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Cost-Effectiveness of 5G Teleoperated Automated Buses

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Abstract for Master's Thesis

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Abstract: The emerging trends in automation and changes in people's mobility habits have increased interest in using automated buses for public transportation. Integrating automated buses into current public transportation systems is believed to provide many benefits, such as increased safety, flexibility and accessibility. This thesis explores whether cost-effectiveness is another benefit that could be realized by utilizing automated buses. Labor costs currently account for a large share of the total public transportation costs. Automated buses can save on driver costs, provided that each bus does not require a dedicated driver. Labor costs cannot be entirely eliminated as the buses, while mainly driving on their own, still occasionally need human attention. Cost savings are possible if in-vehicle drivers can be replaced by remote operators, who can operate multiple buses at the same time. To assess the magnitude of the potential cost savings, this thesis forms an estimation of the number of buses that can be designated to a single operator. A simulation is used as the method to establish the operator capacity. The input data for the simulation and background information on automated buses are gained by analyzing data from three different robot bus trials that were organized in Finland. A literature review and a small-scale practical remote driving experiment are used to assess the feasibility of remotely operating automated buses over a 5G network. The results of this thesis demonstrate that no insurmountable barriers exist for remotely operating several automated buses at the same time. The number of buses that can still be reasonably supervised by one operator depends on the frequency and duration of human interventions required by the fleet of automated buses. For the current class of automated buses, the operator capacity is estimated to be a maximum of five buses. The capacity is expected to increase once automated buses become more autonomous and less reliant on human operators. Although automated buses have higher purchase prices than conventional buses, their total cost of ownership is already lower when at least two buses are designated to the same operator. This means that once regulations allow vehicles without designated drivers and automated driving technology reaches sufficient reliability, automated buses can provide a compelling and cost-effective option to conventional buses.
Keywords: automated bus, robot bus, public transportation, 5G, teleoperation, remote driving, operator capacity, total cost of ownership
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List of Abbreviations

2D	Two-dimensional
3D	Three-dimensional
3G	Third-Generation Cellular Network Technology
4G	Fourth-Generation Cellular Network Technology
4K	Horizontal display resolution with approximately 4,000 pixels
5G	Fifth-Generation Cellular Network Technology
CAN	Controller Area Network
CO_2	Carbon Dioxide
COVID-19	Coronavirus Disease 2019
CSV	Comma-Separated Values
ERTRAC	European Road Transport Research Advisory Council
GLONASS	Global Navigation Satellite System (Russia)
GNSS	Global Navigation Satellite System
GPS	Global Positioning System (United States)
HMD	Head-Mounted Display
IMU	Inertial Measurement Unit
IT	Information Technology
LFP	Lithium Iron Phosphate ($LiFePO_4$)
LiDAR	Light Detection and Ranging
LTE	Long-Term Evolution
LTE-A	LTE Advanced; Long-Term Evolution Advanced
LTO	Lithium Titanate (Li_2TiO_3)
NEDC	New European Driving Cycle
RQ	Research Question
RTK	Real-Time Kinematic
SAE	Society of Automotive Engineers
TCO	Total Cost of Ownership
TV	Television
USB	Universal Serial Bus
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything

| VR | Virtual Reality |
| WLTP | Worldwide Harmonized Light-Duty Vehicles Test Procedure |

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1 INTRODUCTION

Road transportation is at a turning point, as it is expected to undergo a major transformation with the emergence of connected and automated vehicles. The current digitalization and automation trends have already disrupted other industries and road transport is not thought to be an exception to this. The transformation is driven not only by the rise of new technological breakthroughs, but also by the change in consumer preferences and attitudes as well as the introduction of more stringent environmental sustainability policies and commitments. The European Commission has recognized four emerging trends that are believed to reshape road transportation in the coming years: automation, connectivity, decarbonization and sharing (Alonso Raposo et al., 2019).

Automation refers to the development of road vehicles that are capable of performing some or all driving related tasks independently without constant human intervention or supervision. Connectivity refers to the utilization of modern technology, such as contemporary mobile networks, to enable vehicles to communicate with one another and with the roadside infrastructure. Decarbonization refers to the use of renewable energy and alternative fuels, such as electricity and biofuels, to lower the dependence on fossil fuels and to reduce CO_2 emissions. Sharing allows individuals to gain a temporary access to different transportation modes without the need of permanent ownership. Examples of this type of sharing economy include concepts such as car and ride sharing.

The trends in road transportation and the changes in people's mobility habits will before long revolutionize public transportation as well. Increasing urbanization, aging population, worsening traffic congestion and the aim to reduce private car use in cities will generate demand for new public transportation modes and services. Public transportation should be safe and accessible to everyone while also meeting the varying needs of individuals with increasingly diverse demographic and socio-economic backgrounds. Conventional modes of public transportation with high capacities will likely remain central to urban transportation, but new and innovative mobility services are expected to be introduced to complement them. The new trends and needs concerning public transportation have sparked the development of novel solutions for automated public transportation, of which automated buses are one of the most advanced and developed. While the technology is not yet completely ready, automated buses are

envisioned to provide a cost-effective, flexible and convenient transportation solution that can be easily integrated into existing public transportation networks.

1.1 Objective of the Study

The purpose of this study is to assess, both from an economic and technological perspective, whether it is feasible to use automated buses for public transportation. For automated buses to be cost-effective their costs need to be comparable to those of the corresponding means of transportation or the added value generated by automation needs to outweigh the need for additional investments. In order to assess the cost-effectiveness of automated buses, a general understanding of bus transportation costs will be developed, and the costs of automated buses will be compared to those of conventional buses.

The purchase prices of automated buses are higher than those of conventional buses, but to offset the high initial costs, their operating costs are assumed to be lower, as drivers are no longer needed to drive the buses. This does not mean, however, that automated buses would never need any human intervention. Instead of having a dedicated in-vehicle driver, automated buses are envisioned to be supervised and controlled remotely over mobile networks. If one person can remotely supervise several buses, cost savings can potentially be achieved. Therefore, the factors affecting the capabilities of remotely operating automated buses will also be discussed.

The effects of automation on the costs of public transportation have been studied previously at least by Wadud (2017), Bösch et al. (2018), Tirachini and Antoniou (2020) and specifically in Finland by Huhta (2017). These studies have predominantly shown that automation of public transportation has a favorable cost impact. However, the studies did not concentrate on labor costs or the feasibility of remote operation, which constitute the main focus of this study. The research in this thesis is guided by the following three research questions:

RQ1: How many automated buses can a single operator supervise simultaneously?

RQ2: What are the costs of automated buses and how do they compare to other bus types?

RQ3: Are the capabilities of modern mobile networks sufficient for supporting remote operation of automated buses?

1.2 Structure of the Thesis

This study is composed of nine chapters. This current chapter provides a short introduction to the topic of the research and presents the research questions. The rest of this thesis is organized as follows:

Chapter 2 provides background information on automated vehicles and related concepts. The chapter discusses the different levels of driving automation and the challenges associated with using automated vehicles. The technological components enabling automated driving are also introduced.

Chapter 3 discusses concepts related to remote operation of vehicles. The chapter reviews existing literature about remote driving and delivering 360° video over mobile networks for enhanced immersion.

Chapter 4 presents the overall approach chosen for the research process and describes the research methods. The chapter also details how and what type of data was obtained to support the research.

Chapter 5 discusses how three robot bus trials were organized in Finland and what kind of robot buses were used in those trials. The chapter also presents an overview of the data collected from the trials.

Chapter 6 gives an overview of the economic side of bus transportation. The chapter first discusses the costs of the robot bus trials and provides insight into the battery and kilometer costs of automated buses. The latter part of the chapter discusses the unit costs of different bus types.

Chapter 7 presents the results of the study. The chapter provides an estimation of operator capacity, a cost analysis of the use of automated buses and an assessment of the feasibility of remote driving over contemporary mobile networks.

The final two chapters conclude the research. **Chapter 8** discusses the key findings and contributions of this study, describes the limitations and offers some considerations for future research while also providing condensed answers to the research questions. **Chapter 9** summarizes the research and presents the main conclusions.

2 AUTOMATED VEHICLES

This chapter aims to provide background information on automated vehicles and concepts related to automated driving. Automated vehicles, which are also often referred to as autonomous vehicles, self-driving vehicles or driverless vehicles, are defined as vehicles that are capable of driving themselves with little or no human intervention and control. Automated driving is enabled by the vehicles' ability to sense the surrounding environment, detect and classify objects they encounter and establish navigation paths in varying environments and conditions (Campbell et al., 2010). Autonomous navigation in complex scenarios, while obeying traffic rules and maintaining the safety of the passengers and other road users, is achieved with the help of information collected from several different sensors integrated in the vehicle.

Automated buses, which are also known as robot buses or autonomous shuttles, are automated vehicles that are larger in size and have a higher passenger capacity than passenger cars. Automated buses, like their conventional counterparts, are intended to carry multiple passengers typically on specific, fixed routes according to predefined schedules. Once an automated bus has learned a route, it is expected to be able to drive the route automatically without deviating from the planned route as if it were running on virtual tracks. Most of the automated buses that have been trialed to date have been minibuses that can fit somewhere between 10 to 15 passengers. These types of buses are envisioned to be used for the first and last mile connections to mass transit, i.e., the commute to and from transport hubs, and to supplement trunk lines. In the future, automated buses could potentially also be used in an on-demand manner on flexible routes instead of them having predefined schedules and routes. (Ainsalu et al., 2018)

2.1 Levels of Driving Automation

Automated vehicles can be divided into different categories based on their level of automation and capabilities related to autonomous driving. The Society of Automotive Engineers (SAE) has created a detailed multilevel taxonomy of vehicle automation that establishes characteristics and capabilities for each level of automation. The levels within the taxonomy describe how driving responsibilities and dynamic driving tasks are divided between a human driver and a driving automation system. Dynamic driving tasks

encompass all the operational and tactical functions required to operate a vehicle. Operational tasks include lateral and longitudinal vehicle motion controls, i.e., steering, acceleration and braking. Tactical functions include planning the movement of the vehicle and the use of lights, signals and other gestures. Monitoring the environment where the driving is done and reacting to objects and events that the vehicle encounters can be classified as both operational and tactical functions. Tasks, such as scheduling trips and selecting destinations, are strategic functions that are not part of the dynamic driving tasks.

Table 1   *Levels of driving automation (adapted from SAE International, 2018)*

Level	Name	Description	Vehicle Motion Control	Monitoring of Driving Environment	Driving Fallback	Capabilities of Automated Driving
Driver monitors the driving environment						
0	No Driving Automation	Driver performs all actions related to operating the vehicle although some warnings and support might be provided by active safety systems.	Driver	Driver	Driver	None
1	Driver Assistance	The driving automation system performs actions related to either steering or adjusting the speed of the vehicle.	Driver and System	Driver	Driver	Limited
2	Partial Driving Automation	The driving automation system performs actions related to both steering and adjusting the speed while the driver supervises the system.	System	Driver	Driver	Limited
System monitors the driving environment						
3	Conditional Driving Automation	The driving system performs all actions related to operating the vehicle while the user needs to be ready to take control when needed.	System	System	Driver	Limited
4	High Driving Automation	The driving system performs all actions related to operating the vehicle within designated areas and under specific conditions.	System	System	System	Limited
5	Full Driving Automation	The driving system performs all actions related to operating the vehicle under all typical road, traffic and weather conditions.	System	System	System	Unlimited

The taxonomy by SAE defines six levels of vehicle automation. The levels range from zero to five, where level 0 describes a vehicle that is fully manual and level 5 a vehicle

with full driving automation. A summary of the different levels is shown in Table 1. In levels 1 and 2, a human driver is responsible for monitoring and overseeing the driving environment. The driving automation system takes care of either lateral or longitudinal motion control in level 1 and both forms of motion control in level 2. Starting from level 3, the driving automation system is capable of performing all dynamic driving tasks, including all forms of vehicle motion control and monitoring the driving environment. In level 3, a human is expected to act as a fallback and be available for taking the control of the vehicle in case the driving system requires intervention or assistance. In levels 4 and 5, the automated driving system is capable of performing all dynamic driving tasks without requiring any human intervention at any point in time. In level 4, the driving system can autonomously operate the vehicle under certain predefined conditions and restrictions, such as within enclosed or geo-fenced areas. In level 5, no restrictions exist on where and when the driving system can operate the vehicle, provided that conditions, such as road and weather conditions, are suitable for safe driving.

2.2 Current Challenges and Future Development

Precisely predicting the future evolution of vehicle automation is difficult due to uncertainties related to technological progress, acceptance of self-driving vehicles and changing regulatory environment. Despite the unpredictable future of automated driving, high expectations are placed on it. Automated driving is expected to alleviate many of the issues that the society currently experiences with regard to road transport, such as safety, energy efficiency, congestion, urban accessibility as well as social inclusion (ERTRAC, 2019). Introducing vehicle automation to the public transportation scheme is seen as an enabler for making the public transportation system more accessible and available for the aging population as well as for people with disabilities.

Many impediments continue slowing down a wider scale adoption of self-driving vehicles. Technological barriers are the most obvious ones. The technology used for automated driving should be scalable so it can be used on different vehicle models and geographical markets. The driving automation system needs to adhere to strict safety requirements and the hardware and software components of the system need to be designed so that, in the event of a critical component failure, the vehicle can still operate in a safe manner. Automated vehicles need to be well protected against cyber-attacks

because, due to being almost always connected to a network, they are very susceptible to different types of attacks. Many different advanced and novel technologies need to be integrated together to make automated driving possible and the vehicles need to be able to communicate and co-operate with various external systems. These factors contribute to the complexity of automated vehicles and increase the need for aftermarket software updates and maintenance.

Another challenge related to automated driving is the availability and readiness of the systems and services supporting and promoting the use of automated vehicles. The physical and digital road infrastructure needs to evolve to better support automated driving and to allow for new services to be built on top of them. In the coming years, new innovative business models and mobility services utilizing automated driving are expected to emerge and disrupt the transportation industry. Sharing economy combined with automated driving could potentially create new societal trends and greatly impact individual mobility behavior. Car sharing and ride hailing services serve as examples of types of sharing economy that could benefit from automated driving.

Advancements in artificial intelligence and machine learning are paramount for the success of automated vehicles as the vehicles need to be able to interpret and predict traffic conditions at a level that corresponds or even exceeds the capabilities of humans. The more diverse traffic scenarios the vehicles experience, the better the algorithms for automated driving get at handling varying real-life traffic situations. Huge amounts of data are generated by the sensors in automated vehicles as well as by other sensors placed across traffic. Better utilization of big data analytics and deep learning are thought to lead to significant improvements in self-driving functions of automated vehicles.

The society and users can set certain limitations on the pace that automated vehicles are adopted as well. Users may exhibit prejudice against automated driving due to trust and acceptance issues. This calls for increasing user awareness and educating users about how automated vehicles behave in different traffic situations. The interaction between humans and automated vehicles, including the interaction between an automated vehicle and its passengers as well as the interaction between an automated vehicle and other road users, needs to be well understood. Ethicality and liability aspects need to be also considered when a human driver is not in control of the vehicle. Questions related to liability in the event of an emergency and responsibility for the actions and decisions taken by the

automated vehicle need to be addressed. Current policies and regulations are outdated and do not cater for fully driverless vehicles. Driver training, safety validation of vehicles and roadworthiness testing need to be revised to consider the self-driving capabilities of future vehicles. Socio-economic challenges relate to the impact that automated driving can have on jobs and employment in the transportation and automotive industries. Automated driving will undoubtedly reduce the future need for human drivers but at the same time the need for IT specialists and engineers with expertise in self-driving technologies can potentially increase.

...	2018	2020	2022	2024	2026	2028	2030	2030+

Level 5: Full Automation

Level 4: Auto Pilot
Automated buses on dedicated roads — Automated buses in mixed traffic

Level 3: Chauffeur
Automated urban bus chauffeur

Level 2: Driving Assistance
Urban bus assist
Traffic jam assist
Parking assist
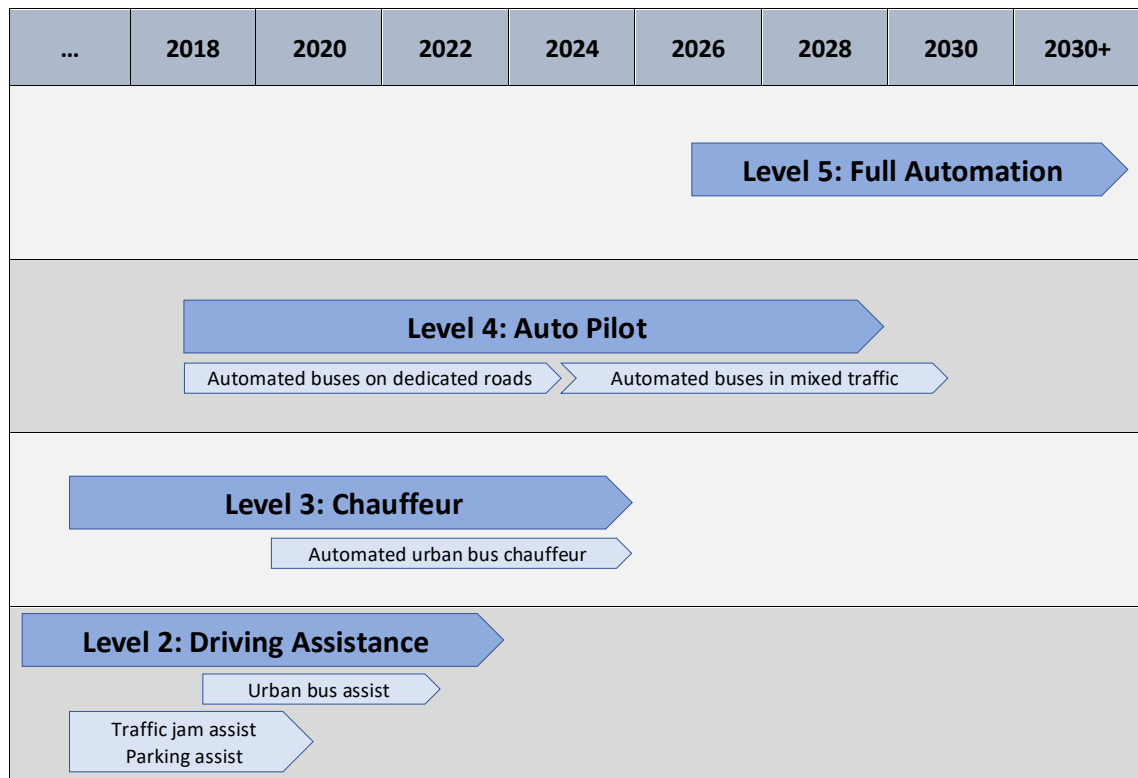
Figure 1   Roadmap for automated vehicles (adapted from ERTRAC, 2019).

Despite all the challenges and hindrances, the development path for automated vehicles is firmly set towards fully autonomous driving. It is difficult to predict in which exact year each level of automated driving will be achieved but ERTRAC has presented some estimations, which are depicted as a timeline in Figure 1. To date, automation levels 0 through 2 are, for the most parts, considered to be established in the form of features such as adaptive cruise control, lane keeping assist, lane change assist, parking assist and so on. Next major breakthroughs are expected particularly in automation level 4. High automation driving features will be initially taken in use on highways and other rural roads and later in urban settings. Automated buses will likely be first operated in

dedicated bus lanes along with traditional buses before they can drive among regular city traffic and on open roads.

2.3 Technology

From a technical perspective, automated driving is enabled by different hardware and software components that seamlessly work together. The hardware components include different kinds of sensors, vehicular communication devices and actuators. The software system of an automated vehicle can be roughly divided into three distinctive subsystems based on their functions: perception, planning and control (Pendleton et al., 2017). Figure 2 below gives an overview of the system architecture of an automated vehicle, including the different functional components and their interactions with each other and with the driving environment.
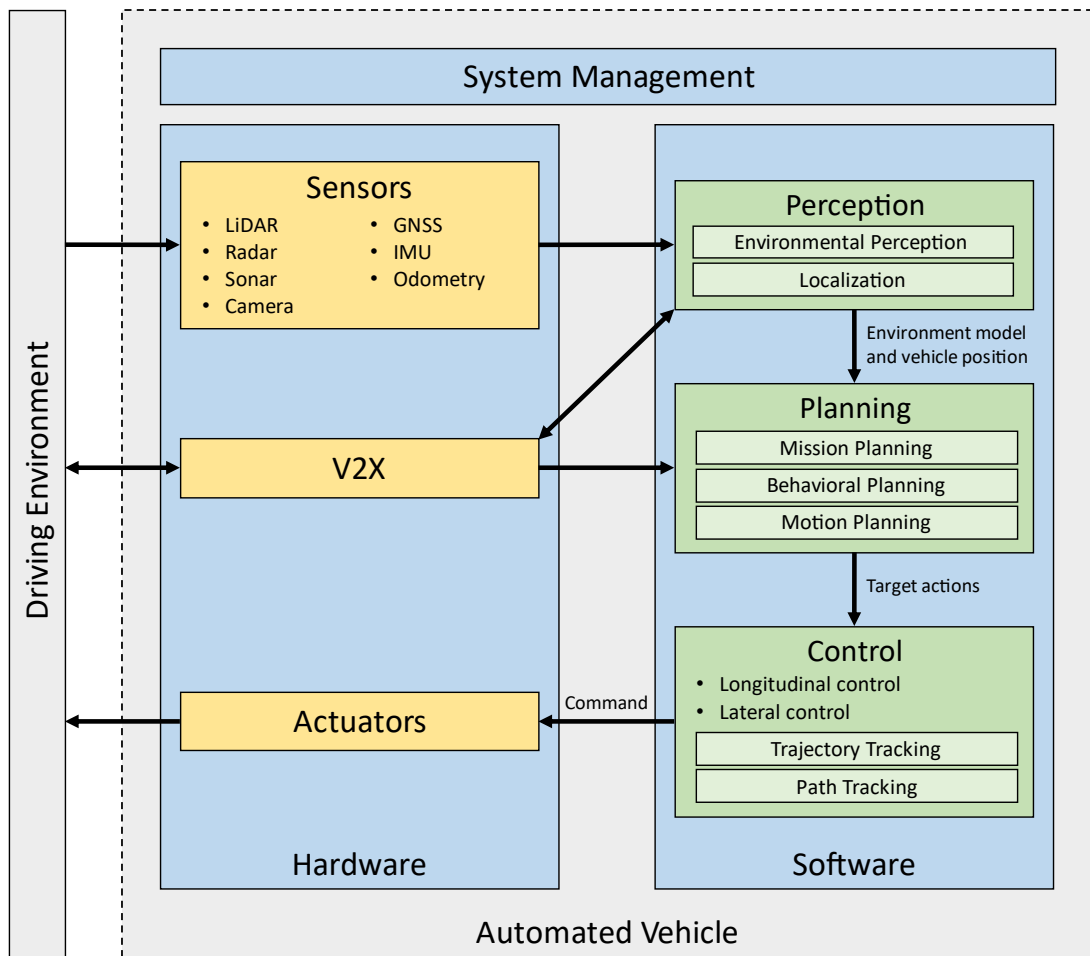
Figure 2 *An overview of an automated vehicle system and its core components (adapted from Pendleton et al., 2017; Jo et al., 2014).*

Perception is the ability of the automated vehicle to sense its surrounding area and acquire relevant knowledge from the driving environment. Environmental perception provides the vehicle with information about the current driving conditions, such as determination of areas in which driving is safe and detection of objects on and around the road. Localization refers to the ability of the vehicle to determine its current position relative to its environment. Perception is achieved with the help of number of different sensors integrated in the vehicle. In practice, perception refers to the process of turning raw sensor data into meaningful insight of the driving environment that the vehicle can use to evaluate the current situation and to make decisions about future actions.
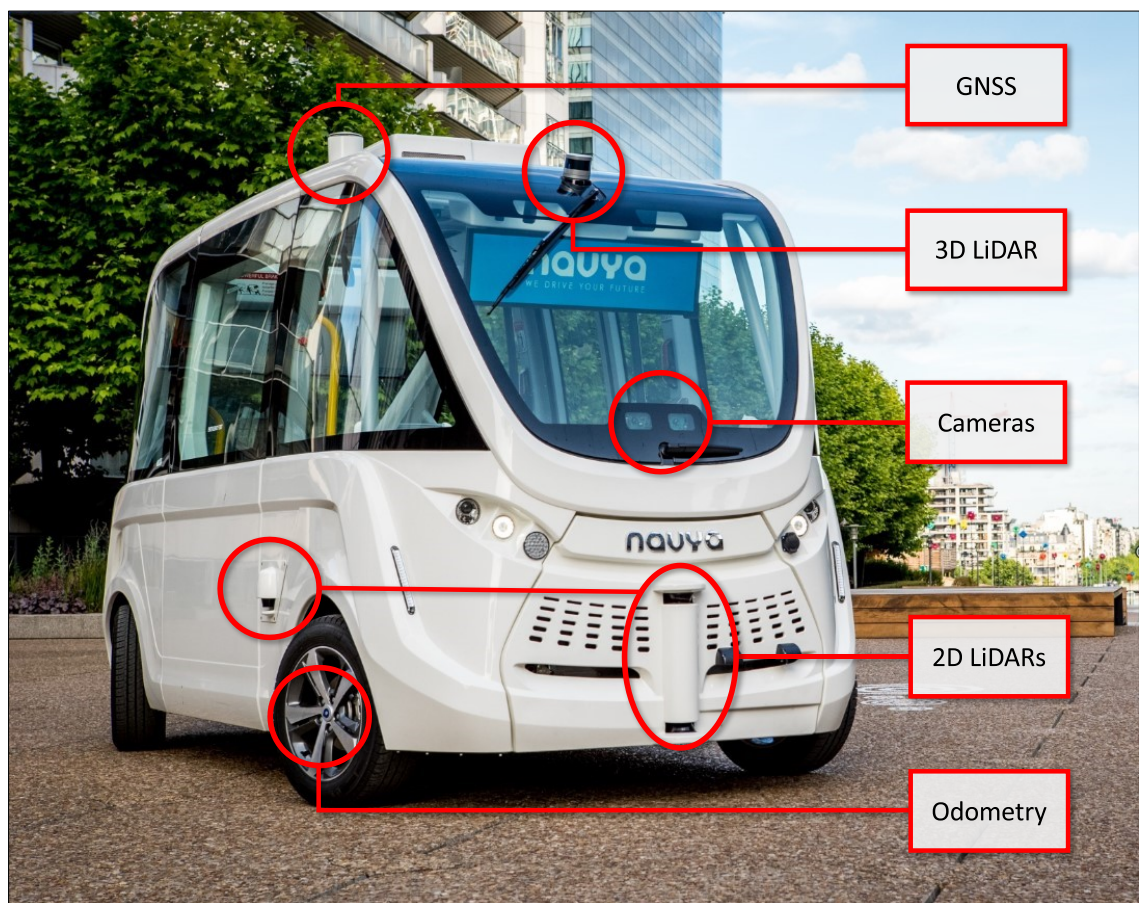
Figure 3 *Typical sensors in automated vehicles (Original photo courtesy of Navya).*

For most automated vehicles, the Light Detection and Ranging (LiDAR) sensor is at the center of object detection. LiDAR sensors use laser beams to scan the surroundings in order to develop a map of the nearby environment, which depicts the objects, both moving and stationary, around the vehicle and distance from the vehicle to those objects. LiDAR sensors come as both 2D and 3D variants and as rotary and solid-state variants. 2D LiDAR sensors use a single, rotating laser beam to measure the distance to objects both

on the X and Y axes. 3D LiDAR sensors, by contrast, use multiple laser beams to form an accurate 3D map of the environment. Other sensors that can be used in combination with LiDAR sensors for environmental perception include cameras, radars and ultrasonic sensors. Figure 3 above shows typical sensors automated vehicles use for environmental perception and localization.

Localization refers to determining the estimated position and orientation of the vehicle. Localization in automated vehicles is typically achieved by using both satellite-based navigation systems and inertial navigation systems. The Global Navigation Satellite System (GNSS), which encompasses satellite navigation systems such as GPS and GLONASS, can regularly provide the vehicle with information about its absolute position coordinates. The accuracy of satellite navigation systems depends on the reliability and strength of the signals from the satellites. The accuracy can at best be a few millimeters and at worst a few tens of meters. Satellite navigation systems are usually accompanied by inertial navigation systems that do not depend on external infrastructure. Inertial navigation systems use motion and rotation sensing to estimate the position and heading of the vehicle based on previously determined positions in a process referred to as dead reckoning. Odometry is a simple form of position estimation that utilizes data from rotary sensors fixed to the wheels of the vehicle. Odometry is not capable of capturing all movement of the vehicle precisely, which is why it is complemented with inertial measurement units (IMUs), such as accelerometers, gyroscopes and magnetometers.

Planning is the process that guides the vehicle in making meaningful decisions based on information obtained about the environment and the vehicle's position. Planning can be thought of as a three-level hierarchical framework that includes mission planning, behavioral planning and motion planning. Mission planning considers the high-level objectives of the vehicle, such as finding the appropriate route for driving from the current location to the desired destination. Behavioral planning is concerned with making decisions in specific situations to ensure that road rules are followed and that interaction with other road users is done in an appropriate and safe manner. Examples of local objectives generated through behavioral planning include changing lanes, overtaking other vehicles and driving through intersections. Motion planning refers to deciding the next sequence of actions to be taken in order to reach a specific, local objective while avoiding obstacle collision.

Control or motion control is the process of converting intended actions generated by the higher-level processes into concrete actions. The planned actions are executed by providing the necessary input to the actuators of the vehicle, which will adjust the lateral and longitudinal movement of the vehicle accordingly. The typical methods used for controlling the motion of the vehicle are path and trajectory tracking. Path is defined as a geometric representation of the plan to move from the starting position to the goal position, while trajectory also includes velocity information of the motion, i.e., information on how to traverse the path with respect to time.

Vehicular communication is an emerging technology that allows vehicles to connect to other nearby vehicles and to the roadside infrastructure over a wireless network. The technology enabling communication between vehicles is referred to as Vehicle-to-Vehicle (V2V), which has the potential to prevent accidents by allowing vehicles to share their position and speed with one another. Vehicle-to-Infrastructure (V2I) is a communication model that allows vehicles to interact with components of the road infrastructure, such as traffic lights and parking meters. Vehicle-to-Everything (V2X), which encompasses both V2V and V2I, is an umbrella term referring to communication between vehicles and other related entities in and around the driving environment. (Arena & Pau, 2019)

Vehicular communication is seen as an integral part of automated driving because it enables cooperation between automated vehicles. Cooperative sensing increases the sensing range through the exchange of sensor data between vehicles. This allows an automated vehicle to obtain sensor data beyond the capabilities of its own sensors. Cooperative maneuvering enables a group of automated vehicles to coordinate their driving according to a common centralized or decentralized strategy. Such coordination could for instance enhance traffic flows at intersections. (Hobert et al., 2015)

2.4 Safe State

When an automated vehicle encounters a serious issue, such as a technical failure or a hazardous event that prevents the vehicle from continuing its intended trip, the vehicle is brought to a minimal risk condition. A minimal risk condition is a low-risk condition the vehicle tries to achieve in order to reduce the probability of a crash and to ensure the safety of the passengers of the vehicle, pedestrians and other traffic users. What the

precise minimal risk condition is, depends on the level of automation of the vehicle, how the vehicle is controlled and the situation in which the minimal risk condition should be reached. At automation levels 4 and 5, the vehicle is expected to achieve the minimal risk condition by itself automatically when needed, whereas at lower levels of automation, a human driver is responsible for achieving the minimal risk condition.

Automated vehicles can face a wide range of different traffic events, which makes it difficult to define a safe state for every possible scenario. Typical actions to maintain a safe state include passing the control of the vehicle to a human driver, if a human driver is present in the vehicle, or bringing the vehicle to a stop. However, a handover to a human driver may not be instantaneous and an immediate stop while driving with higher speeds on a highway, for instance, could potentially be dangerous. Hence, more complex actions are often needed, such as carefully maneuvering the vehicle off from an active lane of traffic and gradually decelerating the vehicle.

An article by Reschka and Maurer (2015) studied several use cases of events that impact the safety of automated vehicles and identified the following conditions for a safe state of an automated vehicle operating within public traffic: (1) a human driver is in control of the vehicle, (2) the vehicle is controlled by a remote operator, (3) the vehicle is driving automatically within its functional boundaries with a safe speed and adequate safety distances to other vehicles and objects, and (4) the vehicle is stopped with the condition that the relative speed to other traffic users is below a certain level, the vehicle and its current state is visible to other traffic participants, and the vehicle is not blocking emergency vehicles or emergency routes. In practice, for current automated vehicles, the course of action upon encountering a foreign object on their path is to stop and wait until the obstacle is cleared away or alert a human operator to respond to the situation. In the event of a system failure caused either by a software or a hardware issue, the vehicle almost always requires some level of human intervention.

3 VEHICLE TELEOPERATION

This chapter gives an overview of vehicle teleoperation, which refers to the ability to remotely monitor and drive automated buses. Teleoperation is primarily needed to assist automated vehicles remotely in situations that the driving automation is not yet able to handle on its own. The general concept of teleoperation and its challenges are briefly introduced in this chapter. This is followed by a literature review concerning remote driving and delivery of 360° video over contemporary mobile networks to enhance the teleoperation experience.

3.1 Teleoperation

To date, automated vehicles operated on public roads have generally had safety drivers present in the vehicles to take over the control on the occasions the vehicles run into situations they are not capable of handling. Level 3 automated vehicles require a human driver as a fallback, while level 4 and 5 automated vehicles do not have the same requirement as they are expected to be able to drive themselves without human supervision or having a fallback option. Automated vehicles without fallback drivers are still susceptible to encountering unknown situations and experiencing malfunctions. When such incidents occur, the vehicle must bring itself into a minimal risk condition. This typically means slowing the vehicle down to a standstill. With no driver present in the vehicle and a person capable of fixing the issue potentially far away, the stalled vehicle can block a lane for a long time. As an alternative to having a safety driver inside the vehicle or dispatching a field technician to the scene, teleoperation is envisioned as a more time and cost-efficient solution for bringing automated vehicles back to autonomous driving after an incident. (Georg & Diermeyer, 2019)

Teleoperation, in the context of automated vehicles, refers to remote control of vehicles from a distance outside a line-of-sight to the vehicles by human operators located in operation centers. In the event of an incident, an operator remotely connects to the vehicle to assess the situation and to take control of the vehicle if needed. The advantage of teleoperation is that fewer operators are needed as not every vehicle needs to be equipped with a safety driver. Additionally, the use of automated vehicles might be subject to certain restrictions, such as the areas where they are allowed to operate and the speeds

they are permitted to drive. Upon reaching its operational boundaries, the control of the vehicle could be passed to an operator until the conditions are again appropriate for the vehicle to continue automated driving. (Georg et al., 2018)

Generally, teleoperated systems are composed of three main elements: the teleoperated device, the operator interface and the communication link between the two (Winfield, 2000). The teleoperated device refers to the robot that is remotely controlled, which in the context of automated vehicles is the vehicle itself. The operator interface displays sensor and status information from the robot and allows commands to be sent to the robot. The communication link is a two-way connection that is needed for exchanging sensor data and commands between the robot and the operator. Since automated vehicles are not fixed to specific locations, the communication between the vehicle and the operator has to occur over a wireless connection.

