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Cost Modelling and Decision Making Model Generation for Urban Rail Transport Systems

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Abstract

Urban rail transport systems play a vital role in providing efficient and sustainable mobility solutions for growing metropolitan areas. This thesis focuses on the case of Stockholm's urban rail transport, managed by Region Stockholm, which serves nearly 900,000 daily passengers amid rapid population growth. However, the aging power supply system poses challenges to the system's efficiency and capacity expansion. To address these issues, this study develops cost modeling and decision-making tools aimed at evaluating future energy-saving business cases within the urban rail transport system. These tools, though preliminary, provide decision-makers with a techno-economic perspective to compare the cost-effectiveness of various measures and inform future interventions.

The research methodology involves a system engineering approach, with continuous collaboration between the academic institution (KTH), transport authority (TF), and industrial partner (MTR). Weekly meetings facilitated the understanding of the urban rail transport system and the development of a decision-making algorithm. The study identifies stakeholders, primarily TF and passengers, and outlines a decision-making framework to assess proposed business cases. The tools generated undergo validation through expert feedback, laying the foundation for future empirical testing.

Key findings highlight two main methods for energy-saving measures: technological modifications (e.g., Energy Storage Systems - ESS) and operational adjustments. Both On-board and Wayside ESS installations demonstrate significant energy-saving potential, while operational adjustments such as HVAC modifications present challenges in automation. Qualitative reviews were made on these measures. The thesis proposes a preliminary Decision-Making Tool to quantify Key Performance Indicators (KPIs) and facilitate informed decision-making. Future work includes expanding stakeholder inclusion, refining cost models, and integrating additional business cases into the decision-making framework.

In conclusion, this thesis contributes to the understanding of cost-effective measures for enhancing energy efficiency within urban rail transport systems. The developed tools offer an initial approach for decision-makers to navigate complex trade-offs and prioritize interventions, ultimately contributing to the sustainability and resilience of urban mobility infrastructure.

Keywords:

Urban rail transport, Cost modeling, Cost-benefit analysis, Energy-saving measures, Decision-making algorithm, Techno-economic perspective, Stakeholder engagement, Sustainability, System approach, KPIs, ESS installation, HVAC modifications

Sammanfattning

Järnvägstransportsystem i städerna spelar en viktig roll för att tillhandahålla effektiva och hållbara mobilitetslösningar för växande storstadsområden. Detta examensarbete fokuserar på fallet med Stockholms stadstrafik, som drivs av Region Stockholm, som servar nästan 900 000 dagliga passagerare i en snabb befolkningstillväxt. De åldrande strömförsörjningssystemen innebär dock utmaningar för systemets effektivitet och kapacitetsutbyggnad. För att ta itu med dessa frågor, utvecklar denna studiekostnadsmodellering och beslutsfattande verktyg som syftar till att utvärdera framtida energibesparande affärscases inom det urbana järnvägstransportsystemet. Dessa verktyg, även om de är preliminära, ger beslutsfattare ett tekniskt-ekonomiskt perspektiv för att jämföra kostnadseffektiviteten för olika åtgärder och informera framtida insatser.

Forskningsmetodiken innebär ett systemtekniskt tillvägagångssätt, med kontinuerligt samarbete mellan den akademiska institutionen (KTH), transportmyndigheten (TF) och industriell partner (MTR). Veckomöten underlättade förståelsen av det urbana järnvägstransportsystemet och utvecklingen av en beslutsalgoritm. Studien identifierar intressenter, främst TF och passagerare, och skisserar en ram för beslutsfattande för att bedöma föreslagna affärsfall. Verktygen som genereras genomgår validering genom expertfeedback, vilket lägger grunden för framtida empiriska tester.

Nyckelresultat belyser två huvudmetoder för energibesparande åtgärder: tekniska modifieringar (t.ex. Energy Storage Systems - ESS) och driftsanpassningar. Både ESS-installationer ombord och längs vägen uppvisar betydande energibesparingspotential, medan operativa justeringar som HVAC-modifieringar innebär utmaningar inom automatisering. Kvalitativa granskningar gjordes av dessa åtgärder. Avhandlingen föreslår ett preliminärt beslutsfattande verktyg för att kvantifiera Key Performance Indicators (KPI:er) och underlätta välgrundat beslutsfattande. Framtida arbete inkluderar att utöka inkluderingen av intressenter, förfina kostnadsmodeller och integrera ytterligare affärscase i beslutsfattandet.

Sammanfattningsvis bidrar detta examensarbete till förståelsen av kostnadseffektiva åtgärder för att förbättra energieffektiviteten inom stadstrafiksystem. De utvecklade verktygen erbjuder ett första tillvägagångssätt för beslutsfattare att navigera i komplexa avvägningar och prioritera insatser, vilket i slutändan bidrar till hållbarheten och motståndskraften hos mobilitetsinfrastrukturen i städerna.

Nyckelord:

Järnvägstransporter i städer, Kostnadsmodellering, Kostnads-nyttoanalys, Energibesparande åtgärder, Beslutsalgoritm, Teknoekonomiskt perspektiv, Intressenternas engagemang, Hållbarhet, Systemansats, KPI:er, ESS-installation, HVAC-modifieringar

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Stockholm, June 2024

Zekeriya Gökmen Dursun

Nomenclature

ESS – Energy Storage System

HVAC – Heating, Ventilation and Air Conditioning

KPI - Key Performance Indicator

KTH – Kungliga tekniska högskolan

MTR - Mass Transit Railway

NPV – Net Present Value

PMV – Predicted Mean Vote

PTA – Public Transport Authority

PTO – Public Transport Operator

TF – Trafikförvaltningen

TRL – Technology Readiness Level

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1. Introduction

1.1. Background

Urban rail transport refers to the metros and light rail systems and is a fundamental public transport infrastructure system for any city above 300,000 population [1]. Region Stockholm is responsible for managing, operating, and developing the public transport system in the Stockholm region to provide safe, accessible, efficient, and sustainable modes of transport to residents and visitors. Nearly 900,000 people use public transport daily in Stockholm County [2]. The region's population growing rapidly, and Region Stockholm is continuously working on expansions, modernizations, and upgrades to the system [2]. The spatial vision for the Stockholm region for 2050 is based on six spatial principles, focusing on urban development in the best public transport nodes. Building and densifying in areas with high public transport accessibility creates closeness and supports services and good public transport, leading to shorter distances in people's daily routines [3].

Stockholm Metro is a fast urban rail transport system in Stockholm, Sweden. The first line opened in 1950, making it the first metro line in the Nordic region. Today, the system has 100 stations, 47 underground and 53 above ground. The network is made up of three colored lines, as depicted on tube maps, that connect seven numbered routes with various termini: routes 17, 18, and 19 (green line), 13 and 14 (red line), and 10 and 11 (blue line). All of these routes travel through the city center, resulting in a concentrated system with T-Centralen station serving as the primary interchange. There are three additional line interchanges at Fridhemsplan, Slussen, and Gamla stan stations [4].

The power supply systems have become bottlenecks for the development of Stockholm's local rail transport. Even though rail transport is very energy-efficient and runs on green electricity, the power supply systems of the local rail transport are relatively old and weak, which lowers energy efficiency and limits the increase in transport capacity. Therefore, new decisions have to be taken by the PTAs to provide substantial public transport services to the people. Consequently, the decision-making process for the responsible authorities is crucial to meeting the planned target areas for urban rail transport.

1.2. Purpose

The objective of this master's thesis is to develop cost modeling and cost-benefit analysis (decision-making) tools on a preliminary level. A key purpose of this thesis is to explain the functionality of these tools, including data flow and the decision-making algorithm within the developed models. These tools are mainly for evaluating future energy-saving business cases within urban rail transport systems. Although these tools are primarily preliminary and require further refinement, they will enable decision-makers to compare the cost-effectiveness of different measures and make informed decisions once additional details are incorporated in the future. Therefore, these tools should be regarded as an initial step toward understanding a broader objective. These tools will provide a techno-economic perspective for decision-makers, rather than a purely financial one.

Another purpose of this thesis is to present specific business cases proposed for the Stockholm C30 metro line. Through a literature review, several promising business cases aimed to be identified and commented on qualitatively. However, given the complexity of urban rail transport systems, this thesis refrains from making specific recommendations to the TF. Instead, it aims to provide valuable insights and information that can inform future decision-making processes regarding potential interventions or improvements for the Stockholm C30 metro line. The research question can be titled: "*How can a quantifiable decision-making algorithm be generated for business case comparison to be utilized by decision-makers?*"

1.3. Delimitations

The thesis focuses on a system engineering perspective, deliberately excluding intricate details to provide a broader vision and ensure completion within the allocated timeframe of 5 months. Given the complexity and interdependencies at the systems level, it was necessary to narrow the scope further.

Due to electrical safety regulations, the thesis does not further detail broader urban rail infrastructure, emphasizing the conditions of train operation and the train itself, excluding detailed electrical infrastructure specifications. Urban rail transport systems are highly complex and interconnected, involving numerous subsystems and stakeholders. To complete the thesis within the allocated timeframe, the primary stakeholders identified for the decision-making process were TF and the passengers. However, in real-world scenarios, potential bottlenecks in implementing business cases would likely arise from interactions with train manufacturers and infrastructure managers. Therefore, the inclusion of all important stakeholders in the decision-making process is particularly important for the future development of the decision-making tool.

It should be noted that the novel aspect of this work is the proposal of a decision-making algorithm from a system engineering perspective. This would eventually lead to staying on a broader perspective in a complex system. The reliability of the developed tools is based on feedback from industry experts at TF and supervisors at KTH, rather than empirical testing with real-world data. However, as future work, since the models are suitable for quantifiable comparison, they can be further refined and validated with empirical data in subsequent studies.

1.4. Method

Given the complex nature of this thesis, a broader perspective was essential, necessitating continuous meetings. At KTH, weekly meetings were conducted, with the first month focused more on understanding urban rail transport systems rather than immediately developing the decision-making model. These meetings facilitated the generation of the decision-making algorithm. Furthermore, monthly joint meetings with KTH, TF, and MTR provided industrial feedback, allowing for redirection and refinement of the developed models. Consequently, the tools were developed under continuous supervision from both KTH and TF, ensuring compliance with the thesis objectives. With continuous meetings and feedback, the KPIs and the models were ensured to be able to be used in practice.

The study relies on data obtained from TF and other online sources to understand the availability and interrelationships of parameters necessary for creating the decision-making model. This involves evaluating how different parameters interact with one another. The delimitations are primarily guided by the availability of data from TF. The size of TF and the complexity of identifying and accessing relevant data proved time-consuming, with obtaining permissions and ensuring data accuracy adding to these challenges. A representation of the data research and availability process is illustrated in Figure 1.

