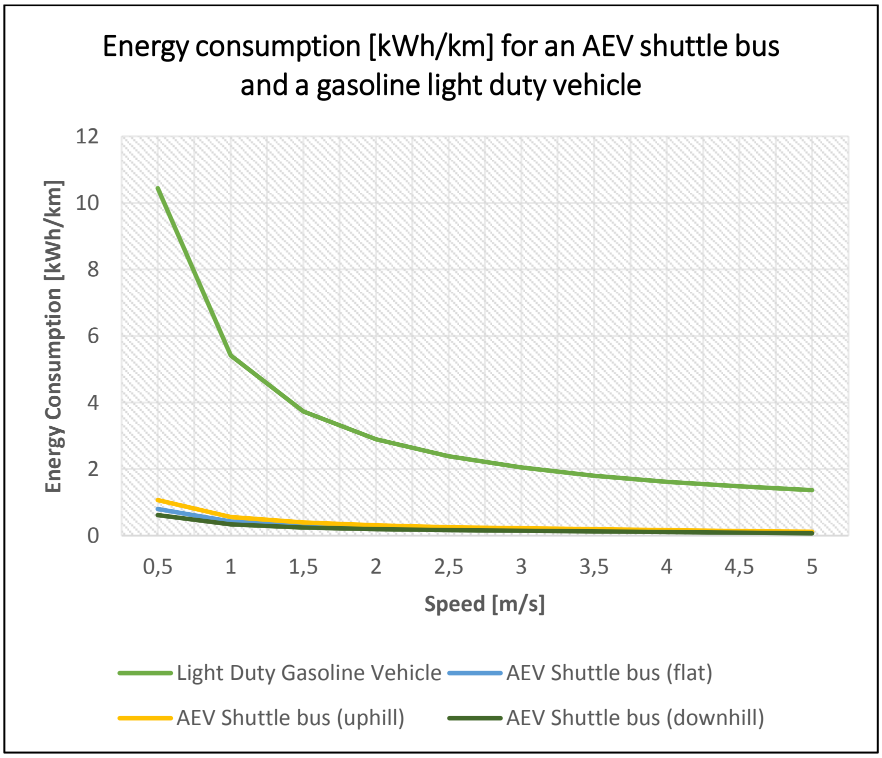

Figure 4.4-1 Energy consumption comparison of a gasoline light duty vehicle and the automated electric shuttle Digibus for the speed range from 0,5 to 5 m/s

Since the optimum speed range for ICEs is between 50 and 70 km/h (He et al. 2020), the energy consumption, calculated based on (6), for up to 100 km/h was also taken into consideration. Additionally, since the Digibus shuttle does not cover this range, a regression formula for the energy consumption of an electric light duty vehicle, provided by Yao et al., was used for comparison (Yao et al. 2013b):

$$Energy\ Consumption = 0{,}247 + \frac{1{,}520}{v} - 0{,}004v + 2{,}992 * 10^{-5}v^{-2} \tag{7}$$

Figure 4.4-2 emphasizes how the energy consumption of the ICE does not decrease below 0,7 kWh/km which is twice the average energy consumption of the automated electric shuttle. The lowest energy consumption of the ICE is estimated for a speed of approximately 16 m/s which is equivalent to almost 60 km/h. For electric light duty vehicles, the curve starts at a much lower energy consumption than that of an ICE and slowly decreases until slightly increasing again at a speed of 20 m/s, but always staying below the energy consumption of an ICE. While these curves might not be representative of all light duty ICEs and EVs, they show a significant difference in energy consumption at all speeds.