The main problems with teleoperation are associated with time delay and lack of situational awareness (Georg et al., 2018). Although wireless connections have over time become faster and more reliable, especially with the introduction of 5G mobile networks, the connection between the operator and the vehicle can never be expected to be entirely latency free. In practice, this means that the sensor data the operator sees from the vehicle are delayed and the control of the vehicle is not immediate. The fact that the person operating the vehicle is not physically present at the vehicle's location causes a loss of situational awareness. Situational awareness is defined as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future" (Endsley, 1988). The operator must build a mental representation of the remote vehicle based on the feedback provided by the vehicle's sensors. The information from the vehicle's sensors is not perfect, which means that the operator needs to compensate the missing information. This is tiring and leads to operator fatigue and weakened sense of telepresence, i.e., the feeling that the operator would be present in the remote vehicle.

The focus of recent developments in vehicle teleoperation systems has been in reducing operator-load by better immersing the operator into the remote vehicle's environment. In order to improve the situational awareness and telepresence of the operators, as many human senses as possible should be stimulated by the information transmitted from the remote vehicles. This has motivated researchers to seek novel ways to utilize technology,

such as head-mounted displays (HMD) and 360° camera views, to provide deeper immersion in teleoperation.

Most recent studies have concentrated on how to improve the visual feedback. A study by Hosseini and Lienkamp (2016) found that using an HMD-based mixed reality system for vehicle teleoperation significantly improved situational awareness. Bout et al. (2017) conducted a user study, which compared using a laptop display and an HMD as an interface for determining what caused an automated vehicle to stop. The participants of the study indicated that using an HMD made it easier to interpret the situation, gave them better visibility around the vehicle and made them feel more strongly connected to the vehicle. Georg et al. (2018) also compared using a conventional computer screen and an HMD for vehicle teleoperation. The study showed that using an HMD allows for a higher feeling of immersion, but does not necessarily lead to improved driving performance.

While vision is the most important sense needed for driving, haptic and audio feedback can be used to further increase the immersion of the operators (Georg & Diermeyer, 2019). Vibrations and movements added to the operator's seat and steering wheel can be used to simulate for example the sensation of acceleration or going over speed bumps. Two-way audio not only heightens the feeling of telepresence by introducing for example ambient noise, but it is also needed for hearing sirens of emergency vehicles and for verbal communication with the people inside and around the vehicle.

3.2 Remote Driving over Mobile Networks

While the general concept of robot teleoperation has been reasonably well studied, remote driving over mobile networks and the impact of latency on driving are topics that are not as widely studied. The results from the studies that have been conducted on these subjects are also somewhat inconsistent. A study by Liu et al. (2017) assessed the impact of delay on remote driving over LTE networks. The study concluded that the variability of network delay rather than the magnitude of the delay significantly degrades the driving performance of remote drivers. Another study by Neumeier et al. (2019b), however, established that a constant latency of about 300 ms leads to a degraded driving performance, while variable latency was found to have no effect on driving performance. An earlier study by Gnatzig et al. (2013) found that an operator was able to safely keep a vehicle moving with a speed of 30 km/h on a track and react to dynamic obstacles even

though there was a constant delay of 500 ms in the video coming from the vehicle. Based on these studies, it can be safely assumed that the delay in remote driving should not exceed 300 ms and that the variability in the delay should preferably be kept to a minimum.

Some studies have also been conducted on whether the capabilities of 3G and 4G networks are sufficient for remote driving. According to Chucholowski et al. (2014) the delay in the transmission of video data over a 3G network can vary between 65 and 1,299 ms with an average delay of 121 ms. Shen et al. (2016) conducted a driving test where network latencies were measured for video, vehicle controls and camera pan tilt on different networks. A 4G network was observed to perform almost twice as fast as a 3G network in terms of average latency. Even a 3G network was considered to be usable for remote driving although the recorded maximum latencies sometimes reached values over 500 ms. Kang et al. (2018) experimented with streaming video over an LTE connection from a moving car and observed a median latency of about 100 ms.

A study by Neumeier et al. (2019a) established that remote driving can be possible in modern mobile networks, particularly in LTE and LTE Advanced (LTE-A) networks. The study found that signal strength, the distance of the vehicle to the operation center and network handover affect the latency and throughput of the network in remote driving, while the speed of the vehicle and the distance of the vehicle to the cellular base station do not. The study proposed the use of whitelisting as a possible approach for mitigating the high variance in network performance. In whitelisting remote driving would only be allowed in areas, which are measured to have adequate network capacity. In a similar vein, Inam et al. (2016) suggest that intelligent routing logic could be used to re-route vehicles around areas with challenging network conditions. In addition to route planning, the speed of the vehicle could, in order to compensate for the increasing latency, be lowered to a level, which would still allow safe and controlled remote driving (Neumeier & Facchi, 2019). Multi-operator setups and algorithms for driver selection have been discussed in papers by Gohar and Lee (2018), Gohar et al. (2018), Gohar and Lee (2019) and Gaber et al. (2020). The use of multiple, distributed remote drivers allows passing the control of the vehicle according to a specific algorithm to the operator who at that moment is closest to the vehicle or has the connection with the lowest latency available to the vehicle.

Remote driving and teleoperation in general over a 5G network have not yet been studied to a great extent. A study by Uitto et al. (2019) measured the delay, jitter and throughput of a 5G test network in a remote control scenario. The measured average delays in the 5G test network for video and control were observed to be 1.65 and 1.09 ms, respectively. In an LTE-A network the recorded delays were manyfold compared to the 5G test network, with the delay for video being on average 15.9 ms and 32.8 ms for control. As the 5G radio technology seems to be capable of providing nearly 1 ms radio link delay, which is significantly better than LTE-A, the benefit of 5G in remote control scenarios is apparent. Isto et al. (2020) detailed an experiment where a virtual excavator was remotely controlled with a real machine control system over a 5G test network. The study concluded that, with a suitable edge computing architecture, significant improvements can be expected in terms of delay and jitter from future 5G networks over current LTE networks.

A study by Saeed et al. (2019) assessed the feasibility of remote driving within a wide city area, namely Vienna, Austria. The study considered whether the network requirements for remote driving can be fulfilled everywhere in the city and how densely base stations would need to be deployed to ensure wide availability of remote driving. The results from the study indicated that widescale adoption of remote driving can be problematic. The network deployment costs can grow considerably high if remote driving is enabled everywhere. Remote driving also continuously generates large amounts of upload traffic, which can lead to overutilization of the network's upload capacity. Using an exclusive frequency band for remote driving is not thought to provide an effective and sufficient mitigation. The study suggests that support for remote driving should be ensured only on certain routes with careful network planning. The connectivity requirement of 99.999 % that is needed for remote driving is not seen feasible in wider areas.

3.3 Delivery of 360° Video

While using HMD for teleoperation and remote driving has been shown to improve immersion, using HMD with live video streaming places stringent requirements not only for the quality of the network connection but also for computing performance. The motion-to-photon latency, which describes the time it takes for user movement, such as

head rotation, to be reflected on the display, should be less than 15–20 ms for users not to experience motion sickness. The end-to-end latency in 360° video delivery consists of sensor sampling delay, image processing delay, network delay and display refresh delay. Sensor and display refresh delays are believed to contribute only for about 6 ms of the total delay, which leaves about 14 ms for image processing and communication. Applying heavy image processing efficiently on 360° video can require more computing power than traditional HMDs have available. Therefore, image processing and communication are currently believed to be the biggest bottlenecks in 360° video delivery. (Elbamby et al., 2018)

Delivering 360° video also requires large amounts of bandwidth. Mangiante et al. (2017) estimated that delivering a virtual reality (VR) resolution corresponding to a standard-definition TV resolution requires a bandwidth of 100 Mbps while equivalent of a high-definition TV resolution requires a bandwidth of 400 Mbps. For a VR resolution that corresponds to a 4K TV resolution, the bandwidth requirement goes as high as 1 Gbps for smooth playback and 2.35 Gbps for interactive use. The high bandwidth requirements have led to the development of creative solutions to reduce the amount of needed bandwidth, such as predicting users' head movements (Qian et al., 2016).

The capabilities of 4G mobile networks are not enough to meet the high bandwidth and latency requirements for delivering high-quality 360° video (Mangiante et al., 2017). 5G mobile networks, however, have higher throughput and lower latency, which are needed to facilitate the streaming of 360° video. The high bandwidth volatility in 5G connections can, however, be a hindrance to stable and smooth video streaming (Sun et al., 2018). Different 5G-based solutions that would alleviate the bandwidth, latency and computing requirements have been researched recently with promising results. Uitto and Heikkinen (2020) studied using the Common Media Application Format, which is a file format specifically developed for streaming media, in a 5G test network. Rigazzi et al. (2019) proposed using fog computing to offload resource-intensive computing tasks to edge servers. This approach would bring the computing resources closer to the end users, which would lower the latency.

4 METHODOLOGY

The previous two chapters introduced and discussed concepts related to achieving higher levels of driving automation and reliable and seamless teleoperation, which are assumed to be preconditions for using automated buses effectively in public transportation. These concepts provide the needed context for exploring and assessing the overall maturity of automated buses. In addition to that, this thesis seeks to determine and evaluate the cost-effectiveness of automated buses. This entails establishing the costs related to owning and operating automated buses and other similar means of public transportation used as comparison. Estimating the number of buses a single operator can supervise is an integral part of the cost assessment, as the operator capacity is believed to have a considerable impact on personnel costs. All these aspects need to be considered in order to form a comprehensive picture of the technological and economic viability of automated buses.
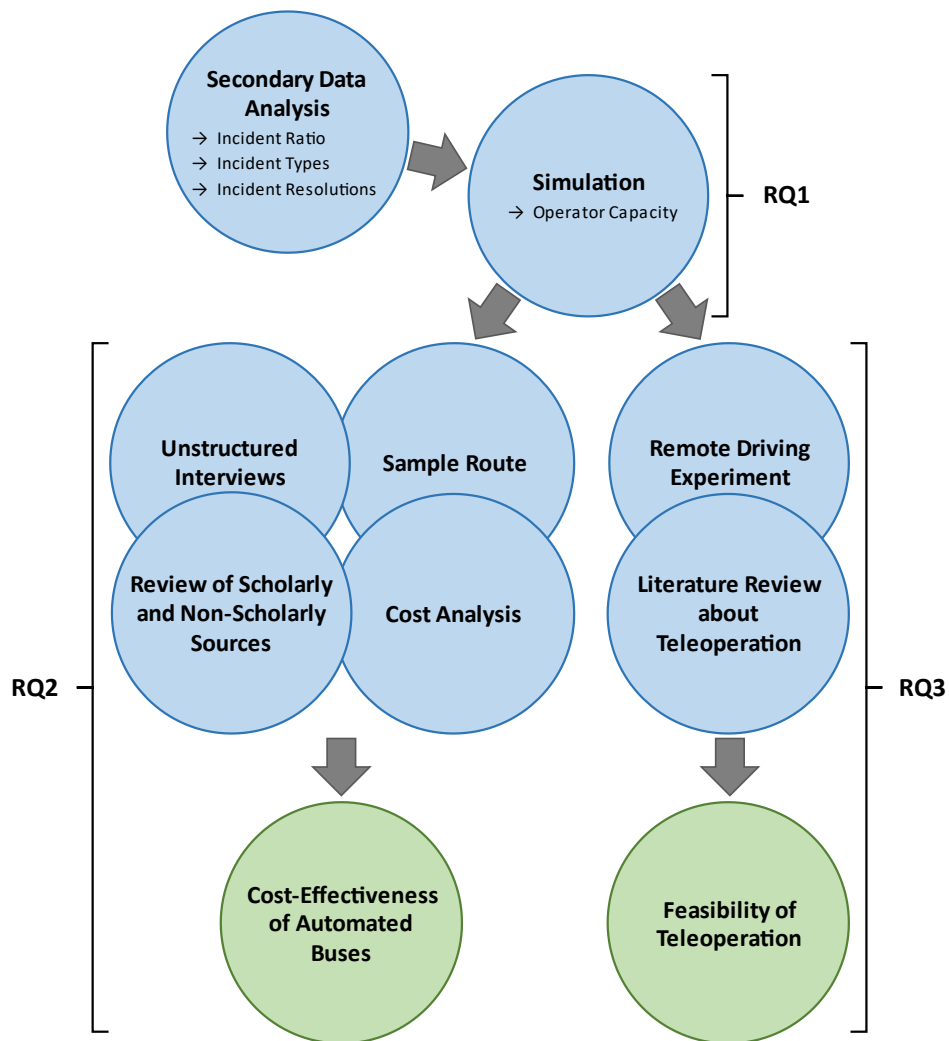
Figure 4 *Illustration of the research process.*

Due to the complex and broad nature of the topic of this thesis, several interlinked research methods had to be employed to reach the research objectives. The purpose of this chapter is to give an outline of the overall approach used for the research process and provide insight into the chosen research methods. An illustration of the overview of the research methods, their relationships and how they link to the three research questions are presented above in Figure 4. The different procedures and techniques used for data collection and analysis are also described in this chapter. This includes introducing the tools and materials, which facilitate the research process. The rationale behind using the specific methods is also discussed.

4.1 Research Methods

The research in this thesis can be considered to be quantitative in nature, since it is, for the most part, based on statistical analysis of collected data. Data were obtained from three different robot bus trials conducted in three different locations in Finland. Having data from three different locations collected at different times improves the diversity of the data and ensures that the findings from the data can be better generalized and applied also to other settings. The data from the robot bus trials can be described as secondary data as they were originally collected by the organizers of the trials and received directly from them. In order to gain better insight into the robot bus trials and the collected data, the organizers were asked a series of clarifying questions about the practicalities around arranging the trials and operating the robot buses during the trials. The goal of analyzing the data from the robot bus trials was to establish what type of incidents automated buses typically encounter, how often those incidents occur and how they are resolved.

The analysis of the incidents was used to develop an estimation of the frequency of the incidents and understanding of the underlying reasons leading to them. Knowing the number of the incidents and the kilometers traveled during the robot bus trials allowed determining an incident ratio for each trial. An incident ratio describes the ratio at which a robot bus on average encounters an incident per each kilometer it travels. Information about the characteristics of the incidents, their causes and how they were resolved was used to assess the general readiness of automated buses for autonomous operation and the feasibility of remotely supervising them. Automated buses can be expected to be better

suited for public transportation purposes if most of the incidents encountered by the them are non-critical and can be resolved remotely.

The hypothesis of this study is that operating robot buses is less expensive than other bus types because there is no driver inside the vehicle and labor costs can therefore be lower. Yet, robot buses are not thought to be completely autonomous as they still occasionally need human intervention to get them through unexpected situations. There appears to be very little existing research on how often and for how long automated buses or robots comparable to them need human intervention. To study how many robot buses a single operator could remotely supervise simultaneously while the buses still maintain an acceptable average speed, a simulation was conducted where a variable number of buses drove a route and encountered incidents at random intervals. The parameters for the simulation were determined based on the data obtained from the robot bus trials. The results of the simulation were analyzed to assess the extent to which each simulation variable affects the effective speed and the delays experienced by the buses. Once the variables and their relationships had been determined, a model could be established to estimate the capacity of bus operators. The analysis of the simulation results and the determination of the operator capacity provide an answer to the first research question (RQ1) about how many automated buses a single operator can supervise simultaneously.

Multiple robot bus manufacturers and operators were approached with inquiries about their vehicles and costs of operating them. An unstructured interview was conducted with a representative of one of the robot bus manufacturers. Explicit information about the costs related to owning and operating robot buses was difficult to obtain directly from the robot bus manufacturers, and therefore online sources and existing literature concerning the subject needed to be studied. Public transportation costs encompass many other costs in addition to those that can be directly and readily attributed to the operation of a single bus. Hence, the cost factors of public transportation were studied in order to develop an understanding of how public transportation costs are formed and how they are broken down into unit costs. An estimation of robot bus costs when the bus is operated as part of a public transportation system was formed based on the costs of similarly sized diesel and electric minibuses. The cost estimation also took into account what kind of impact the remote operator capacity obtained by analyzing the results of the simulation had on labor

costs. The cost assessment provides an answer to the second research question (RQ2) about what the costs of automated buses are and how they compare to other bus types.

The obtained robot bus costs were applied to a practical context by examining what it would cost to operate a sample route in the city of Turku. While the sample route is hypothetical, it is based on an actual plan the Turku region public transport service had for a route near the city center of Turku. The description of the sample route includes the days of the week and the hours during which the route was planned to be operated. Cost calculations are presented for operating the route by a diesel minibus, an electric minibus and a robot bus. The use of a sample route allowed theoretical passenger volumes and costs per passengers to be calculated for different bus types and comparing those values.

Automated vehicles may sometimes need a human driver to manually maneuver the vehicle around obstacles on the roads. As the human driver is not thought to be physically present in the vehicle, manual driving needs to be performed remotely over a mobile network. To study the feasibility of remote driving, observations were made from a small-scale remote driving experiment that examined how well a tractor can be operated over a 5G network. Existing literature and research on remote driving over mobile networks were also reviewed. The literature review and the results from the remote driving experiment are used to answer the third research question (RQ3) about whether the capabilities of modern mobile networks are sufficient for supporting the remote operation of automated buses.

4.2 Data from the Robot Bus Trials

Incident reports and driving logs from three different robot bus trials were obtained in order to assess what kind of incidents robot buses face, how many incidents occur on average and what is the average energy consumption of robot buses. The trials were organized during the years 2018 and 2019 in different parts of Helsinki, Finland. The routes are described in detail in section 5.2. The data from the trials were acquired directly from the parties responsible for operating the robot buses during the trials. The incident reports and driving logs were received as CSV and Excel workbook files.

For trials that were organized in Kivikko and Kalasatama, the driving logs had information about both planned and completed drives for each day the robot buses were

scheduled to drive. The daily data included the number of departures, driving time, kilometers driven, passenger counts, battery charge levels both at the start and end of the day and the daily energy consumption. Incidents were logged manually by the person who was operating the robot bus at the time. The incidents were recorded using a detailed form that had fields for the time and date of the incident, location of the vehicle at the time of the incident, operator's assessment of the severity of the incident, whether the bus was driving itself or if it was manually driven, cause of the incident, classification of the incident, textual description of the incident and the consequences of the incident. As the incidents were logged manually by different operators, there were some variations and inconsistencies in how the incidents were described and classified.

The different fields of the incident logs were analyzed and interpreted in order to consolidate and divide the causes of incidents and their resolutions into meaningful categories. The causes of incidents describe the circumstances leading to the incidents while the resolutions describe what had to be done to resolve the incidents and continue driving. Also, while analyzing the incident logs, the sources for stopping were identified. Sources for stopping describe who or what initiated the stopping of the bus. The bus can be stopped by the bus's software if the sensors of the bus identify an obstacle or the stopping can be initiated by the operator or a passenger onboard the bus. The categories for the incident causes and for the incident resolutions are described in detail below.

Incident Causes

- *Cabin problem* – An incident that occurred inside the cabin of the bus, such as a passenger falling or pressing the emergency stop button.
- *Mechanical problem* – Mechanical failure of a part of the bus, such as powertrain, air suspension, tires or doors.
- *Other road users* – A stop caused by a close encounter with another road user, such as an oncoming or overtaking vehicle, a pedestrian or a bicyclist.
- *Parking on road* – A vehicle that is parked on the road blocked the path of the bus.
- *Road infrastructure* – Roadwork or other obstacles on the road that blocked the path of the bus.
- *Technical problem* – An issue of technical nature that is further divided into the following causes:

- o Network issue – Problem with the wireless mobile connection.

- o Positioning system – Problem with determining the location of the bus using satellite navigation.

- o Sensor problem – Problem with a sensor of the bus, such as one of the LiDAR sensors.

- o Software/algorithm defect – Problem caused by unexpected behavior of the software of the bus.

- *Weather* – A stop caused due to severe weather conditions, such as heavy rain or snowfall.

Resolutions

- *Manual driving* – The bus was manually driven around an obstacle.
- *Resume driving* – Automated driving was resumed after a stop.
- *Other* – The incident was resolved through other, unspecified means.
- *Restart* – The software of the bus was restarted.
- *Termination of driving* – Driving could not be continued.

For the third robot bus trial that was organized in Aurinkolahti, the recorded data were not as extensive as they were for the other two trials. The recorded data included kilometers driven every day and the number of passengers but not, for instance, the daily energy consumption. Also, the incident log did not contain as many details about the incidents as the incident logs for the other two trials did. The incident log had separate fields for a timestamp, location of the bus at the time of the incident in the form of latitudinal and longitudinal coordinates, description of the incident and weather conditions at the time of the incident. Hence, it was not possible to comprehensively infer from the incident log how the incidents were resolved and who or what initiated the stopping of the bus. The categories for the incident causes were also slightly different from the categories used in the other two trials. The categories of the incident causes for the trial in Aurinkolahti are described below.

Incident Causes

- *Cabin problem* – An incident that occurred inside the cabin of the bus, such as a passenger falling or pressing the emergency stop button.

- *Intentional disturbance* – People intentionally trying to see if they can stop the bus.

- *Mechanical problem* – Mechanical failure of a part of the bus, such as powertrain, air suspension, tires or doors.

- *Other road users* – A stop caused by a close encounter with another road user, such as an oncoming or overtaking vehicle, a pedestrian or a bicyclist.

- *Parking on road* – A vehicle that is parked on the road blocked the path of the bus.

- *Potential collision* – An operator initiated stop due to a near collision.

- *Road infrastructure* – Roadwork or other obstacles on the road that blocked the path of the bus.

- *Shuttle reset* – The bus had to be reset due to a software defect.

- *Switch to manual driving* – The bus had to be switched to manual driving in order to go around an obstacle.

4.3 Simulation

A simulation was performed to assess the feasibility of one operator supervising multiple buses at the same time. A simulation program was written in Python with the help of the SimPy[1] library. The SimPy library is a process-based discrete-event simulation framework that allows real-world processes to be modeled and simulated using the Python programming language. The library features different types of shared resources that can be used to model limited capacity congestion points, such as the operators responsible for monitoring buses and handling their incidents. The simulation program was run within the Jupyter Notebook[2] interactive computational environment.

The purpose of the simulation was to give an indication of how different variables, such as the number of buses, affect the effective speed of the buses. Effective speed is defined as the distance traveled by the bus divided by the total time it took the bus to finish the drive, taking into account all the delays. The simulation program iterated over all the

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[1] https://simpy.readthedocs.io/

[2] https://jupyter.org/

simulation variables and ran a simulation for each combination of the variables. The variables and the range of their values used in the simulation are described in Table 2.

Table 2 *Variables used in the simulation.*

Variable	Range of Values	Description
Number of buses	1 – 50	Number of buses that was driving at the same time.
Speed	25 and 40 km/h	The speed at which each bus was driving the route.
Distance	25, 50, and 100 km	Distance of the route driven by each bus.
Incident ratio	0.03, 0.16, 0.22 and 0.36	The ratio at which incidents occurred at each driven kilometer. Values were determined based on the data collected from the robot bus trials
Resolution time	10, 30, 60 and 180 seconds	The time it took to resolve a single incident.

During a simulation, a predetermined number of buses simultaneously drove a predetermined distance at a predetermined speed. After each driven kilometer, the simulation program checked whether the bus had encountered an incident. If an incident had occurred, the bus stopped and it did not continue its route until an operator had resolved the incident. If a bus encountered an incident while the operator was already in the process of resolving an incident for another bus, the bus needed to wait until the operator became available, which prolonged the total time it took to resolve the incident.

Incidents for each bus were distributed at the start of every simulation run randomly over a course of 100 kilometers according to an incident ratio. In practice, this meant that, with an incident ratio of 0.20, for instance, a bus would have encountered 20 incidents during a drive of 100 kilometers at random intervals. The resolution time variable was used to set the time it took to resolve an incident. A simulation run comprising every combination of the simulation variables was run 10 times to ensure consistency of the results. The results of every simulation run were saved to a CSV file individually for every bus. The collected data included the following information:

- *Duration* – The total time it took the bus to finish the predetermined distance, including time spent driving and potential delays.

- *Driving Time* – The time the bus spent driving.

- *Incidents* – The number of incidents the bus encountered.

- *Interaction Time* – The total time the operator interacted with the bus resolving the incidents.

- *Wait Time in Queue* – The total time the bus had to wait for the operator to become available.

- *Delay* – The delay caused by the incidents (i.e., *Interaction Time + Wait Time in Queue*).

- *Actual Speed* – The effective speed of the bus (i.e., *Distance / Duration*).

The results were analyzed using the R statistical computing environment[3]. Based on the results, Pearson correlation coefficients were calculated for the variables and multiple regression models were built to establish how the variables impacted both the effective speed and the delay. Traffic congestion and the time spent at bus stops were not considered in the simulation, as their impact on robot buses were assumed to be similar to traditional buses.

Pearson correlation coefficient is a method used for measuring the strength and direction of a linear association for a pair of variables. The magnitude of the correlation coefficient represents the strength of the relationship while the sign of the coefficient indicates the direction of the relationship between the two variables. When variables are observed to have linear relationships, they can be used in a linear regression model.

Multiple regression is a method for modelling the relationship between a single response variable and more than one explanatory variables. The equation describing how the dependent variable Y is related to the independent variables X_1, X_2, …, X_p and an error term ε is referred to as a multiple regression model, which can be expressed in the form of formula (1). In the regression model, β_0, β_1, ..., β_p are the model parameters whose values are estimated based on existing data. The error term ε accounts for the variation in

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[3] https://www.r-project.org/

Y that the independent variables do not explain. (Anderson et al., 2011) Multiple regression can be used to predict the value of a dependent variable when the values of other variables are known. When analyzing the simulation results, the dependent variables whose values are predicted are the effective speed and the delay caused by the incidents.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \varepsilon \qquad (1)$$

4.4 Sample Route

To assess the practical feasibility of using robot buses in the city of Turku, the operation of a hypothetical sample route was studied. The sample route runs between the city's railway and bus stations, which are about one kilometer away from one another. This means that a round-trip on the route is roughly two kilometers in length. Many of the local and regional buses arriving to the city center of Turku from the northern parts of the city, including the bus from the Turku airport, have their routes run very close to the bus station. A bus line that connects the bus station and the railway station would provide a convenient way for passengers of those buses to reach the railway station. Currently, passengers need to continue their trips all the way to the local transport hub at the city center, which is roughly one kilometer away from both stations. At the local transport hub, the passengers need to change to another bus, which extends their travel time between 10 to 20 minutes, depending on the time of the day.
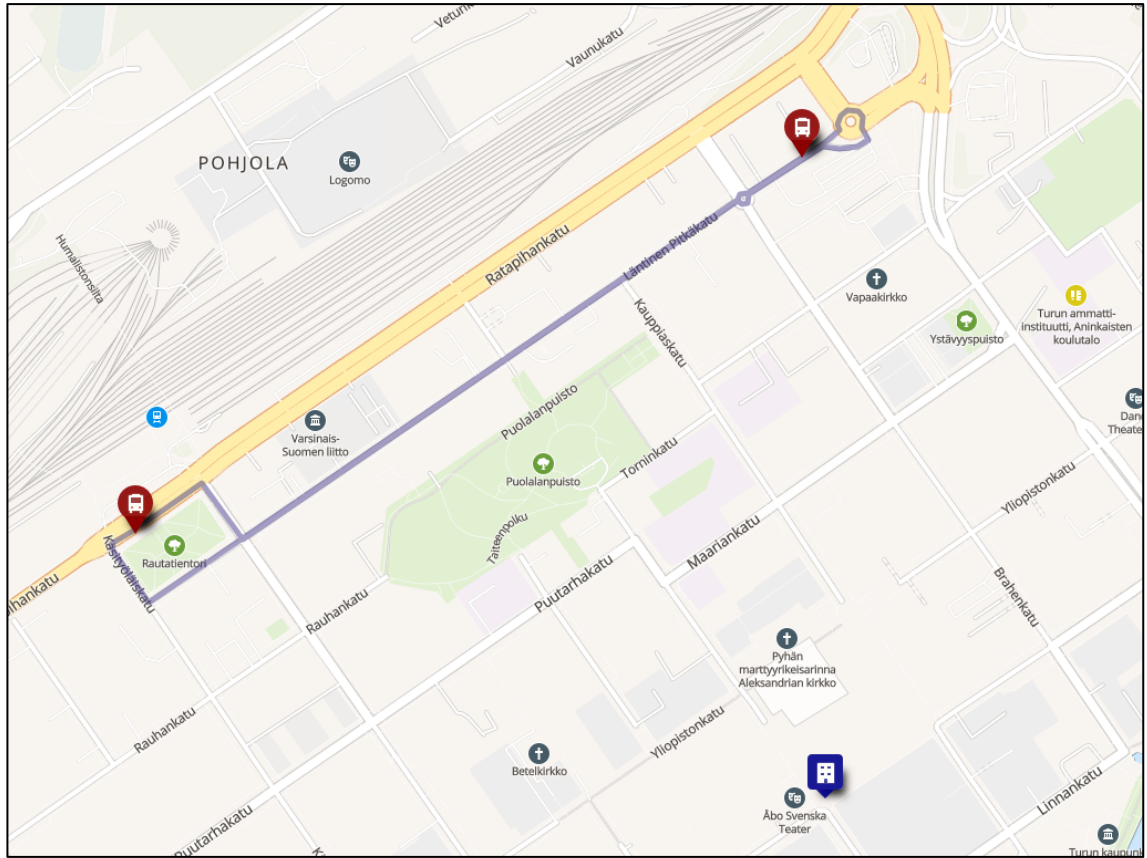
Figure 5 *A potential robot bus route in Turku (Map by OpenStreetMap).*

The route is expected to be driven by a single vehicle that makes a new departure every 20 minutes. This means that the bus should be able to drive the route three times within an hour. With two vehicles the service interval would be half of that, i.e., 10 minutes. Only two stops are placed along the route, one in the close proximity of the railway station and another one at the bus station. The locations of the stops as well as the route running between them are depicted in Figure 5. The bus stops are denoted in the figure with red markers and the location of the local transport hub at the city center with a blue marker. The bus waits at both stops for five minutes, which leaves another five minutes for the bus to make the one-kilometer drive between the stops.

Instead of taking the shortest path between the two stops that would run along a multi-lane road, the bus drives on a street that has less traffic and fewer traffic lights. The bus makes a loop at both ends of the route, so it does not need to reverse its direction or make a U-turn. The bus will not drive directly in front of the railway station as the space there is limited and often occupied by many parked cars. Figure 6 gives a closer look at the route near the two stops. The stop at the railway station is seen in the figure on the left and the stop at the bus station on the right.
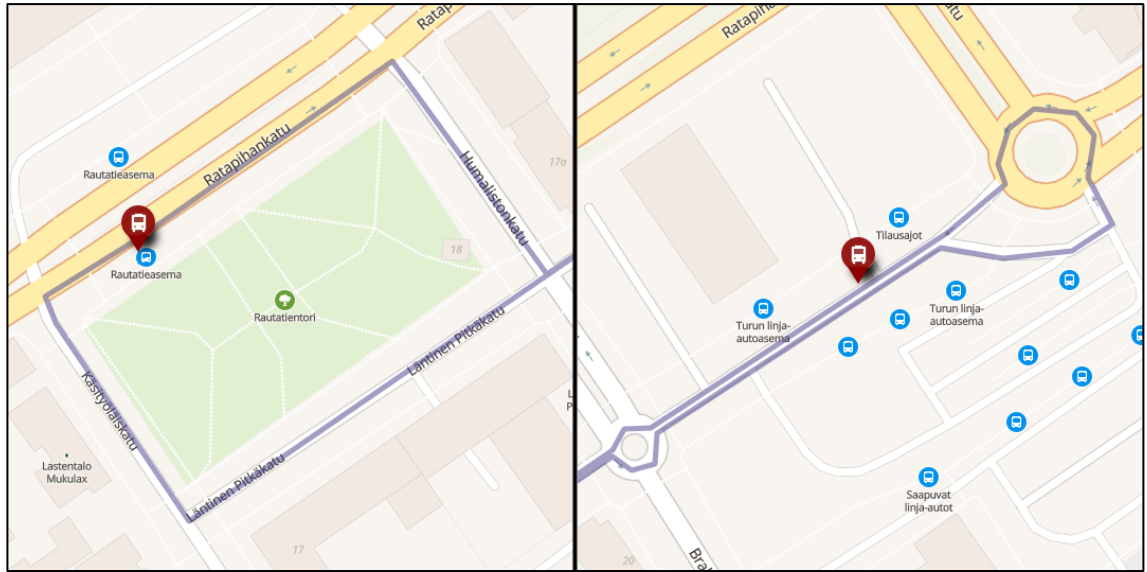
Figure 6 *Close-ups of the maps around the bus stops (Map by OpenStreetMap).*

The route is expected to be operated every weekday from 6:30 a.m. until 6:30 p.m., with a two-hour break between 11:30 a.m. and 1:30 p.m. This means that the bus line is operated 10 hours a day, of which five hours are spent on actual driving and another five hours on waiting idly at the stops. The two-hour service gap around midday could be used, for instance, to charge the batteries of an electric bus. Half an hour should be reserved for taking the bus to and from the bus depot, where the bus can be charged and left over the night.

4.5 Remote Driving Experiment

In order to demonstrate and assess how well vehicles can be remotely operated over a 5G connection, a remote driving experiment was arranged. In the experiment, a modern farm tractor was equipped with a laptop computer, a 5G router and a 360° video camera. The camera was mounted on the roof of the tractor to provide an unobstructed view on all sides. The 5G router was also placed on the roof to maximize cellular reception. A photo of the tractor can be seen in Figure 7. The tractor was placed on a closed course with a decent 5G coverage in the city of Raisio, Finland.