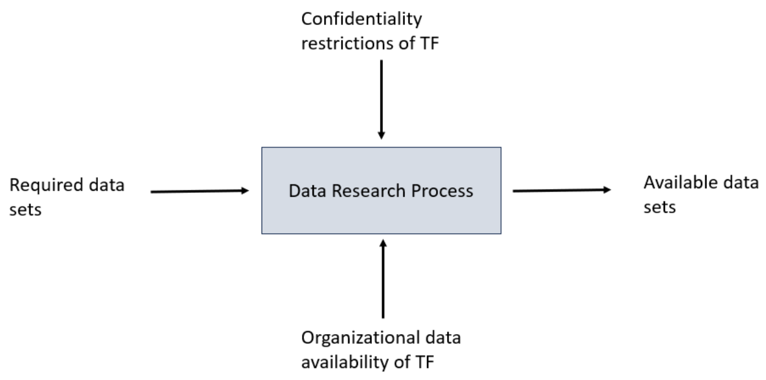

Figure 1: Data availability and research flow representation

The input comprises the required parameter sets to be incorporated into cost and decision-making models which will output the business case performance for selected KPIs. The organizational data availability from TF acts as a constraint, compounded by TF's confidentiality restrictions. Utilizing the data research process explained in Figure 1, the output is the available parameter sets to be used for the formation of the cost and decision-making models.

Furthermore, since the cost models require consideration of LCC, additional research was needed to be conducted on financial terminologies and models. For instance, insights were gathered from the LCC model utilized at TF and subsequently enhanced with information obtained from articles on ESS installations. Notably, the tool from TF, *"LCC Vallentuna pellets mot borrhål,"* was utilized to ensure compatibility with the current system at TF.

1.5. Structure of the Thesis

The structure of the thesis follows a system engineering perspective to provide a broad vision of Stockholm's urban local rail transport, which is complex and interconnected. Therefore, it was particularly important to clearly state the problem and possible limitations beforehand. This was achieved through continuous weekly meetings with TF and KTH.

The literature review chapter examines the problem at a systems level, additionally exploring the strategies employed by other municipalities and countries to address similar issues. Furthermore, it investigates the methodologies used for the creation of cost models. The methodology chapter explains the development of the decision-making model and the KPI decision algorithm. The generic decision-making model chapter provides a detailed explanation of the decision-making model developed in this thesis and outlines how stakeholders can utilize it in the decision-making process. The models for individual business cases chapter details the formation of cost models for the selected business cases and further explains the data flow algorithm for the relevant parameters within these models.

The results and discussion chapter offers a brief discussion of some of the specific business cases that would require further investigation, as well as a simulation of the decision-making process utilizing the developed decision-making tool in this thesis. The conclusion and future works chapter will mainly explain the general takeaways from the thesis and the future works to be done to further develop the decision-making tool.

2. Literature Review

The long life cycles of trains and even longer life cycles of train infrastructures highlight the need for effective decision-making tools. Therefore, the supporting management tools and decision-making tools for policymakers and strategic management play a significant role [5].

Understanding the urban rail transport system begins with familiarizing it with its terminology and components. Rail vehicles are classified as rolling stock (without traction) and tractive stock (with traction), with traction referring to the vehicle's ability to provide power for movement. A rail vehicle comprises the car body, which carries the payload or traction equipment, and the running gear, which includes wheels, axles, and suspension [6]. Passenger weight, load characterization, and standee numbers are vital considerations in vehicle specifications. Standard freight wagons often feature simple braking systems chosen for cost considerations, with traction power being essential for acceleration and maintaining speed, transferred through overhead wires or conductor rails [6]. Electric braking is common in modern electric traction stock, with traction motors acting as generators during braking to enable regenerative braking and energy feedback to the grid [6]. Metro trains, known for their high starting acceleration and top speeds, exemplify these features with regenerative electric braking contributing to energy efficiency.

After having a brief overview of the urban rail transport systems, the methodology employed to understand the solution to the problem involves examining the approaches taken by other cities to address similar challenges. Given that metro infrastructures serve as the backbone of urban transportation, it is logical to adopt proven solutions rather than untested ones. By learning from the experiences and strategies implemented in other urban rail systems, it is possible to identify effective practices and tailor them to fit the specific needs of Stockholm's metro system. This comparative approach ensures leveraging existing knowledge and expertise, thereby increasing the likelihood of successful implementation and optimization of our urban rail transport solutions.

To better understand the possible solutions and the structure of the roadmaps the literature review is, structured into four parts. The first part involves researching the problem at a system level to gain a broader view of the challenges and their interdependencies as well as the decision-making understanding and KPIs to include. This will help in identifying the overarching issues and setting a solid foundation for detailed analysis.

The second part of the literature review focuses on the plans and measures that municipalities have implemented to make energy-efficient decisions. This involves understanding the KPIs and trends that guide these decisions. By examining municipal strategies, we can identify successful practices and insights that are relevant to our context.

The third part of the literature review examines the technical details of specific technologies aimed at increasing energy efficiency. By examining these technologies in depth, we can understand their effectiveness and applicability to our urban rail transport system.

For the final part of the literature review subchapter, the focus will be placed on the development of the decision-making model in terms of cost modeling. This emphasis will form the understanding of the tools to be generated in this thesis and provide a clearer structure for the overall research. With this structured approach, the aim is to achieve a comprehensive understanding of the problems and potential solutions, facilitating the generation of a decision-making model.

2.1. Measures on Systems' Level

The first step is to understand the energy usage patterns and the relevant units of consumption. This understanding will provide a roadmap for selecting measures and making comparisons. Additionally, gaining insights into the decision-making process and identifying the main KPIs that are particularly important to include will be a key focus in the following articles. This approach will help create a structured framework for evaluating different measures, ensuring that the decision-making process is both informed and aligned with critical performance metrics.

By examining these aspects, we aim to gather a comprehensive understanding that will lead to the development of a decision-making model for evaluating and comparing energy-saving measures in urban rail transport. Therefore, reviewing papers at the system level would be beneficial. These papers can offer insights into the methodology of evaluating business cases, and overall energy consumption patterns, identifying the major energy-consuming units, and highlighting potential areas for improvement. Understanding these patterns is crucial for developing an effective decision-making algorithm.

Regarding power consumption and subsystem identification, the paper, titled "An Assessment of Available Measures to Reduce Traction Energy Use in Railway Networks," begins with an analysis of the power consumption distribution in trains, focusing on the various elements that consume power [7]. Understanding this distribution is crucial for identifying potential areas for energy savings.

The main energy-saving measures are categorized into five groups from the same article. The first is reducing auxiliary use, which involves implementing energy-efficient technologies and better management practices for non-traction systems like lighting and HVAC. The second is improving drive chain efficiency, which can be done by using advanced materials and technologies to enhance the efficiency of the traction supply drive chain. Third is reducing motion resistance, which can be achieved through enhancements in vehicle aerodynamics, improved track design, and the adoption of efficient driving techniques to minimize resistance. Fourth, implementing efficient driving techniques and improved network design involves training drivers in energy-efficient methods and optimizing network operations. Lastly, reducing braking losses with regenerative braking includes installing systems that recover energy during braking and reuse it within the network, significantly cutting down on overall energy consumption [7]. Typically, the auxiliaries consume around 10-30%, whereas the driving consumes 60-80% of the total traction energy supplied into the train [7].

The primary takeaway from the article is that many energy-saving procedures can be easily implemented through software modifications or adjustments by operators. These procedural changes, such as optimizing driving techniques or adjusting operational schedules, generally do not require significant infrastructure changes. In contrast, technology-based solutions, like upgrading the traction drive systems or installing regenerative braking systems, typically necessitate substantial infrastructure modifications and hardware installations. This distinction highlights the relative ease and cost-effectiveness of procedural changes compared to the more resource-intensive technological upgrades.

Considering energy-saving measures, it's noted from the article that On-board ESS for urban rail transport systems typically enables savings ranging from 15% to 35%, while Wayside ESS can contribute to savings within the range of 10% to 35%. Additionally, adjustments to on-board auxiliary systems, such as temperature adjustments, typically yield energy savings between 1% and 7%. Similarly, CO_2 ventilation adjustments and control when stable are estimated to provide energy savings in the range of 1% to 7% and around 3% to 5%, respectively [7].

The article further underscores the importance of interconnections among various subsystems and proposed solutions. This aspect enables decision-makers to gain a comprehensive understanding of how each measure may impact the broader system. Such a holistic perspective is essential for identifying synergies, minimizing potential conflicts, and optimizing the overall energy efficiency and performance of the rolling stock system. Although the visualization of this aspect was not included in this thesis, its incorporation would be crucial for better identifying and understanding the complexity inherent in the decision-making process. By visualizing the interconnectedness of proposed solutions with other subsystems of the rolling stock system, decision-makers can more effectively assess the potential impacts and interactions of various measures. This enhanced understanding can lead to more informed decisions, ultimately contributing to the optimization of energy efficiency and performance within the railway network.

The second article titled "A system's approach to reduce urban rail energy consumption," takes a comprehensive look at how to cut energy usage in urban rail systems [8]. Instead of focusing on individual parts, it examines the system as a whole. It suggests that by improving things like train schedules, how trains are driven, and managing comfort features, or the installation of Wayside ESS, energy consumption could potentially be reduced by around 25–35% [8]. Such measures underscore the importance of considering the broader system dynamics when devising energy-saving solutions for urban rail networks.

In more detailed business cases, both On-board and Wayside ESS are estimated to offer energy-saving potentials ranging from 5% to 25%. Additionally, when considering both in-service and depot conditions, adjustments to HVAC systems and light controls in combination are projected to reduce energy consumption by approximately 1% to 5% [8].

In the same article, it has been stated that the HVAC systems typically consume a substantial portion of energy in urban rail systems, and their usage is greatly impacted by climate conditions [9]. For example, heating systems alone make up 28% of the total traction energy usage in Metro Oslo [10]. Similarly, all auxiliary systems collectively represent approximately 10% of the total vehicle consumption in the London Underground [11]. These outcomes underscore the significant role of HVAC equipment in overall energy consumption within urban rail networks.

Five key clusters of actions have been identified as a general outcome in the paper to minimize energy consumption within urban rail systems. Firstly, regenerative braking systems can be implemented to capture and reuse energy generated during braking, thus reducing overall energy demand. Secondly, adopting eco-driving strategies including the introduction of driving techniques that prioritize energy efficiency, such as smoother acceleration and deceleration. Thirdly, efforts to minimize traction losses aim to decrease inefficiencies within the traction system, optimizing energy usage. Additionally, strategies to reduce the energy demand of comfort functions, such as HVAC systems, can contribute significantly to energy savings. Lastly, efficient measurement and management of energy flows are crucial, involving the implementation of tools and practices to monitor and control energy consumption across the rail network effectively [8].

Similar to the previous article's suggestions, there are two main implementation approaches for the business cases [7]: operation and technology-focused. Operation-focused solutions typically involve software or operational regime adjustments, while technology solutions may require hardware modifications or installations. This categorization facilitates a structured approach to assessing and implementing energy-saving measures within urban rail systems for decision-makers [8].

Interdependences between energy efficiency measures in urban rail systems are crucial to consider during evaluation. Combining measures can result in either a higher or lower potential benefit compared to their application [8]. Therefore, it's essential to assess not only the benefits of each measure independently but also the interactions between them. For example, eco-driving measures aim to minimize resistive losses in the power supply line by reducing current flow in the network. Additionally, deceleration profiles that align with the characteristics of the traction motors can lead to fewer losses in braking energy recovery [8]. This holistic approach ensures a comprehensive understanding of how various measures interact and contribute to overall energy efficiency improvements.

The assessment and rating of energy efficiency measures in urban rail systems involve considering various factors to determine their feasibility and effectiveness. Measures that require the introduction of heavy and bulky systems into existing vehicles, such as On-board ESS or HVAC, are likely to face challenges and may be declined due to practical constraints.