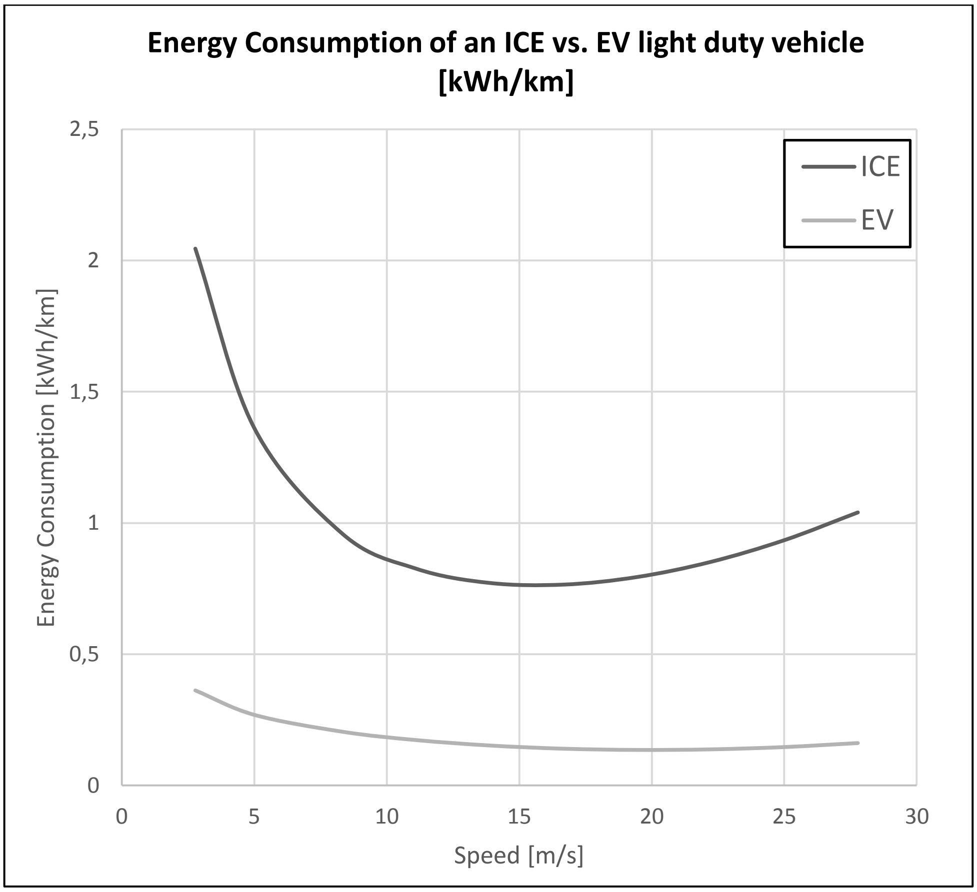

Figure 4.4-2 Energy consumption of an ICE and an EV light duty vehicle for a speed range up to 28 m/s (equivalent to 100 km/h)

4.5. Limitations of the study

In order to clarify the framework of this thesis, the limitations of the study need to be addressed. Firstly, it is important to understand that the Digibus has two batteries that are interacting with each other, but only the State of Charge for the main battery of 30,72 kWh is given. Therefore, it is unknown how much energy is lost during the interaction between the two batteries and how much is used for the sensors of the vehicle as well as air conditioning and heating. By consequence, the model cannot fully control for these factors. This is also an explanation for the State of Charge sometimes slightly increasing during usage as the system is probably adjusting itself. Moreover, the energy consumption rate that was used in the regression model is only an approximation of energy flow since the exact power (given by current and voltage) used each second is unknown. Under this premise, the results cannot be used for predicting the exact energy consumption of an AEV, but rather as an indication for correlations between energy consumption and explaining variables. In order to understand the relationship between energy consumption and road gradient in all its detail, the power the vehicle is using at every moment would have to be measured on a second-by-second basis as well as all other factors that are of interest in this regard.

In addition to data limitations, another limitation is the current technological and legal framework of AEVs. A comparison with an internal combustion engine is difficult as automated electric shuttles have a strict speed limit they cannot surpass. Therefore, the resulting regression model can only control for the range from 0 to 5 m/s (18 km/h) while average energy consumption of vehicles usually covers a much wider range up to more than 100 km/h. Another important factor is that the shuttle bus does not possess a regenerative braking system which allows for recovering energy during braking phases by using the electric machine in generator mode. This usually improves powertrain efficiency and optimizes EV range and is state-of-the-art for electric vehicles (Badin et al. 2013). Since the Digibus does not have such a system installed, the vehicle does not represent the full potential of AEVs in respect to energy consumption. As Cregger et al. put it, “Many of the problems associated with low-speed automated shuttles are related to the evolving nature of these vehicles.” The automated electric shuttle buses are produced and manufactured by small start-up companies which has an impact on their technology and performance. They do not have the same budget or experience designing and validating systems or mass-producing vehicles compared to traditional automakers (Cregger et al. 2018).

5. Discussion

Automated electric vehicles offer new possibilities for mobility services, especially for public transport. Through reducing operational and personnel costs, they are able serve routes that are not economically feasible at the moment (Guo et al. 2021; Riener et al. 2020). This is a huge problem in peripheral areas where the public transport system can be very unattractive since the demand is not high enough. As a consequence, people usually opt for private vehicles and the vicious cycle continues as demand decreases even more (Brake and Nelson 2007). Automated electric shuttle buses could be one of the solutions to stop this trend and provide better accessibility in these regions. However, rural terrains are different to urban settings as the road conditions as well as gradients are much more varied (European Road Safety Observatory 2006) which can affect energy consumption of vehicles negatively. The results of this study confirm a correlation between energy consumption and road gradient. They indicate that steep uphill slopes do cause a significantly higher energy consumption than flat terrains, but they also illustrate how less energy is spent on downhill slopes compared to flat terrains. As vehicles will both drive uphill and downhill in hilly areas, especially serving a pre-defined route, these counteracting effects will likely balance each other out.