Figure 7 *Remotely drivable tractor with a 360° camera mounted on the roof.*

The 360° camera on the roof of the tractor and the computer inside the tractor were both connected to the 5G router. The computer was also connected to the tractor itself over a USB-to-CAN interface. A custom software was running on the computer that listened for incoming messages sent over the network connection and translated the received messages into commands that could be sent to the tractor over the CAN bus. While it would have been technically possible to control many features of the tractor over the CAN bus, during the experiment the set of allowed commands was limited to driving forward and backward, turning to different directions and raising and lowering the bucket of the tractor. Figure 8 below shows the internals of the tractor, including the computer used as a message gateway.

Figure 8 *Internals of the remotely drivable tractor's cabin.*

During the experiment, the tractor was remotely controlled from a facility in Helsinki, Finland, which is about 170 kilometers away from the course where the tractor was. An armrest controller similar to the one inside the tractor was attached to a chair at the remote driving facility. The joystick in the armrest controller was used to control acceleration and steering of the tractor. The remote driver could wear a virtual reality headset that showed live high-definition video from the camera mounted on the tractor's roof. By moving his head, the driver could view the entire surrounding environment and different sides of the tractor. Figure 9 shows how the tractor was remotely operated using the VR headset and the armrest controller. For safety reasons, the speed of the tractor was programmatically limited to 5 km/h and a safety person was at all times present in the cabin ready to take over the control if problems were to occur.

Figure 9 *Setup at the remote driving facility (Photo courtesy of Elisa Corp.).*

The experiment started in March 2020 in the form of a demonstration and a proof-of-concept trial that were to be followed by a study to measure the latency in the video feed as well as the time delay associated with controlling the tractor. However, due to unforeseen circumstances, namely the COVID-19 outbreak, the experiment had to be terminated early before proper data collection could be started. Hence, the results from the experiment are to be considered preliminary and more anecdotal than evidence based.

5 ROBOT BUS TRIALS

This chapter details the routes driven during the robot bus trials and presents statistics and a summary of the data collected during the trials. The general statistics include information on driving times, number of departures, number of kilometers driven and number of passengers. More detailed information is presented about incidents and energy consumption. The robot buses that have been used in the trials in Finland and their main features are also briefly introduced.

5.1 Robot Buses

To date, at least three different robot buses have been tested in Finland. These three buses share many common features and characteristics with one another. They are all roughly the same physical size and can fit around 15 passengers. During the trials, the maximum speed of the buses in automated driving mode is often limited to 25 km/h or even lower than that for safety reasons. The battery sizes and driving ranges of the buses can vary between trials. Of the three buses, Sensible 4's Gacha is the only robot bus that is advertised as being able to work in all weather conditions and claimed to have been tested in temperatures as low as -28 °C (Sensible 4, 2020). Table 3 lists the main specifications of the three robot buses.

According to the vendors, the three robot buses conform with the SAE level 4 autonomous vehicle classification. This is, however, somewhat debatable, since most trials conducted with the buses in Finland have had a safety driver inside the vehicle ready to stop the bus or manually overtake obstacles on the bus's path. Hence, it could be argued that the buses actually fall under the level 3 category of the classification, at least during the majority of the trials conducted in Finland.

Table 3   *Specifications of automated buses that are being tested in Finland (Easymile, 2020; Navya, 2020; Sensible 4, 2020; Fabulos, 2020).*

	EasyMile EZ10	**Navya Autonom Shuttle**	**Gacha**
Passenger capacity	15	15 11 seated, 4 standing	16 10 seated, 6 standing
Dimensions (LxWxH)	4.1 x 1.9 x 2.9 m	4.8 x 2.1 x 2.7 m	4.5 x 2.4 x 2.8 m
Weight	2,130 kg (net) 3,130 kg (gross)	2,400 kg (net) 3,450 kg (gross)	2,500 kg (net) 4,000 kg (gross)
Maximum speed	45 km/h limited to 25 km/h	25 km/h	40 km/h (automated) 80 km/h (manual)
Powertrain	Electric	Electric (2WD) 15 kW nominal, 25 kW peak	Electric (4WD) 2 x 55 kW
Battery	30.72 kWh (LFP)	33 kWh (LFP)	24 kWh
Driving range	16 h	9 h (average)	100+ km
Operating temperature	-15 °C to 45 °C	-10 °C to 40 °C	

5.2 Routes

All the robot bus trial routes evaluated in this thesis were driven with the Navya Autonom Shuttle robot bus in mixed traffic on public roads. This means that there were other road users, such as other motor vehicles, bicyclists and pedestrians, using the roads at the same time with the bus. Riding the bus was free of charge for the passengers. Even though there would have been capacity for more passengers, only eight people were allowed on board at the same time in addition to the safety driver who was present in the vehicle at all times. The limit of eight passengers is due to driving license regulations in Finland that allow

holders of regular passenger car driving licenses to only operate vehicles with a passenger capacity of no more than eight persons in addition to the driver.

When choosing a suitable location for a robot bus trial, many aspects need to be considered. As the speed of robot buses in automated driving mode is relatively slow, robot buses should not generally be placed on roads where other road users can drive considerably faster. When the speed of the robot bus is closer to the speed of other road users, risky overtakes by other road users can potentially be avoided. Within urban environments, the route should ideally be surrounded by static structures, such as buildings that have well-defined boundaries, as those enable the bus to better map its environment using its LiDAR sensors.

Areas that are in a constant change, such as roads passing active construction sites, are not ideal for robot buses. Heavy vegetation, especially moving trees and bushes, at a close proximity of the road can obstruct the regular function of the LiDAR sensors and the positioning system of the bus. On-street parking can also be a cause for problems since robot buses are not able to overtake obstacles on their path without assistance from an operator. Likewise, intersections with heavy traffic can be problematic. In order to drive at an intersection with traffic lights in automated driving mode, the bus needs to be able to communicate with the traffic light system to obtain the traffic light's state.

5.2.1 Kivikko

The robot bus trial in Kivikko, Helsinki was organized between May 14 and November 14, 2018. During that period, the route was operated three times an hour on weekdays between the hours of 9:00 a.m. and 3:00 p.m. A one-way trip of the Kivikko route was approximately one kilometer in length, meaning that a round-trip was altogether two kilometers. The route had two stops at both ends of the route. One stop was at a local sport park and the other one near a large ring road used by many local and regional buses. This arrangement allowed passengers of the robot bus to easily connect to the regular public transport operated in Helsinki. Figure 10 below shows a map of the route in Kivikko. The stop at the sport park can be seen in the map on the top and the stop near the ring road on the bottom.
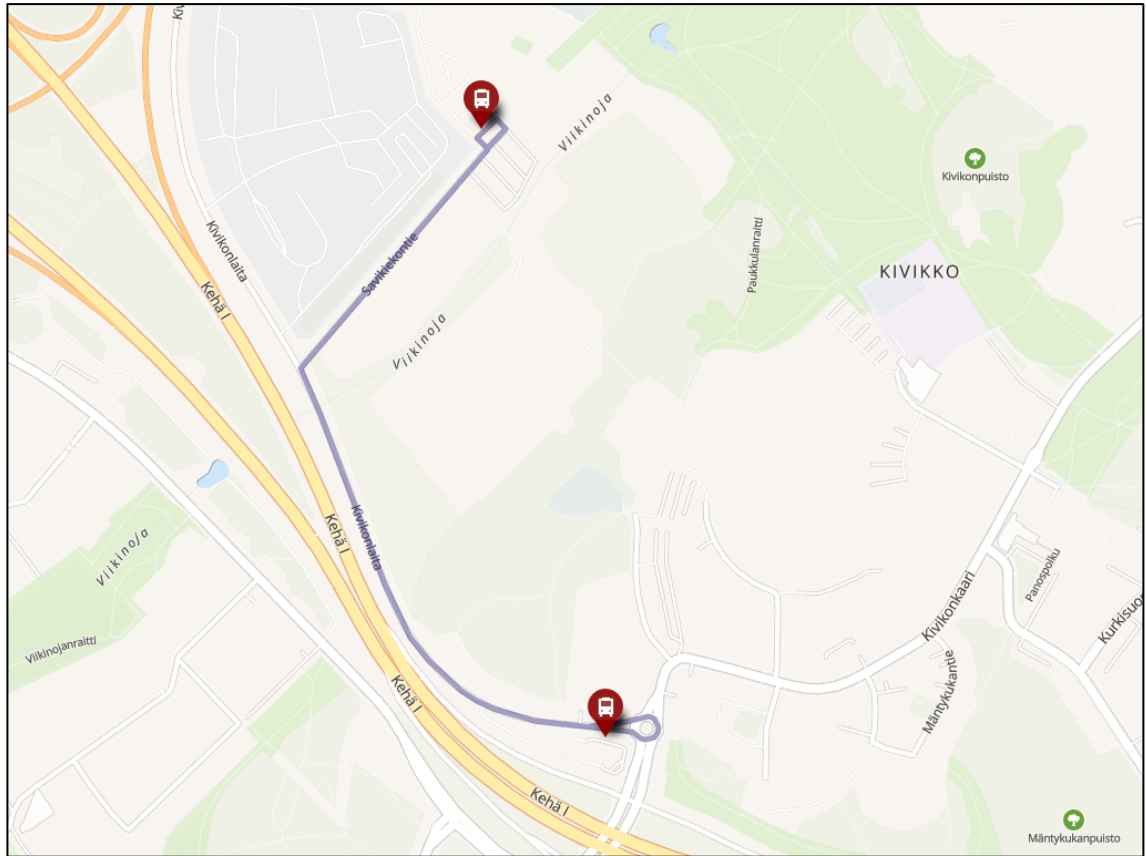
Figure 10 The route for the Kivikko trial (Map by OpenStreetMap).

The route featured two intersections: a roundabout and a T junction. The bus, when operating in automated driving mode, had problems with reacting quickly enough in the T junction due to the driving speed of other road users. This happened even though the speed limit in the area of the route was lowered from 50 km/h to 40 km/h for the period of the trial. Due to this reason, the bus was programmed to always stop in front of the T junction and wait for the onboard operator to manually resume driving at the right time. In order to provide more precise positioning data to the robot bus, a Real-Time Kinematic (RTK) reference station was installed on the roof of a building near the bus stop in the sport park. The accuracy of a positioning system can at worst be many meters, which an RTK reference station can reduce to only a few centimeters. (Rutanen & Arffman, 2019)

Table 4 and Table 5 show the general statistics and incident statistics, respectively, for the Kivikko robot bus trial. Driving should have continued until November 14, but towards the end of the planned trial period, the bus started experiencing problems. This explains why there were fewer driving days in September and October than planned and why no driving days were recorded in November. A full day of operation included 18

departures and about 36 kilometers of driving. Table 6 shows the incident statistics only for those days when all 18 departures were achieved.

Table 4   *Statistics from the Kivikko trial.*

Month	Driving Time		Departures	Kilometers Driven	Number of Passengers
	Days	Hours			
May	12	61.65	186	367	144
June	20	111.99	334	653	360
July	21	119.30	358	693	322
August	21	123.29	370	720	287
September	13	65.64	197	384	136
October	9	39.48	118	233	45
Total	**96**	**521.35**	**1,563**	**3,050**	**1,294**

Table 5   *Incident statistics from the Kivikko trial.*

Month	Kilometers Driven	Number of Incidents	Incidents per Kilometer
May	367	16	0.04
June	653	9	0.01
July	693	6	0.01
August	720	19	0.03
September	384	12	0.03
October	233	26	0.11
Total	**3,050**	**88**	**0.03**

Table 6   *Incident statistics from the Kivikko trial for full operating days.*

Month	Kilometers Driven	Number of Incidents	Incidents per Kilometer
May	212	10	0.05
June	527	8	0.02
July	420	2	0.00
August	491	17	0.03
September	175	5	0.03
October	105	7	0.07
Total	**1,930**	**49**	**0.03**

The distance to the depot, where the bus was charged overnight, was 0.18 kilometers. The drive to and from the depot therefore increased the daily kilometers by 0.36 km. This extra distance must be factored in when calculating the total energy consumption of the bus. Table 7 shows the monthly energy consumption during the trial. The values in Table 8 only take into account the days when all 18 departures were completed. Energy usage measurements were missing for May, June and the beginning of July, which is why May and June are missing from the tables altogether and why the kilometers for July in the tables are less than they actually were.

Table 7   *Energy consumption in the Kivikko trial.*

Month	Total Kilometers Driven	Energy Usage (kWh)	Energy Consumption (kWh/km)
July	665.20	589.90	0.89
August	722.56	518.10	0.71
September	388.68	232.21	0.60
October	236.24	161.07	0.68
Total	**2,017.68**	**1,501.28**	**0.74**

Table 8   *Energy consumption in the Kivikko trial for full operating days.*

Month	Total Kilometers Driven	Energy Usage (kWh)	Energy Consumption (kWh/km)
July	388.96	309.00	0.79
August	496.04	299.40	0.60
September	176.80	97.84	0.55
October	106.08	62.30	0.59
Total	**1,167.88**	**768.54**	**0.66**

Figure 11 represents a chart displaying the proportions of the different incident causes. The total number of incidents recorded during the trial was 88. Of these, "Technical problem" and "Parking on road" were the biggest causes with proportions of 44 % and 40 %, respectively. Figure 12 further dissects the technical problems. The main cause for technical problems was "Software/algorithm defect", which explains 79 % of all the problems of technical nature.
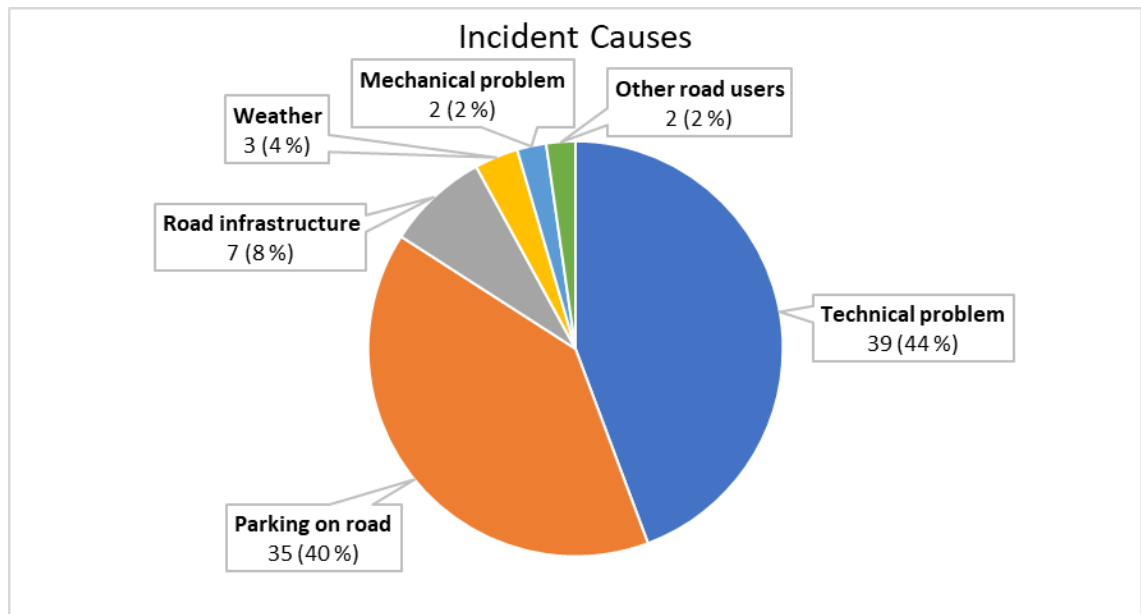
Figure 11   *Incident causes in the Kivikko trial.*
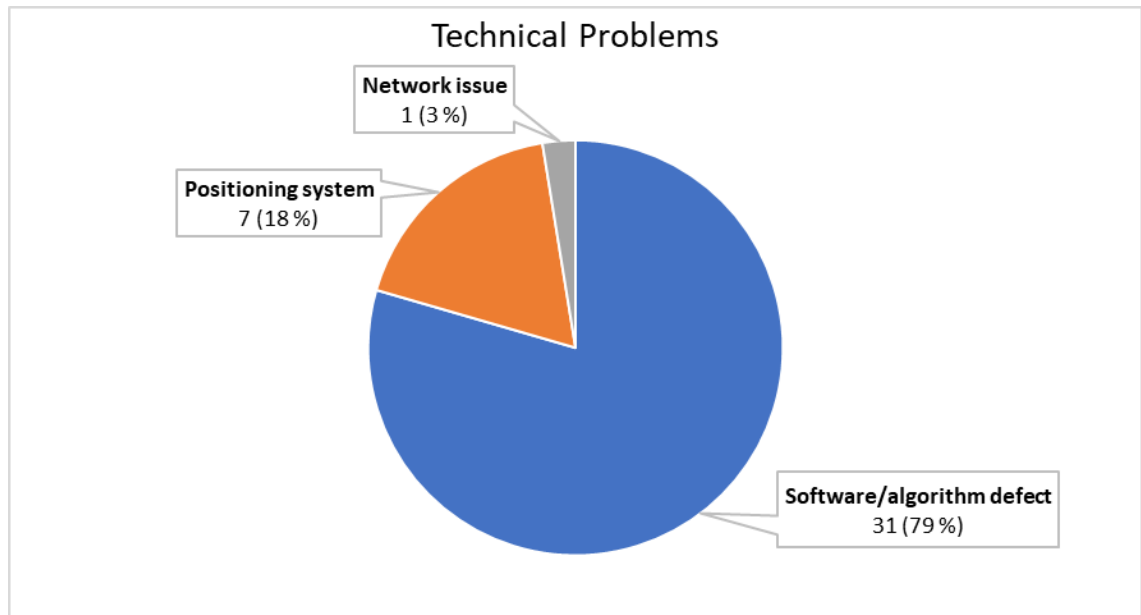
Figure 12 *Technical problems in the Kivikko trial.*

Figure 13 shows the proportions of different sources for stopping during the trial. As can be seen from the chart, 62 % of the time the bus was able to recognize the incident and make a stop by itself. About 22 % of the time the operator had to stop the bus and 16 % of the time the source for stopping was either unknown or it was not recorded. Figure 14 shows the distribution of incident resolutions. Most of the time, an incident could be resolved by resuming driving (57 %) or by the operator manually driving the bus around an obstacle (39 %).
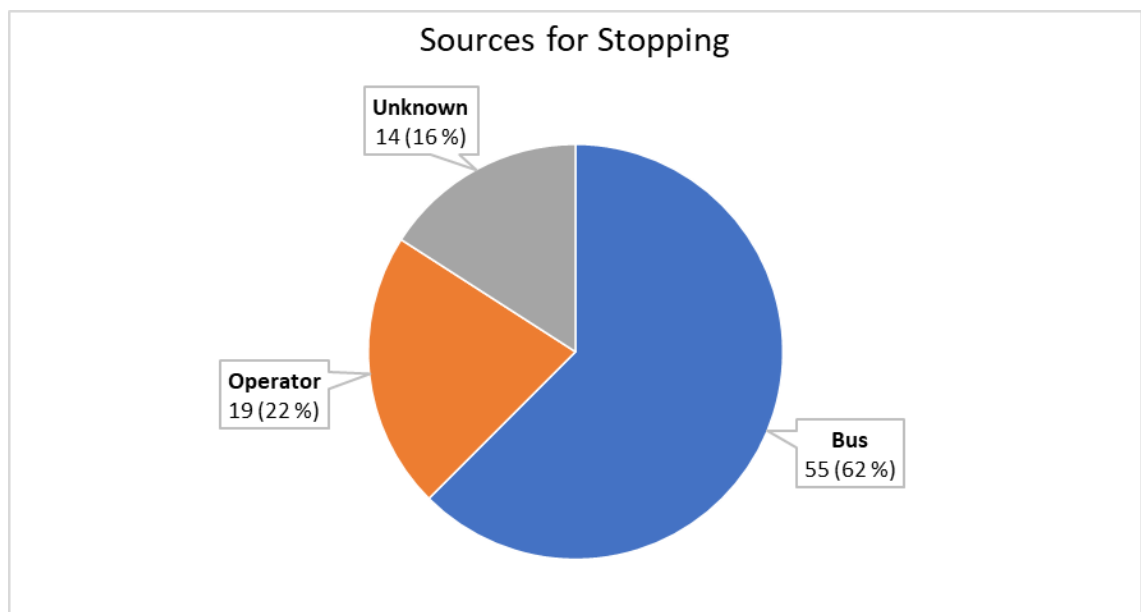
Figure 13 *Sources for stopping in the Kivikko trial.*
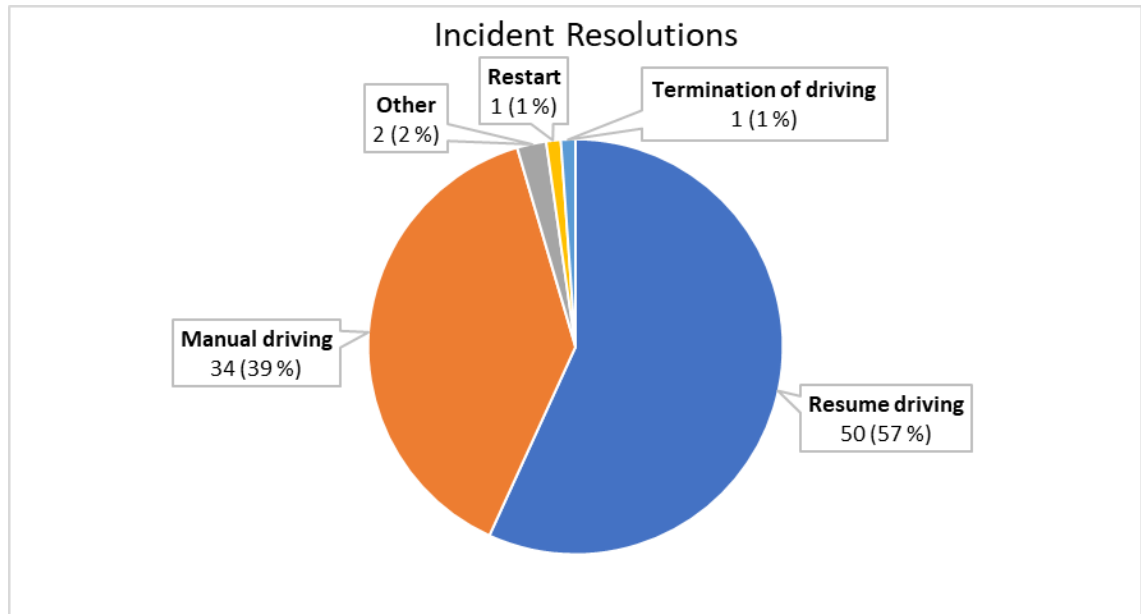
Figure 14 Incident resolutions in the Kivikko trial.

5.2.2 Kalasatama

The robot bus trial in Kalasatama, Helsinki started on May 21 and continued until November 22, 2019. During that time, the route was operated three times per hour on weekdays between the hours of 9:00 a.m. and 3:00 p.m. The route was a little over 900 meters in length and ran from the vicinity of the shopping center "REDI" to the waterfront and back to the shopping center. Three stops were placed along the route. One of the stops was placed near the shopping center, another one near the Kalasatama elementary school and kindergarten and the last one near the bridge "Isoisänsilta", which connects the island of Mustikkamaa to Kalasatama. A map of the route and the locations of the stops can be viewed in Figure 15.
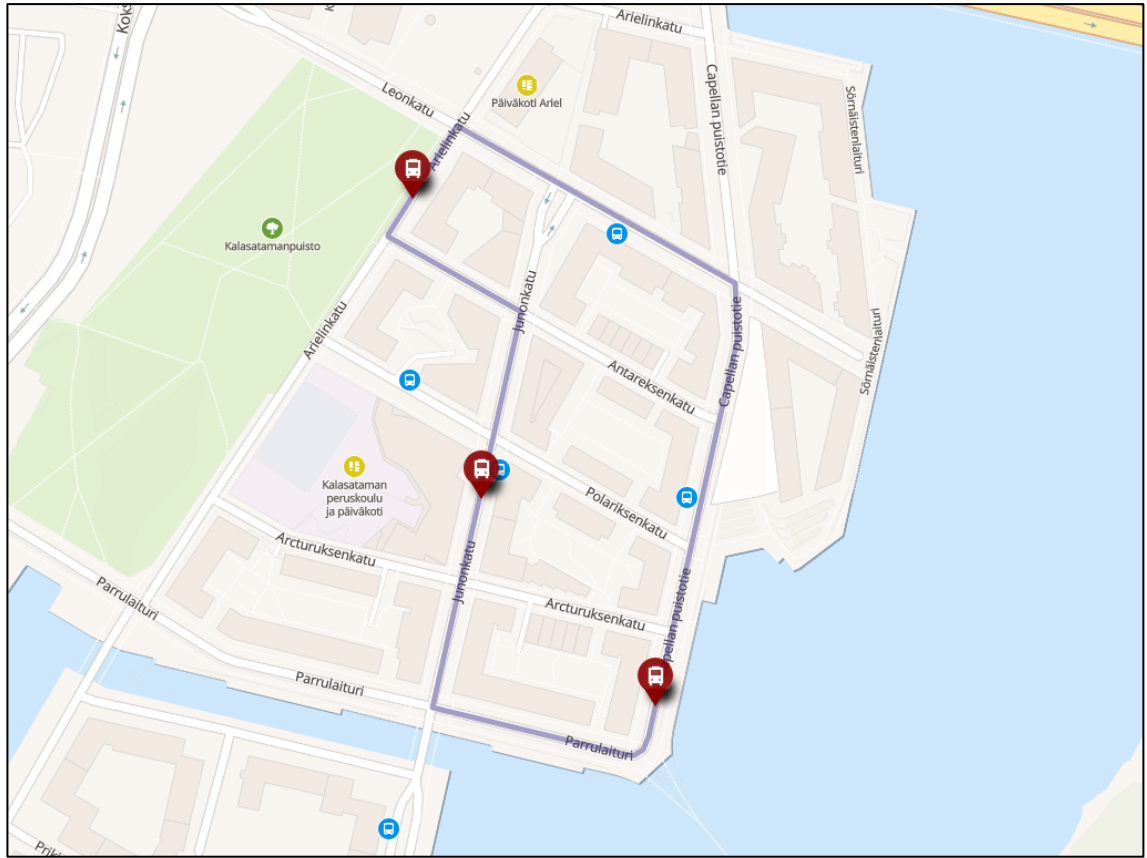
Figure 15 *The route for the Kalasatama trial (Map by OpenStreetMap).*

General statistics as well as statistics about incidents for the Kalasatama robot bus trial are shown in Table 9 and Table 10, respectively. Between June 14 and July 16, the bus experienced major problems and could not perform its scheduled driving. During August and in the beginning of September the bus again missed some driving days due to problems in the bus and because of training of operators. In October, the bus and the route information were updated, which led to a five-day interruption in the service. A full day of operation in Kalasatama consisted of 18 departures and about 17 kilometers of driving. Table 11 shows the incident statistics only for those days when all 18 departures were accomplished.

Table 9   *Statistics from the Kalasatama trial.*

Month	Driving Time		Departures	Kilometers Driven	Number of Passengers
	Days	**Hours**			
May	8	46.50	142	136	307
June	8	39.30	120	115	378
July	11	62.00	194	178	869
August	14	75.30	228	212	612
September	8	46.50	124	134	311
October	18	106.20	331	306	786
November	16	93.10	285	267	457
Total	**83**	**468.90**	**1,424**	**1,348**	**3,720**

Table 10   *Incident statistics from the Kalasatama trial.*

Month	Kilometers Driven	Number of Incidents	Incidents per Kilometer
May	136	74	0.54
June	115	28	0.24
July	178	63	0.35
August	212	74	0.35
September	134	65	0.49
October	306	104	0.34
November	267	77	0.29
Total	**1,348**	**485**	**0.36**

Table 11 *Incident statistics from the Kalasatama trial for full operating days.*

Month	Kilometers Driven	Number of Incidents	Incidents per Kilometer
May	121	59	0.49
June	103	25	0.24
July	150	49	0.33
August	166	59	0.36
September	102	50	0.49
October	306	104	0.34
November	236	66	0.28
Total	**1,184**	**412**	**0.35**

The distance to the depot in Kalasatama was half a kilometer, which is an additional distance that had to be driven twice a day. In the morning, the bus was driven from the depot to the start of the route and in the evening the bus was driven back to the depot for overnight charging. Hence, when the energy consumption of the bus was calculated, an additional kilometer had to be added to the distance driven for every day. Table 12 shows the energy consumption for each month during the trial. Table 13 shows the energy consumption values when only those days when the bus was able to achieve all 18 departures are taken into account.

Table 12 *Energy consumption in the Kalasatama trial.*

Month	Total Kilometers Driven	Energy Usage (kWh)	Energy Consumption (kWh/km)
May	144	130.55	0.91
June	123	141.69	1.15
July	189	254.61	1.35
August	226	216.89	0.96
September	142	210.02	1.48
October	324	254.62	0.79
November	283	350.27	1.24
Total	**1,431**	**1,558.64**	**1.09**

Table 13 *Energy consumption in the Kalasatama trial for full operating days.*

Month	Total Kilometers Driven	Energy Usage (kWh)	Energy Consumption (kWh/km)
May	128	117.10	0.91
June	109	116.44	1.07
July	159	227.93	1.43
August	176	148.26	0.84
September	108	160.63	1.49
October	324	254.63	0.79
November	250	319.49	1.28
Total	**1,254**	**1,344.46**	**1.07**

Distribution of different incident causes are depicted in Figure 16. "Parking on road" was by far the biggest cause for incidents in the Kalasatama trial, as it constituted over half of all the incident causes. It was followed by "Other road users" and "Technical problems", which had roughly the same proportions with 19 % and 17 %, respectively. Further dissection of the causes for technical problems reveals that 70 % of them were caused by problems related to software. The dissection of technical problems can be seen in Figure 17.
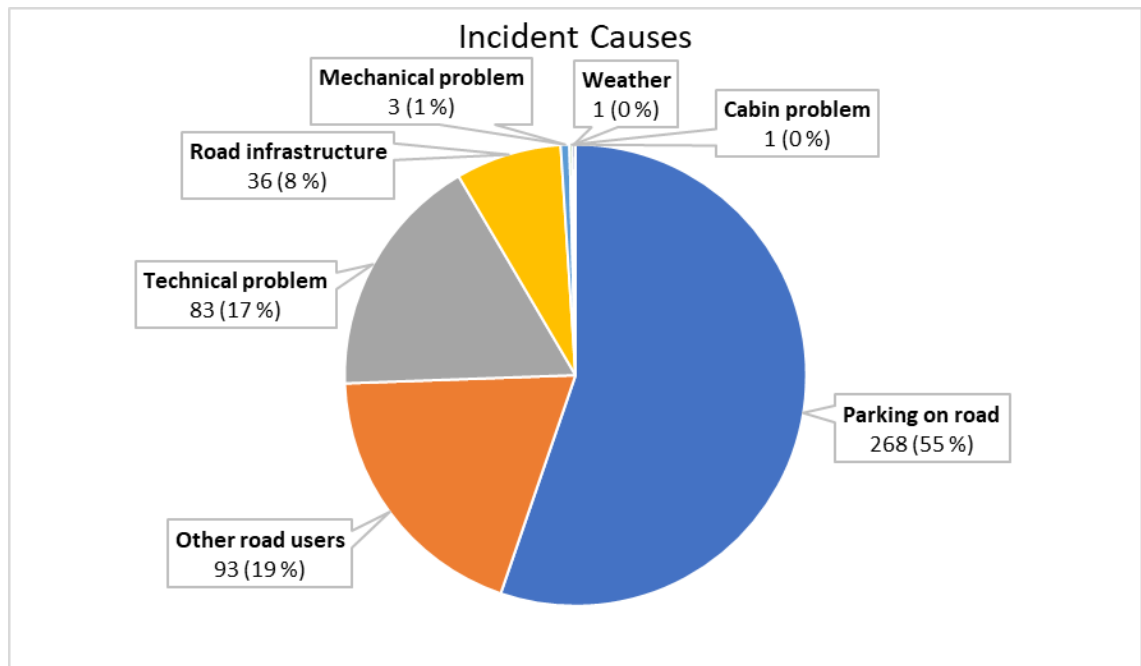
Figure 16 *Incident causes in the Kalasatama trial.*
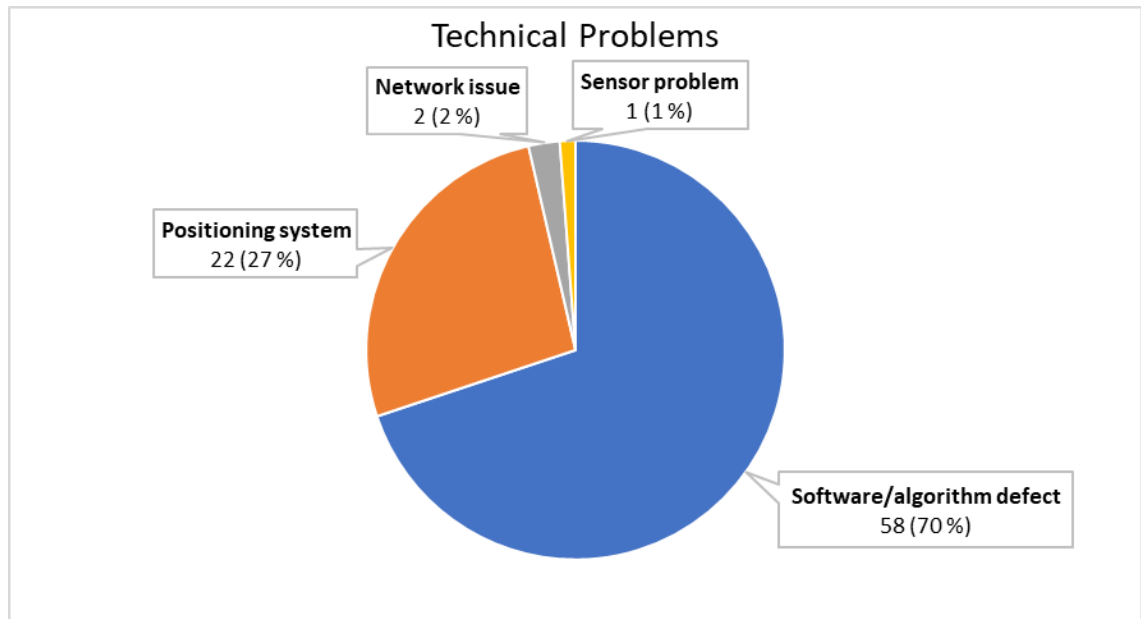
Figure 17 Technical problems in the Kalasatama trial.