As a summary of both papers referenced, the methodology outlined in Figure 2 for evaluating and deciding on business cases has been implemented in this thesis work. The figure is generated by reference to the article discussed [8]. It involves identifying key areas of improvement and preselecting measures based on selecting business cases with high energy-saving potential within every price range. This approach ensures that solutions are chosen strategically to maximize energy efficiency while considering cost constraints.

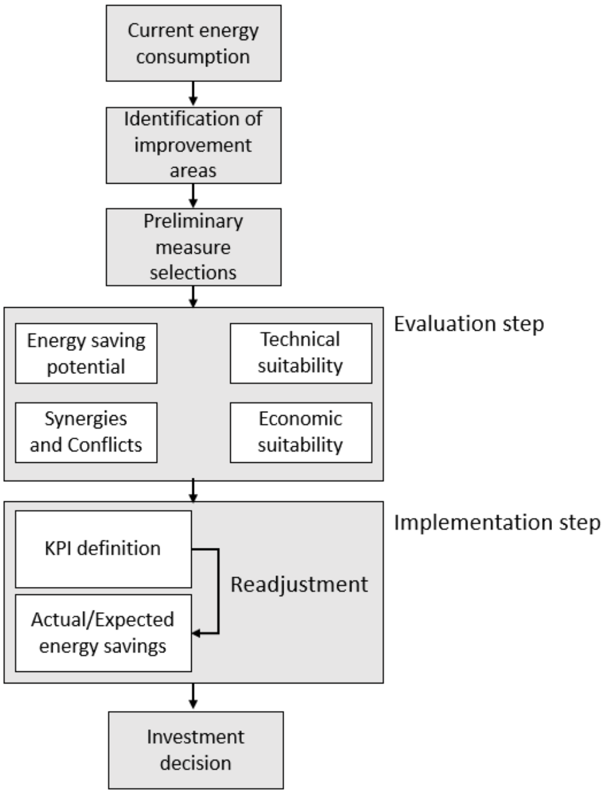

Figure 2: Methodology for a successful implementation of energy efficiency measures in urban rail

Analyzing the actual energy consumption of the system is particularly important when proposing any energy efficiency business cases. Understanding the energy flows within the system facilitates the identification of areas with the greatest potential for improvement, thus enabling the preselection of suitable measures.

These preliminary solutions must then undergo evaluation to prioritize their implementation effectively. The principal criteria for this evaluation include assessing the energy-saving potential of the solutions from a systems perspective and considering synergies and conflicts that may arise between measures. Additionally, technical suitability for the system in question is crucial as some measures may be deemed impractical. Economic suitability is another critical factor, influenced by potential energy savings at the systems level and technical suitability, among other economic considerations concerning various stakeholders.

Solutions deemed most promising after the evaluation process must be fully defined in an implementation program, which should also include a set of KPIs to monitor their effect. Comparing expected and actual energy savings enables the readjustment of the original program to optimize results. Evaluating measures involves developing detailed models for each business case to assess both cost and energy-saving potentials. If the KPI performances of the proposed business measures are not promising, readjustment of KPIs can be utilized. This ensures that the evaluation criteria align closely with the objectives and priorities of the decision-makers, facilitating informed decision-making.

2.2. Municipality Plans

After gaining a general understanding of energy reduction measures and the methodology of evaluation, the next step is to explore the practicality of these measures and how municipalities worldwide approach achieving the thesis goal. By analyzing real-world implementations within urban transit systems, we can gain key insights into the feasibility, challenges, and outcomes of these measures. This approach will inform the selection and investigation of specific business cases in this thesis. By studying these real-world examples, we can identify effective strategies, potential obstacles, and best practices, providing a solid foundation for the development of our proposed tools and decision-making algorithms.

2.2.1. Ticket to Kyoto

The collaboration between five European public transport companies under the Ticket to Kyoto (T2K) project signifies a collective effort to combat climate change by adopting concrete energy-saving measures. The participating companies include GMPTE from Manchester, moBiel from Bielefeld, RATP from Paris, RET from Rotterdam, and STIB from Brussels.

moBiel, as part of its "moBiel 2030" strategy, aims to significantly increase ridership in Bielefeld by implementing various energy-saving measures. Among these initiatives, the installation of fast-closing doors and the optimization of depot lighting through relighting and daylight-dependent controls are highlighted. Additionally, moBiel emphasizes eco-driving practices for bus drivers and focuses on the efficient storage of braking energy from new tram vehicles, utilizing supercapacitors or reversible substations [12]. In addressing HVAC systems, moBiel plans to optimize energy consumption by grouping heated points and implementing sensor-controlled heating. By installing sensors to monitor temperature, air humidity, and surface wetness, moBiel aims to reduce power-on time for heating, thereby achieving significant energy savings, particularly during humid winter conditions [12].

RATP, operating a multimodal network in the Greater Paris Region, also implements energy-saving measures under the Ticket to Kyoto project. The company's eco-driving challenge involves regular training sessions for bus drivers and maintenance teams, resulting in a notable reduction of bus consumption by 5 to 6%. Furthermore, RATP aims to reduce CO_2 emissions by adjusting setpoint temperatures in regional trains and investing in relighting projects. By testing low-consumption technologies like LEDs and implementing lighting-dimming strategies, RATP seeks to minimize energy usage while ensuring safety and security, even in tunnel environments [12].

2.2.2. Transport for London 2018

The forecasted increase in energy costs for TfL (Transport for London) presents a significant financial challenge, particularly considering its current annual expenditure of £160 million on direct energy costs, with rail traction constituting the primary portion [13]. Projections indicate a notable escalation in these costs over the next decade, primarily due to anticipated rises in unit prices [13]. This underscores the urgency for TfL to implement effective strategies to mitigate these cost escalations and ensure the sustainability of its operations. Additionally, London's transit system has the potential to leverage demand-shifting mechanisms to address peak loads and optimize energy consumption. TfL can reduce system strain during peak periods by strategically managing and redistributing passenger demand across different times or routes, resulting in more efficient energy utilization and potentially lower overall energy costs. Figure 3 and Figure 4 primarily highlight the optimization strategy, including detailed information on the example business cases and providing relevant specifics for each.

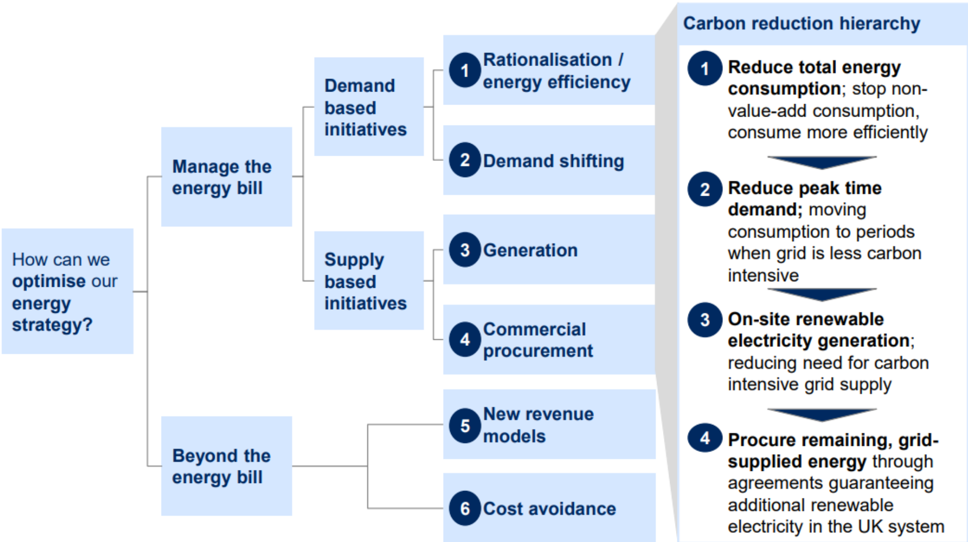

Figure 3: Optimization strategy from TfL [13]

1 Energy efficiency	Traction efficiency	**Reducing consumption** through **coasting**, regen and battery storage
	Non-traction efficiency	**Energy efficiency** across stations, depots, garages and road network
2 Demand Shifting	Demand side response	Use of **battery or other storage** to shift consumption to lower cost times
3 Generation	Solar PV	**Deploying solar** across TfL estate and beyond (buildings/land/garages)
	Combined Heat and Power (CHP)	Opportunity to utilise **CHP** at TfL assets to generate heat and power - though subject to LES and London Plan
4 Commercial procurement	Private wire	Connecting directly to energy generators to **save pass-through costs**
	Procurement optimisation	Determining the best **procurement strategy and framework** in which to deliver wider initiative benefits
	Renewable power purchase agreement (PPA)	Closing the carbon gap by **buying renewable energy** through a PPA
5 New revenue models	Optimised EV charging	Delivering EV infrastructure in a **financially sustainable** way
	Waste heat	Capture waste heat from **tunnels** to provide to **developments** / other users
	Zero-carbon homes	**TfL**-enabled **housing developments** deliver **zero-carbon homes**
6 Cost avoidance	Optimised / accelerated bus electrification	**Accelerating bus electrification** in a **commercially viable** way through **optimised** vehicle/charger **technology** and **contracting mix**

Figure 4: Detailed optimization strategy from TfL [13]

The outcome of the paper emphasizes the importance of enhancing traction efficiency and implementing demand-shifting strategies. To improve traction efficiency, a key focus should be on refining driving styles to incorporate more coasting, which can significantly reduce energy consumption. Additionally, the installation of ESS can further enhance traction efficiency by capturing and reusing energy that would otherwise be lost [13].

On the demand side, ESS remains a viable solution. By strategically deploying ESS, the system can store excess energy during periods of low demand and release it during peak times, thus balancing the load and improving overall efficiency. These measures, when combined, offer a comprehensive approach to optimizing energy use in urban rail systems, addressing both supply and demand aspects effectively [13].

2.2.3. RATP Group Efficiency Plan

The RATP Group's initiatives in energy efficiency highlight significant advancements in eco-driving and lighting within their network. Basic training for all bus drivers includes energy-efficient driving techniques, which contribute to reducing overall vehicle energy consumption. Additionally, RATP has integrated energy optimization goals into the software systems for automated lines, further enhancing traction efficiency [14].

In terms of lighting, RATP has achieved a remarkable milestone by becoming the first network globally to be fully equipped with LEDs, deploying 10 million LEDs across their system by 2016. This transition has resulted in a 50% reduction in energy consumption from station lighting, demonstrating a significant improvement in energy efficiency [14]. These outcomes underscore the importance of training, technological upgrades, and strategic implementations in achieving substantial energy savings and operational efficiency.

2.2.4. Copenhagen Metro Vision 2023-2026

The Copenhagen Metro's Vision 2023-2026 document provides a valuable framework for developing a long-term vision for our case, emphasizing the value proposition and positioning Stockholm as a role model. The aim is to ensure that, with the help of innovation and advanced technology, projects are attractive and effective from the day they are put into operation.

To fully understand the demand, gathering relevant data in the future scope may be beneficial for Stockholm implementations. For instance, the Copenhagen Metro currently boasts a +64 NPS score (customer satisfaction), 99.3% operational stability, and 107 million passengers annually. Before the Covid-19 pandemic, the company projected 149 million annual passengers in 2022, which was revised to 107 million due to the pandemic. They anticipate an increase to 166 million passengers by 2026 [15].