With all driving conditions based on road gradient having a significant effect, the model confirms that road gradient should not be omitted from energy consumption models of AEVs. As studies on the energy consumption of EVs have found, the consequence of not incorporating road grade can be an over- or underestimation of a vehicle's power output which can cause inaccuracy in the estimation of energy consumption or emissions (Wyatt et al. 2014; Graser et al. 2015; Liu et al. 2017). In line with Liu et al. who investigated the impact of road gradients on energy consumption of EVs by using a macro-scale model, steep road gradients were found to have a positive correlation with the energy consumption rate. However, while they demonstrated an almost linear increase of energy consumption with increasing absolute gradient (Liu et al. 2017), this was not the case for the Digibus. The AEV spent most energy driving uphill between 3 and 6 % of road gradient, a little bit more than in areas with over 6 % slope. This can be attributed to the driving behavior of the automated vehicle or difficult road conditions during certain parts along the route that could cause more energy to be consumed. For downhill slopes, however, an almost linear decrease of energy consumption was estimated. Driving slightly downhill does not reduce energy consumption much compared to moving on flat ground, but for slopes less than -6 %, energy consumption is by far the lowest coming close to the energy spent during idling. This can be explained by the automated vehicle driving energy-efficiently and utilizing gravitational force to keep it moving downhill instead of spending extra energy on braking. As the coefficients for steep downhill slopes are much smaller than for flat areas and especially compared to uphill scenarios, there are two counteracting effects on the overall energy consumption in a hilly area. This implies that the reduction of spent energy during downhill road sections could be able to balance out the increase during uphill sections. Especially on a pre-defined route, the share of downhill and uphill sections are generally equal.

Liu et al. and Wang et al. estimated the energy consumption of EVs utilizing kinetic energy to generate electricity to the supply side which resulted in a rise of energy levels when going downhill (Chen et al. 2021; Liu et al. 2017; Wang et al. 2017). Since the Digibus did not possess a regenerative braking system, this implies that there is great potential for future AEVs to further reduce total energy consumption by adding this system. Braun and Rid, for example, measured a reduction of consumption by recuperation of electric energy between 11,6 and 16,3 percent (Braun and Rid 2017). The amount of energy that can be captured depends on the technological efficiency of the system as well as the driving behavior, whether vehicles brake gradually or severely (Muneer et al. 2017). For automated vehicles, algorithms can take energy recuperation into account and adapt the driving style accordingly in order to maximize its effects (Wadud et al. 2016).

By examining the vehicle's driving characteristics, the AEV generally showed a smooth driving behavior which was indicated by low means for acceleration and deceleration. Only the maximum for deceleration was quite high with 3,2 m/s^2 implying abrupt stops instead of slow deceleration. This is in line with reports from multiple pilot projects deploying automated electric shuttle buses where issues with obstacle detection have been mentioned. The vehicles often captured moving objects too late or wrongly came to a halt (Cregger et al. 2018; Zankl and Rehrl 2018; Transport Canada Innovation Centre 2021). However, as the technology is still advancing and evolving, these problems are likely going to be solved in the future. Flores et al. already showed how automated driving can lead to a reduction of energy consumption by 17 % compared to manual driving on the same route due to an eco-driving algorithm (Flores et al. 2015). Similarly, Lv et al. emphasized how algorithms for smoother driving can significantly decrease energy consumption (Lv et al. 2019). While the Digibus was not driven manually by the operator for the whole route which makes comparison between the modes difficult, its driving characteristics signify smooth driving cycles by low acceleration and deceleration means.

Aside from road gradients, the results show how temperature including heating and air conditioning impact energy consumption significantly. As multiple studies on the HVAC system have illustrated, extreme temperature, both low and high, are the cause for a big increase in energy consumption up to 30 or 40 % (Evtimov et al. 2017; R. Farrington and J. Rugh). However, in contrast to literature where heating was found to have the biggest impact (Doyle and Muneer 2019; Liu et al. 2018; Desreveaux et al. 2020), the results show that AC during very high temperatures had the biggest effect on the battery of the Digibus. Nonetheless, as it is unknown when either AC or heating were turned on, there is an uncertainty around these coefficients. This could be related to the number of passengers using the bus, as more passengers might have been using the shuttle bus during the summer months, while on the last days of deployment, there were more test runs without people on board and heating was not in use. Especially during low speeds and idling, the HVAC system consumes a lot of energy which is in line with Evtimov et al. who found that during low speeds, the auxiliaries are responsible for a big share of the vehicle's energy consumption (Evtimov et al. 2017; Badin et al. 2013).