Proportions of different sources for stopping during the trial are shown in Figure 18. In a little more than half of the cases the bus could recognize the impending incident and stop itself. The operator had to stop the bus in almost half of the cases. A passenger stopped the bus once during the trial by pressing the emergency stop button. The vast majority of the incidents were resolved by the operator manually driving the bus (77 %). Automated driving could be resumed after an incident in 18 % of the cases. The full distribution of the incident resolutions can be seen in Figure 19.
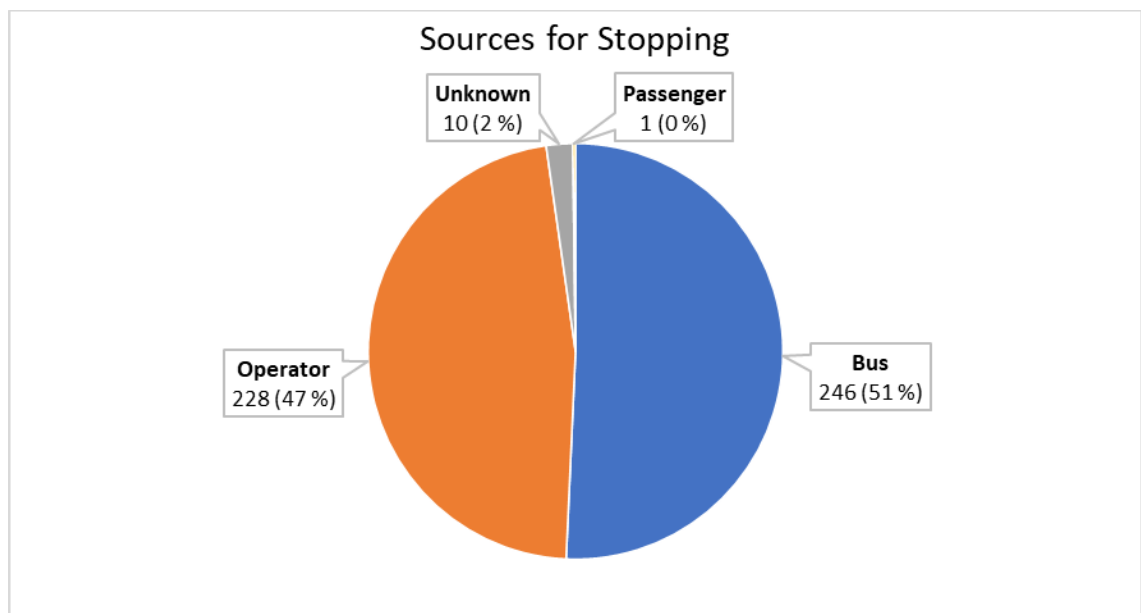
Figure 18 Sources for stopping in the Kalasatama trial.
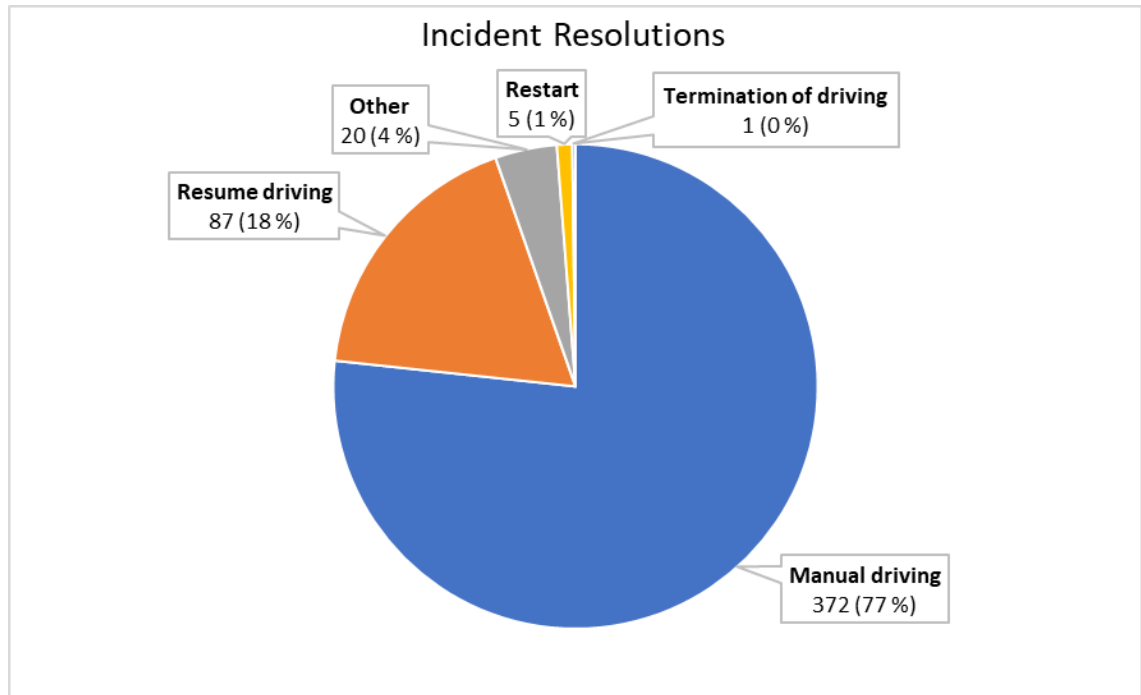
Figure 19 *Incident resolutions in the Kalasatama trial.*

5.2.3 Aurinkolahti

The robot bus trial route in Aurinkolahti, Helsinki was operated between June 18 and September 11, 2019. The length of the route was 2.5 km and altogether seven stops were placed along the route. The route started from the Vuosaari subway station and ran through the brim of Aurinkolahti back to the subway station. The route was operated daily for six hours, on weekdays between 9:00 a.m. and 3:00 p.m. and on weekends between 12:00 p.m. and 6:00 p.m. A map of the route with approximate locations of the bus stops is depicted in Figure 20.
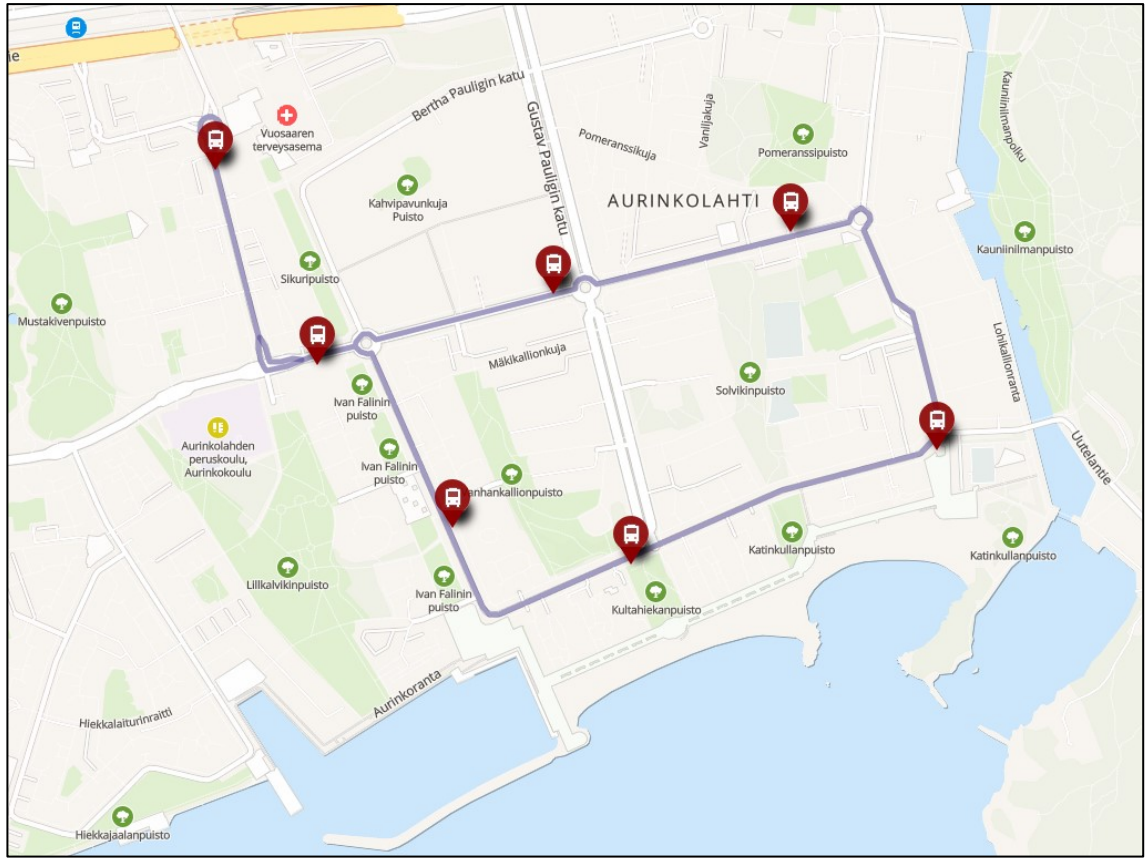
Figure 20 *The route for the Aurinkolahti trial (Map by OpenStreetMap).*

Table 14 shows the statistics from the Aurinkolahti robot bus trial. The table only shows data from the days for which both the number of kilometers driven and the number of passengers were recorded. In the early stages of the trial in June there were six days for which either of the information was missing, which explains why the table states that there were only seven driving days in June. The driving logs did not include data about energy consumption but the crew operating the bus measured it to be an average of 0.796 kWh/km for the whole period of the robot bus trial.

Table 14 *Statistics from the Aurinkolahti trial.*

Month	Driving Days	Kilometers Driven	Number of Passengers	Number of Incidents
June	7	384	268	5
July	29	968	1,626	211
August	28	882	1,270	371
September	11	329	434	72
Total	**75**	**2,563**	**3,598**	**659**

Figure 21 shows the proportions of the different incident causes. Of the 659 incidents recorded during the robot bus trial, the two biggest causes for incidents by large margins were "Road infrastructure" and "Switch to manual driving" with proportions of 39 % and 36 %, respectively. These were followed by "Parking on road" and "Other road users" with 13 % and 6 %, respectively. This means that incident causes related to obstacles on the road and overtaking those obstacles accounted for 94 % of all incidents. "Shuttle reset", which in most cases is a result of a software problem, accounted only for 3 % of the incidents.
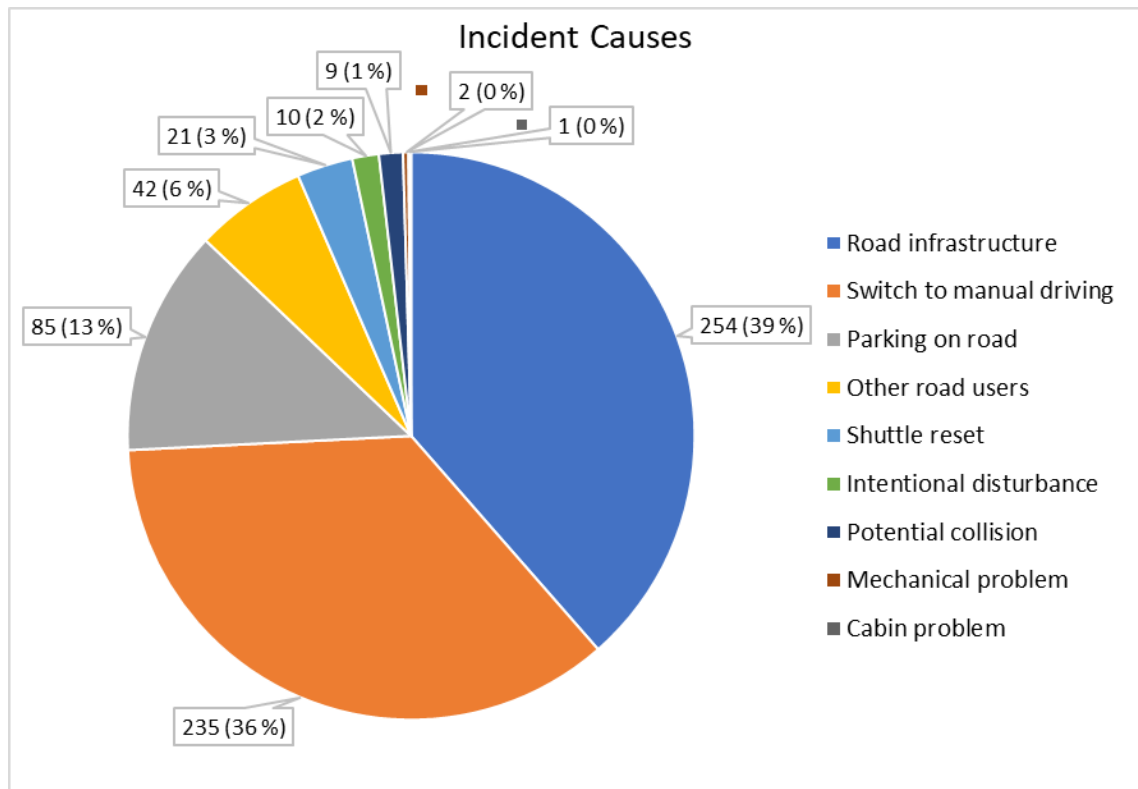
Figure 21 Incident causes in the Aurinkolahti trial.

The incident log seemed to feature some duplicate entries. Altogether 27 incidents were deemed duplicates and removed, because they followed another incident with exactly the same cause and the difference in time between the incidents was less than 30 seconds and the difference in the locations of the incidents was less than five meters. Additional 58 incidents with the causes "Shuttle reset" and "Switch to manual driving" were removed when they followed right after another incident as they were assumed to be resolutions to previous incidents rather than new incidents. The incident statistics and the incidents per kilometers after the removal of the 85 incidents can be seen in Table 15. The incident

ratio from the Aurinkolahti robot bus trial was determined to be 22 incidents per 100 kilometers.

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Table 15   *Incident statistics from the Aurinkolahti trial.*

Month	Kilometers Driven	Number of Incidents	Incidents per Kilometer
June	384	4	0.01
July	968	173	0.18
August	882	328	0.37
September	329	69	0.21
Total	**2,563**	**574**	**0.22**

6 ECONOMICS OF BUS TRANSPORTATION

Finding precise information about the costs related to acquiring and operating robot buses is difficult. The prices of the buses are not publicly available as vendors consider them to be trade secrets. As the buses are not yet in mass production, prices can vary greatly depending on the number of buses being acquired and the routes the buses are being deployed to. This chapter aims to give an understanding of the estimated costs of robot buses by referring to information from different sources. Intricacies of public transportation costs are also examined on a general level in this chapter.

This chapter begins with an overview of the costs incurred when robot buses are used in trials. The overview provides a baseline of the various costs related to owning and operating robot buses. Next, a detailed look is taken at the different battery technologies used in electric buses and the costs related to using the batteries. This is followed by a breakdown of kilometer costs. Finally, the robot bus costs are applied to a public transportation context. This involves establishing unit costs for traditional buses and then using the obtained costs to derive unit costs for diesel minibuses, electric minibuses and robot buses. The unit costs are used in the next chapter when the costs of different bus types are further analyzed and compared.

6.1 Costs of Robot Bus Trials

The cost of a single automated bus is between 230,000 and 300,000 euros. This typically includes, in addition to the vehicle itself, the sensors and batteries. Some vendors may charge an additional one-time fee for the license of the software used in the buses while other vendors charge for the software license on a monthly or yearly basis.

Deploying the bus on a route costs between 20,000 and 40,000 euros depending on what the deployment entails. Typically preparing a route includes analysis of the site where the bus will be operated, mapping the environment, determining a path that the bus will follow and running several tests of the route. Training of operators and supervisors can also be included in the deployment costs. Other costs that might be incurred are the costs of charging capabilities (around 2,000 euros per unit for simple Type 2 cable chargers)

and traffic light controllers (5,000–10,000 euros per unit) that allow automated buses to retrieve the states of traffic lights at intersections.

Annual maintenance fees are between 18,000 and 24,000 euros. In addition, support and monitoring cost between 12,000 and 20,000 euros per route each year. A software license costs between 6,000 and 12,000 euros per year. Software upgrades and licensing fees can also be charged separately. The fees for insurance and permits are negligible, amounting to some hundreds of euros. Operator training costs between 2,000 and 3,000 euros, depending on whether operators are trained individually by the bus vendor or if the organization operating the route is capable of training additional operators itself.

In summary, the total cost of the bus is composed of both one-time costs and recurring costs. One-time costs include the price of the vehicle, which is around 260,000 euros, and the costs related to deploying the bus on a route, which are around 30,000 euros. Recurring costs include maintenance and support costs, which are annually around 30,000 euros. Infrastructure costs are heavily dependent on the route and location, so estimating them is difficult.

6.2 Battery Costs

A major part of the robot bus costs is explained by the costs of sensors and especially the batteries. Currently, two different battery technologies are generally used to power electric buses. These two battery types are lithium iron phosphate (LFP) battery and lithium titanate (LTO) battery (Vilppo & Markkula, 2015). When comparing the two battery types, LTO batteries have a higher purchase price but they can be used longer as they can withstand more charge cycles. Charge cycles can be used to estimate the total lifetime of batteries. One charge cycle corresponds to recharging a completely drained battery back to its full capacity. Although LFP batteries have a much lower purchase price, they need to be replaced more often due to their shorter cycle life. Besides the stated cycle life, other aspects that affect the lifetime of batteries are the temperature at which the batteries are used, depth of discharge (i.e., how much of the battery's capacity is used before it is recharged) and the current at which the batteries are used.

Batteries in electric buses are mainly charged using conductive opportunity charging. In opportunity charging no additional standstill time is reserved for charging, but the

batteries are charged during regular service breaks, such as during scheduled layovers. Three main strategies for battery charging exist, which are depot charging, end-stop charging and bus stop charging that is performed along the route (Vilppo & Markkula, 2015). With depot charging, the bus is charged at the depot during the night. When only depot charging is used, the battery needs to be big enough to last a full day's worth of mileage, but on the upside the depot only needs to have one charger for each bus. With end-stop charging, the battery is charged several times a day at the terminus. Bus stop charging, in which charging is done during dwell times at bus stops when passengers are embarking and disembarking, is a complementary charging strategy that is not enough on its own. End-stop and bus stop charging require having several fast chargers, which makes them more expensive as charging strategies than depot charging.

LTO batteries can be charged using a higher power charger than LFP batteries. This makes LTO batteries better fitted for charging strategies employing fast charging. By contrast, LFP batteries are typically charged at lower power overnight at depots. LFP batteries have a higher energy density and hence can store more energy by weight. In fact, 1 kWh of energy in LTO batteries weights roughly two times more than in LFP batteries. This could help explain why most automated buses, which are relatively small in size, are equipped with LFP batteries. Yet, LFP batteries charged at the depot need to have the capacity to last the entire day, which means that the bus needs to carry enough battery packs to be able to reach the desired daily driving range. Table 16 below lists the most important characteristics of the two battery types.

Table 16 *Characteristics of LFP and LTO batteries*
(Markkula & Vilppo, 2014; Vilppo & Markkula, 2015).

	LFP	LTO
Price	700 – 1,000 €/kWh	2,000 – 2,900 €/kWh
Cycle Life	3,000	12,000 – 16,000
Energy Density	130 Wh/kg	60 – 65 Wh/kg
Maximum Charging Rate	1 C (1 x capacity)	6 C (6 x capacity)

As an example, the LFP battery pack of a robot bus with a capacity of 33 kWh would cost between 23,100 and 33,000 euros. Assuming an energy consumption of 0.66 kWh/km, the batteries of the bus would last for about 150,000 kilometers. With an annual mileage

of 60,000 kilometers, the battery pack would be good for about two and a half years. With 100,000 kilometers annually, the battery pack would need to be replaced after one and a half years. Supposedly robot buses, and electric buses in general, will become more energy efficient in the future and battery prices will decrease. Still, battery packs that cost around 20,000 euros or even more need to be substituted to new ones every one to four years, depending on the annual mileage.

6.3 Kilometer Costs

With conventional buses, costs that are directly attributable to the use of the bus include the cost of diesel fuel and urea. Electric buses, by contrast, do not need fuel but the energy used to power the vehicles is instead stored in batteries. As batteries are charged with electricity, the energy costs of electric buses are directly linked to the price of electricity and subject to local electricity tariffs. Table 17 below lists the average electricity prices in Finland for companies and institutions. The prices include the cost of energy, distribution and taxes. Electricity prices depend on the annual energy use, since the more energy is consumed, the lower the price is per kWh. The average electricity price of 8.63 cents per kWh will be used in the calculations throughout this thesis.

Table 17   *Electricity prices for companies and institutions as of March 2020*
(Tilastokeskus 2020).

Annual energy use	Electricity price (cents/kWh)
Less than 20 MWh	12.27
20 – 499 MWh	10.74
500 – 1,999 MWh	8.54
2,000 – 19,999 MWh	7.95
20,000 – 69,999 MWh	6.34
70,000 – 150,000 MWh	5.92
Average	**8.63**

Using the aforementioned average electricity price, the energy cost of each kilometer traveled for a robot bus with an energy consumption of 0.66 kWh/km would be 5.70 cents. Charging LFP batteries during the night at the depot could potentially be less expensive

due to time-of-use tariffs that incentivize energy consumption with less expensive rates during off-peak hours such as nighttime.

Maintenance costs can also be allocated to each kilometer traveled. Per kilometer maintenance costs of traditional diesel buses are estimated to be between 20 and 25 cents. Tire costs, collision repairs and cleaning costs, which account for roughly one third of the total maintenance costs, are believed to be the same for electric buses. Brakes in electric buses will wear slower than in traditional buses due to regenerative braking and hence need less maintenance. Electric buses are also believed to require less regular servicing and repairs as they do not need frequent motor oil and filter changes and electric motors are less susceptible to wear and tear than diesel motors. Hence, maintenance costs of electric buses can be estimated to be slightly less than those of diesel buses, between 18 and 22 cents per kilometer traveled. (Vilppo & Markkula, 2015) Current robot buses are on the smaller scale of electric buses, which should result in lower maintenance costs. However, since robot buses need to be serviced by specialist mechanics, they feature delicate and expensive sensors and they require regular software updates, their maintenance costs are presumably proportionally higher, at least for the time being when robot buses are not yet all too common.

When calculating the costs per kilometer, battery wear should also be taken into account. With current battery technologies, the cost related to the wear of the battery can actually be more substantial than the cost of energy. When considering the total cost of batteries, not just the initial purchase price, but also the number of kilometers that can be driven with a battery during its lifetime needs to be considered. The lifecycle cost associated with using a certain type of battery and allocating that cost to kilometers traveled can be calculated using formula (2). The formula assumes that the capacity of the battery degrades linearly and that during the battery's lifetime the capacity is on average at 90 % of the original capacity. A battery is thought to be at the end of its life when its capacity is at or below 80 % of the original capacity. (Markkula & Vilppo, 2016)

$$a = \frac{p * c}{0.9 * y} \qquad\qquad (2)$$

a = Price of the battery per kilometer (€/km)

p = Purchase price of the battery (€/kWh)

c = Energy consumption (kWh/km)

y = Number of battery cycle life (n)

By using formula (2), an LFP battery that has a purchase price p of 700 €/kWh and a battery cycle life y of 3,000 that is used in an electric bus with an energy consumption c of 0.66 kWh/km can be calculated to have a per kilometer cost of 22 cents. Table 18 below summarizes the total estimated cost of an electric bus per kilometer. The estimation does not factor in the unique characteristics of robot buses, and as such the estimation should be considered to be a general estimation of a per kilometer cost of an electric bus with a particular energy efficiency. Nevertheless, the estimation already gives a strong indication that the cost of energy consumption only accounts for a minor part of the total kilometer costs.

Table 18   Estimated cost of an electric bus per kilometer (€/km).

Battery wear	0.17 €
Maintenance costs	0.18 €
Energy	0.06 €
Total cost	**0.41 €**

6.4 Public Transportation Costs

Size-wise current automated buses correspond to minibuses while from a technical perspective they are close to electric buses. Hence, to get an understanding how the costs related to acquiring and operating automated buses compare to other means of public transportation, it is meaningful to inspect the costs of both diesel-powered minibuses and electric minibuses.

In the city of Turku different bus lines are operated by different operators. As the companies operating the bus lines are private, their exact operating costs are not public information. Typically, however, costs of operating bus traffic are divided into unit costs pertaining to vehicle kilometers, vehicle hours and vehicle days based on whether the

particular cost can be allocated to kilometers driven, hours operated, or days operated, respectively. Vehicle kilometer costs typically include the costs for fuel and lubricants, tires, replacement parts, maintenance and repairs. Vehicle hour costs are mainly composed of the costs for drivers' wages. Vehicle day costs include depreciation of capital, interest, insurance and other overhead costs. Capital depreciation period for buses is typically between seven and 14 years. For regular-sized buses it is either the full 14 years or 10 years, which is the length of a typical contract between cities and the traffic contractors.

Although the exact unit costs for different vehicle types are not publicly available, the city of Turku has disclosed average unit costs for traditional buses. A traditional bus is assumed to be a two-axle diesel bus. A vehicle kilometer for a traditional bus in Turku costs 57 cents, a vehicle hour 37.39 euros and a vehicle day 153 euros (City of Turku, 2019). Total operating cost can be calculated from the unit costs by using formula (3). In the city of Turku, the total daily cost of operating a bus that is driven 250 kilometers during a time span of 12 hours would be 744.18 euros. A bus cannot be driven every single day of the year as it must go under regular servicing and maintenance. Assuming 320 operating days per year, the yearly cost of a single bus would be 238,137.16 euros with an annual mileage of 80,000 kilometers.

$$C_{tot} = C_{km} * A_{km} + C_h * A_h + C_{day} * A_{day} \qquad (3)$$

C_{tot} = Total cost (€)

C_{km} = Unit cost of a vehicle kilometer (€/km)

A_{km} = Number of kilometers (km)

C_h = Unit cost of a vehicle hour (€/h)

A_h = Number of hours (h)

C_{day} = Unit cost of a vehicle day (€/day)

A_{day} = Number of days (day)

6.4.1 Cost Index

Statistics Finland maintains a cost index of bus and motor-coach traffic, which describes price changes of cost factors from the perspective of the transport operators. In the index

different cost factors have been assigned weights according to their relative impact on the total costs. Included in the index are weight structures for an overall index as well as separate weight structures for contract, urban, regular service, express and charter transport. The bus traffic operated in Turku and in other major cities in Finland is generally contract transport. In contract transport, the city keeps all the revenue from the ticket sales and pays a compensation to the operators according to predetermined procurement contracts, which are regularly tendered.

Table 19 shows the weight structures of the overall index and contract transport from the cost index of bus and motor-coach traffic. In the table cost factors are grouped under the type of unit cost they are related to in order to give an idea what and how the unit costs are composed of. As can be seen from the table, costs related to wages, which can be allocated to vehicle hours, make up a significant proportion of the total costs. The table also shows how the unit costs of traditional buses in Turku can be divided into cost factors using the corresponding weight factors from the contract transport index.

Table 19   *Cost-index based distribution of public transport costs (Tilastokeskus, 2017; Karvonen, 2012; City of Turku, 2019).*

	Overall Index (weight factor, %)	Contract Transport (weight factor, %)	Traditional Bus		
			%	€	
Vehicle kilometer	**25.3**	**22.0**	100	0.57	€ / km
Fuel and lubricants	15.1	14.2	65	0.37	
Tires and replacement parts	3.7	2.8	13	0.07	
Repair and maintenance	6.5	5.0	23	0.13	
Vehicle hour	**49.8**	**54.6**	100	37.39	€ / h
Wages	30.3	33.0	60	22.60	
Indirect wages	19.5	21.6	40	14.79	
Vehicle day	**24.9**	**23.5**	100	153.00	€ / day
Depreciation of capital	7.9	9.0	38	58.60	
Interest	0.7	0.9	4	5.86	
Insurance	1.4	1.3	6	8.46	
Overhead costs	14.9	12.3	52	80.08	

According to the contract transport index, the depreciation of capital is 38 % of the vehicle day costs. With a vehicle day cost of 153 euros that makes 58.60 euros. The cost of a new traditional bus is assumed to be around 250,000 euros (Lehtinen & Kanerva,

2017). Using straight-line depreciation, the amount of annual vehicle days would be 427 with a daily depreciation amount of 58.60 euros and a depreciation period of 10 years, 388 days with a period of 11 years, 356 days with a period of 12 years, 328 days with a period of 13 years and 305 days with a period of 14 years. Of these, 356 annual vehicle days is closest to a full calendar year while allowing some days of downtime. Hence the depreciation period for traditional buses is assumed to be 12 years.

6.4.2 Unit Costs of Diesel Minibuses

The unit costs for traditional buses can be used to draw an estimation of the corresponding unit costs for diesel-powered minibuses. According to Karvonen (2012), the price of a new minibus is around 105,000 euros, while Huhta (2017) estimates that the price falls between 140,000 and 180,000 euros. In the calculations here, the cost is estimated to be 145,000 euros, which translates into being 58 % of the cost of a traditional bus.

Based on a study by Karvonen (2012) the fuel consumption of diesel minibuses is 41 % of the consumption of traditional buses. The same percentage of 58 % that was determined to be the ratio between a purchase price of a traditional bus and a diesel minibus is used to calculate the cost of tires and replacement parts and the cost of repair and maintenance. As a result, the vehicle kilometer costs of a minibus are in total 48 % of the corresponding costs of a traditional bus. Vehicle hour costs are estimated to be 20 % lower than the vehicle hour costs for traditional buses. Salary costs are lower for minibuses because minibuses are rarely operated outside regular work hours when additional compensation needs to be paid.

For a minibus the capital depreciation period used in the calculations is eight years, which is four years shorter than for a traditional bus. With straight-line depreciation, the annual depreciation amount of a minibus is 87 % of the annual depreciation amount of a traditional bus. The same ratio is also applied to interest. Insurance and overhead costs are estimated to be half of the corresponding costs of a traditional bus. Table 20 shows the estimated unit costs of diesel-powered minibuses in the city of Turku and how they relate to the unit costs of traditional buses percentagewise.

Table 20 *Estimated unit costs of a diesel minibus.*

	Traditional Bus (€)	Conversion Rate (%)	Diesel Minibus		
			%	€	
Vehicle kilometer	**0.57**	**48**	**100**	**0.27**	€ / km
Fuel and lubricants	0.37	41	56	0.15	
Tires and replacement parts	0.07	58	15	0.04	
Repair and maintenance	0.13	58	30	0.08	
Vehicle hour	**37.39**	**80**	**100**	**29.91**	€ / h
Wages	22.60	80	60	18.08	
Indirect Wages	14.79	80	40	11.83	
Vehicle day	**153.00**	**66**	**100**	**100.35**	€ / day
Depreciation of capital	58.60	87	51	50.98	
Interest	5.86	87	5	5.10	
Insurance	8.46	50	4	4.23	
Overhead costs	80.08	50	40	40.04	

The estimated costs are in line with the average costs for minibuses that were disclosed in 2016 by the Turku region public transport service. In 2016, vehicle kilometer costs for minibuses were between 0.21 and 0.31 euros with an average of 0.24 euros. Vehicle hour costs were between 25.78 and 33.79 euros with an average of 29.85 euros. Vehicle day cost were between 84.47 and 135.18 euros with an average of 115.38 euros. (City of Turku, 2016)

6.4.3 Unit Costs of Electric Minibuses

Estimating unit costs of electric minibuses is slightly more complicated due to different battery technologies and battery capacities used in electric buses. The choice of charging strategy between depot and end-stop charging also affects initial infrastructure costs considerably. Annual mileage also needs to be considered because it affects how often the battery of the bus needs to be replaced.

While a regular-sized electric bus comparable to a two-axle diesel bus costs around 500,000 euros (Lehtinen & Kanerva, 2017), it is difficult to find prices for electric minibuses. A price of an electric van that has similar proportions as a minibus can serve as an indication for the price level of electric minibuses. As an example, a *Volkswagen*

eCrafter 35 electric van costs 70,160 euros or 71,992.86 euros including an estimated vehicle tax (Volkswagen, 2020a). A diesel-powered van from the same manufacturer with similar specifications costs 40,710 euros or 46,931.86 euros including an estimated vehicle tax (Volkswagen, 2020b). This means that the price of the electric version is 53 % more expensive than the price of the diesel version when using the prices with the vehicle tax included. By applying the same ratio to the price of a diesel minibus, which was estimated to be 145,000 euros, the price of an electric minibus can be estimated to be around 220,000 euros.

No information is available on the exact type of the battery used in Volkswagen's electric van used as a reference in the cost calculations. The van's battery has a capacity of 35.8 kWh and the range of the van is specified to be 114 kilometers (WLTP) or 173 kilometers (NEDC) with a single charge. The energy consumption of the van is stated to be 21.54 per 100 kilometers with a load of 975 kilograms. Since the battery can be fast charged with a maximum power of 40 kW, it can be assumed that the battery characteristics are closer to an LFP battery than an LTO battery, which supports higher charging rates. (Cision, 2019)

Using the minimum range specification of the Volkswagen van, the WLTP range, which is 114 kilometers, the energy consumption of the van would be about 0.32 kWh/km. Assuming the battery can withstand 3,000 charging cycles, the van would be able to drive about 336,000 kilometers before the battery would need to be changed. With an annual mileage of 80,000 kilometers that would mean about four years. Hence, with an estimated lifetime of eight years, at least a single change of battery needs to be factored in the costs.

Maintenance costs are estimated to be 44 % of the maintenance costs of a regular-sized electric bus, which were earlier determined to be 0.18 euros per kilometer. The percentage of 44 % is the ratio between the purchase price of an electric minibus (220,000 euros) and a regular-sized electric bus (500,000 euros). Battery wear per kilometer is calculated using the characteristics of an LFP battery and using a price of 700 euros per kWh and an energy consumption of 0.32 kWh/km. The cost of a battery with a capacity of 35.8 kWh is calculated to be about 25,000 euros. The battery cost can either be allocated to vehicle kilometers or it can be regarded as a capital cost that is allocated to vehicle days.