For prioritizing eco-driving or Driver Advisory Systems (DAS), analyzing accident data and other performance metrics between stations and lines could be beneficial. This approach can help identify which stations or blocks would benefit most from these measures, especially if implementing them network-wide is cost-prohibitive. By taking cues from Copenhagen's strategic approach, we can develop a robust, forward-looking plan for Stockholm's metro system, ensuring it remains a benchmark for efficiency and innovation in urban rail transport.

2.3. Technical Reviews on Measures

Currently, the general system of solutions for addressing energy bottlenecks in urban rail transport has been investigated, alongside the array of solutions implemented by various municipalities. This chapter aims to conduct a more technical analysis of these measures and their specific details to better understand their convergence. By doing so, we can identify common strategies and technical nuances that have proven effective.

This deeper understanding will inform the development of models and tools in this thesis work, enabling the creation of robust and practical solutions for decision-makers by comprehending the cost elements. Through this approach, a comprehensive framework for the proposed decision-making algorithm begins to take shape, grounded in both theoretical insights and practical applications.

Furthermore, the understanding of creating cost tools and the framework for a decision-making tool will also begin to form at a hypothetical level, thanks to the following articles. These papers will help us comprehend the cost elements and how they interact with energy consumption. By examining these elements, we can better understand the financial implications of various energy-saving measures and how to effectively compare them. This foundational knowledge is crucial for developing a robust decision-making algorithm that integrates both cost and energy efficiency considerations.

2.3.1. Reducing Train Energy Consumption in Norway

The NSB's energy project, based in Norway, focuses on reducing train energy consumption through various initiatives. While the paper provides general suggestions rather than a quantitative approach, it emphasizes the importance of educating on-board crew to significantly improve efficiency.

Key focus areas of the energy project include optimizing energy usage for stabled trains, particularly in managing heating and other equipment. In addition, attention is given to HVAC operation, with initiatives such as labeling switches and temperature controllers, lowering indoor temperatures, and improving automatic control of doors to enhance energy efficiency [16].

Another significant aspect highlighted in the paper is eco-driving, which involves optimizing train operation to minimize energy consumption. Collecting accurate energy consumption data is also emphasized as a crucial step towards improving the system, enabling informed decision-making based on real-time insights rather than estimates [16].

Overall, the NSB's energy project underscores the importance of holistic strategies and continuous improvement efforts to reduce train energy consumption and promote sustainability in railway operations.

2.3.2. ESS Installation in Poland by ABB

ABB's involvement in supporting the metro system in Poland provides valuable insights and specific hardware details that can be applied to our system. The project, which accommodates 100,000 commuters per day, involved the design, supply, installation, and commissioning of seven underground substations. These substations deliver DC traction power to the metro line and AC auxiliary power to the metro stations, ensuring redundancy and an uninterrupted power supply.

The key hardware components supplied include medium- and low-voltage AC and DC switchgear, dry-type rectifier and auxiliary transformers, protection and control devices, substation automation, and supervisory control and data acquisition (SCADA) systems. Notably, the substations are equipped with a super-capacitor-based DC Wayside ESS the largest of its kind globally. This 40-megajoule system enhances the energy efficiency of the metro system [17]. The findings from this project can provide a better understanding of the cost elements for ESS installation business cases that can be applied to Stockholm, offering a practical for future implementations.

2.3.3. ESS Capacity Determination in New York

Kawasaki's high-capacity Battery Power System (BPS), utilizing Ni-MH batteries, has been implemented as a Wayside ESS for DC electric railways at New York City Transit. This project follows a successful application of the system in Japan, underscoring its potential in diverse urban environments.

The BPS leverages GIGACELL, a nickel-metal hydride (Ni-MH) battery technology, chosen for its low internal resistance which facilitates rapid charge and discharge cycles—crucial for railway applications. One of the standout features of this system is its ability to connect directly to the traction power system without requiring additional power conversion systems or controlling devices. This direct integration is made possible through the use of High-Speed Circuit Breakers (HSBCs) and manual disconnection switches, ensuring both safety and ease of maintenance [18].

Following the installation of the BPS, a series of tests were conducted with several notable outcomes. Firstly, the BPS significantly stabilized fluctuations in the third rail voltage, ensuring a more consistent and reliable power supply. This voltage stabilization is critical for maintaining the efficiency and safety of the rail system [18]. Additionally, the system demonstrated a substantial increase in the capture of regenerative energy, which led to a notable reduction in CO2 emissions. Specifically, the amount of stored regenerative energy increased by 71.4% post-installation, highlighting the system's effectiveness in energy recovery. The BPS also proved its capability to reduce peak demand, thereby smoothing out spikes in power consumption. This feature is particularly beneficial for managing energy costs and improving the overall efficiency of the power supply network. Moreover, the BPS was tested for emergency operations and successfully started a 10-car train, completing a full test track journey from a standstill with all auxiliary systems operational. This capability suggests that during an emergency, 17 similar trains could be moved to the next station, enhancing the system's resilience and reliability [18].

The installation process of the BPS was straightforward, involving a direct connection to the third rail line voltage without the need for electronic controls. Importantly, there was no measurable impact on electromagnetic interference (EMI), ensuring the system's compatibility with existing infrastructure. The analysis of voltage fluctuations before and after the BPS installation revealed a significant reduction in voltage drops during full-throttle acceleration and throughout daily service intervals. This improvement in voltage stability is crucial for maintaining the efficiency and reliability of the railway system.

The successful implementation and testing of the BPS at New York City Transit confirm the high potential of Ni-MH battery-based ESS for urban rail systems. The technology not only stabilizes the power supply and reduces emissions but also enhances operational efficiency and emergency readiness. These findings support the importance of having rush hour differentiation, which may be useful for including potential applications in Stockholm’s transit system [18].

2.3.4. ESS Cost Determination in Rome

This paper can be particularly useful for detailed cost calculations. The authors use the Annual Cost of Ownership Estimate (ACOE) as an economic metric to evaluate the costs associated with the Auxiliary Battery System (ABS), considering the time value of money. This metric is widely used in technical literature and helps railway system operators estimate the annual cost of feeder systems while implementing strategies to increase revenue.

The authors compare two different methods for sizing the ABS: the proposed optimal sizing method (ACOE_size) and a typical battery-sizing method aimed at minimizing the rated power and capacity of the ABS (MIN_size), ensuring it operates within the safe constraints of the feeder system [19]. Additionally, the paper compares the performance of brute-force search methods with the PSO algorithm as solutions. It highlights the importance of suggesting an oversized TPS to account for future demands, which is a crucial consideration during the selection process. Although this comparison is beyond the technical scope of this thesis, it is still beneficial to understand the sizing of the ESS implementation is based on the capacity requirements.

The cost estimation involves four main contributors: rectifier set, operation and maintenance, civil works, and connection to the AC grid [19]. For a detailed understanding of ABS sizing methods, the paper references another source [18]. Although it does not specify which method is more suitable for particular importance rankings, it notes that the MIN_size method results in a smaller ABS, which might lead to reduced battery module lifetime due to stressful operation.

2.3.5. ESS Selection in Tokyo

The paper discusses the installation of a Lithium-ion battery in a traction power supply system for regenerative energy utilization, primarily focusing on Wayside ESS applications. The system was installed in a DC 750V system in Japan, marking its first application not solely for voltage drop compensation but also for regenerative energy utilization, which includes emergency power supply.

Different types of Wayside ESSs are highlighted in the paper, each serving various purposes. For instance, Li-ion batteries are used for compensation for voltage drop, while EDLCs are utilized for regenerative energy cancellation, and Ni-MH batteries for emergency power supply [20]. The criteria for determining suitable locations for Wayside ESS installation include factors such as long intervals between traction substations, preferably located near stations on long slopes, and high numbers of trains equipped with regenerative braking technology, with moderate operation frequencies ranging from 5 to 12 trains per hour. These candidate substations are typically around 50 km away from central downtown areas or stations [20].

The paper also describes the installation scheme of the Li-ion battery and details adjustments made during the operation, particularly in response to the battery's performance and energy-saving effects. Adjustments were made to the voltage threshold to optimize the charging and discharging of the battery system. The study found that the portion of regenerative energy fed back to the ESS decreases depending on ambient temperature, mainly due to the utilization of regenerative energy for heating or cooling auxiliary systems when temperatures are outside the 10-20 degree Celsius range [20].

Regarding energy savings, traction energy was reduced by 3% in summer and 6% in autumn, with a projected annual energy-saving effect of around 400MWh/year, considering weekends and major events. The paper notes that during rush hours, regenerated energy is directly utilized to power trains, resulting in less residual energy stored in the ESS. Conversely, during periods with fewer operated trains, the effect of the ESS diminishes, emphasizing the importance of specifying train frequency when selecting the appropriate substation for ESS installation [20].

2.3.6. Cost Relevance of HVAC in Hong Kong

The paper focuses on simulating the energy usage of Mechanical Ventilation and Air-Conditioning (MVAC) systems in train compartments, aiming to estimate the cost of electrical energy consumption associated with various ventilation rates and maintaining low CO_2 levels. They utilized the TRACE 600 software package to track the energy consumption data of MVAC system operation [21].

Parameters were analyzed for both stationary (SM) and normal traveling mode (NM). In the stationary mode, key parameters such as peak cooling load, annual heat gain, and electrical consumption were measured. Similarly, in the normal moving mode, these parameters were assessed to understand energy usage during typical train operation. One of the key variables studied was the Air Changes per Hour (ACH), which directly impacts ventilation rates. Adjusting this value influences electrical consumption, highlighting its significance in energy-efficient MVAC system operation [21].

While the paper highlights the technical details regarding MVAC systems and simulation methodologies, its findings could provide valuable insights into optimizing energy consumption and cost-effectiveness in train compartment ventilation and air conditioning. It is also understood that having business cases for both in-service and depot conditions may be beneficial. However, the technical complexity of the paper may require further assistance or clarification for practical application.

2.4. LCC Modelling

The development of a life cycle cost (LCC) model and analysis for railway switches and crossings involves several key elements and methodologies, as outlined for Sweden in the referenced article [22]. These methodologies can be adapted and implemented for a broader perspective, specifically for the technical upgrades of solutions addressed in this thesis work. Gaining this understanding is essential for the development of comprehensive cost models, which will act as a foundation for the decision-making algorithm proposed in this thesis.

By applying the LCC model methodologies to our context, we can evaluate the long-term cost implications of various energy-saving measures and technical upgrades in urban rail transport. This approach allows us to consider not only the initial investment costs but also the ongoing operational and maintenance expenses over the life cycle of the infrastructure and rolling stock. By doing so, we ensure that the decision-making algorithm is grounded in a thorough financial analysis, providing decision-makers with a clear understanding of the cost-effectiveness of different measures. According to IEC standards, a product's life cycle consists of six major phases, including concept and definition, design and development, manufacturing, installation, operation and maintenance, and disposal [22].

Different cost calculation methods can be used, such as the analogous cost method, parametric cost method, and engineering cost method, depending on the availability of historical data and the level of detail required for cost estimation. The model described in the articles includes three main phases: initial acquisition, operation and maintenance, and phase-out. Initial acquisition costs include investment material and installation costs, as well as worker costs. Operation and maintenance costs consider factors such as mean time between failure/maintenance (MTBF/MTBM), mean time to repair (MTTR), mean logistic delay time (MLDT), material and equipment costs, and consequences of failures [22].