In line with literature on the correlation between speed and energy consumption, a non-linear relationship was confirmed (Yao et al. 2013b; Yao et al. 2013a; Liu et al. 2018; Galvin 2017; Chen et al. 2021). Extremely low speeds cause higher energy consumption due to low efficiency of the drivetrain and relatively high energy consumption for supply of the auxiliary systems. Evtimov et al. estimated that at a speed of 5 km/h, for example in heavy traffic which also includes a lot of stop-and-go waves, the energy consumption can be equal to that one at 100 km/h. At high speeds, on the other hand, the energy spent for air resistance becomes the largest. Following this pattern, the AEV's energy consumption has been found to be the lowest while driving at its maximum speed. An optimum for EVs is usually reached at speeds around 40 km/h, however, this could not be measured for the Digibus due to the speed limit of 20 km/h (Evtimov et al. 2017).

Since the energy consumption of AEVs has not been tested with real-world data, there might be hesitation whether to deploy AEVs in environments with high slopes and whether other vehicles might be a better option given the current technology. Evaluating the energy consumption of an ICE compared to the AEV, the results show that there is no scenario where ICEs perform better than the automated electric shuttle. No matter which speed, temperature or road grade was assumed, the energy consumption of the Digibus was only a fraction of that of an ICE. However, the comparison was done within the AEV speed limitation of 20 km/h, which is the range that the performance of ICEs is usually worst (Cho and Choi 2017). ICEs typically reach their optimum energy efficiency at 50 to 70 km/h depending on the vehicle's mass, which is above the optimum for EVs (He et al. 2020; Wang and Rakha 2016). However, comparing the energy consumption of light duty ICEs and EVs for increasing speed up to 100 km/h, it becomes clear how the energy consumption of ICEs does not come down to the same level as that of electric vehicles. These results are supported by Martins et al. who evaluated the energy consumption of electric vehicles against Diesel cars and found that the electric powertrain presents higher efficiency than the ICE engine for all speed ranges. They argue that the difference is reduced as the average speed and required power is increased, nevertheless, EVs have a lower energy consumption within every scenario (Martins et al. 2013). This leads to the assumption that, even at high speeds, AEVs would still consume less energy than traditional ICEs.

6. Conclusion and Outlook

Automated electric shuttle buses have been brought out by small manufacturers over the last decade and deployed within pilot projects all over the world. Automated vehicles are seen as a solution to increase accessibility in rural areas since they reduce operational and personnel costs and can serve routes that are not economically feasible at the moment. However, the energy consumption of AEVs has not been tested with real-world data which is important for future deployment of the vehicles.

This research aimed to explore the impact of rural road characteristics on the energy consumption of automated electric vehicles. Based on the empirical data of the Digibus project, an AEV shuttle bus service deployed in the rural municipality Koppl, a panel regression analysis was performed to estimate the effect of road gradient, temperature and different driving characteristics on energy consumption. The results of this study confirm a correlation between energy consumption and road gradient. They indicate that steep uphill slopes cause a significantly higher energy consumption than flat terrains, but they also illustrate how less energy is spent on downhill slopes compared to flat terrains. As vehicles drive both uphill and downhill in uneven peripheral areas, especially serving pre-defined routes, these counteracting effects will likely balance each other out. Evaluating the energy consumption of the AEV against ICEs of the same mass, the AEV consumed less energy in every scenario that was tested.

Since the energy consumption rate based on the State of Charge is an approximation of the actual energy consumption at each moment, the model can be used to describe correlations rather than predict the exact energy consumption. It gives insight into the effects of road gradient and how AEVs operate in rural areas. Further studies are recommended to capture the power for each second in order to evaluate scenarios in more detail. However, this analysis signifies how the operation in rural areas will have similar energy consumption to the operation within urban settings. It is also already more energy-efficient than an ICE would be. With the installment of a regenerative braking system, the energy consumption could be even further reduced which would make the implementation of AEVs for public transport more appealing and shows the potential of AEVs in rural areas.

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List of abbreviations

AV	Automated Vehicle
AEV	Automatic Electric Vehicle
EV	Electric Vehicle
HVAC	Heating, Ventilation and Air Conditioning
ICE	Internal Combustion Engine
LSDV	Least Squares Dummy Variable
OLS	Ordinary Least-Squares
SAE	Society of Automotive Engineers
SoC	State of Charge