Table 21   *Estimated unit costs of an electric minibus.*

	Electric Minibus A Battery as a capital cost		Electric Minibus B Battery wear allocated to vehicle kilometers		
	%	€	%	€	
Vehicle kilometer	**100**	**0.11**	**100**	**0.19**	€ / km
Energy	27	0.03	16	0.03	
Battery wear	0	0.00	42	0.08	
Maintenance	73	0.08	42	0.08	
Vehicle hour	**100**	**29.91**	**100**	**29.91**	€ / h
Wages	60	18.08	60	18.08	
Indirect Wages	40	11.83	40	11.83	
Vehicle day	**100**	**139.02**	**100**	**119.69**	€ / day
Depreciation of capital	62	86.14	57	68.56	
Interest	6	8.61	6	6.86	
Insurance	3	4.23	4	4.23	
Overhead costs	29	40.04	33	40.04	

Table 21 shows the estimated unit costs of an electric minibus that were obtained as a result of the calculations. Vehicle hour costs are assumed to be the same as for diesel minibuses. Depreciation of capital is calculated using straight-line depreciation over a period of eight years, which is the same as for diesel minibuses. For an electric bus with the cost of the battery regarded as a capital cost, the battery change is assumed to occur after four years of operation, which makes the annual depreciation amount on average 53 % higher than for a traditional bus. For an electric bus with the battery wear allocated to vehicle kilometers, the initial purchase price is considered to be lower by the price of the battery (25,000 euros), making the annual depreciation amount 23 % higher than for a traditional bus. The same rates are also used for calculating the interest. Insurance and overhead costs are estimated to be half of the costs of a traditional bus, which follows the same logic as the unit cost calculations for diesel minibuses.

6.4.4 Unit Costs of Robot Buses

What sets robot buses apart from electric minibuses are the sensors and software needed to make automated driving possible. Currently robot buses are not yet in mass production, so their costs are disproportionately high and not yet in line with the costs of mass-

produced diesel and electric buses. Using the estimated unit costs of an electric minibus as a basis, a conservative estimation of the near-future unit costs of robot buses can be drawn.

Robot buses can feature from six up to ten LiDAR sensors for mapping the environment and detecting obstacles. All the LiDAR sensors do not have the same characteristics and there typically are more 2D sensors than 3D sensors installed on the buses. A popular 3D LiDAR sensor VLP-16 from Velodyne costs around 4,000 USD (Krok, 2018), which translates into roughly 3,500 euros. Using that price as a baseline, eight sensors would cost altogether 28,000 euros. Other sensors used in robot buses are considerably less expensive and have costs in the hundreds rather than in the thousands. Hence, sensor costs are estimated to be in total 30,000 euros.

Currently with the robot buses used in the trials, annual fees are around 30,000 euros. The annual fees include the cost of maintenance, monitoring and a software license. With 80,000 annual kilometers, that would mean 38 cents per kilometer, which is over four times more than what the estimated maintenance cost of an electric minibus is. 80,000 annual kilometers is rather generous, considering that robot bus trials are generally organized for a maximum period of six months during the warmer seasons of the year. The lifetime of the robot buses used in trials is also estimated to be much shorter than the lifetime of electric buses, which means that sensor and battery replacement does not need to be taken into account when considering their costs.

The unit costs are estimated for two different versions of a robot bus – one that is based on the robot buses used during the trials and one that is considered to be more established, mass-produced. The robot buses used during the trials are estimated to cost 250,000 euros with the setup costing 20,000 euros. During the trials, the lowest recorded average energy consumption was 0.66 kWh/km (see Table 8), which is used in the unit cost calculations here. Vehicle hour costs are estimated to be 20 % less during robot bus trials because the buses can be operated by people who are not professional bus drivers and who have just a regular driver's license. However, as was mentioned earlier, this limits the number of concurrent passengers in the bus to eight because of legislative reasons. Depreciation of capital and interest are calculated based on a lifetime of only four years.

The more established version of a robot bus is estimated to have a base price of 220,000 euros, which is the same as the electric minibus. When the sensors (30,000 euros) and setup fees (20,000 euros) are added on top of that, the purchase price comes to a total of 270,000 euros. The established version of the robot bus is assumed to have, for the most parts, the same costs as the electric minibus. Energy consumption is estimated to be the same even though robot buses could potentially be able to drive more energy efficiently than human drivers. Maintenance costs are also estimated to be the same, although the more economical driving style of robot buses can reduce the need for replacing parts. Monitoring and a software license are estimated to cost 18,000 euros per year, which translates into 23 cents per kilometer with an assumed annual mileage of 80,000 kilometers. Depreciation of capital and interest are calculated based on a lifetime of eight years, the same as the electric minibus. Both the battery pack (25,000 euros) and the sensors (30,000 euros) are assumed to be replaced after four years of use. Table 22 below shows the estimated unit costs for an established robot bus and a robot bus that is being used in trials. Infrastructure costs, such as smart traffic lights, are not taken into account in the calculations.

Table 22   Estimated unit costs of a robot bus.

	Robot Bus A Established		Robot Bus B Trial		
	%	€	%	€	
Vehicle kilometer	**100**	**0.34**	**100**	**0.44**	€ / km
Energy	9	0.03	14	0.06	
Maintenance	24	0.08	86	0.38	
Monitoring and software licenses	68	0.23			
Vehicle hour	**100**	**29.91**	**100**	**23.93**	€ / h
Wages	60	18.08	60	14.46	
Indirect Wages	40	11.83	40	9.47	
Vehicle day	**100**	**169.96**	**100**	**284.31**	€ / day
Depreciation of capital	67	114.26	77	218.22	
Interest	7	11.43	8	21.82	
Insurance	2	4.23	1	4.23	
Overhead costs	24	40.04	14	40.04	

6.4.5 Cost Comparison

Some studies have been conducted in the recent years in Finland on the costs of fully electric buses as well as hybrid buses and how they compare to traditional diesel buses. A study by Pihlatie et al. (2014) compared the total cost of ownership (TCO) of electric buses to traditional diesel buses and established that especially the costs of short-range electric buses can be competitive as they have smaller capacity and hence less expensive batteries.

A study by Lehtinen and Kanerva (2017) examined the current state of electric bus use in Finnish cities. The study, which examined the life-cycle costs of electric buses for a period of 15 years, concluded that using electric buses becomes more cost-effective when the annual mileage increases above 80,000 km. This is explained by electric buses having high investment costs, largely due to cost of batteries, and low operating costs when compared to traditional buses.
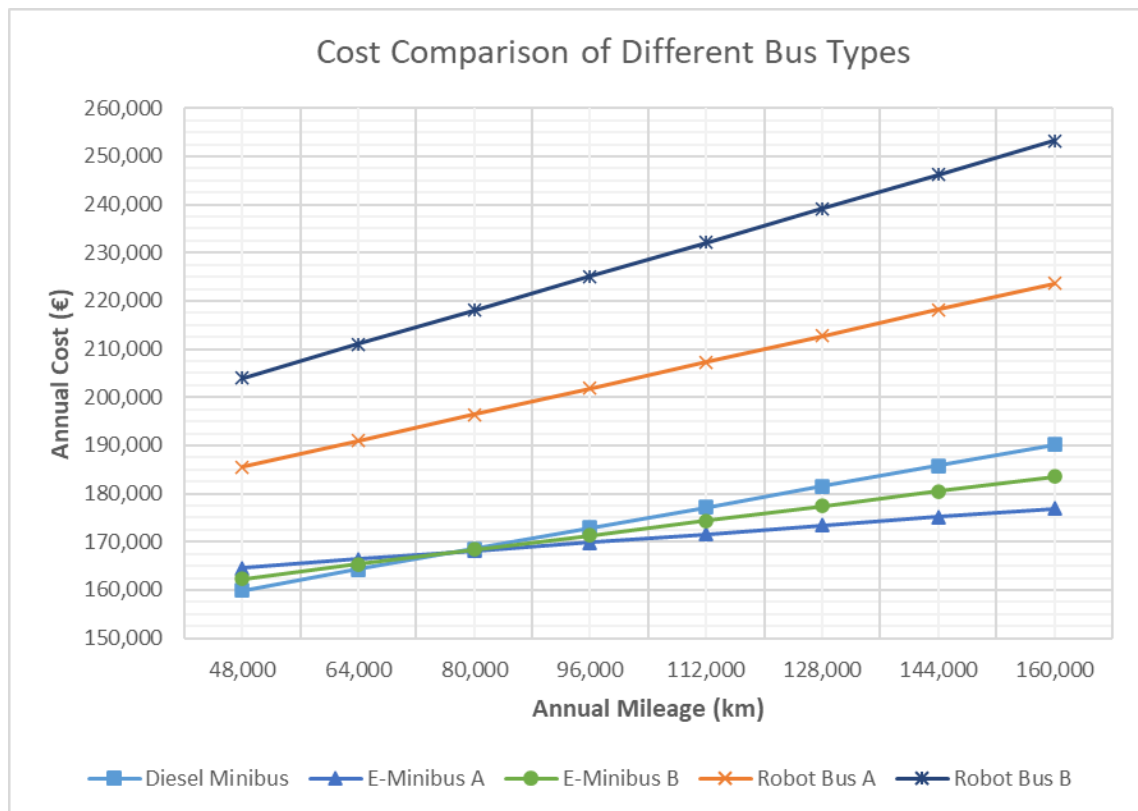

Figure 22 *Impact of annual mileage on annual costs of different bus types.*

The unit cost estimations calculated previously for diesel minibuses and electric minibuses corroborate the earlier studies conducted in Finland. Assuming 12 vehicle hours per day and 320 vehicle days per year, operating an electric bus becomes less

expensive after 80,000 annual kilometers regardless of whether the battery cost is allocated to vehicle kilometers or vehicle days. With the aforementioned parameters, 80,000 annual kilometers means 250 daily vehicle kilometers. Figure 22 above depicts a chart showing how annual mileage affects the annual cost for different bus types.

As can be seen from the chart, robot buses are considerably more expensive than the other bus types. Robot buses have an even higher initial purchase price than electric buses because of the number of sensors needed in the buses and the additional costs related to preparing routes for automated driving. Per kilometer costs are also higher because of monitoring and software licensing fees. The unit cost estimations were made with the assumption that the buses always have a driver or an operator inside the vehicle. Having a single person operate multiple buses would yield lower vehicle day costs, which would greatly improve cost-efficiency of robot buses.

7   RESULTS AND ANALYSIS

In this chapter the results of the simulation are presented along with an analysis of the costs of robot buses and other minibus types. The simulation results are presented by considering the impact of each simulation variable and in the form of correlation and regression analyses, which lead to the estimation of operator capacity. The variables are analyzed to determine the extent to which each variable affects the operator capacity. The analysis of the simulation results provides an answer to the first research question about the ability of a single operator to control multiple buses simultaneously. The cost analysis includes a TCO analysis and an assessment of the costs for the sample route in the city of Turku. This provides an answer to the second research question about the costs of automated buses and how they compare to other bus types. The feasibility of remote driving over a mobile network is also discussed in this chapter to provide an answer to the last research question about the capabilities of modern mobile networks to support remote operation of automated buses.

7.1 Simulation Results

The incident ratios recorded during the robot bus trials were 0.03 for Kivikko, 0.36 for Kalasatama and 0.22 for Aurinkolahti. An average incident ratio that takes into account the data collected during all the three robot bus trials is 0.16. This means that on average a robot bus operated in mixed traffic on public roads encounters 16 incidents every 100 kilometers it drives.

The three different incident ratios recorded during the trials and the average ratio were used as values for the incident ratio variable in the simulation. Altogether the five simulation variables and their different values formed 4,800 different variable combinations. A simulation with each combination of variables was run 10 times, which means that altogether 48,000 simulation runs were performed. In total 1,224,000 rows of observations were recorded as part of the simulation, since the simulation results were gathered individually for every bus during every simulation run. An average was taken of the results of the simulation runs, which reduced the number of observations to 122,400.

7.1.1 Variable Analysis

The impact of each simulation variable was studied individually while always retaining the number of buses as a second independent variable. While studying an impact of a specific variable, average values of the other variables were used. The purpose of the simulation was to assess how the different independent variables affect the actual speeds of the buses and the delays experienced by the buses. For convenience and due to having several different independent variables with different units, the dependent variables were decided to be expressed as relative changes. In practice, this means that the decrease of the actual speeds of the buses and the increase of the travel times while the number of simultaneously driving buses increases are depicted as percentage changes. The formulas used to calculate the percentage changes are shown in Table 23 below.

Table 23   *Simulation dependent variables and their formulas.*

Dependent Variable	Formula
Actual Speed (relative Δ)	$\dfrac{ActualSpeed - Speed}{Speed} * 100$
Travel Time (relative Δ)	$\dfrac{Duration - DrivingTime}{DrivingTime} * 100 = \dfrac{Delay}{DrivingTime} * 100$

Figure 23 below shows how the speed variable on average affects the actual speed and the travel time of the buses while the number of simultaneously driving buses increases. The lines in the graphs represent different speeds, specifically 25 and 40 km/h. The graphs indicate that the faster the buses drive, the more drastic the relative effect is on the actual speed and travel time. This is understandable, since when driving at a higher speed a bus is expected to finish its route faster than when driving at a lower speed. However, since in the simulation the number of incidents experienced by the buses and the time it takes to resolve those incidents are the same regardless of the speed, the relative impact of incidents is more significant to buses driving at higher speeds.
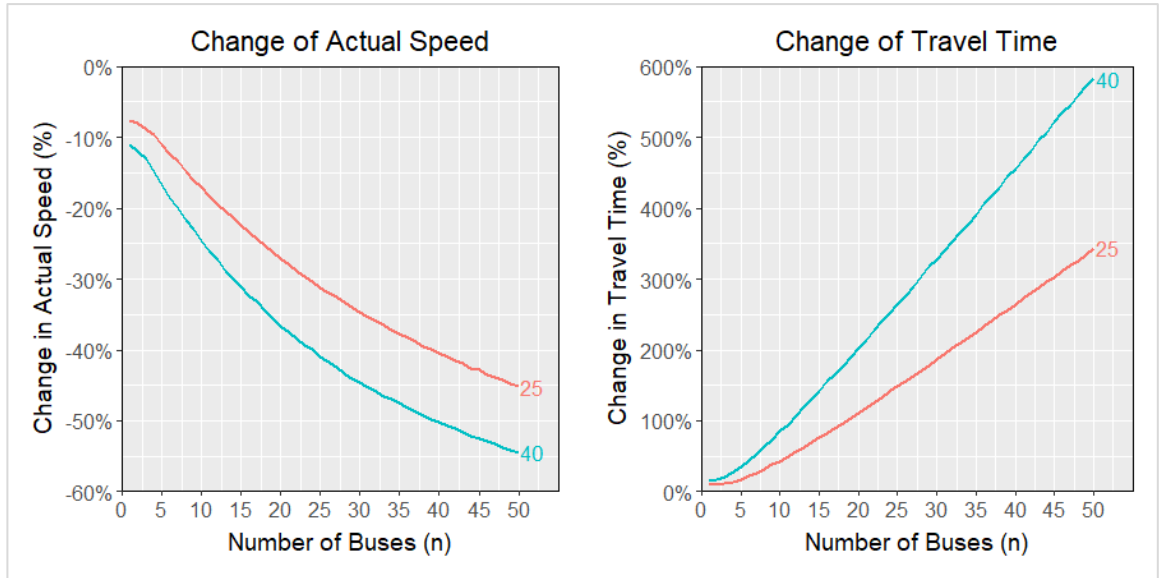
Figure 23 *Impact of speed on actual speed and travel time.*

Figure 24 *Impact of distance on actual speed and travel time.*

Figure 24 above shows the impact the distance driven by the buses has on the dependent variables. During the simulation, the buses drove distances of 25, 50 and 100 kilometers. As can be seen from the graphs, distance does not appear to have a huge impact on either of the dependent variables. This is evidenced by the lines representing the different distances having only slight deviations from one another. This, of course, makes sense since the incidents are distributed evenly along the distances driven. Apparent differences only appear at the tail ends of the lines.
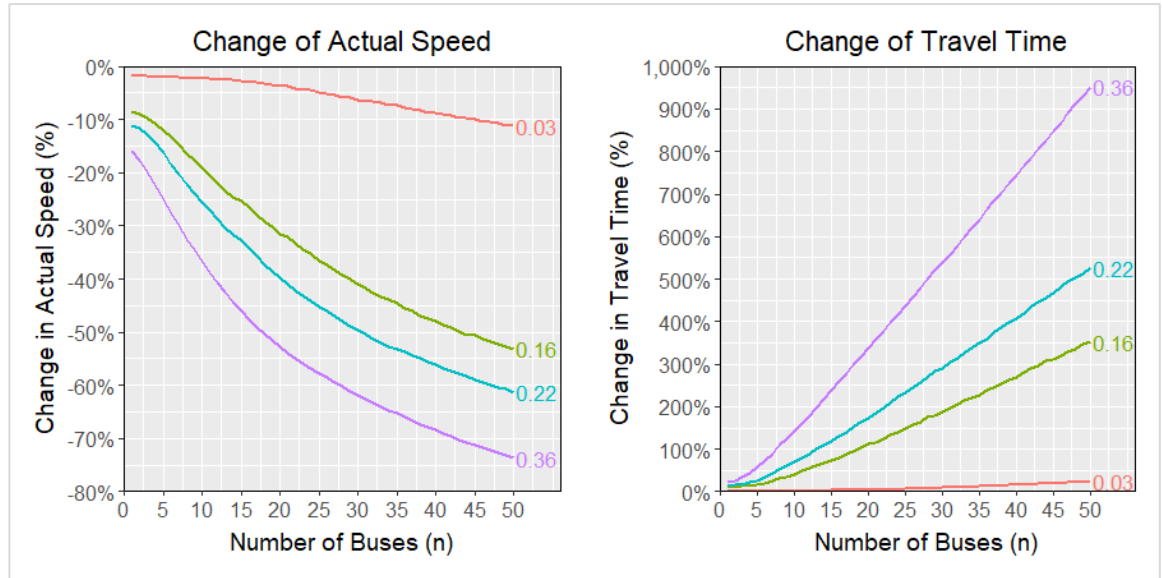
Figure 25 *Impact of incident ratio on actual speed and travel time.*

More notable differences start to show up when looking at how the incident ratio and the incident resolution time affect the dependent variables. The impact of incident ratio is depicted above in Figure 25. With the highest incident ratio, which is 36 incidents per every 100 km, the actual speed of the buses decreased by over 70 % when the number of simultaneously driving buses reached 50. However, with the lowest incident ratio, which is 3 incidents per 100 km, the actual speed of the buses did not decrease by more than 10 % until there were more than 40 buses driving at the same time. The differences are even more striking when the impact of incident ratio on travel time is examined. With the lowest incident ratio, the change in travel time always stays under 50 %, while with the highest incident ratio it increases to over 900 %.

Impact of resolution time, which is depicted below in Figure 26, appears to be following a similar pattern as above. In fact, incident ratio and incident resolution time seem to have comparable impacts on the independent variables. With the lowest resolution time of 10 seconds, the changes in both actual speed and travel time appear to be rather moderate. With the highest resolution time of 180 seconds, however, the changes in both independent variables appear to be much steeper.
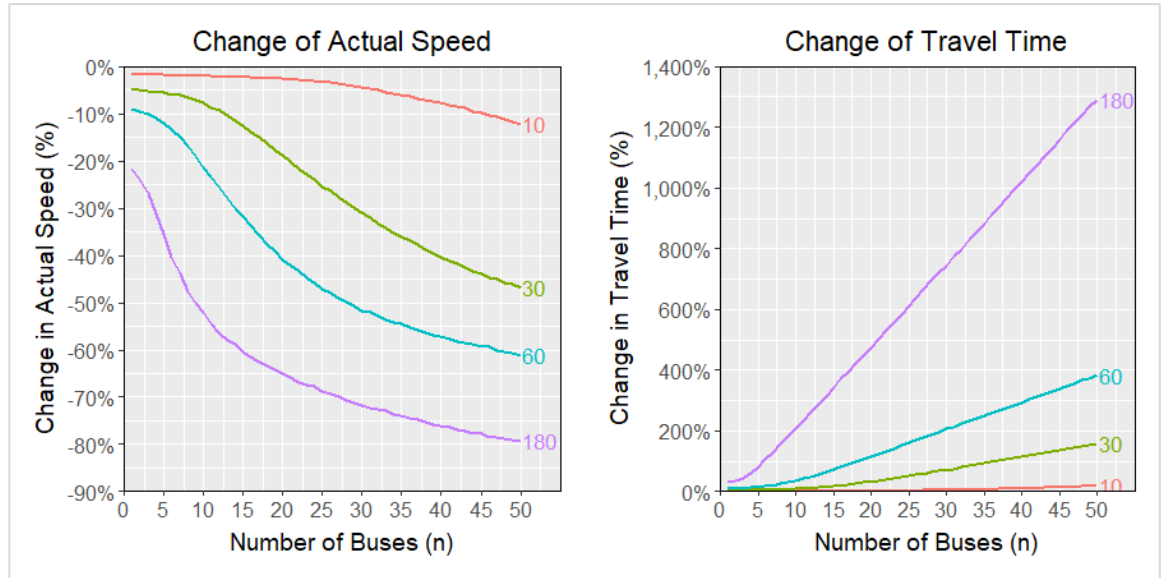
Figure 26 *Impact of resolution time on actual speed and travel time.*

Since both the incident ratio and the incident resolution time affect the travel time greatly, it is interesting to examine how the relative shares of the constituents of travel time change when both the incident ratio and the incident resolution time change. The travel time is composed of driving time, interaction time and wait time in queue. Driving time is defined as the time the bus is driving. Interaction time is defined as the time the operator is spending on resolving incidents the bus has encountered. Wait time in queue is defined as the time the bus is idle after encountering an incident and while waiting for the operator, who is busy resolving an incident for another bus. Ideally, as much of the travel time as possible should be spent driving.
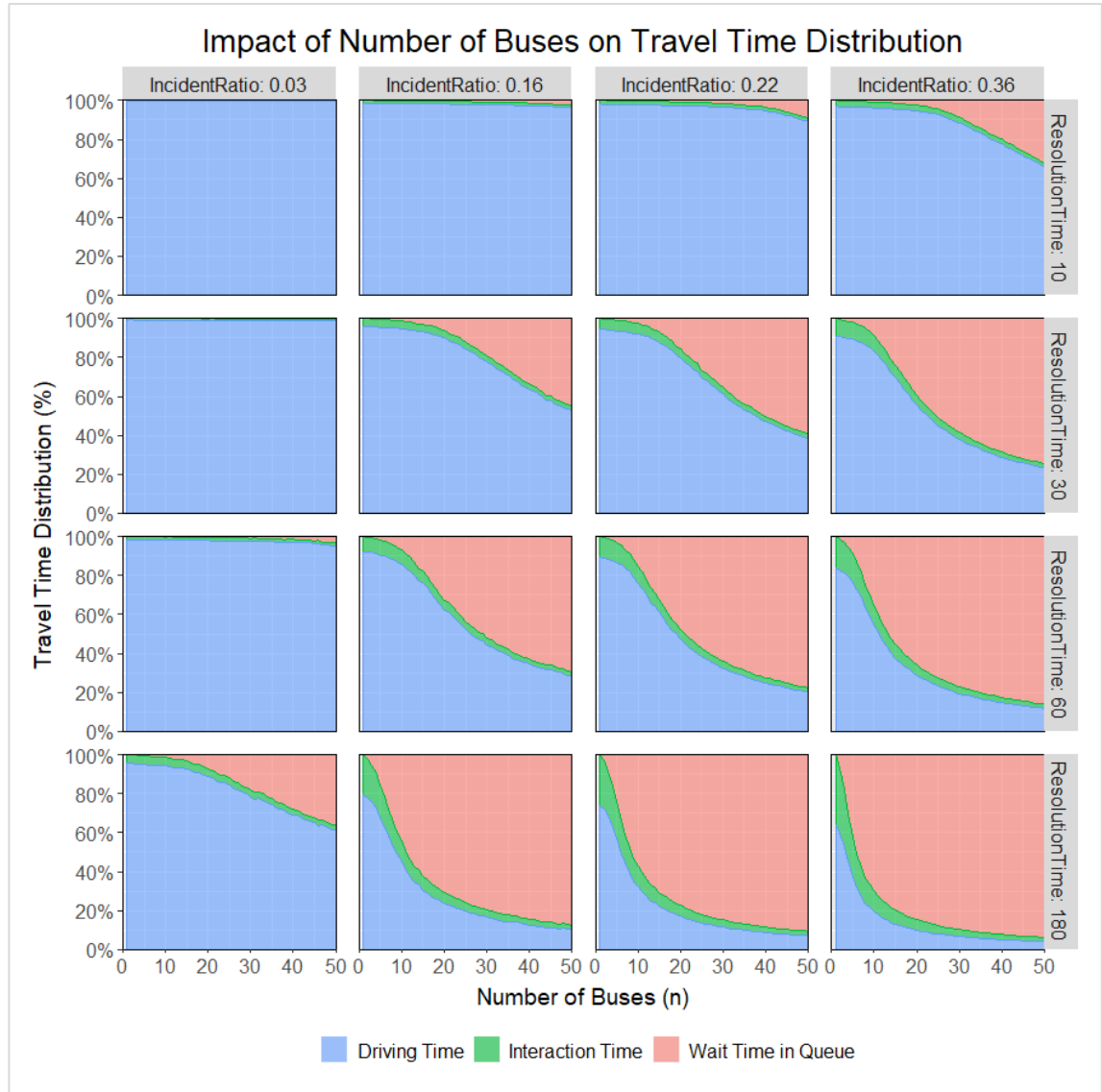
Figure 27 *Distribution of travel time constituents.*

Figure 27 above shows what portion of the total travel time driving time, interaction time and wait time in queue make up with different combinations of the incident ratio and incident resolution time variables. The graph in the upper-left corner of the figure depicts a condition where the incident ratio is 0.03 and the incident resolution time is 10 seconds. In that graph, almost the entire travel time is made up solely by the driving time regardless of the number of buses driving simultaneously. That is in huge contrast to the graph in the lower-right corner, which depicts a condition where the incident ratio is 0.36 and the incident resolution time is 180 seconds. In that graph, wait time in queue makes up by far the largest portion of the travel time when the number of buses increases above 10. Looking at the graphs, wait time in queue can be seen to increase consistently along with the increase of the number of buses driving simultaneously.

7.1.2 Correlation and Regression Analysis

Although the variable analysis presented above already gives a decent idea about the quality of the relationships between the independent and dependent variables, correlation coefficients were calculated to measure the strength and direction of the relationships. The correlation coefficients are expressed as numeric values ranging from -1 to 1. Values above zero indicate a positive correlation, with 1 denoting the strongest possible positive correlation between two variables. In positive correlation both variables move in the same direction. In practice, this means that when one variable increases in value, the other one increases as well, and similarly, when one variable decreases in value, the other one decreases. Values below zero indicate a negative correlation, with -1 denoting the strongest possible negative correlation. In negative correlation, the variables move in opposite directions, meaning that, when one variable increases, the other one decreases. A correlation coefficient value of zero indicates a zero correlation, which means that there appears to be no relationship at all between the two variables.

Figure 28 below depicts a correlation matrix, which is essentially a table showing the correlation coefficients between different variables. The matrix shows the strength of the relationships both numerically and as a heatmap. The redder the color, the stronger the positive correlation and the bluer the color the stronger the negative correlation between two variables. Blank white squares indicate that no relationship exists between the variables.
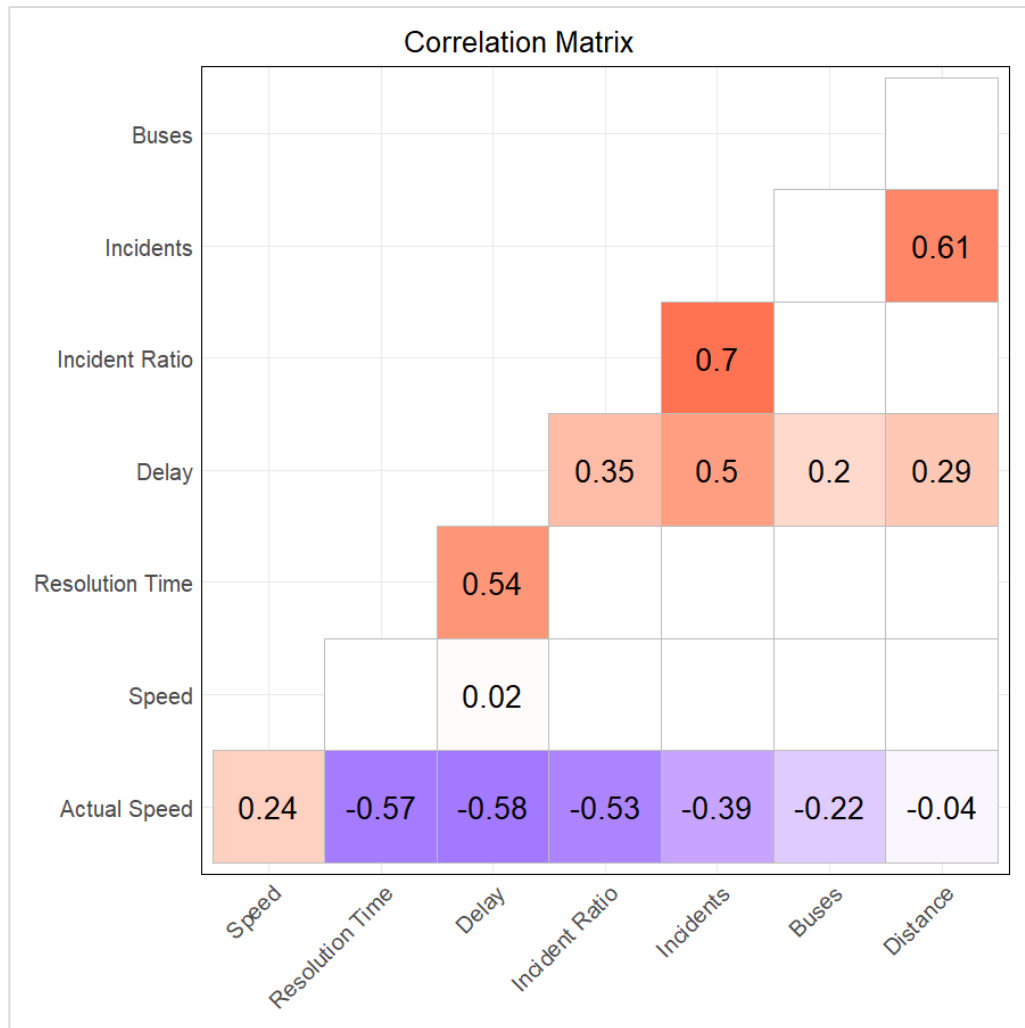
Figure 28 *Pearson correlation matrix of simulation variables.*

The correlation matrix includes the dependent variables *Actual Speed* and *Delay*, the simulation variables, and also a variable called *Incidents*, which represents the number of incidents. When examining the correlation between actual speed and the independent variables, it can be seen that speed has a positive impact on it, while resolution time, incident ratio and number of buses have a negative impact. In practice, this means that when the values of these three variables increase, actual speed decreases. Delay is positively impacted by incident ratio, number of buses and distance driven. This means that when these three variables increase in value, delay increases as well.

In addition to the correlation coefficients, the relationships between the variables were also studied through the means of multiple linear regression. Linear regression gives a better overall picture of how the independent variables are associated with the dependent variables and also enables predicting or estimating the values of the dependent variables

based on known values of independent variables. Linear regression models were built both for actual speed and delay using the simulation variables as predictors.

A summary of the linear regression model created for actual speed can be seen in Table 24. The R-squared (R^2) of the model was found to be 0.7107. R-squared indicates how much of the variance of the dependent variable is explained by the predictors. The obtained R-squared value means that the model can explain 71.07 % of the variance in actual speed. F-statistics for the model is 60,133.94, which is large enough to conclude that the model is statistically significant. The probability values (p-values) of all the predictors and the whole model were less than 0.001, which means that they are statistically significant.

Table 24   *Summary of the multiple regression on actual speed.*

Predictor	B	SE	t	β	sr	sr^2	p
(Intercept)	32.72	0.11	294.0	0.00			< 0.001
Speed	0.39	0.00	155.4	0.24	0.24	0.06	< 0.001
Buses	-0.23	0.00	-145.5	-0.22	-0.22	0.05	< 0.001
Distance	-0.01	0.00	-22.8	-0.04	-0.04	0.00	< 0.001
Incident Ratio	-54.55	0.16	-344.1	-0.53	-0.53	0.28	< 0.001
Resolution Time	-0.11	0.00	-369.3	-0.57	-0.57	0.32	< 0.001

In the summary of the multiple regression, *Intercept* is a constant describing the value of the dependent variable when all the predictor variables take on the value zero. *B* stands for the unstandardized coefficient or unstandardized beta, which represents the slope of the regression line between the predictor and the dependent variable. In practice, *B* expresses how much the dependent variable changes for every one-unit change in the predictor variable. *SE* is the standard error of the unstandardized coefficient, which describes how spread out the coefficient estimates are from the regression line. *t* is the t-statistics value, which denotes how many standard deviations the coefficient estimates are away from zero. *β* is the standardized beta, which is similar to a correlation coefficient and shows the relationships between variables on a scale from -1 to 1. *sr* is the semipartial correlation, which, when squared, indicates the unique contribution of the independent variable and tells how much R-squared would decrease if the variable was removed from the model.

Table 25 shows the summary of the linear regression model created for delay. The R-squared for the model is 0.5421, which means that the predictors in the model explain a little over half of the variance in delay. F-statistics for the model is 28,984.60 and p-values of the whole model and all predictors are less than 0.001, which means that the results are statistically significant.

Table 25   *Summary of the multiple regression on delay.*

Predictor	B	SE	t	β	sr	sr²	p
(Intercept)	-75,614.80	467.26	-161.8	0.00			< 0.001
Speed	112.65	10.52	10.7	0.02	0.02	0.00	< 0.001
Buses	674.36	6.63	101.7	0.20	0.20	0.04	< 0.001
Distance	380.00	2.53	150.1	0.29	0.29	0.08	< 0.001
Incident Ratio	121,363.89	665.46	182.4	0.35	0.35	0.12	< 0.001
Resolution Time	335.69	1.20	280.5	0.54	0.54	0.29	< 0.001

Calculating the correlation coefficients and creating the linear regression models did not reveal any divergent findings. It can be concluded that actual speed decreases while the number of buses, incident ratio and resolution time increase. Incident ratio and resolution time make the highest unique contributions with semipartial correlations of 28 % and 32 %, respectively. The R-squared of the model is 71 %, which means that other, unknown, variables account for the remaining 29 % of the variance.