In the phase-out stage, factors such as technical lifetime (TLT) and residual values of components replaced during restoration are considered. Sensitivity analyses and cost driver analyses are conducted to identify parameters that significantly influence LCC results and determine which parts of the system have the greatest impact on costs [22].

Overall, the paper provides a comprehensive framework for analyzing the life cycle costs of railway switches and crossings, offering insights into cost estimation methodologies and factors influencing LCC outcomes. Similar approaches could be applied to assess the LCC of other railway components or infrastructure solutions.

3. Decision-Making Methodology for Energy-Saving Measures

The naming of cost-benefit analysis reflects its fundamental role in guiding decision-making processes across various domains, from business and economics to public policy and project management. Therefore, the cost-benefit analysis can be described as a decision-making process. Upon revising the articles, the methodology for generating the decision-making tool is outlined in this chapter.

It has been identified that the selection of stakeholders is particularly important. For simplicity, TF and passengers have been identified as the primary stakeholders. Additionally, it has been determined through the literature reviews that modifications can primarily be categorized as either hardware installations, classified as technology-based solutions, or operation-based solutions. The main distinction between these two clusters lies in the cost, with technology-based solutions being more expensive compared to operation-based ones. Therefore, a review of the costs associated with the proposed measures was deemed necessary for decision-makers. This necessitates the generation of cost models for both technology-based and operation-based modifications. This approach allows decision-makers to utilize the models generated in this thesis for urban rail transport in general, as the perspective is broad and follows a system engineering approach.

3.1. Decision-Making Flow Chart

To equip decision-makers, particularly TF, with an efficient decision-making tool, it was crucial to identify foundational factors for assessing any proposed business case in the future. Upon the convergence of business cases from the literature review, business case clusters such as *Energy usage, Total Cost, Passenger Capacity, Socio-Economic aspects,* and *Interdependencies* with other systems were organized. However, to streamline the decision-making process, the primary factors were consolidated, with detailed factors and respective KPIs categorized under the *Cost, Benefit,* and *Others* clusters. Subsequently, iterative refinement of the chart has been created, informed by feedback from both KTH and TF stakeholders.

Essentially, a four-level system will be followed for decision-making model generation. At the highest level, the decision is made. To facilitate decision-making, three main clusters have been identified for a lower level: *Costs, Benefits,* and *Others*. Under these clusters, numerous factors are subcategorized. Lastly, at the lowest and most detailed level, the KPIs for respective factors are identified, for example, Initial acquisition, Operation cost, and Travel comfort. Through this hierarchical structure, decisions will be evaluated for each KPI. The tree schematic of the identified KPIs, factors, and clusters is visualized in Figure 5.

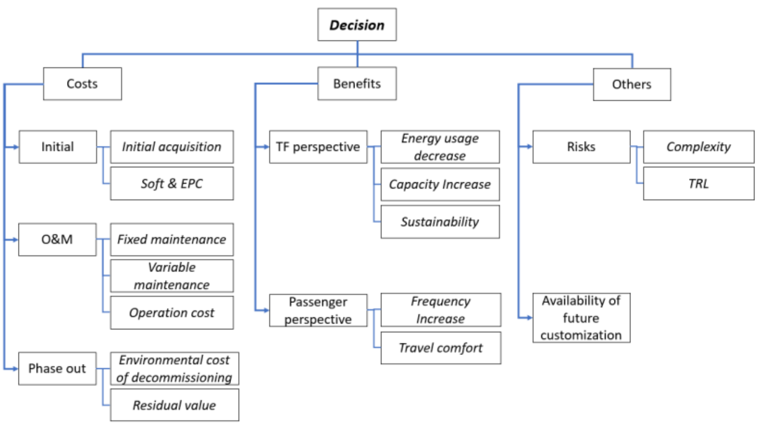

Figure 5: Factors and KPIs for the decision-making algorithm in tree branches

Drawing from this flowchart, a preliminary decision-making tool will be generated to evaluate business cases. The objective of this tool is to standardize the evaluation of each business case, thereby ensuring accuracy and minimizing bias in decision-making. The following sections will further detail the clusters and their respective KPIs.

For the evaluation process of the proposed business cases, the following Figure 6 will aim to serve as the primary methodology for decision-makers. Although it is a preliminary model, it would give the main decision-making steps. Detailed models need to be generated for each metric to better understand the dynamics of the business cases within the specified clusters and KPIs. This approach would aim to enable the comprehensive quantification of KPIs for each cluster, thereby enhancing accuracy in the decision-making process.

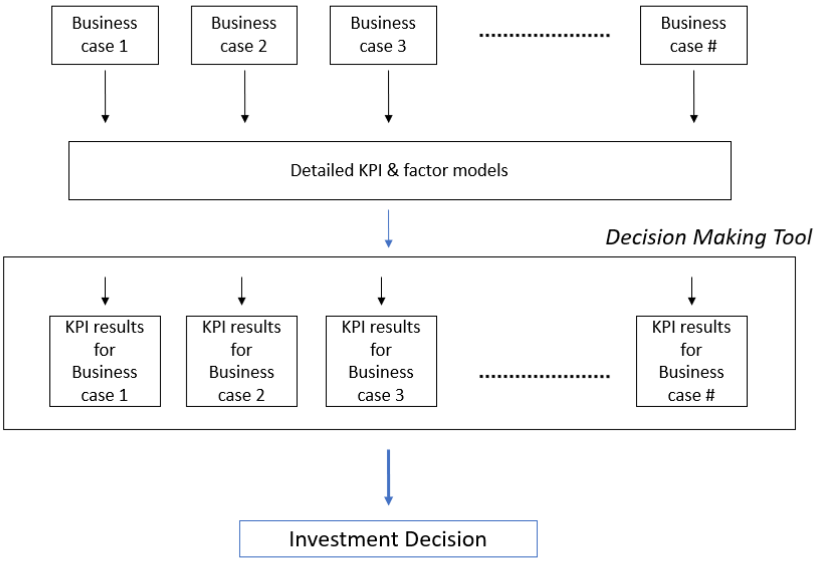

Figure 6: Workflow algorithm proposal for the decision-making

Regarding the decision-making process with stakeholders, data visualization serves as a powerful tool for making data more useful and comprehensible. By presenting data in visual formats, such as charts, graphs, and diagrams, it becomes easier to identify trends and patterns that might otherwise remain hidden within a large dataset in the tool. Moreover, data visualization not only facilitates quicker and more efficient analysis but also contributes to saving time and resources [23].

In alignment with this information, one of the primary objectives in constructing the decision-making model is to present the outputs visually to decision-makers. Given that the number of decision-making stakeholders in real-life scenarios is far more complex than in this thesis, it is crucial to have a visual representation of the KPI performance of the business cases for each decision-maker to understand. This visual representation helps in simplifying complex data and ensures that all stakeholders can quickly grasp the key insights and implications of the proposed measures.

Utilizing Radar Charts to visualize the output of the decision-making process is a practical choice, especially when dealing with numerous business case proposals. These charts provide a clear and concise way to compare multiple options across different KPIs, allowing decision-makers to quickly identify the strengths and weaknesses of each proposal. By applying weights to the KPIs and filtering out less significant factors, Radar Charts may become even more effective in highlighting key differences and guiding decision-making towards the most suitable business cases.

Firstly, they enable visual comparison of multiple variables across different categories, aiding in the identification of patterns and outliers within complex datasets. Secondly, they help pinpoint strengths and weaknesses, allowing decision-makers to allocate resources efficiently and plan strategies effectively. Moreover, radar charts assist in risk assessment by visualizing risks across dimensions, supporting the development of mitigation strategies. Furthermore, they serve as effective communication tools, simplifying the presentation of complex data for stakeholders. Therefore, the incorporation of Radar Charts was beneficial during model generation, and this consideration was upheld throughout the model development process.

3.1.1. Cost

The principal methodology for generating a cost model involves outlining the cost elements in general and identifying corresponding cost items within the LCC framework. This understanding serves as a general perspective and can be further detailed for each business case with necessary modifications. The process primarily included reviewing research papers, examining current applications, and analyzing relevant reports of different PTAs. This comprehensive approach ensures that the cost models are robust, adaptable, and reflective of both theoretical insights and practical considerations in urban rail transport.

To ensure a clear and structured decision-making flow chart, it is crucial to provide precise definitions within the LCC framework. Throughout the development of both general and detailed cost models, efforts were made to adhere to specific logic, as documented in the [24]. This process resulted in the identification of three main cost factors: Initial costs, O&M costs, and Phase-out costs. Firstly, during the development stage, acquisition and installation costs are evaluated. Secondly, during the operational phase, ongoing operational costs are assessed. Finally, during the phase-out stage, costs associated with asset retirement are examined.

The Net Present Value (NPV) calculation serves to standardize various cost aspects into present value, thereby facilitating a more informed decision-making process. This technique is commonly employed in the economics and finance departments of engineering firms, underscoring its significance for decision-makers [25]. The formulation for calculating NPV can formulated as

$$NPV = \sum_{t=0}^{n} \frac{R_t}{(1+i)^t} \qquad (1)$$

R_t represents the net cash flow during a single period " t ". The variable “i” denotes the discount rate, while “t” signifies the number of periods [25].

Once the cost items for the business cases are identified, utilizing the NPV method enables the leveling of costs, providing a comprehensive perspective for comparing different business case proposals. The NPV method calculates the present value of future cash flows, discounting them to reflect the time value of money. This approach is particularly beneficial for technology-based measures, as they often involve significant upfront hardware acquisition costs and ongoing operational expenses. With the utilization of the NPV method, the phase-out and the O&M costs can be levelized to the date that the acquisition of the hardware was made. By applying NPV, stakeholders can assess the long-term financial viability and cost-effectiveness of various proposals, ensuring informed decision-making that aligns with budget constraints and financial goals.

To calculate the total cost of ownership for a business case, it's important to have a general equation that integrates the three main cost elements: initial costs, operation, and maintenance (O&M) costs, and phase-out costs. The generalized total cost of ownership formulation for any business case can be formulated as

$$\text{Cost of total ownership} = \text{Initial costs} + \text{NPV(O\&M costs)} + \text{NPV(Phase out costs)} \quad (2)$$

For a comprehensive understanding of individual cost elements for general cost models, the following sections will provide in-depth explanations of terminologies and what should be included within them. This detailed exploration aims to clarify each cost component, enabling a more thorough analysis of the overall cost structure that can be generalized for both technology and operation-based cost models.

Initial Costs

Initial costs refer to the total expenses associated with acquiring an asset. This includes all expenditures attributed to the purchase and deployment of the asset or hardware. As described in [26], initial costs include various components such as the costs of purchasing the item and other accessories, hardware costs, soft costs (including industry education, licensing fees, and labor costs), as well as engineering, procurement, and construction (EPC) expenses [27].

Soft Costs refer to expenses associated with professional services, interim costs, financing fees, syndication costs, and developer's fees, as defined in [28]. These costs are distinct from operating or replacement reserves.

The term "EPC" stands for Engineering, Procurement, and Construction, as explained in [29]. Typically, EPC costs include licensing fees, labor, and construction costs, as well as expenses related to operator education. This education component addresses the requisite training for operators responsible for annual or periodic maintenance activities and the associated costs thereof.