Based on the correlation coefficients and the regression model, delay can be observed to increase when the number of buses, distance driven, incident ratio and resolution time increase. Preliminary findings from the variable analysis indicated that the change in distance does not appear to have a major impact on the percentage change of travel time. This still holds true as the delay used in the regression model is expressed as seconds rather than as a percentage change. The absolute values of total travel time and delay understandably increase when the distance becomes longer. When looking at the model's semipartial correlations, it can be seen that resolution time has the highest unique contribution with 29 %. With an R-squared value of only 54 %, almost half of the variables explaining the variance in delay are unknown.

7.1.3 Estimation of Operator Capacity

The purpose of estimating operator capacity is to establish how many buses a single person can remotely monitor and operate simultaneously while keeping actual speed and delay at reasonable levels. In the previous section, it was observed that resolution time and incident ratio had the highest impact on both actual speed and delay, while other variables only had a negligible impact. Hence, when estimating operator capacity from the simulation results, the highest variable values can be used for speed and distance, i.e., 40 km/h for speed and 100 km for distance. The value used for incident ratio is 0.16, which is the average incident ratio of the robot bus trials. Since incident resolution times were not recorded during the robot bus trials, an average resolution time needs to be approximated. Figure 29 below compares what kind of an impact different resolution times have on travel time when the speed of the bus is 40 km/h, distance driven is 100 km and the incident ratio is 0.16.
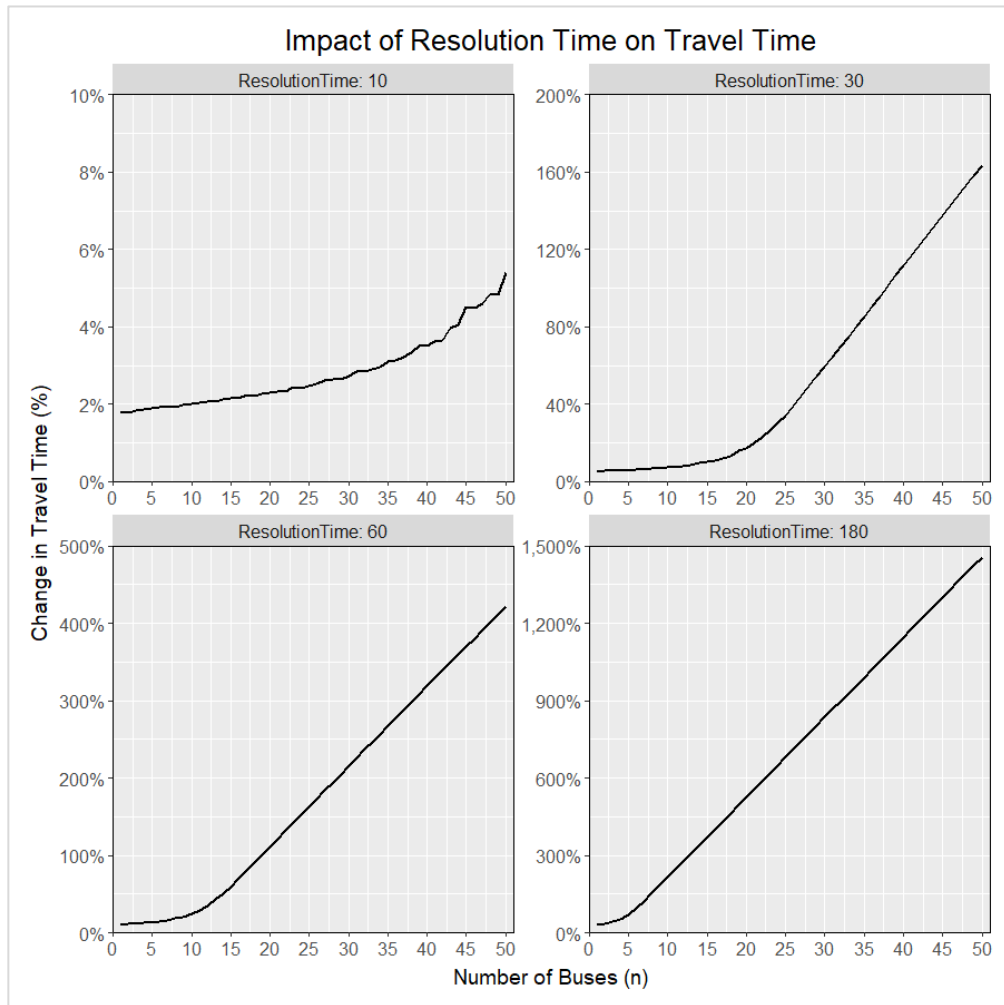

Figure 29 *Comparison of the impact of different resolution times on travel time.*

For the purpose of estimating the resolution time, it helps to consider what the operator needs to do while interacting with the bus. Not only does resolving the incident itself take time but so does orienting to the bus's current situation. This includes establishing the location of the bus, finding the exact nature of the incident, viewing the internal and external cameras of the bus and deciding the correct course of action. The incident itself can be resolved by resuming automated driving, manually driving the bus or dispatching a field team, which all can take a variable amount of time. The lowest value used in the simulation for resolution time was 10 seconds, which likely does not leave enough time for the operator to orient to the situation and perform the needed actions. Hence, 10 seconds is eliminated as a potential resolution time value, while the other values are retained. This yields an average resolution time of 90 seconds, which seems reasonable. Figure 30 below shows how the travel time changes with an average resolution time of 90 seconds.
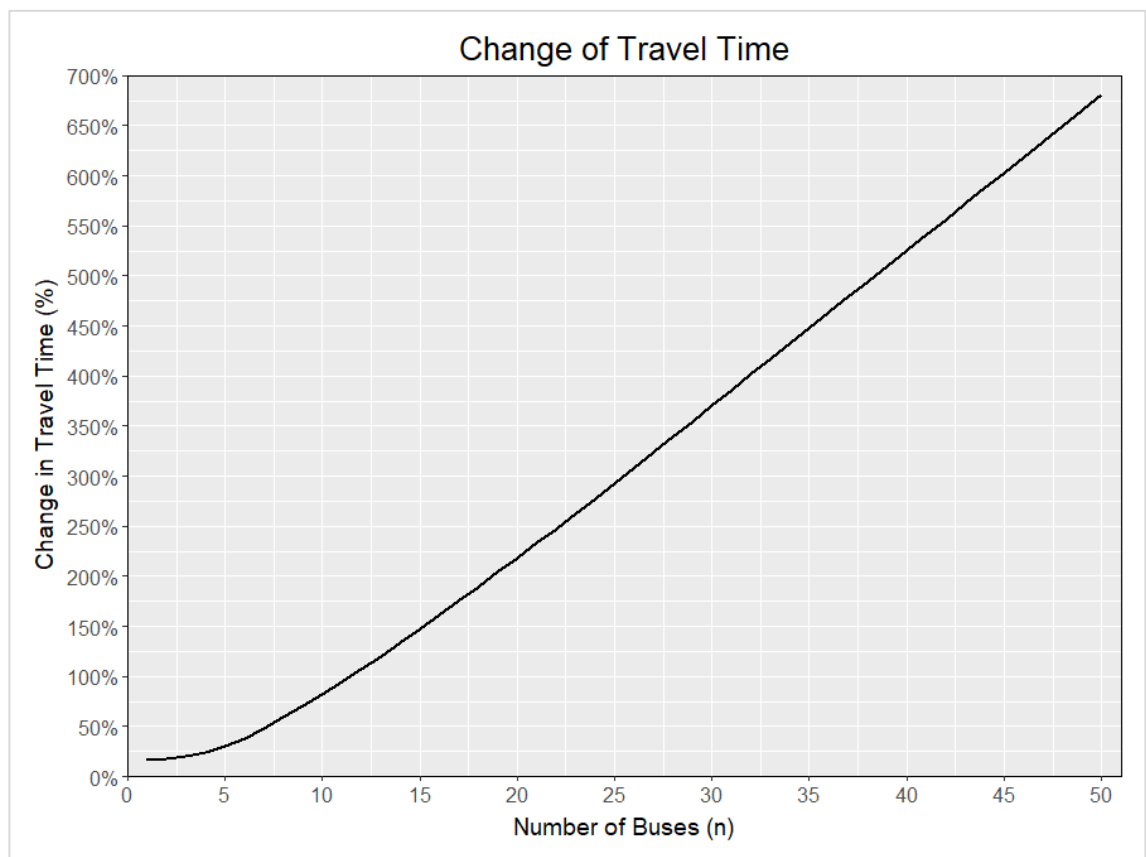

Figure 30 Change of travel time with a 90 sec average resolution time.

The main question in estimating operator capacity is considering what level of change in travel time is acceptable and warrants the cost savings introduced by having a single person operate multiple buses. The question is very subjective and has no clear answer.

However, it is reasonable to expect that the ratio between driving time and delay should at the very least be 3:1. In practice, this would mean that, for every 15 minutes the bus drives, it spends on average 5 minutes waiting for the operator to resolve incidents. Figure 31 below gives a close-up of the graph showing the change of travel time when the speed of the buses is 40 km/h, the distance driven is 100 km, incident ratio is 0.16 and the incident resolution time is on average 90 seconds. As can be seen from the graph, when the number of simultaneously driving buses is more than five, the change in travel time goes over the 3:1 ratio (33 %). The same information is conveyed in more detail numerically in Table 26.
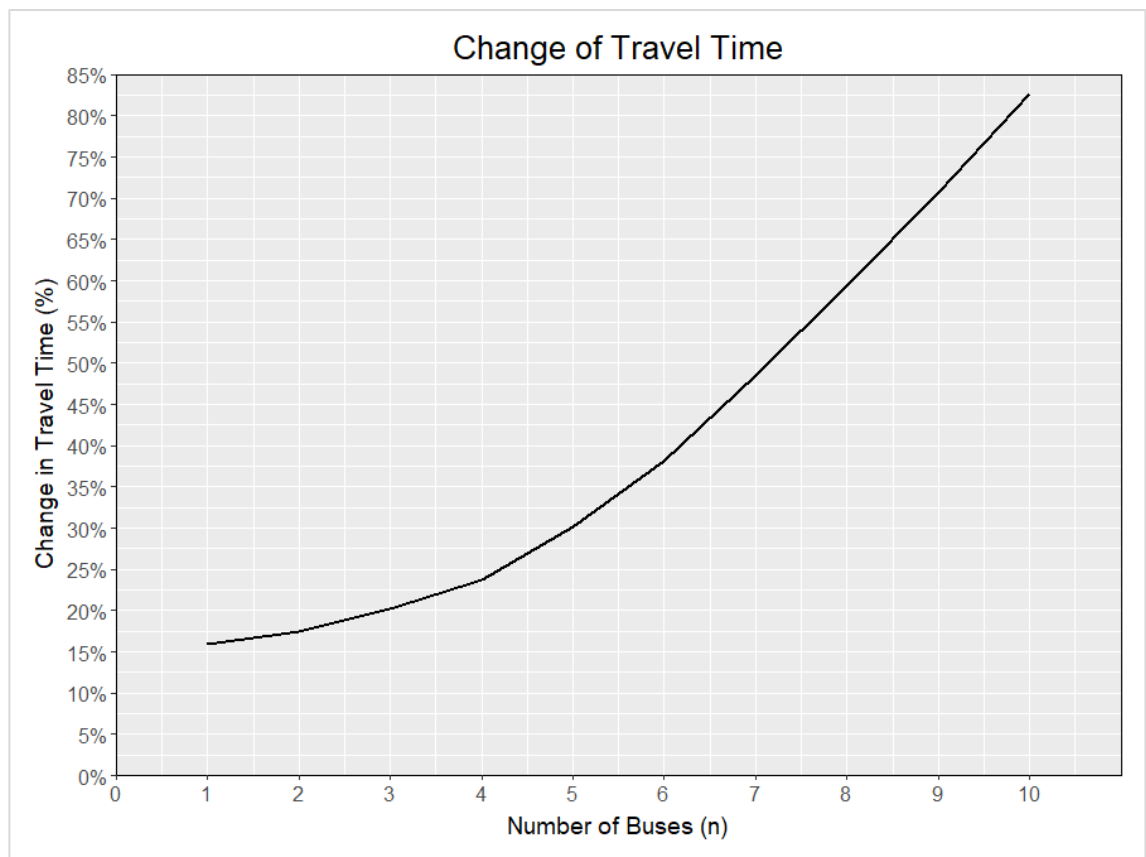

Figure 31 *Close-up of the graph showing the change of travel time.*

Table 26 *Numerical results of the simulation.*

Buses	Wait Time in Queue (sec)	Delay		Actual Speed	
		Absolute (sec)	Relative Δ	Absolute (km/h)	Relative Δ
1	0	1,440	16.0 %	34.8	-13.0 %
2	132	1,572	17.5 %	34.5	-13.9 %
3	382	1,822	20.2 %	33.9	-15.3 %
4	699	2,139	23.8 %	33.2	-17.0 %
5	**1,276**	**2,716**	**30.2 %**	**32.1**	**-19.7 %**
6	1,988	3,428	38.1 %	31.1	-22.3 %
7	2,928	4,368	48.5 %	30.0	-25.0 %
8	3,912	5,352	59.5 %	29.0	-27.4 %
9	4,920	6,360	70.7 %	28.3	-29.3 %
10	5,994	7,434	82.6 %	27.4	-31.5 %

7.2 Cost Analysis

Having established the operator capacity, it can now be studied what impact having an operator responsible for five buses at the same time has on costs. In order to analyze and compare the costs related to acquiring and operating the different bus types, a TCO analysis is performed. The unit costs that were calculated in the previous chapter are used as a basis for the analysis. Costs are further studied by assessing what different bus transportation types would cost for the sample route introduced in section 4.4.

7.2.1 TCO Analysis

The purpose of TCO is to give an overall estimation of all the costs related to owning and operating a certain type of asset or equipment. TCO provides a convenient method for assessing the long-term value of an investment, as it takes into account the capital and operational expenditures over the asset's lifespan. TCO is an often-used method for comparing the costs related to owning different kinds of vehicles.

For calculating the TCO for the different bus types, all costs need to be expressed either on a temporal basis (per hour or per day) or on a spatial basis (per kilometer). In the calculations here, all costs are assumed to be on a per kilometer basis. Hence, all running costs need to be converted to a spatial basis by assuming a certain average number of kilometers driven and a certain average number of operation hours per year. As a baseline,

the buses are estimated to be driven daily for 175 kilometers, which can be considered to be a maximum distance an electric minibus could be able to cover in ideal conditions. Assuming 320 operation days per year, the annual mileage would be 56,000 kilometers and with 10 hours of operation per day, the annual amount of operation hours would be 3,200 hours.

Typically, when performing cost analysis, costs that will be incurred in the future and investments done sometime after the present need to be discounted back to their present values. However, given the current unprecedented times when interest rates on European government bonds are zero or even negative, the present values of future investments are considered to be the same as the future values, and therefore no discount rate is used in the calculations.

When calculating the per kilometer capital costs for different bus types, the purchase prices and other equipment costs from the previous chapter are used. All the buses are assumed to have the same eight-year lifetime. Batteries and sensors are assumed to have a lifetime of four years, which means that they need to be replaced once during the buses' lifetimes. Neither the buses nor the sensors and batteries are thought to have any residual value after their effective lifetime. Table 27 below shows the capital costs for different bus types.

Table 27   Calculation of the depreciations for different bus types.

	Diesel Minibus	Electric Minibus (35.8 kWh)	Robot Bus (35.8 kWh)
Purchase price	145,000 €	220,000 €	270,000 €
Battery change		25,000 €	25,000 €
Sensor change			30,000 €
Annual depreciation	18,125 €	30,625 €	40,625 €

For calculating the labor costs per kilometer, the hourly rate of 29.91 euros, which was obtained in the previous chapter as the vehicle hour cost for minibuses, is used as a basis. The hourly rate is multiplied by the assumed annual operating hours of 3,200 and then allocated to kilometers. Since robot buses are thought to be remotely operated and one operator is thought to be able to supervise five buses simultaneously, the labor costs for robot buses are assumed to be 20 % of the corresponding cost for other minibus types.

Monitoring and a software license were estimated in the previous chapter to cost 18,000 euros per year, which translates into 0.32 euros when allocated to the assumed annual mileage. Other vehicle kilometer costs calculated in the previous chapter are used as such in the calculations here.

Table 28   Per kilometer costs of different bus types (€/km).

	Diesel Minibus	Electric Minibus	Robot Bus	Robot Bus (with a driver)
Energy	0.15	0.03	0.03	0.03
Maintenance and parts	0.12	0.08	0.08	0.08
Monitoring and software licenses	0.00	0.00	0.32	0.32
Wages	1.71	1.71	0.34	1.71
Depreciation	0.32	0.55	0.73	0.73
Total	**2.30**	**2.37**	**1.50**	**2.87**

The results of the calculations and the TCO analysis can be seen in Table 28 and as a chart in Figure 32. When a single operator supervises five buses, the per kilometer cost of a robot bus is 34.8 % less expensive than the per kilometer cost of a diesel minibus, 36.7 % less expensive than the per kilometer cost of an electric minibus and 47.7 % less expensive than the per kilometer cost of a robot bus with a driver. The line in the chart shows how large of a proportion of the total costs is spent on labor costs. For bus types other than a remotely operated robot bus, labor costs appear to make up well over half of the total costs.
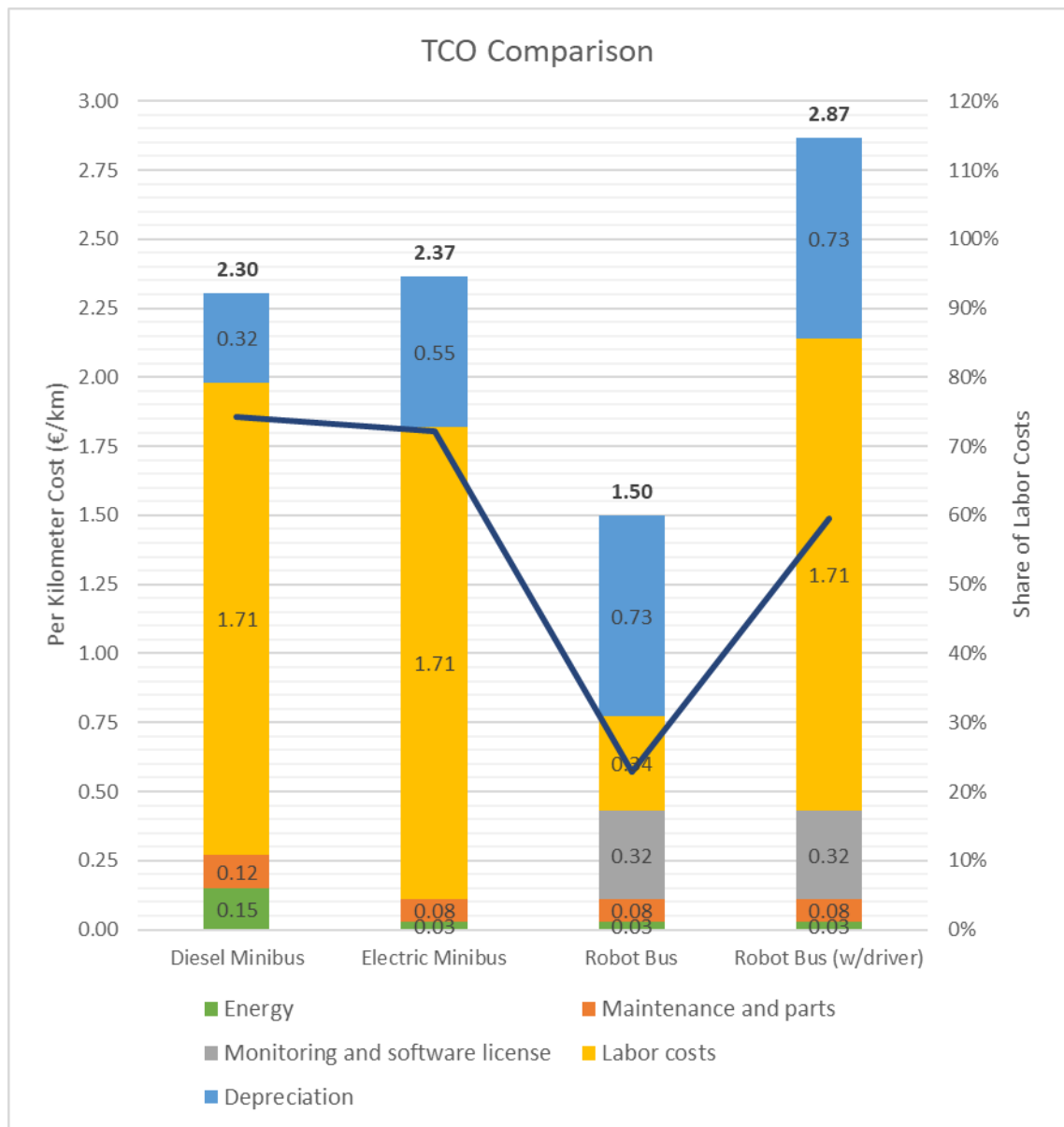
Figure 32 *TCO comparison of different bus types.*

It is also interesting to assess how the per kilometer cost of a robot bus changes when operator capacity either increases or decreases. When each bus requires a dedicated operator, the per kilometer cost is the same as the bus would have a driver inside. If the operator capacity could be doubled from five to ten, the per kilometer cost would decrease only by 11.3 %, as the share of labor costs of the total costs is not as prominent when operator capacity increases. Even with an operator capacity of two, the per kilometer cost of a robot bus is 12.6 % less expensive than the per kilometer cost of a diesel minibus and 15.2 % less expensive than the per kilometer cost of an electric minibus. Figure 33 below shows how the per kilometer cost of a robot bus decreases when the operator capacity increases.
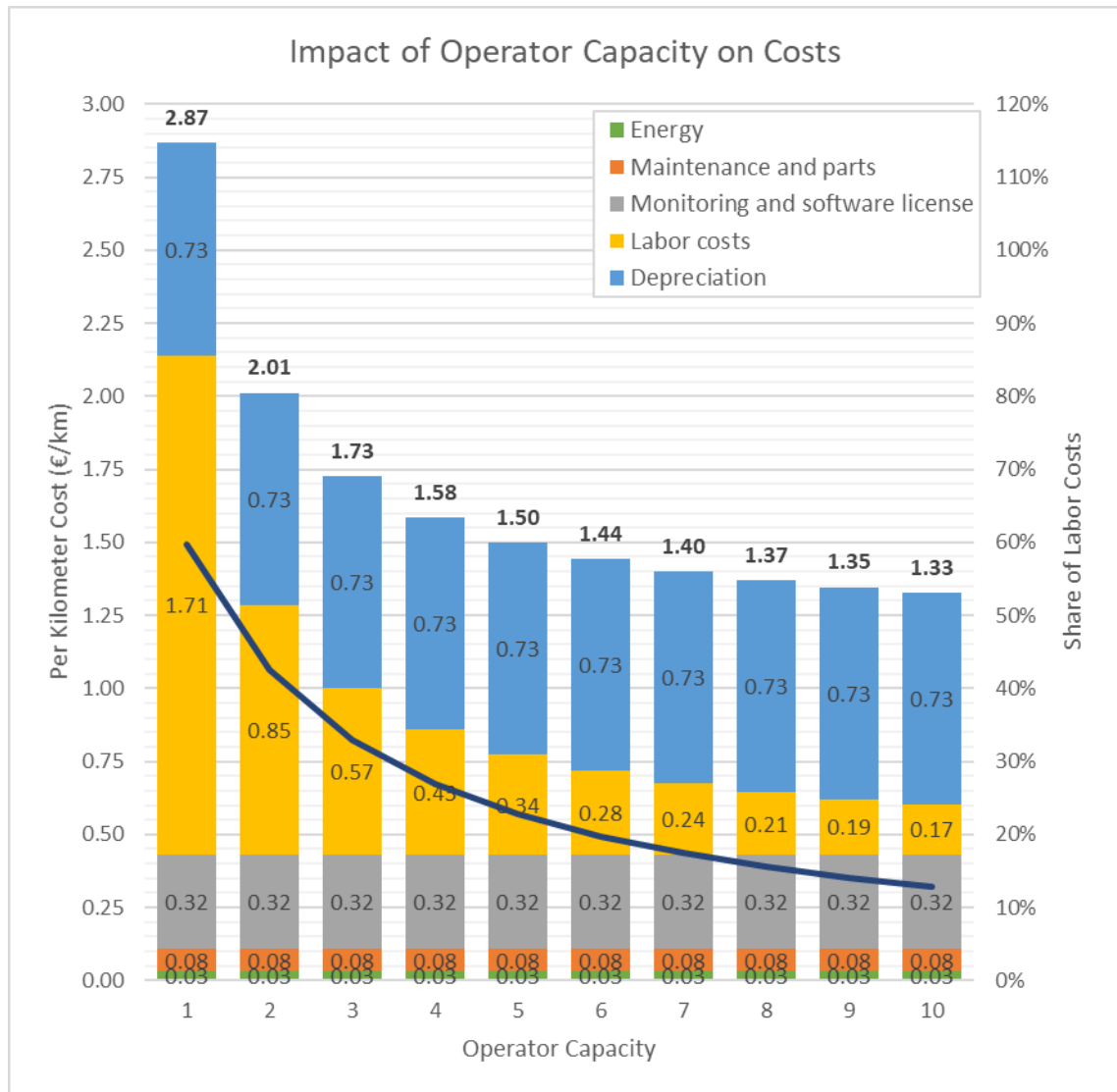
Figure 33 Per kilometer cost of a robot bus with different operator capacities.

7.2.2 Sensitivity Analysis

The TCO analysis above did not take into account the costs related to building and maintaining the charging infrastructure for electric minibuses and robot buses. According to Vilppo and Markkula (2015), a depot charger per bus would cost 5,000 euros and its maintenance 250 euros per year. The purchase price of the depot charger is allocated to capital costs, which increases the annual depreciation of an electric minibus to 31,250 euros and the annual depreciation of a robot bus to 41,250 euros. When the annual maintenance cost of the charger is allocated to 56,000 annual kilometers, the increase in maintenance costs is 0.4 cents per kilometer. Figure 34 below shows what kind of an impact including the charger cost has on the per kilometer costs of an electric minibus, a robot bus and a robot bus with a driver.
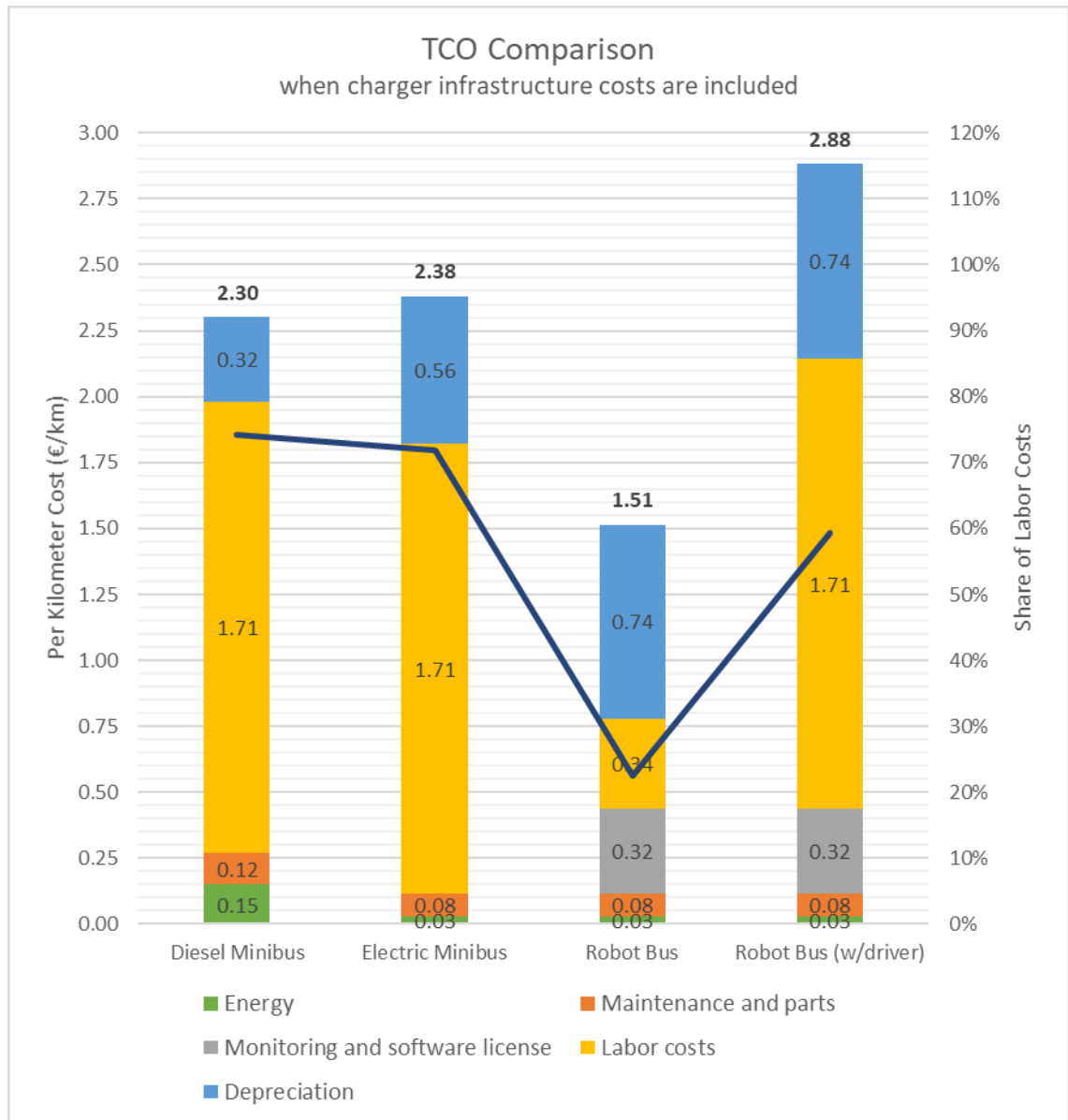
Figure 34 *TCO comparison when charger infrastructure costs are included.*

In the TCO analysis the buses were assumed to be operated on 320 days per year, which translates into 6.15 days per week. The routes driven by minibuses could very well be operated only on weekdays, so it makes sense to assess what the per kilometer costs would be if the buses were operated only on 260 days per year while retaining the same daily number of kilometers as in the original TCO analysis. Figure 35 shows how the per kilometer costs change if the buses are driven for 45,500 kilometers annually and operated for 2,600 hours.
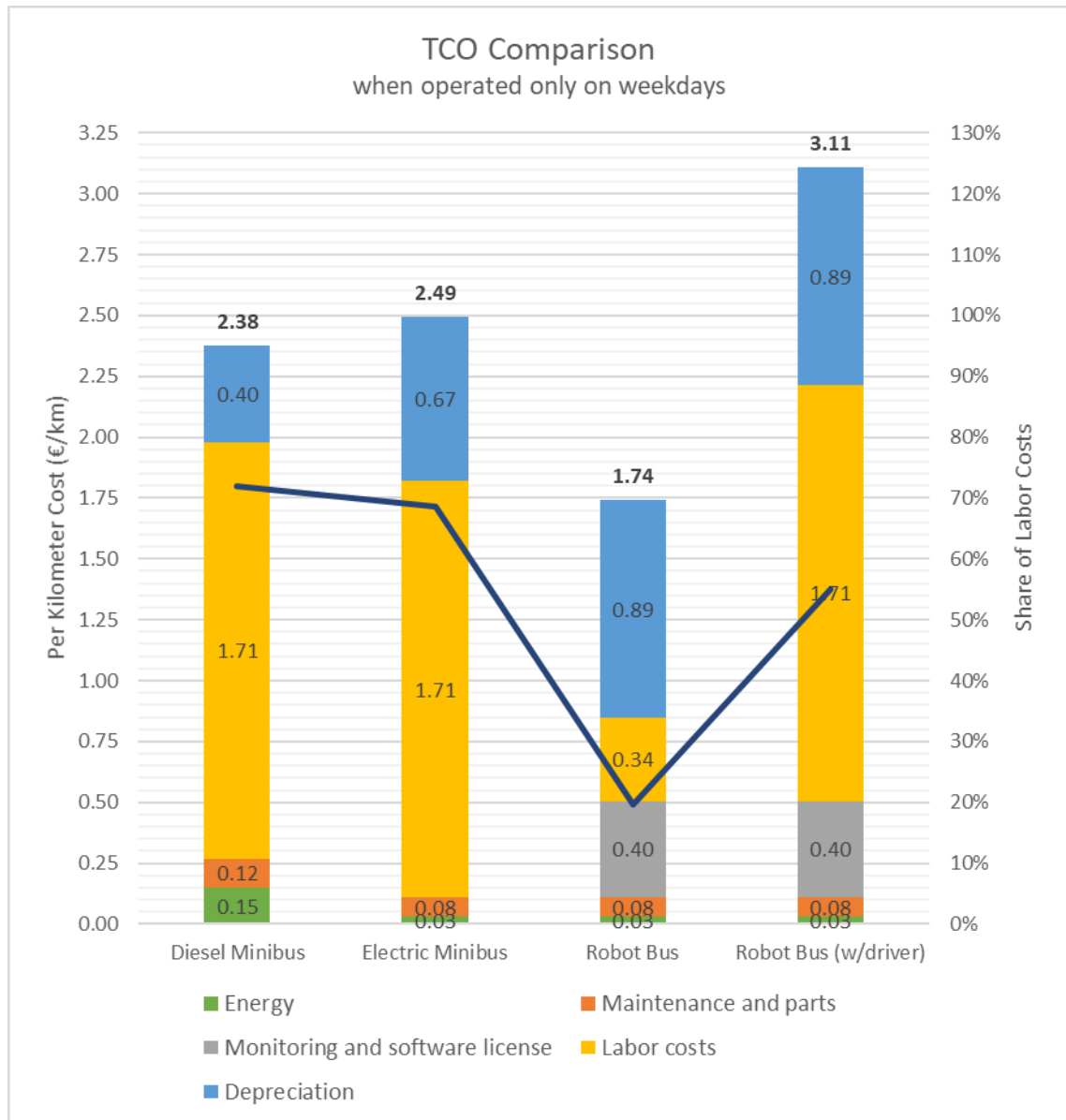
Figure 35 *TCO comparison when buses are operated only on weekdays.*

Many assumptions had to be made while calculating the costs related to robot buses. For instance, the hourly rate of the remote operators was assumed to be the same as the hourly rate of bus drivers. However, remote operators might be required to have specific expertise and qualifications as well as a higher-level education, which could increase their hourly rate. Energy consumption and maintenance costs could also be higher than what they were estimated to be. In order to account for underestimation of certain costs, all robot bus costs were increased by 25 %. Figure 36 shows the results of this exercise. As can be seen from the chart, the per kilometer cost of a robot bus remains considerably less expensive than other bus types even after the cost increase.
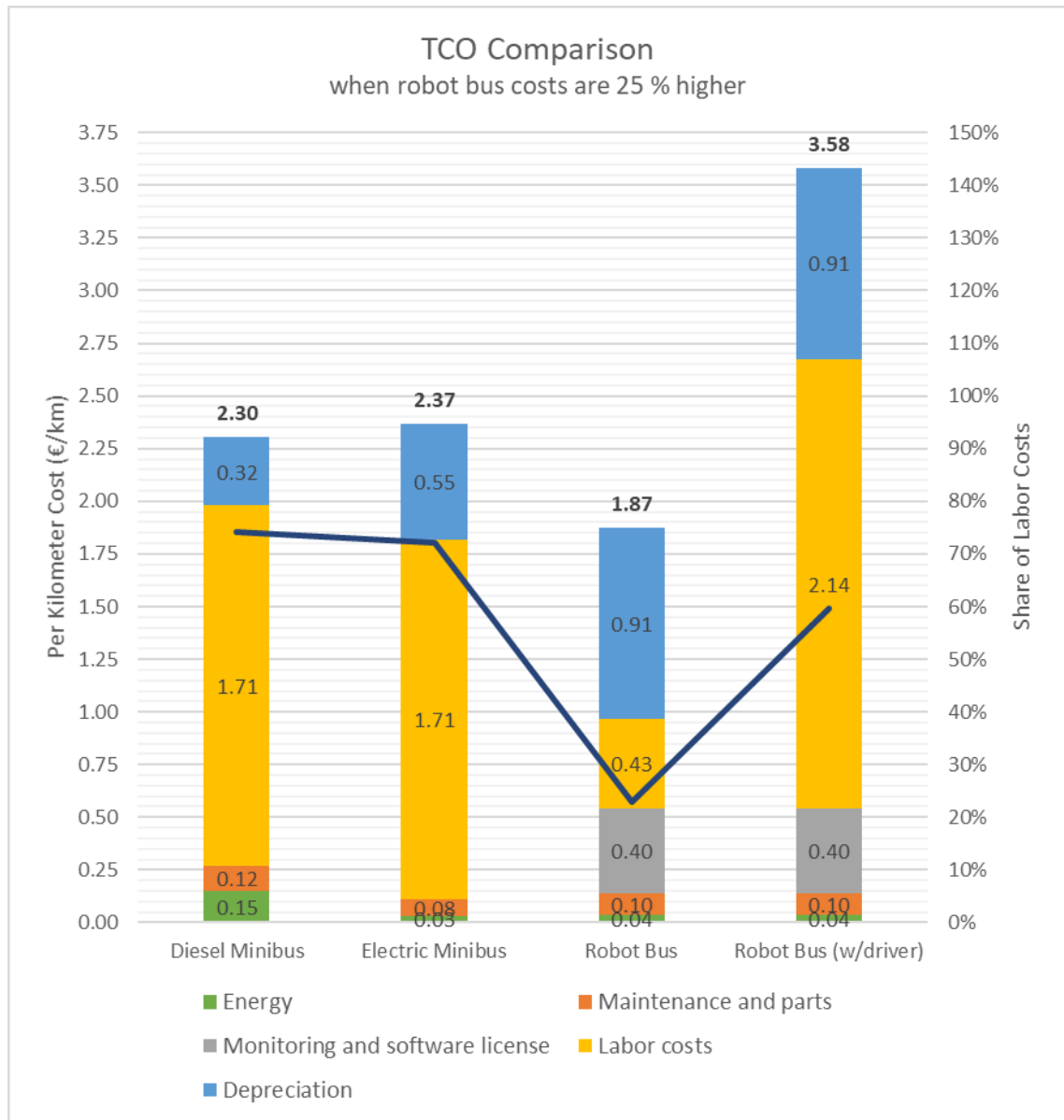
Figure 36 *TCO comparison when robot bus costs are 25 % higher.*

Next, it was assessed how an increase or a decrease in the daily mileage would affect the costs. The baseline was set to be 175 kilometers driven per day over a period of 10 hours on 320 days per year. When assessing the impact of different daily kilometers, the pessimistic scenario was chosen so that the buses would only drive 100 kilometers per day, which equals to 32,000 kilometers per year, and the optimistic scenario was chosen so that the buses would drive 250 kilometers per day, which equals to 80,000 kilometers per year. Figure 37 compares the pessimistic and optimistic scenarios to the baseline. Regardless of the scenario, the per kilometer cost of a robot bus remains the least expensive. What is noteworthy in the optimistic scenario is that with 250 daily kilometers, the per kilometer cost of a diesel minibus and an electric minibus become equal.
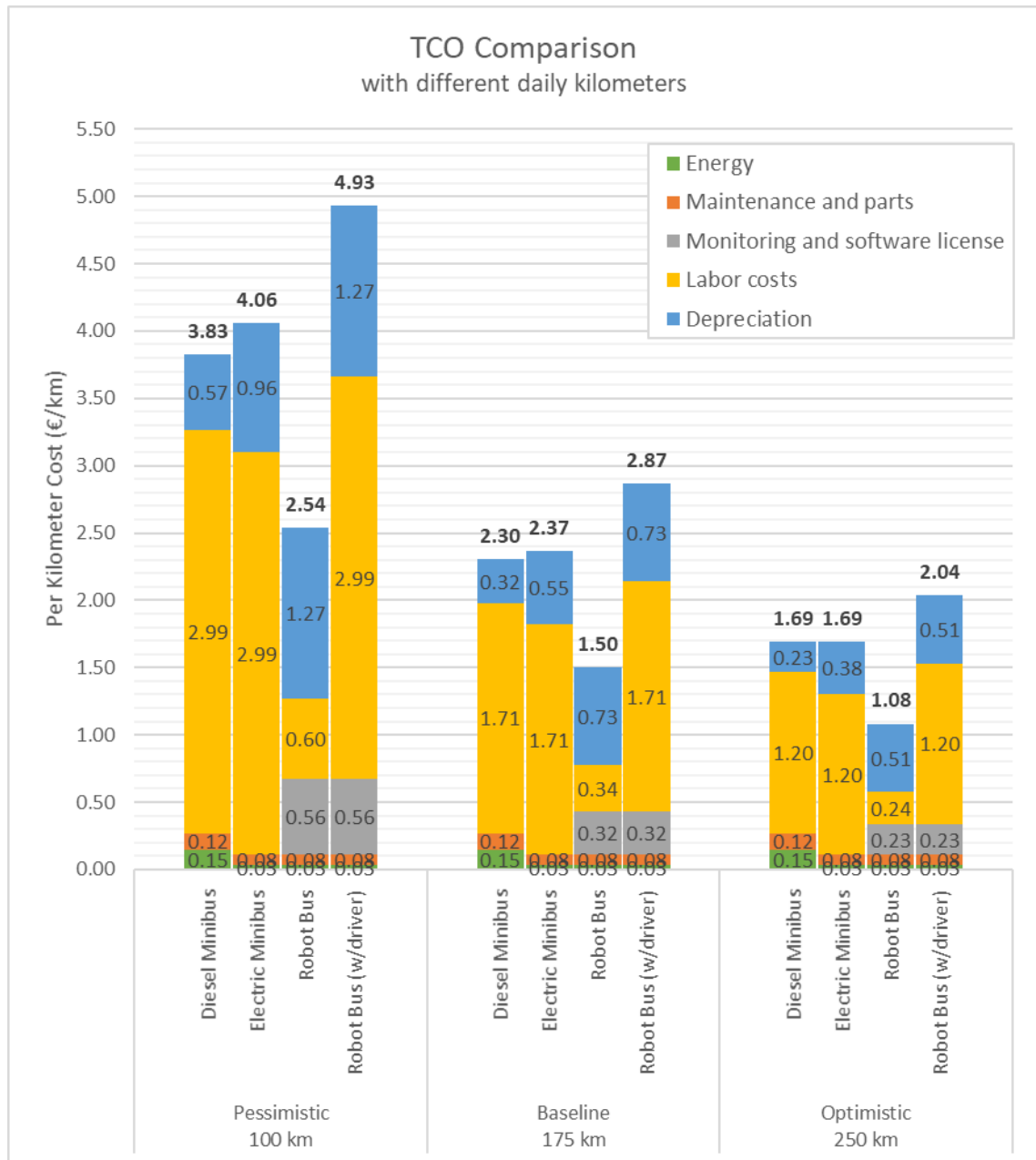
Figure 37 TCO comparison with different daily kilometers.

Finally, it was assessed how a change in the daily operation hours would affect the costs. In the pessimistic scenario buses are operated only six hours per day while in the optimistic scenario the buses are operated 14 hours per day. Other parameters, such as the annual mileage and the annual days of operation, were kept intact. Figure 38 shows the results of this assessment. When the buses are only operated for six hours per day, the difference between the per kilometer costs of a robot bus and other bus types is not as notable as it is at higher numbers of operation hours.
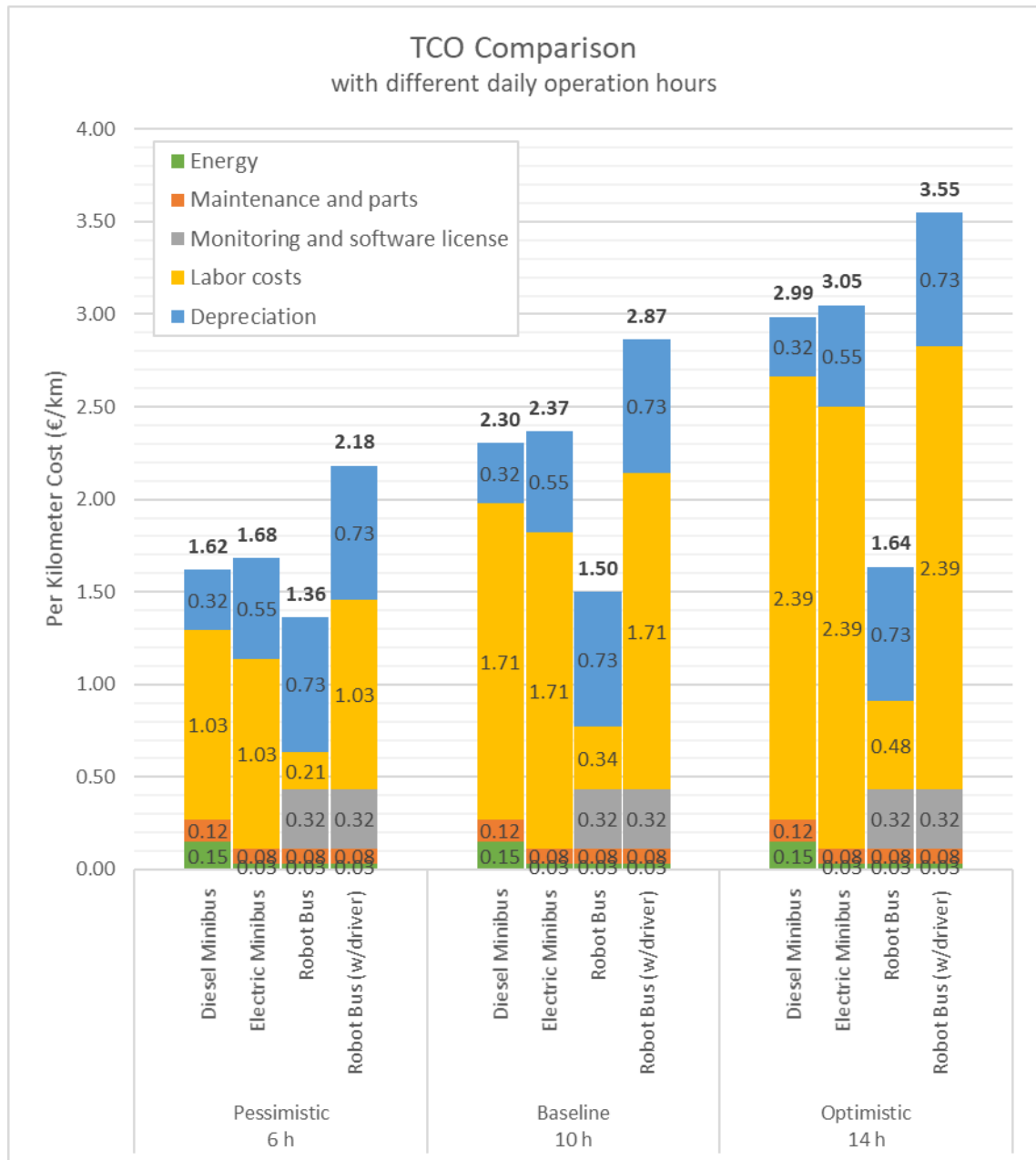
Figure 38 TCO comparison with different daily operation hours.

7.2.3 Sample Route Costs

A round-trip of the sample route described in section 4.4 is two kilometers in length and is driven three times per hour. As the route is operated for 10 hours per day, the daily mileage is 60 kilometers. The route is operated only on weekdays, which translates into 2,600 annual operation hours and an annual mileage of 15,600 kilometers. However, the two hours per day that are reserved for taking the bus back and forth from the depot to the start of the route need to be also factored in. This increases the annual operation hours to 3,120.
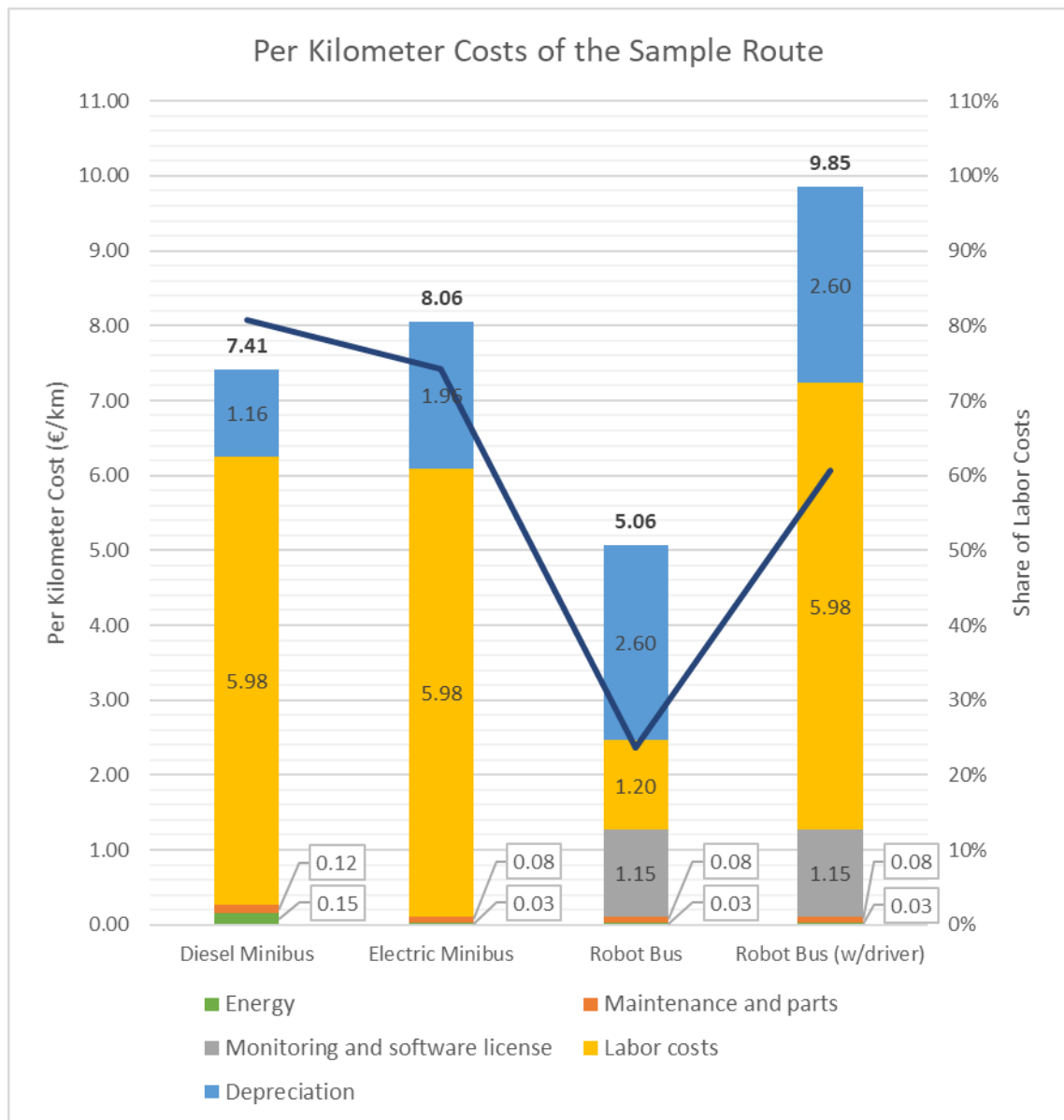
Figure 39 *Per kilometer costs of the sample route.*

Figure 39 above shows the per kilometer costs of the sample route with the given parameters. Operating the sample route with a robot bus is 31.7 % less expensive than with a diesel minibus and 37.2 % less expensive than with an electric minibus. A robot bus with a driver, however, would be 32.9 % more expensive than a diesel minibus and 22.2 % more expensive than an electric minibus. Figure 40 below shows what the costs would be for the sample route on an annual basis. The labor costs are proportionally somewhat higher than in the TCO analysis due to the two additional hours accounted for moving the bus to and from the depot.
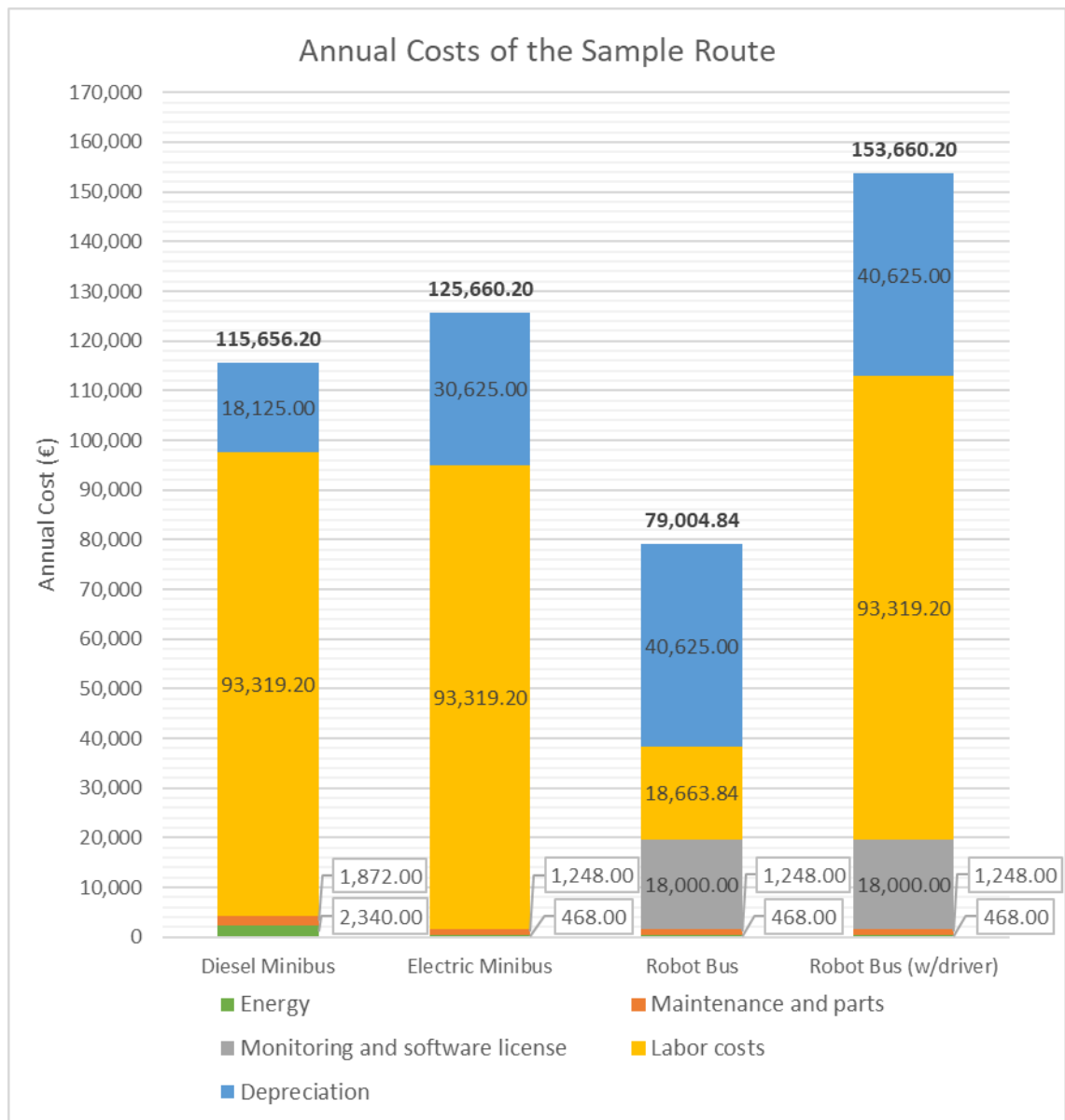
Figure 40 *Annual costs of the sample route.*

Theoretically, a robot bus with a capacity of 15 passengers could transport 45 passengers on the sample route in an hour. This translates into 450 passengers per day and 117,000 passengers per year. Assuming that all the bus types have the same capacity, the per passenger costs would be 0.99 euros for a diesel minibus, 1.07 euros for an electric minibus, 0.67 euros for a robot bus and 1.31 euros for a robot bus with a driver. A diesel minibus would need to have a capacity of 22 passengers and an electric minibus a capacity of 24 passengers for the per passenger costs to be at the same level with the robot bus. Operating the route with a robot bus that has a driver inside does not appear to make economic sense.

7.3 Teleoperation of Automated Buses

In the previous section it was shown that robot buses can be cost-effective when a single operator supervises multiple buses simultaneously. However, for that to be possible, the operator needs to be able to remotely resolve the incidents the buses encounter. To establish whether that can be done, the types of incidents experienced by the buses need to be analyzed, along with determining what it takes to resolve the incidents from a distance.

7.3.1 Incident Analysis

In order to assess the feasibility of remotely operating a fleet of robot buses, it is useful to first try to understand the different types of incidents robot buses encounter and how those incidents are resolved. Based on the three robot bus trials, Figure 41 below shows the proportions of the different incident types. What is noteworthy about the incident types is the fact that 84 % of the incidents are related directly to the driving environment and were caused by either stationary obstacles (i.e., parking on road and road infrastructure) or moving obstacles (i.e., other road users) in the traffic blocking the path of the bus. Only 16 % of the incidents were caused by technical problems and other issues, such as mechanical problems, weather conditions and problems occurring inside the cabin. The robot bus trials were organized during the warmer months of the year, which likely explains why weather conditions were not a major contributor to the incidents encountered by the buses. Snow, heavy rain and other adverse weather conditions are inclined to cause more incidents when the buses are driven around the year.
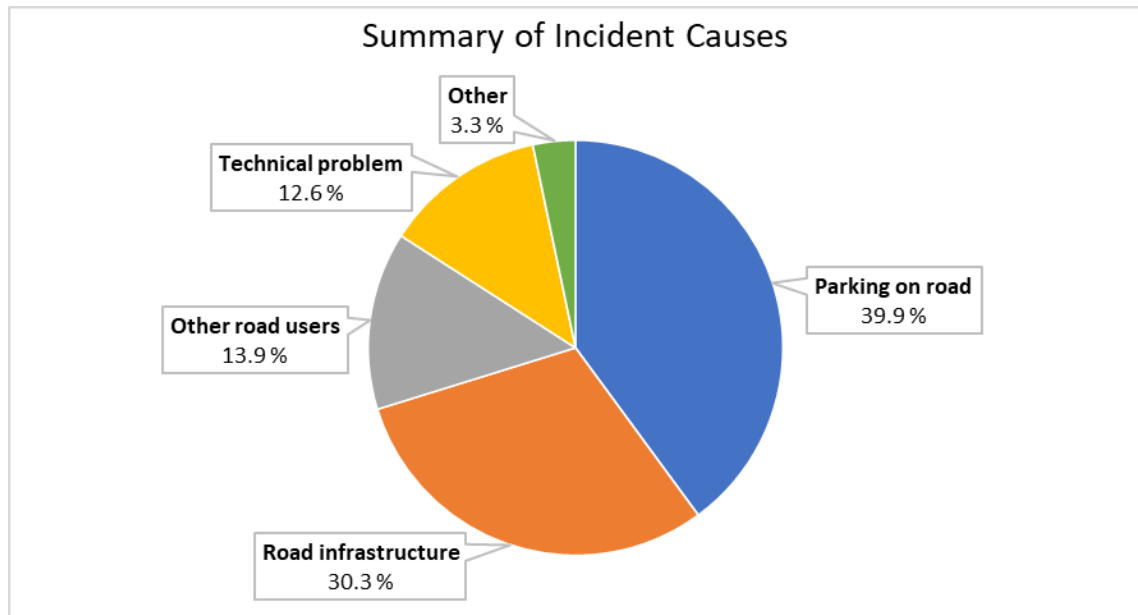
Figure 41 Summary of the incident causes during the robot bus trials.

An even more relevant factor with regard to the feasibility of teleoperation is whether the incidents can be resolved remotely or if they require a physical visit by a field operator or technician. The proportions of different means to resolve the incidents are depicted in Figure 42. Based on the chart, it is evident that manual driving is the most often used method to resolve incidents as over three-quarters (77 %) of the incidents are resolved using that method. The second most often used method is to resume driving with 18 % of incidents being resolved that way.

When driving is resumed the bus is just instructed to recommence automated driving after an interruption. This is something that can be done remotely provided that the operator is able to review that the cause of the incident, which could be for instance an oncoming or passing vehicle, is no longer in the path of the bus. Manual driving is needed to circumvent obstacles in the traffic that do not clear themselves in a timely manner, such as improperly parked cars and roadworks. Manual driving should theoretically also be possible remotely. However, it is subject to certain reservations, such as the latency in the video feed from the bus to the operation center being low enough.
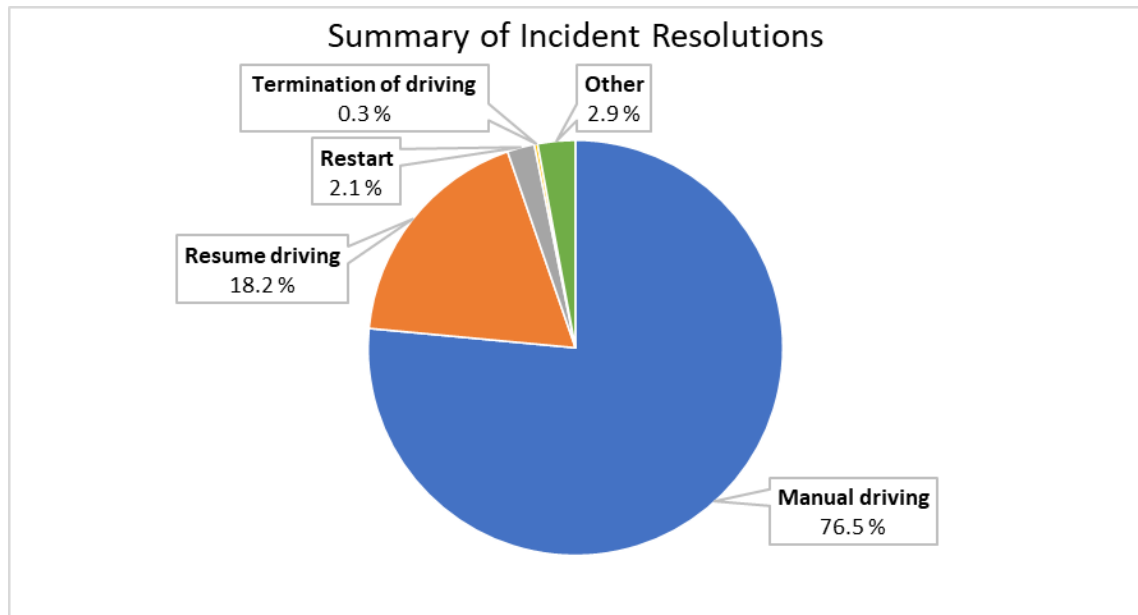
Figure 42 *Summary of the incident resolutions during the robot bus trials.*

It is also interesting to review the different sources for stopping during the robot bus trials. This information is reflected in Figure 43 in the form of a chart. A little over half of the time the bus was able to detect the incidents by itself and make a stop. However, about 43 % of the time the operator had to intervene and either stop the bus or take over the control and manually maneuver the bus. When multiple buses are operated by a single person, the operator cannot be expected to monitor every bus incessantly and be always ready to stop the bus to avoid collisions. Instead, the driving automation system of the bus needs to be able to stop the bus under all circumstances. Operator initiated stops are presumably overrepresented in the statistics from the robot bus trials, as operators can easily take over the control in difficult driving conditions well before the driving automation system takes effect in order to provide a smoother ride for the passengers. Currently no good data is available on how many times a bus would have actually crashed with an object if the operator had not intervened.

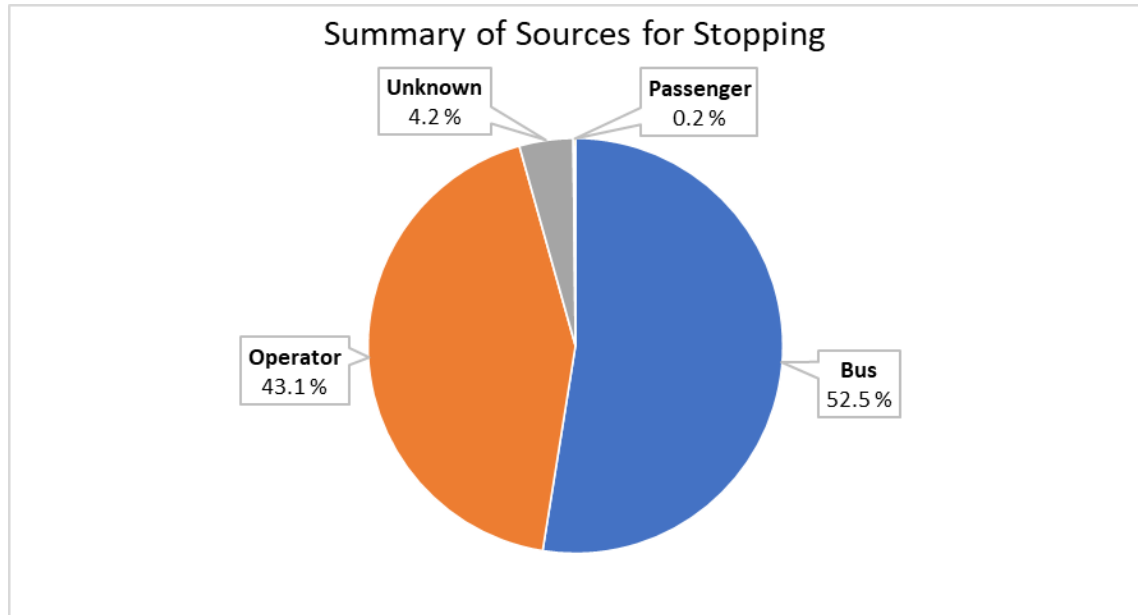**Figure 43** *Summary of the sources for stopping during the robot bus trials.*

7.3.2 Feasibility of Teleoperation

As was shown in the previous section, most incidents that robot buses encounter should be able to be resolved remotely. Some incidents, like mechanical problems and technical problems affecting the connection between the bus and the operation center, require dispatching a field team to the scene to take care of the incident. These types of incidents should be rather rare as only 0.3 % of the incidents encountered in the robot bus trials led to the termination of driving. Resuming driving and restarting the software of the bus are something that can be achieved remotely without having a real-time, low-latency video link with the bus. Manual driving, by contrast, when done remotely, requires a low-latency connection not only for the video feed from the bus but also for the control of the bus's steering and acceleration. When the operator issues a command to alter the bus's movement, the bus should react near instantly with the video feed providing a prompt visual cue for the operator that the command was successfully executed and the movement of the vehicle was changed.

The anecdotal evidence from the experiment where a tractor was remotely driven over a 5G connection, as described in section 4.5, matches with the previous studies on remote driving over a mobile network. In the first location where the tractor was driven the signal strength of the 5G connection was less than optimal, which led to a delay about 6 seconds in the video feed from the tractor to the remote driving facility. When the tractor was moved to a location with a better signal strength, the latency in the video decreased to

about 1 to 2 seconds. With VR glasses the experienced delay was about 2 to 4 seconds, which was likely caused due to stitching of images from multiple camera lenses. The latency in the 5G connection was measured to be between 20 and 30 ms, which meant that sending acceleration and steering commands to the tractor was perceived to be instant. This supports the notion that 360° video processing and video delivery in challenging network conditions are major contributors to the latency experienced in teleoperation.

The literature review presented in section 3.2 indicated that remote driving over a mobile network can be possible and that 5G, with better reliability and lower latency, can make remote driving more widely available. However, many challenges still remain for achieving a seamless remote driving experience. In order to properly perceive the surrounding environment, the remote operator needs real-time high-definition video streamed from all sides of the vehicle. To date, studies have not thoroughly addressed whether the capacity of mobile networks adequately supports this. Another shortcoming of current studies that have examined 5G capabilities is that most of them have been conducted in test networks that do not experience similar network congestion that publicly deployed networks can experience during peak times. Whether the capacity of 5G networks will be sufficient at the edge areas of the network when 5G is taken in broader use is also something that needs to be addressed. Increasing capacity and density of the network or deploying a private network intended for remote driving are possible solutions but they could be too expensive to be economically viable.

8 DISCUSSION

The aim of this study was to assess whether automated buses can be used for public transportation in terms of their technological maturity and economic viability. The main contribution of this study is the establishment of constructs and variables that allow estimating the capacity of remote operators. Another important contribution is the thorough analysis of the costs related to using automated buses for public transportation.