O&M Costs

Operation and Maintenance (O&M) costs include two main components: fixed and variable costs. Fixed O&M costs include routine system maintenance, component replacement, and associated labor expenses, as explained in [30]. Conversely, variable O&M costs include expenses for upkeep such as inspection, spare parts, facilities, and insurance, as outlined in [30]. The variable maintenance costs do not apply each year and differ from product to product. Therefore, the frequency of the variable costs and the details of the inspections on these occasions have to be understood clearly before purchasing the product.

For energy recovery business cases, the energy saved, and the associated cost savings should indeed be accounted for within the O&M costs, but as a positive cash flow rather than an expense. Incorporating this factor allows for a more accurate assessment of the financial benefits of energy recovery business cases. The generalized cost formulation can be adjusted to reflect these savings.

Phase Out Costs

The phase-out phase involves various potential outcomes regarding the treatment of the asset post-operation and maintenance, as outlined in the case study from the Swedish railway network [24]. Firstly, if the technical lifespan of the asset permits, it can continue to be used for a specified period. Secondly, the asset may undergo refurbishment and relocation to a lower-frequency operation. Finally, if necessary, the asset may be decommissioned and disposed of entirely. These outcomes represent the various options available for managing assets at the end of their operational lifespan.

The environmental cost of decommissioning KPI includes expenses associated with dismantling and removing infrastructure or equipment at the end of its operational lifespan. This KPI is particularly relevant for hardware installation measures, which often require extensive decommissioning processes. This process involves considerations such as the proper disposal of hazardous materials, and restoration of impacted systems, aiming for responsible and sustainable management of infrastructure.

In addition, the residual value KPI includes assessing the unit's monetary worth at the end of its service life. Factors such as depreciation, wear and tear, technological deterioration, and market conditions are considered in this estimation. Furthermore, it should be noted that the proposed measures and units can potentially be repurposed for different or alternative applications that may require lower performance standards. This aspect can also be investigated within the framework of this KPI.

3.1.2. Benefits

Describing the benefits KPIs is fundamental as the business cases aim to propose benefits in return for the costs incurred by utilization of the business case proposals. Although stakeholders may have more detailed considerations within the scope of this thesis work, it has been concluded that there are two main stakeholder perspectives for evaluating the business cases. The first perspective is from the TF, or PTA in this context, while the second perspective relates to the passengers that would use the urban rail transport system of choice. This conclusion aligns with findings from a relevant paper, which identifies PTAs and passengers as important stakeholders to consider [31].

TF Perspective

The benefit KPIs that TF or any other PTAs generally consider revolve around several key factors, which have been explained in detail in the following paragraphs. These primary benefit KPIs include Energy Usage Decrease, Capacity Increase, and Sustainability.

Decreasing energy consumption not only reduces operational costs for the PTA and PTOs but also contributes to overall sustainability efforts. This reduction can be achieved through two main approaches. Firstly, decreasing energy consumption during operation translates as optimizing the efficiency of the urban rail transport system to minimize energy requirements while maintaining operational effectiveness. Secondly, energy recovery involves the capture and utilization of potential energy, such as ESS that recovers energy during braking and feeds it back into the third rail or grid infrastructure, thereby reducing overall energy demand. Evaluating the potential for energy usage reduction within various business cases is crucial for quality decision-making and the development of sustainable transportation solutions.

The projected increase in passenger demand for the Stockholm metro infrastructure highlights the importance of further increasing the operational passenger transport capacity of the metro infrastructure [32]. Ensuring the urban rail transport system can effectively handle the expected increase in passenger demand or adapt to future changes is vital. This ensures the system remains responsive and capable of meeting evolving transportation needs over time. By enhancing the operation passenger capacity of urban rail transport, the system can effectively meet the growing transportation needs of the region, aligning with long-term infrastructure planning objectives. Therefore, taking into account the capacity increase is a fundamental KPI to be evaluated.

Given Stockholm's commitment to sustainability, further supported by its transition to fully electric metro infrastructure by 2017 and its aspiration to serve as a model for other cities [33], sustainability serves as a pivotal KPI in evaluating business cases. This KPI typically revolves around assessing the material or energy consumption associated with proposed business cases, reflecting the TF's dedication to environmentally conscious practices.

Passengers' Perspective

As urban rail transport systems are predominantly utilized by passengers throughout the year, any technological or operational changes resulting from business cases will directly impact them [31]. Therefore, including the perspective of passengers as key KPIs for evaluating business cases is particularly important. Passenger-centric KPIs ensure that the implemented measures align with the needs and expectations of those who rely on the system daily. This approach not only enhances the overall user experience but also supports the system's sustainability and efficiency.

The KPI of frequency increase is closely correlated with the *Capacity Increase* KPIs perspective from the TF standpoint. However, a key differentiating factor may lie in passengers' perceptions. Rather than focusing on the specific passenger capacity of trains, passengers typically gauge train performance based on the frequency of train arrivals at platforms. Consequently, evaluating train frequency increases may be good to include when assessing business cases, as it directly impacts passenger experience and satisfaction.

Given that passenger travel comfort significantly influences the commuting experience, it is essential to prioritize the evaluation of business cases and their impact on travel comfort. Following standards for passenger comfort would be beneficial for decision-makers to evaluate business cases on a quantifiable level. By considering passenger comfort as a crucial aspect, stakeholders can make informed decisions that enhance overall passenger satisfaction and contribute to a positive commuting environment.

3.1.3. Others

The "Others" factor aims to emphasize the customization and associated risks of the proposed business cases. It includes the unique nature of the business cases, considering factors beyond technical details alone. This category acknowledges the specific characteristics and potential challenges inherent in each business case, providing a broader perspective for decision-making and risk assessment.

Risks

The complexity KPI evaluates and emphasizes the degree to which a business case can be seamlessly integrated into the current configuration of the urban rail transport system. It considers various factors, including technical compatibility, legal compliance, installation requirements, operational considerations, and operator expertise, to assess the level of complexity associated with implementing the new business case. The value for this KPI can be given from a value range.

The Technology Readiness Level KPI evaluates the readiness level of the technology proposed within the business case. It assesses the extent to which the technology has been developed, tested, and proven for implementation within the current layout of the urban rail transport system. The higher the practicality of installation and availability of the system, the more "proven" the business case is in real-life scenarios.

This assessment shall involve examining the availability of the proposed business case on the market by reviewing its current applications in other cities. It considers factors such as the technology's demonstrated performance, reliability, and scalability in operational environments. By evaluating the TRL of the proposed technology, stakeholders can gauge the level of risk associated with its implementation and make informed decisions regarding its feasibility and potential impact on the urban rail transport system.

Availability of Future Customization

Incorporating the KPI assessing the availability of the business case to future customizations is crucial in the decision-making process for urban rail transport systems. As these systems are continually evolving, it is essential to evaluate the flexibility and scalability of the chosen business case to accommodate new requirements from PTAs in the future.

This KPI assesses the extent to which the proposed business case can be modified or expanded upon to meet evolving needs and emerging technologies in the urban rail transport sector. It considers factors such as the modularity of the solution, compatibility with future upgrades, and the ease of integration with new technologies or infrastructure.

By evaluating the adaptability of the business case, stakeholders can ensure that investments made today will remain relevant and effective in the face of changing operational, regulatory, and technological landscapes. This proactive approach to decision-making enables PTAs to future-proof their urban rail transport systems and maximize the long-term value of their investments.

It's important to note that while the KPIs mentioned above provide an initial foundation, further detailing could enhance the realism of the decision-making algorithm. However, given the constraints of the allocated timeframe and the ongoing discussions with TF and KTH, the current KPI scope outlined in this thesis was assumed. This decision was made to ensure the completion of the thesis within the given parameters while still addressing key aspects of the decision-making process for urban rail transport systems.

4. Developed Decision-Making Model:

To comprehensively assess various business cases to be proposed, a decision-making tool with a broad perspective is essential. As discussed earlier, the primary approach involves evaluating these cases within a single interface, comparing them based on suitable KPIs identified for urban rail transport systems. Consequently, a tool has been developed in this thesis to assist decision-makers in evaluating different business cases clearly and graphically. It should be noted that the current state of the tool is preliminary and will serve as a foundation for further development towards actual usage capability. Therefore, the model should be regarded as a preliminary iteration.

The tool that has been generated is in Excel format and named "*Decision Making Tool*". This serves as the primary tool for the decision-making process, comprising detailed spreadsheets with various sections for comprehensive evaluation. Each spreadsheet within the tool provides additional insights and details pertinent to the decision-making process, ensuring a thorough analysis of the different business cases. In this section, the spreadsheets, and the tool itself will be explained in depth, providing a detailed explanation of their components and functionalities.

4.1.1. Clusters & Factors & KPIs

The first spreadsheet, titled *Clusters & Factors & KPIs*, serves as the foundation for the decision-making process. The KPIs listed in this spreadsheet are those that are explained in the tree branches previously. The visualization of the list can be found in Figure 7.

List of clusters
Costs
Benefits
Others

	Weight level
Most important	5
Least important	1

Clusters	*Factors*	*KPIs*	*Weight of KPIs*	*Comments*
Costs	*Initial costs*	Initial acquisition		
		Soft&EPC		
	O&M costs	Fixed maintenance costs		
		Variale maintenance costs		
		Operation costs		
	Phase out costs	Environmental cost of decommissioning		
		Residual Value		
Benefits	*TF perspective*	Energy usage decrease		
		Capacity increase		
		Sustainability		
	Passenger perspective	Frequency increase		
		Travel comfort		
Others	*Risks*	Complexity		
		TRL		
	Availability of future customization	Availability of future customization		

Figure 7: List of KPIs in the decision-making Excel tool

The evaluation of business cases for urban rail transport infrastructure projects can be a complex and multifaceted process, often requiring decision-makers to consider a diverse set of KPIs to ensure the optimal allocation of resources and the achievement of project objectives. To enhance the accuracy and effectiveness of this evaluation process, it is important to consider the inclusion of weights for the KPIs. Including weights for KPIs is crucial as it allows decision-makers to prioritize the most critical success factors for metro infrastructure projects. By assigning weights to different KPIs, it becomes possible to reflect their relative importance in the overall evaluation process. This not only helps in aligning the evaluation with the strategic objectives of the project but also ensures that the most impactful KPIs are given appropriate consideration during the decision-making process.

Introducing weighted KPIs in the evaluation process can lead to several benefits. It provides a structured and transparent approach to decision-making, aligns the evaluation with the project's strategic goals, and enables more accurate comparisons between alternative investment options [34]. Moreover, it can also facilitate a deeper understanding of the trade-offs involved in project decision-making, ultimately leading to improved resource allocation and project outcomes.

The methodology for assigning weights to KPIs should be carefully designed to capture the preferences and requirements of stakeholders. One approach could involve conducting meetings or surveys with relevant stakeholders to understand their perspectives on the significance of different KPIs. Additionally, a thorough analysis of historical project data and industry best practices can provide valuable insights into the relative importance of various KPIs. Based on the input from KTH and TF, adjustments can be made to the weight scale to accurately reflect their preferences. This might involve assigning higher weights (closer to 5) to KPIs that are deemed most critical or impactful, and lower weights (closer to 1) to those considered less significant. It's important to note that the weight range can be adjusted accordingly depending on the desired accuracy of KPIs. A broader range would translate into a more precise decision compared to a smaller range, allowing for finer distinctions between different business cases.

In the scope of this thesis, the weights are not proposed to be a multiplication factor, as the real implementation of business cases is more complex. Utilizing weights as a KPI filter rather than as a multiplication factor is an innovative approach that could streamline the decision-making process. By assigning higher weights to critical KPIs, decision-makers can effectively prioritize key factors without the need to individually assess every KPI. This approach acts as a highlighting factor, emphasizing the most important aspects of each project and facilitating more efficient evaluations.

Moreover, concerning the KPIs that are challenging to quantify with a precise model, values from a range of numbers can be assigned. In the proposed model, relevant KPIs can be identified as Sustainability, Complexity, TRL, and Availability of Future Customization. One approach is to populate the relevant cells of these KPIs for the business cases by assigning numbers between 1 and 5, with 5 indicating the highest. For Sustainability, TRL, and Availability of Future Customization, higher numbers would denote positive attributes, while a higher number for Complexity would indicate a negative aspect for the business case of interest.

4.1.2. Decision Matrix

The second spreadsheet, titled *Decision Matrix*, functions as the primary decision-making tool, integrating the KPIs with their respective business cases within a single table. This format was chosen to facilitate a comprehensive overview of all factors at once, minimizing potential biases that may arise during the decision-making process. The spreadsheet can be found in Appendix A. Ideally, users can input relevant quantities for each business case directly into the designated cells, with units specified for clarity and consistency. By offering a centralized platform for evaluating different options, the tool enhances efficiency and promotes informed decision-making based on quantitative analysis.

Following feedback from TF, two additional parameters, namely the NPV of total cost and the cost per kWh, have been incorporated into the spreadsheet. While not the main KPIs, these parameters are valuable additions to the decision-making process, tailored to the TF's decision-making tradition. The NPV of total cost provides insights into the long-term financial implications of each business case, aiding decision-makers in assessing the overall cost-effectiveness. On the other hand, the cost per kWh offers a measure of the energy efficiency of each solution, helping decision-makers to compare the energy-saving potential across different scenarios. By including these parameters, the decision-making process becomes more comprehensive and robust, enabling a more informed evaluation of the proposed solutions.

The evaluation process is as follows. All of the business cases will be listed under the *Business Cases* column in the Excel file. After that, the weights assigned for each KPI will be inserted into the *Weights of KPIs* row. Following the selection process of the business cases, efforts will be made to fill the cells corresponding to each KPI for the relevant business case. This data will be sourced from various channels, including the models generated in this thesis, technical specifications provided by suppliers, and feedback from relevant departments within TF. The aim is to gather comprehensive and accurate information to enable a thorough evaluation of each business case across multiple dimensions. As the decision-making tool is comprehensive and designed to provide a single interface for a facilitated decision-making process, not every business case may have a relevant KPI value. In such cases, the relevant cell shall be filled with "*NA*" (Not Applicable) to indicate that the business case is not relevant to the corresponding KPI.

As the units are determined for each KPI, data gathering shall be conducted according to the specified units. This ensures consistency and accuracy in the evaluation process, allowing for meaningful comparisons between different business cases. By adhering to the designated units, decision-makers can effectively assess the performance of each solution and make informed decisions based on reliable data.

Once all steps have been completed, the next step involves the selection process, where decision-makers will carefully evaluate each business case based on predetermined criteria and priorities. Ultimately, the goal is to identify the most suitable business case or combination of business cases that best meet the needs and objectives of the PTA.

One option that is proposed in this thesis is to determine the best business case for each KPI. To determine the best business case for each KPI, the Excel function XLOOKUP has been utilized. Specifically, for the costs cluster, XLOOKUP identifies the lowest value since lower values for cost KPIs indicate lower costs. Conversely, for the energy and frequency KPIs under benefits, XLOOKUP seeks the highest values retrieves the corresponding business case name from the table and lists it in the row of *"Best individual"*. This approach ensures that decision-makers can easily identify the most optimal business case based on the specific criteria being evaluated.

Upon selecting the optimal individual business cases for each KPI, the assigned weights can be utilized to prioritize the business cases for further consideration. The utilization of weights serves as a filtering mechanism, aligning with the decision maker's perspective as previously discussed, and facilitates the streamlining of the pool of business cases for in-depth evaluation.

As the number of business cases selected for investigation decreases due to the weighting of the KPIs, Radar Charts would serve as a valuable tool for visually comparing the most promising business cases. The utilization of Radar Charts can involve keeping the KPI constant and evaluating different business cases solely for that KPI or comparing business cases across a set of KPIs within the same figure. The choice of visualization is contingent upon the decision makers' preferences, in alignment with their corporation selection process.

5. Models for Individual Business Cases:

As the decision-making tool is developed, as outlined in the procedure for filling cells to acquire relevant quantity values for KPIs, understanding the methodology for quantity calculation would be advantageous. As outlined in the literature review, the primary categories of solutions branch into technology and operation-based business cases. Therefore, it has been concluded to select representative business cases to simulate cost calculation models and explain them in the following sections.

The convergence of the solutions mainly revolves around the installation of ESS and the HVAC modifications from literature reviews. Having these 2 main solutions is particularly valuable as they are solutions classified as technology and operation respectively. The cost models for both that would be created in this thesis would be particularly important to have as these models would be a primary tool for any future business cases that could be implemented either in technology or operation-based clusters. Depending on the type of future modifications, the tools that would be created in this thesis would be for further detailing on them as the ESS tool would be more detailed for a technology-based modification whereas the HVAC tool would be more towards the operation-based measures.

The choice to focus on ESS installation originates from its clear requirement for hardware implementation, representing a substantial technological upgrade. This aligns with the goal of enhancing system efficiency through tangible infrastructure improvements. Conversely, HVAC modifications were selected as they present a flexible operational solution that may or may not necessitate hardware changes, depending on the specific business case proposal. This flexibility allows for a potentially lower-cost, quicker-to-implement solution compared to the more extensive requirements of ESS installations.

By generating cost models for these two areas, the project ensures a comprehensive approach to improving urban rail energy efficiency, covering both immediate operational adjustments and longer-term technological investments. This dual focus enables a balanced assessment of cost, feasibility, and energy-saving potential, facilitating informed decision-making for future implementations.

For the practical representation of individual cost models, the C30 train was selected as the vehicle of choice. Hence, the ensuing calculations and generated models are based on the information and system architecture for the C30 obtained from TF and MTR. To grasp the scope of parameters to be included in the cost models, access to the energy flow chart of the C30 trains was necessary. TF provided the following energy flow chart, which illustrates the energy supply to the train from the third rail. Certain energy parameters are bidirectional, returning a portion of the energy into the grid via the third rail as regenerated energy. The parameters and the energy flow chart are illustrated in Figure 8. By investigating the parameters available, the individual cost models for ESS and HVAC are generated.

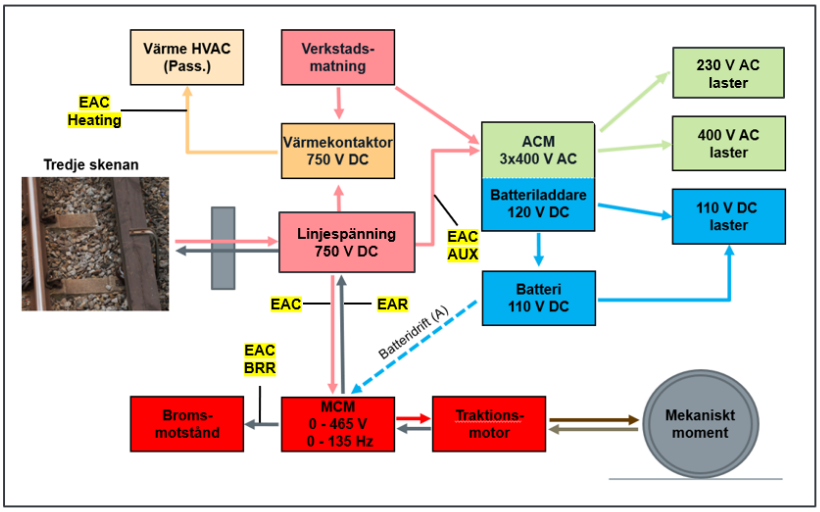

Figure 8: Energy flow chart of C30Figure X: Energy flow chart of C30 [35]

As the energy flow chart illustrates how the energy from the third rail is distributed within the C30 train, it is particularly beneficial to understand the parameters to identify relevant data readings from the accumulated database for C30 trains [33]. The total energy requirement of the C30 is formulated as

$$\text{EAC Tot} = \text{EAC} - \text{EAR} + \text{EAC Heating} + \text{EACAUX} \quad (3)$$

The primary tool for monitoring the energy flow charts of the C30 is the Tableau Reader software that is currently utilized in TF. This software enables the tracking of line ID, vehicle, driver, and date, as well as the energy parameter readings over time, etc. Through this software, parameters and their units are suitable for investigation, enabling the formation of cost and cost-benefit models for specific business cases in the future.

5.1. Model for HVAC Modifications for In-Service / Depot Mode

The main options for the HVAC modifications could be classified under 2 main categories. The first one is changing the interior set-point temperature, and the second one is changing the ventilation flow rate. As they are the 2 main parameters that affect energy usage, a simulation tool must be generated to evaluate these modifications and their energy consumption changes for different values. As a direct output, different energy consumption values would output different costs for each configuration.

The main output of the energy usage and the respective cost for this modification incorporates 2 main tools. The first tool is called *"HVAC Energy Demand Calculator"* which has been developed by Sidharth Kapoor, Zhendong Liu, and Mats Berg based on the master's thesis of Erik Vinberg [36]. It is a combination of Excel and MATLAB. The code can be found in Appendix B. This simulation tool can be used for any rolling stock vehicle, in our case it is C30 once the respective vehicle parameters are supplied inside of the model. Following discussions with Vinberg and incorporating his feedback, the tool's reliability was confirmed, further supported by its ownership by SL as currently in use by them. The main output of this model is the electrical power consumption at that configuration of parameters.

The second tool, titled "HVAC Annual Energy Model," has been developed in this thesis work using Excel. It inputs the power consumption values from the HVAC Energy Demand Calculator tool and other parameters from the respective data sources explained previously. The main outputs of this tool are the annual energy consumption and the respective operating cost of the proposed configuration for interior set-point temperature and ventilation flow rate. The working principles of these tools will be explained in the following section.

It was decided in this thesis to divide the operation period into in-service and depot conditions, which are the two main operational states for an urban rail transport system. The generated models for in-service and depot conditions can be found inside the HVAC Annual Energy Model Excel file in the spreadsheets named after "In-Service operation" and "Depot operation" respectively.

The sections begin with an explanation of the user interfaces of the HVAC Annual Energy Models for both in-service and depot conditions. These interfaces are crucial for demonstrating how an operation-based solution would look for the cost model. The sections then continue with a detailed explanation of the parameters used in these models, along with the data flow algorithms and sources for them.

5.1.1. Data Flow Scheme into the In-Service Model

This chapter will explain the user interface of the In-Service operation inside the *HVAC Annual Energy Model* tool developed in this work. Each column in the interface represents a parameter, and this chapter will provide explanations for each parameter along with their respective data sources. The user interface of the tool can be found in Appendix C. The data flow logic for parameters is listed below.

- *Operation hours [hours]:* Operation hours were determined after examining passenger occupancy rates for February 2019. However, data for different months and years is likely available in the TF servers.

- *Outdoor temperature [Celsius]:* Outdoor temperature data was collected from the SMHI database spanning from 2019 to 2023, covering a total of 5 years. The data was sampled at a rate of 1 hour. The data was acquired from the Stockholm-Observatoriekullen A station, identified by station number 98230.