In light of current knowledge, the costs related to owning and operating automated buses right now are still significantly higher than those for electric buses and diesel buses. This is explained by the high costs of the sensors needed for automated driving as well as costs incurred from route setups, software licenses and remote monitoring. Labor costs currently account for a major part of the total costs of bus transportation, which means that considerable savings can be on the horizon once safety drivers and remote operators are no longer needed for every automated bus. The prices of automated buses and their sensors are also expected to fall when adoption increases and mass production of the vehicles is started.

In order to remove the safety driver from the cabin of the bus, the automated driving technology still needs to mature and become more reliable. Level 3 automated driving can already be considered to be very close to being achieved, evidenced by, for instance, the plans to start the mass production of level 3 autonomous cars (Reuters, 2020). Yet, evidence exist that the current iterations of automated vehicles are actually more often involved in accidents than conventional vehicles (Favarò et al., 2018), including at least one fatal accident to date (NTSB, 2019). Thus, even though steady progress is being made in the development of automated driving capabilities, it might take several years until level 4 and level 5 automated driving are reliably reached.

One factor that could slow down the adoption of automated vehicles in Finland is the harsh weather conditions experienced particularly during winters. To date, robot bus trials have been conducted over periods between spring and autumn in mild weather conditions, and thus the suitability of robot buses for Finnish winter conditions has not yet been conclusively proven. Harsh weather conditions, such as heavy rain, fog and snowfall, have been observed to degrade the performance of LiDAR and other sensors needed for automated driving (Kutila et al., 2016; Kutila et al., 2018). Furthermore, external air

temperature affects the energy consumption and driving range of electric vehicles, because cabin heating and air conditioning require additional energy and battery efficiency can vary in different temperatures (Iora & Tribioli, 2019).

The capacity of the battery packs in the current robot buses vary between 24 and 33 kWh. Even if the energy efficiency of the buses can be significantly improved, the battery capacities might not be sufficient for a day's worth of driving. A straightforward solution for this would be equipping the vehicles with higher capacity batteries. Batteries, however, are still rather expensive even though their prices have recently decreased and are expected to further fall in the future. Battery packs are also large and heavy in terms of their volume and weight, which means that fitting larger-sized battery packs in the existing chassis of robot buses may prove to be infeasible. Alternatively, opportunity charging at end-stops and bus stops could be utilized to charge buses throughout the days but that would incur additional costs for the expansion of the charging infrastructure. The development of battery technologies presently focuses on making batteries more compact and lightweight while at the same time improving their capacity. This implies that in the future the batteries used in electric vehicles will not only be less expensive, but they will also have better energy densities.

Teleoperation and the capabilities of contemporary mobile networks to support remote driving were mainly studied in this thesis by reviewing existing literature. From a technical perspective, even the capabilities of existing 4G networks are enough to enable remote driving. 5G networks provide improved reliability and lower latency when compared to 4G networks, which should enhance the robustness of remote driving over mobile networks. Automated buses will be used initially in city centers where satisfactory network coverage should be available. Whether public 5G networks can support remote driving throughout the network at all times is something that should be studied further. The possibility of deploying private 5G networks or leveraging advanced 5G network features to enhance the remote driving experience also warrant further research.

While 5G provides clear benefits for automated driving, it is still unclear to what extent 5G can improve teleoperation in public mobile networks in the edge areas with bad reception and under conditions of network congestion. 5G infrastructure is currently being gradually built, and it will take time until sufficient network coverage is reached. Even then it is not realistic to expect perfect network coverage and high capacity

everywhere as infrastructure costs would grow to be too substantial. Hence, 5G should not be perceived as a "silver bullet" that magically solves all issues related to teleoperation and automated driving. 5G offers a clear upside, but at the same time other means to improve teleoperation should be studied. Video compression algorithms used in teleoperation could be, for instance, potentially optimized so that they would consume less computing power and bandwidth.

An interesting concept in 5G that could benefit remote driving and automated driving is network slicing (Han et al., 2018; Campolo et al., 2017). Network slicing allows network providers to create virtual networks that are tailored to the requirements of particular use cases and applications. These network slices are operated in parallel on the same physical network infrastructure, but they are logically isolated from one another. A separate slice of network resources could be allocated for teleoperation that would ensure low-latency and high-reliability connectivity between the vehicles and remote operators.

It is envisioned that in the future 5G networks could be utilized to offload some of the automated driving functions from the vehicles either to cloud or edge computing systems (Zhang, 2020). This would give access to larger pools of computing power that is needed to efficiently process the enormous amount of data collected by the sensors of automated vehicles. By leveraging the vast computing resources available in the cloud, the efficiency and reliability of the self-driving algorithms could be enhanced, which would reduce the reliance on human operators. While using edge computing for automated driving looks very promising and it can potentially serve as the key enabler for achieving level 4 and 5 automated driving, it is not without problems and challenges. The main challenge in designing an edge computing ecosystem for automated driving lies in providing enough computing power in a redundant, secure and energy efficient manner that a safe operation of automated vehicles can be ensured in all conditions (Liu et al., 2019; Dong et al, 2020). Even with some of the driving intelligence offloaded from the vehicles, they need to retain enough autonomous capabilities to be able to perform their core functions under varying network conditions.

For the moment, when mobile networks are not yet reliable and comprehensive enough to support automated driving in all locations and under all conditions, the issues encountered by automated buses still need to be predominantly resolved by onboard operators. While coverage and reliability of modern mobile networks are being gradually

improved, having small teams of field operators on standby could be considered as an alternative or a complement to teleoperation. When an automated bus experiences an issue, a field operator could be dispatched in person to the scene to resolve the situation. This would, however, be feasible only if the fleet of automated buses is operated within a limited area and each bus can be reached by a field operator in a reasonable time frame.

When assessing the economic viability of robot buses, their costs were compared to similarly sized diesel and electric minibuses. This was not straightforward, as bus vendors and operators were generally not willing to disclose their vehicle prices and running costs, citing trade secrets as a reason for withholding the information. Having transparent and accurate price and cost information would have improved the accuracy of the comparison. Consequently, the unit costs of minibuses had to be estimated based on the corresponding unit costs of traditional buses and an approximation of the price of an electric minibus had to be made by using an electric van as an analogy. Additionally, the cost comparison between the different minibus types did not comprehensively consider all costs related to building and maintaining the required supportive infrastructure, such as costs of smart traffic lights and charging stations.

The incident ratios obtained for the different robot bus trials varied considerably. The high variation indicates that the driving environments in the trials did not fully match with one another in terms of complexity and traffic conditions. An average incident ratio was determined to be 0.16, which means that on average 16 incidents occurred over a course of 100 kilometers or, alternatively stated, that an incident occurred after every 6.25 kilometers traveled. For robot buses to become a mainstream means of transportation, they should be able to drive in a consistent and predictable manner in all driving environments. Hence, it would be desirable to improve the reliability of the buses and bring the average incident ratio close to the level that was recorded in the Kivikko trial, which was 3 incidents per 100 kilometers traveled. Incident resolution times were not recorded during the trials, which meant that the average incident resolution time had to be formed on the basis of imperfect information. Having real data on incident resolution times would improve the accuracy of the estimation of operator capacity. Also, if and how the number of incidents encountered by the buses is affected by the speed the buses travel is something that should be studied.

Many benefits are associated with the use of robot buses and automated vehicles in comparison to conventional vehicles equipped with internal combustion engines. Automated vehicles almost exclusively have electric powertrains, which means lower carbon emissions, especially when electricity is generated from renewable sources. Due to efficient and economical driving style, automated vehicles are believed to reduce traffic congestion and improve traffic flows while consuming less energy (Fagnant & Kockelman, 2015). The proliferation of automated vehicles is also expected to improve road safety and reduce accidents especially with regard to the "fatal five" causes of vehicular accidents: speeding, alcohol and drug impaired driving, fatigue, distraction and inattention, and failure to wear seatbelts.

The use of automated vehicles also raises some concerns and ethical issues. Before fully autonomous vehicles can be deployed on public roads, the legal implications need to be carefully considered and liability issues resolved. It is currently unclear who is liable for the accidents involving automated vehicles. User acceptance may also pose an issue. Although people generally exhibit positive attitudes towards having automated vehicles on streets, there still are those who are very opposed to the idea (Salonen & Haavisto, 2019; Liljamo et al., 2018). The continuing evolution of technology and mobile connections allows for better immersion and telepresence for users of teleoperation systems. However, before remote operators can be assigned to supervise a large number of automated buses simultaneously, the impact of cognitive load on the performance of the operators needs to be well understood.

The feasibility of using automated buses for public transportation was explored through three research questions. The research questions and answers to those questions are collectively summarized in the following:

RQ1: How many automated buses can a single operator supervise simultaneously?

Taking into account the time it takes for an operator to resolve an incident and the time a bus may have to wait for an operator to become available, the upper limit for the number of simultaneously supervised automated buses was established to be five for the current class of automated buses. This number was reached by considering what level of change in travel time is still acceptable in relation to the benefits introduced by automated driving. Incident ratio, i.e., the number of incidents that on average occur per each kilometer

traveled, and the incident resolution time were observed to contribute the most to the change of travel time, while speed and distance only had a negligible contribution.

RQ2: What are the costs of automated buses and how do they compare to other bus types?

The purchase prices of automated buses are higher than the purchase prices of conventional buses due to the costs of the sensors that enable automated driving and the battery packs that provide the energy for the electric powertrain. Additional costs are also incurred from preparing the routes and in the form of monitoring and software licensing fees. When an automated bus is operated by a dedicated driver, the total cost of ownership of an automated bus is estimated to be up to 25 % higher than that of a conventional bus.

Once higher levels of automated driving are achieved and automated buses no longer require dedicated safety drivers inside the cabins of the buses, the total cost of ownership of an automated bus is expected to be up to 38 % lower than that of a conventional bus. This is explained by automated driving delivering cost savings in labor costs, which currently account for a large proportion of the total costs.

RQ3: Are capabilities of modern mobile networks sufficient for supporting remote operation of automated buses?

Contemporary mobile networks, such as 4G networks, have been shown to be capable of supporting remote driving in terms of their latency and throughput. Remote driving has been observed to be possible even in conditions with a delay as high as 300 ms. Introduction of 5G technology further decreases the latency and improves the reliability of mobile networks, which will benefit teleoperation of automated vehicles. However, it has yet to be shown how well remote driving can be accomplished in public 5G networks in the edge areas of the network with less-than-optimal reception and under heavy network congestion.

9 CONCLUSION

The purpose of this thesis was to establish whether automated buses are ready to be used for public transportation. The topic was approached by reviewing the current technological status and development trends of automated buses and automated vehicles in general. The cost-effectiveness of automated buses was examined by establishing a remote operator capacity and comparing the costs related to owning and operating automated buses to the corresponding costs of conventional buses. Existing literature was reviewed to form an understanding of what types of benefits contemporary mobile networks can provide to automated driving.

Current automated buses are smaller in size than traditional two-axle buses and can fit around 15 passengers. This makes them ideal for first and last mile travels that connect residential areas and final travel destinations with transport hubs. Automated buses are expected to allow public transportation networks to be expanded in terms of their coverage and operating hours. In the future, automated buses are envisioned to be used for on-demand transportation services, where the buses do not have fixed itineraries but instead their routes are dynamically changed based on user needs. Automating public transportation is believed to increase the safety and travel convenience of the passengers as well as make public transportation more accessible.

The automated driving capabilities of vehicles are measured on a six-level scale, starting at zero and going up to a level five. Level 0 vehicles have no driving automation, and the driver is responsible for all tasks related to controlling the vehicle and monitoring the driving environment. Level 5 describes a vehicle with full driving automation capabilities. Vehicles within that category are capable of performing all driving related tasks autonomously without human interaction. Levels 1 through 3 feature varying degrees of driving automation while still requiring a fallback driver. Most vehicles currently referred to as being self-driving or autonomous, including automated buses reviewed in this thesis, fall under the level 3 category.

This thesis used data from three robot bus trials to develop an understanding of how often automated buses run into issues that require human intervention and what the causes of those issues are. Based on the trial data, it could be inferred that on average robot buses encounter 16 incidents for every 100 kilometers traveled. In 40 % of the cases the robot

buses had to stop because other vehicles were parked on the road and either partially or entirely blocked the path of the bus. Roadworks and other obstacles related to the road infrastructure was the second most common cause by accounting for 30 % of the stops. Other road users, such as overtaking vehicles and pedestrians, caused about 14 % of the stops. Technical problems, such as software glitches, were recorded to be the cause only for 13 % of the stops. Thus, it can be concluded that stationary and moving obstacles in the driving environment are the most common contributing factors to the causes of stops. The onboard operator had to manually drive the bus for a period of time in order to resolve about 77 % of the stops. Around 18 % of the stops could be resolved by the operator simply instructing the bus to resume automated driving.

Labor costs currently constitute a large portion of the costs related to operating buses. Automated buses are expected to induce cost savings by reducing labor costs, provided that not every bus needs to have a dedicated operator. A simulation was performed to estimate the number of buses one operator can supervise simultaneously. The simulation modeled a situation where only one operator was available to resolve incidents for a variable number of buses driving at the same time. The buses were set to virtually drive a route during which they encountered incidents at random intervals. If a bus encountered an incident while the operator was already resolving an incident for another bus, the bus had to wait for the operator to become available. The outcome of the simulation was that when five buses are being supervised simultaneously the change in travel time due to incident resolution still remains at an acceptable level.

Automated buses are essentially more evolved versions of electric minibuses. Hence, to estimate the costs of automated buses, the costs related to owning and operating electric minibuses were first established. The costs of sensors and software enabling automated driving were then added on top of that. Considering that one operator can supervise five buses, the labor cost for one automated bus was assumed to be 20 % of the corresponding cost of other minibus types. Although the purchase price of an automated bus is significantly higher than that of a diesel or electric minibus, the total cost of ownership was observed to be less because of the lower labor cost. Operating a sample route, which connects the railway station of Turku with the bus station, with an automated bus was calculated to cost about one third less compared to operating the same route with either a diesel or an electric minibus.

The evolution of mobile networks is expected to promote the growth of automated vehicles. Cellular-based vehicular communication will allow automated vehicles to cooperate with other vehicles, even over a distance, and better utilize cloud-based vehicular services. For instance, exchange of sensor data extends the collective sensing range of vehicles and allows them to obtain information about the driving conditions well beyond the range of their own sensors. Connected driving is seen as an enabler for improving road safety, reducing traffic jams and lowering energy consumption. Leveraging modern mobile networks to offload some of the automated driving functions to cloud or edge servers could potentially serve as the missing link for reliably reaching higher driving automation levels.

Especially initially automated vehicles will frequently require human support for situations which they cannot handle independently. Currently, automated vehicles will simply stop when an obstacle is on their path or the situation is otherwise unexpected. The evolution of self-driving algorithms will allow the vehicles to adapt to more situations, which will reduce the frequency of the need for human interventions. Once automated vehicles no longer require constant monitoring, the operator can be moved from the cabin of the bus to a remote operation facility.

Teleoperation comprises a set of technologies that allows the unexpected situations encountered by automated vehicles to be resolved remotely over a wireless connection. Teleoperation involves reviewing sensor data and controlling the vehicle from afar, which is very network intensive and requires a low-latency connection with adequate bandwidth. A well-functioning teleoperation system is also a precondition for a single remote operator being able to supervise multiple buses. The theoretical capabilities of 4G and especially 5G have been observed to be sufficient for teleoperation and remote driving but more empirical evidence is still needed to confirm the practical feasibility of it. Also, no technology is perfect and even modern mobile networks can experience interruptions and downtime. Therefore, it is important that teleoperation systems are designed so that in the event of a loss of connection, due to for instance the bus driving outside the network coverage area or the network experiencing service disruptions, the bus is still able to maintain a safe operation.

The cost estimates for automated buses presented in this thesis were quite conservative, which explains why the perceived cost savings were not as significant as in some other

studies. The cost estimates were made on the basis of publicly available information and they are representative of the current price levels. The costs are, however, thought to fall once automated buses are taken into broader commercial use. Currently, when automated buses are still required to have a dedicated operator onboard, using automated buses for public transportation cannot be justified on economic grounds. That is likely to change once driving automation levels beyond 3 are reliably achieved and the regulations start allowing buses to be operated on public roads without safety drivers. Furthermore, the number of incidents encountered during the robot bus trials may not be reflective of how often automated buses encounter issues when they are introduced on routes on a more permanent basis. As the technology matures, the number of incidents encountered by automated buses will undoubtedly decrease, which reduces the reliance on human operators and allows each operator to take even more simultaneously driving automated buses under supervision.

As has been shown in this thesis, there still are many outstanding technological, regulatory, and even ethical issues associated with automated driving. Yet, automated driving is believed to also offer many potential benefits, including the reduction of traffic accidents and emissions. Automated buses were proven to provide a competitive option to conventional buses while also exhibiting capabilities to greatly transform and streamline existing transportation systems. Much of the fate of automated vehicles depends on technological breakthroughs and whether automation levels 4 and 5 and reliable teleoperation can be achieved. However, currently it seems it is no longer a question of if but when that happens.

REFERENCES

Ainsalu, J., Arffman, V., Bellone, M., Ellner, M., Haapamäki, T., Haavisto, N., Josefson, E., Ismailogullari, A., Lee, B., Madland, O., Madžulis, R., Müür, J., Mäkinen, S., Nousiainen, V., Pilli-Sihvola, E., Rutanen, E., Sahala, S., Schønfeldt, B., Smolnicki, P. M., Soe, R.-M., Sääski, J., Szymańska, M., Vaskinn, I., Åman, M. (2018). State of the Art of Automated Buses. *Sustainability 10*(9).

Alonso Raposo, M., Ciuffo, B., Alves Dies, P., Ardente, F., Aurambout, J-P., Baldini, G., Baranzelli, C., Blagoeva, D., Bobba, S., Braun, R., Cassio, L., Chawdhry, P., Christidis, P., Christodoulou, A., Corrado, S., Duboz, A., Duch Brown, N., Felici, S., Fernández Macías, E., Ferragut, J., Fulli, G., Galassi, M-C., Georgakaki, A., Gkoumas, K., Grosso, M., Gómez Vilchez, J., Hajdu, M., Iglesias, M., Julea, A., Krause, J., Kriston, A., Lavalle, C., Lonza, L., Lucas, A., Makridis, M., Marinopoulos, A., Marmier, A., Marques dos Santos, F., Martens, B., Mattas, K., Mathieux, F., Menzel, G., Minarini, F., Mondello, S., Moretto, P., Mortara, B., Navajas Cawood, E., Paffumi, E., Pasimeni, F., Pavel, C., Pekár, F., Pisoni, E., Raileanu, I-C., Sala, S., Saveyn, B., Scholz, H., Serra, N., Tamba, M., Thiel, C., Trentadue, G., Tecchio, P., Tsakalidis, A., Uihlein, A., van Balen, M. & Vandecasteele, I. (2019). The Future of Road Transport - Implications of Automated, Connected, Low-Carbon and Shared Mobility. European Commission Document EUR 29748 EN.

Anderson, D. R., Sweeney, D. J. & Williams, T. A. (2011). *Statistics for Business and Economics* (11th ed.). Mason, OH: South-Western Cengage Learning.

Arena, F. & Pau, G. (2019). An Overview of Vehicular Communications. *Future Internet 11*(2).

Bösch, P. M., Becker, F., Becker, H. & Axhausen, K. W. (2018). Cost-based Analysis of Autonomous Mobility Services. *Transport Policy 64*.

Bout, M., Brenden A. P., Klingegård, M., Habibovic, A. & Böckle, M.-P. (2017). A Head-Mounted Display to Support Teleoperations of Shared Automated Vehicles. *Proceedings of the 9th International Conference on Automotive User Interfaces and Interactive Vehicular Applications Adjunct (AutomotiveUI '17)*.

Campbell, M., Murray, R. M. & How, J. (2010). Autonomous Driving in Urban Environments: Approaches, Lessons and Challenges. *Philosophical Transactions of The Royal Society A Mathematical Physical and Engineering Sciences 368*(1928).

Campolo, C., Molinaro, A., Iera, A. & Menichella, F. (2017). 5G Network Slicing for Vehicle-to-Everything Services. *IEEE Wireless Communications 24(6)*.

Chucholowski, F., Tang, T. & Lienkamp, M. (2014). Teleoperated Driving: Robust and Secure Data Connections. *ATZelektronik Worldwide, 9*(1).

Cision. (2019). Volkswagenin täyssähköinen e-Crafter saapuu Suomeen. Retrieved from: https://news.cision.com/fi/volkswagen-hyotyautot/r/volkswagenin-tayssahkoinen-e-crafter-saapuu-suomeen,c2992444

City of Turku. (2016). Korvaushinnat kohteittain 3.2.2016. Retrieved from: https://ah.turku.fi/tksjlk/2016/0210002x/Images/1434469.pdf

City of Turku. (2019). Turun raitiotien yleissuunnitelman tarkennus – Raportti 15.1.2019. Retrieved from: https://www.turku.fi/sites/default/files/atoms/files/turun_raitiotien_yleissuunnitelman_tarkennus_15.1.2019_paaraportti.pdf

Dong, Z., Shi, W., Tong, G. & Yang, K. (2020). Collaborative Autonomous Driving: Vision and Challenges. *2020 International Conference on Connected and Autonomous Driving (MetroCAD)*.

Easymile. (2020). EZ10 – Easymile Best Autonomous Vehicle Enabling Smart Mobility. Retrieved from: https://easymile.com/solutions-easymile/ez10-autonomous-shuttle-easymile/

Elbamby, M. S., Perfecto, C., Bennis M. & Doppler, K. (2018). Toward Low-Latency and Ultra-Reliable Virtual Reality. *IEEE Network 32*(2).

Endsley, M. R. (1988). Design and Evaluation for Situation Awareness Enhancement. *Proceedings of the Human Factors Society Annual Meeting 32*(2).

ERTRAC. (2019). Connected Automated Driving Roadmap. ERTRAC Working Group "Connectivity and Automated Driving" Version 8. Retrieved from: https://www.ertrac.org/uploads/documentsearch/id57/ERTRAC-CAD-Roadmap-2019.pdf

Fabulos. (2020). Helsinki pilot. Retrieved from: https://fabulos.eu/helsinki-pilot/

Fagnant, D. J. & Kockelman, K. (2015). Preparing a Nation for Autonomous Vehicles: Opportunities, Barriers and Policy Recommendations. *Transportation Research Part A: Policy and Practice 77*.

Favarò, F., Eurich, S. & Nader, N. (2018). Autonomous Vehicles' Disengagements: Trends, Triggers, and Regulatory Limitations. *Accident Analysis & Prevention 110*.

Gaber, A., Nassar, W., Mohamed, A. M. & Mansour, M. K. (2020). Feasibility Study of Teleoperated Vehicles Using Multi-Operator LTE Connection. *2020 International Conference on Innovative Trends in Communication and Computer Engineering (ITCE)*.

Georg, J. & Diermeyer, F. (2019). An Adaptable and Immersive Real Time Interface for Resolving System Limitations of Automated Vehicles with Teleoperation. *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*.

Georg, J., Feiler, J., Diermeyer, F. & Lienkamp, M. (2018). Teleoperated Driving, a Key Technology for Automated Driving? Comparison of Actual Test Drives with a Head Mounted Display and Conventional Monitors. *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*.

Gnatzig, S., Chucholowski, F., Tang T. & Lienkamp, M. (2013). A System Design for Teleoperated Road Vehicles. *Proceedings of the 10th International Conference on Informatics in Control, Automation and Robotics*.

Gohar, A & Lee, S. (2019). A Cost Efficient Multi Remote Driver Selection for Remote Operated Vehicles. *Computer Networks 168*.

Gohar, A. & Lee, S. (2018). A Fast Remote Driver Selection Mechanism for Remote-Controlled Driving Systems. *2018 International Conference on Information Networking (ICOIN)*.

Gohar, A., Raza A. & Lee, S. (2018). A Distributed Remote Driver Selection for Cost Efficient and Safe Driver Handover. *2018 International Conference on Information and Communication Technology Convergence (ICTC)*.

Han, B., De Domenico, A., Dandachi, G. Drosou, A., Tzovaras, D., Querio, R., Moggio, F., Bulakci, Ö., Schotten, H. D. (2018). Admission and Congestion Control for 5G Network Slicing. *2018 IEEE Conference on Standards for Communications and Networking (CSCN)*.

Hobert, L., Festag, A., Llatser, I., Altomare, L., Visintainer, F. & Kovacs, A. (2015). Enhancements of V2X Communication in Support of Cooperative Autonomous Driving. *IEEE Communications Magazine 53*(12).

Hosseini, A. & Lienkamp, M. (2016). Enhancing Telepresence During the Teleoperation of Road Vehicles Using HMD-based Mixed Reality. *2016 IEEE Intelligent Vehicles Symposium (IV)*.

Huhta, R. (2017). The Acceptability and Cost Structure of Automated Minibuses as a Part of Public Transport. Master's Thesis. Tampere University of Technology.

Inam, R., Schrammar, N., Wang, K., Karapantelakis, A., Mokrushin, L., Vulgarakis Feljan, A. & Fersman, E. (2016). Feasibility Assessment to Realise Vehicle Teleoperation Using Cellular Networks. *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*.

Iora, P. & Tribioli, L. (2019). Effect of Ambient Temperature on Electric Vehicles' Energy Consumption and Range: Model Definition and Sensitivity Analysis Based on Nissan Leaf Data. *World Electric Vehicle Journal 10(2)*.

Isto, P., Heikkilä, T., Mämmelä, A., Uitto, M., Seppälä, T., & Ahola, J. M. (2020). 5G Based Machine Remote Operation Development Utilizing Digital Twin. *Open Engineering, 10*(1).

Jo, K., Kim, J., Kim, D., Jang, C. & Sunwoo, M. (2014). Development of Autonomous Car - Part I: Distributed System Architecture and Development Process. *IEEE Transactions on Industrial Electronics 61(10)*.

Kang, L., Zhao, W., Qi, B. & Banerjee, S. (2018). Augmenting Self-Driving with Remote Control: Challenges and Directions. *HotMobile '18: Proceedings of the 19th International Workshop on Mobile Computing Systems & Applications*.

Karvonen, V. (2012). Optimization and Allocation of Bus Fleet. Master's Thesis. Aalto University Schools of Technology.

Krok, A. (2018). Velodyne just made self-driving cars a bit less expensive. *Roadshow by CNET*. Retrieved from: https://www.cnet.com/roadshow/news/velodyne-just-made-self-driving-cars-a-bit-less-expensive-hopefully/

Kutila, M., Pyykönen, P., Holzhüter, H., Colomb M. & Duthon, P. (2018). Automotive LiDAR Performance Verification in Fog and Rain. *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*.

Kutila, M., Pyykönen, P., Ritter, W., Sawade, O. & Schäufele, B. (2016). Automotive LIDAR Sensor Development Scenarios for Harsh Weather Conditions. *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*.

Lehtinen, A. & Kanerva, O. (2017). Selvitys sähköbussien edistämiseksi suomalaisilla kaupunkiseuduilla. *Liikenneviraston tutkimuksia ja selvityksiä 21/2017*.

Liljamo, T., Liimatainen, H., Pöllänen, M., Tiikkaja, H., Utriainen, R., Viri, R. (2018). The Impact of Automated Vehicles on Travel Behaviour. *Trafi Research Reports 1/2018*.

Liu, R., Kwak, D., Devarakonda, S., Bekris, K. & Iftode, L. (2017). Investigating Remote Driving over the LTE Network. *Proceedings of the 9th ACM International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI '17)*.

Liu, S., Liu, L., Tang, J., Yu, B., Wang, Y. & Shi, W. (2019). Edge Computing for Autonomous Driving: Opportunities and Challenges. *Proceedings of the IEEE 107*(8).

Mangiante, S., Klas, G., Navon, A., GuanHua, Z., Ran, J. & Dias Silva, M. (2017). VR is on the Edge: How to Deliver 360° Videos in Mobile Networks. *Proceedings of the Workshop on Virtual Reality and Augmented Reality Network (VR/AR Network '17)*.

Markkula, J. & Vilppo, O. (2014). Tampereen bussiliikenteen sähköistäminen. Preparatory study.

Navya. (2020). Autonom Shuttle Technical Specifications. Retrieved from: http://navya.tech/wp-content/uploads/documents/Specifications_Shuttle_EN.pdf

Neumeier, S. & Facchi, C. (2019). Towards a Driver Support System for Teleoperated Driving. *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*.

Neumeier, S., Walelgne, E. A., Bajpai, V., Ott, J. & Facchi, C. (2019a). Measuring the Feasibility of Teleoperated Driving in Mobile Networks. *2019 Network Traffic Measurement and Analysis Conference (TMA)*.

Neumeier, S., Wintersberger, P., Frison, A.-K., Becher, A., Facchi, C., Riener, A. (2019b). Teleoperation: The Holy Grail to Solve Problems of Automated Driving? Sure, but Latency Matters. *Proceedings of the 11th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*.

NTSB. (2019). Collision Between Vehicle Controlled by Developmental Automated Driving System and Pedestrian, Tempe, Arizona March 18, 2018. *Highway Accident Report NTSB/HAR-19/03*. Retrieved from: https://www.ntsb.gov/investigations/AccidentReports/Reports/HAR1903.pdf

Pendleton, S. D., Andersen, H., Du, X., Shen, X., Meghjani, M., Eng, Y. H., Rus, D. & Ang, M. H., Jr. (2017). Perception, Planning, Control, and Coordination for Autonomous Vehicles. *Machines 2017 5*(1).

Pihlatie, M., Kukkonen, S., Halmeaho, T., Karvonen, V. & Nylund, N.-O. (2014). Fully Electric City Buses – The Viable Option. *2014 IEEE International Electric Vehicle Conference (IEVC)*.

Qian, F., Ji, L., Han, B. & Gopalakrishnan, V. (2016). Optimizing 360 Video Delivery Over Cellular Networks. *Proceedings of the 5th Workshop on All Things Cellular: Operations, Applications and Challenges (ATC '16)*.

Reschka, A. & Maurer, M. (2015). Conditions for a Safe State of Automated Road Vehicles. *it – Information Technology 57*(4).

Reuters. (2020). Honda says will be first to mass produce level 3 autonomous cars. *Reuters*. Retrieved from: https://www.reuters.com/article/us-honda-autonomous-level3/honda-says-will-be-first-to-mass-produce-level-3-autonomous-cars-idUSKBN27R0LV

Rigazzi, G., Kainulainen, J.-P., Turyagyenda, C., Mourad, A. & Ahn, J. (2019). An Edge and Fog Computing Platform for Effective Deployment of 360 Video Applications. *2019 IEEE Wireless Communications and Networking Conference Workshop (WCNCW)*.

Rutanen, E. & Arffman, V. (2019). D4.15 Autonomous Last Mile Pilots in Operations. *mySMARTLife – Transition of EU cities towards a new concept of Smart Life and Economy*.

SAE International. (2018). Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles. Society of Automotive Engineers standard J3016. Retrieved from: https://saemobilus.sae.org/content/j3016_201806

Saeed, U., Hämäläinen, J., Garcia-Lozano, M. & David González, G. (2019). On the Feasibility of Remote Driving Application over Dense 5G Roadside Networks. *2019 16th International Symposium on Wireless Communication Systems (ISWCS)*.

Salonen, A. O. & Haavisto, N. Towards Autonomous Transportation. Passengers' Experiences, Perceptions and Feelings in a Driverless Shuttle Bus in Finland. (2019). *Sustainability 11(3)*.

Sensible 4. (2020). Gacha Autonomous Shuttle Bus. Retrieved from: https://www.sensible4.fi/gacha/

Shen, X., Chong, Z. J., Pendleton, S., James Fu, G. M. & Qin, B. Frazzoli, E. & Ang, M. H., Jr. (2016). Teleoperation of On-Road Vehicles via Immersive Telepresence Using Off-the-shelf Components. *Intelligent Autonomous Systems 13*.

Sun, L., Duanmu, F., Liu, Y., Wang, Y., Ye, Y., Shi, H. & Dai, D. (2018). Multi-Path Multi-Tier 360-Degree Video Streaming in 5G Networks. *Proceedings of the 9th ACM Multimedia Systems Conference (MMSys '18)*.

Tilastokeskus. (2017). Linja-autoliikenteen kustannusindeksi 2015=100 käsikirja. Handbook.

Tilastokeskus. (2020). Energy prices. Retrieved from: https://www.tilastokeskus.fi/til/ehi /index_en.html

Tirachini, A. & Antoniou, C. (2020). The Economics of Automated Public Transport: Effects on Operator Cost, Travel Time, Fare and Subsidy. *Economics of Transportation 21*.

Uitto, M. & Heikkinen, A. (2020). Exploiting and Evaluating Live 360° Low Latency Video Streaming Using CMAF. *2020 European Conference on Networks and Communications (EuCNC)*.

Uitto, M., Hoppari, M., Heikkilä, T., Isto P., Anttonen, A. & Mämmelä, A. (2019). Remote Control Demonstrator Development in 5G Test Network. *2019 European Conference on Networks and Communications (EuCNC)*.

Vilppo, O. & Markkula, J. (2015). Feasibility of Electric Buses in Public Transport. *World Electric Vehicle Journal 7*.

Volkswagen. (2020a). eCrafter umpipakettiauto: hinnasto. Retrieved from: https://www.volkswagen.fi/idhub/content/dam/onehub_pkw/importers/fi/hyotyautot/ hinnastot/2020/lokakuu/VW-eCrafter-35-umpipakettiautot-nro.pdf

Volkswagen. (2020b). Crafter umpipakettiauto kattokorotuksella, kokonaispaino 3500 kg: hinnasto. Retrieved from: https://www.volkswagen.fi/idhub/content/dam/onehub _pkw/importers/fi/hyotyautot/hinnastot/2020/toukokuu/VW_Crafter_35_umpipakett iautot_kattokorotuksella_WLTP_nro_49.pdf

Wadud, Z. (2017). Fully Automated Vehicles: A Cost of Ownership Analysis to Inform Early Adoption. *Transportation Research Part A: Policy and Practice 101*.

Winfield, A. F. T. (2000). Future Directions in Tele-Operated Robotics. *Telerobotic Applications*.

Zhang, T. (2020). Toward Automated Vehicle Teleoperation: Vision, Opportunities, and Challenges. *IEEE Internet of Things Journal*.