- Optimum Indoor temperature *[Celsius]:* This will be based on the selection of the indoor set-point temperatures by referencing the upper and lower limits of EN14750:1-2006.

- *Number of passengers [passenger number]:* The number of passengers is calculated by multiplying the Passenger Occupancy Rates by the passenger capacity of the C30, either in its 140-meter or 70-meter configuration. As operations are primarily conducted in the 140-meter configuration, this capacity is predominantly used. Passenger Occupancy Rates are available in the TF servers for each month, per station, and for lines of the C30 metro. The data sampling rate was every 15 minutes, as per the available data. Unfortunately, the limited time of the project prevented me from accessing more.

- *Ventilation flow rate [m^3/h/person]:* The ventilation flow rate is primarily determined by the number of passengers inside the train at any given moment. The allowable range for ventilation flow rates is described in the EN14750 standard.

- *PMV value:* The PMV serves as the primary quantification tool for assessing the socio-economic benefits of HVAC alterations. The detailed function of the calculation is outlined in ISO 7730. It's important to note that the allowable limit for the PMV must be determined by the TF. Typically, the range set by PTAs is between ±1.

- *The power required [kW]:* The power required is primarily calculated using the model *HVAC Energy Demand Calculator*. Depending on the outdoor and indoor temperature settings, this model provides output in kW, corresponding to the power usage at that instant. This power may be for heating or cooling purposes.

- *Annual hours worked [hours]:* The annual hours worked represent the total number of hours elapsed in the specified month and period. Each data point in these cells pertains to the specified time only. For example, the data structure would indicate how many hours the C30 operated on the specified line during January between the period of 05:00 and 07:00. This data is available in the TF database.

- *Annual energy consumed per timeframe [kWh]:* The annual energy consumed per timeframe is calculated by multiplying the annual hours worked by the power requirement for the selected timeframe of the specified month only.

- *Annual energy consumed [kWh]:* The annual energy consumed is determined by integrating the annual energy consumed per time frame.

- *Unit cost of electricity [SEK/kWh]:* The unit cost of electricity is the agreed-upon cost of electricity as specified in the contract between TF and the electric provider company.

- *Annual total cost [SEK]:* The annual total cost is calculated by multiplying the annual energy consumed by the unit cost of electricity. This calculation directly yields the annual cost of the proposed measures for the interior setpoint temperature and ventilation flow rate. Therefore, it serves as a fundamental tool for evaluating the energy and cost implications of the business cases. While PMV may not be directly correlated with the cost at present, further studies could explore incorporating PMV values into the annual total cost by monetizing them.

5.1.2. Data Flow Scheme into the Depot Model

This chapter will explain the user interface of the Depot operation inside the *HVAC Annual Energy Model* tool developed in this work. Each column in the interface represents a parameter, and this chapter will provide explanations for each parameter along with their respective data sources. The user interface of the tool can be found in Appendix D. The data flow logic for parameters is listed below.

- *Operation hours [hours]:* Operation hours were established according to the depot time regimes set by the TF. Initial investigations revealed that operations typically occur between 1-5 am on weekdays, indicating that operations are not conducted round the clock. However, further refinement of this data may be necessary for accuracy and specificity.

- Outdoor temperature [Celsius]: There may be 2 main data sources for this aspect. One is the outdoor temperature data collected from the SMHI database spanning from 2019 to 2023, covering a total of 5 years. The data was sampled at a rate of 1 hour. The data was acquired from the Stockholm-Observatoriekullen A station, identified by station number 98230. The other option is the ambient temperature of the depot area, which was not in the scope of the project.

- Optimum Indoor temperature *[Celsius]:* This parameter can be standardized by identifying a suitable industry standard or by examining the current temperature conditions within the depot. The selection of such a standard was not in the scope of the project.

- Ventilation flow rate [m^3/h/person]: This can be either predetermined or standardized by identifying an appropriate industry standard. Alternatively, it can be determined by assessing the current ventilation conditions within the depot. Further investigation has to be made for exact details.

- *The power required [kW]:* The power required is primarily calculated using the model *Energy Demand Calculator*. Depending on the outdoor and indoor temperature settings, this model provides output in kW, corresponding to the power usage at that instant. This power may be for heating or cooling purposes.

- *Annual hour worked [hours]:* The annual hours worked represent the total number of hours elapsed in the specified month and period. Each data point in these cells pertains to the specified time only. This data is available in the TF database.

- *Annual energy consumed per timeframe [kWh]:* The annual energy consumed per timeframe is calculated by multiplying the annual hours worked by the power requirement for the selected timeframe of the specified month only.

- *Annual energy consumed [kWh]:* The annual energy consumed is determined by integrating the annual energy consumed per time frame.

- *Unit cost of electricity [SEK/kWh]:* The unit cost of electricity is the agreed-upon cost of electricity as specified in the contract between TF and the electric provider company.

- *Annual total cost [SEK]:* The annual total cost is calculated by multiplying the annual energy consumed by the unit cost of electricity. This calculation directly yields the annual cost of the proposed measures for the interior setpoint temperature and ventilation flow rate. Therefore, it serves as a fundamental tool for evaluating the energy and cost implications of the business cases.

5.1.3. Parameter Details

Passenger Occupancy

Passenger occupancy plays a crucial role in evaluating HVAC modifications and identifying rush hour periods. The planning norm guides on achieving reasonable levels of space comfort, considering factors such as passenger comfort, dwell times at stations, demand variations, and disturbances. Data on passenger occupancy rates at each station can be monitored using Tableau Reader software from TF, representing the total number of passengers inside the train upon departure from each station. However, it should be noted that this data is unavailable for stations located on the outskirts of the city, leading to gaps in passenger number representation.

Unfortunately, direct data on passenger numbers is unavailable. Therefore, it is necessary to combine C30 technical specifications with passenger occupancy rates to derive passenger numbers for insertion into the model. The passenger capacity information for the C30 can be found in the TF database [32]. Notably, operations primarily utilize the 140-meter configuration, which consists of two coupled trains. Thus, it is reasonable to assume the respective numbers for the 140-meter configuration for further measurement applications. The understanding of occupancy rates is formulated as

$$Total\ passenger\ inside = \begin{cases} Rate \cdot Number\ of\ seats, & Rate \leq 100\% \\ Number\ of\ seats + (Rate - 100) \cdot Number\ of\ seats, & Rate > 100\% \end{cases} \quad (4)$$

To illustrate, if the passenger occupancy rate is 130% and the vehicle is a C30 140-meter train, the total number of passengers in the train at that instance is calculated as

$$Total\ passanger\ inside\ the\ train\ =\ 300 + 30\% \cdot 300 = 390 \quad (5)$$

Addressing the issue of varying passenger numbers across stations, one approach is to assume an average number per hour based on station data and apply this across the operational section. While this approach may introduce generalization, further detailing can be achieved by dividing the operational line into sections based on passenger occupancy rates and assuming different passenger numbers for each section. This can be accomplished in the future by the inclusion of a three-stage clustering of stations, categorizing them as outskirts, moderate, or highly congested, and assigning different hourly passenger numbers accordingly.

Explanation of Time Framing

It should be noted that the time frame divisions are currently made for weekday operations only, where the operation does not continue for 24 hours. However, extending these divisions to include weekend operation conditions, thus covering all days throughout the year, is feasible. To accomplish this, additional data would need to be supplied from TF, and the respective time frames would be extended accordingly in the model.

Upon analyzing the trend of passenger occupancy rate distribution, it has been observed that the morning rush hour spans from 07:00 to 09:00, while the evening rush hour occurs between 16:00 and 17:00 on weekdays. Notably, the morning rush hours experience a more pronounced increase in volume and occupancy rates exceeding 100% within a shorter duration compared to the evening rush hours. Conversely, the evening rush hours exhibit a more even distribution over the period and are less congested compared to the morning passenger occupancy rates.

Currently, complete data is available for Line 14, traveling from North to South, encompassing stations between Midsommarkransen and Danderyds Sjukhus. However, the available data is limited to February 2019 and can be found in Appendix E. Nevertheless, monthly data for 2019 is accessible in the TF database, enabling the proposal of monthly and hourly HVAC modifications during service periods in the future. The respective data can be found in the "February 2019 Passenger Occupancy Rates Line 14 N-S.xlsx".

Outdoor Temperature

To generate a model for HVAC modifications, outdoor temperature data from a reliable source is required. Consequently, access to the database of SMHI was utilized to obtain this data. As the C30 metro line for Stockholm primarily commutes in the central Stockholm area, a central location for data gathering was deemed necessary. The SMHI data spanning from January 1, 2019, 00:00:00 (UTC) to December 31, 2023, 23:00:00 (UTC) was examined. The data resolution for these five years was 1 hour, with instantaneous values recorded once per hour. The data was acquired from the Stockholm-Observatoriekullen A station, identified by station number 98230. The observation point's GPS coordinates are Latitude (decimal degrees): 59.3417, Longitude (decimal degrees): 18.0549, Altitude (meters above sea level): 43.133, with a measuring height of 2 meters above the ground. The temperature data is measured in degrees Celsius [37].

Quality control measures were implemented, with each hourly data point labeled as either Green (G) for checked and approved values or Yellow (Y) for suspicious or aggregated values. Only three data points were labeled as Y. To address this, an estimation and correction technique, rewriting the data as the average temperature of the hour before and the hour after having applied. This approach linearized the data between these two hours, ensuring confidence in 43,823 data points over the five-year interval.

Since the suggested business case for HVAC modifications is time-dependent, obtaining average outdoor temperatures for specific time intervals was imperative. As such, the following timeframes were proposed: 00:00-09:00, 09:00-19:00, and 19:00-00:00. The methodology employed is as follows: initially, daily average temperatures were calculated, followed by the determination of average temperatures for the proposed 3 time periods daily over the five years. Subsequently, monthly temperature values were computed, along with the monthly averages for the specified timeframes, utilizing the Average function in Excel. The findings of this operation are presented in Appendix F.

Based on the results, it is reasonable to suggest that the temperatures between the 00:00-09:00 and 19:00-00:00 periods exhibit similar trends and can be assumed to follow the same pattern throughout the year for the sake of simplicity. The maximum absolute temperature difference occurring after applying this assumption appears to be around 1 degree Celsius on average between February and April. Nonetheless, for the sake of simplicity, assuming the temperature distribution to be consistent for both timeframes throughout the year remains logical. The collected data can be found in the “Temperature layout” spreadsheet inside the *HVAC Annual Energy Model* Excel file.

EN14750:1–2006 Standard

As HVAC modifications for rolling stocks are standardized globally, adherence to these standards is crucial when proposing business cases. Compliance ensures not only adherence to industry regulations but also enhances passenger comfort within the C30. In the revision of previous theses [38], it has been found that EN14750:1-2006 would be a suitable standard to proceed with, as it is widely used in rolling stock vehicles. This information is primarily required for the calculation of energy consumption for HVAC modifications.

Upon investigating the standard, several key points have been identified. Firstly, the categorization of rolling stock reveals that the C30 falls under category B according to the table specifications provided. Additionally, the standard specifies the location of operation, with Sweden identified as Zone III for both winter and summer periods. It's important to note that zoning resolution is at the country level, and no further detail specific to Stockholm has been identified.

EN14750:1-2006 Standard for Indoor Temperature

According to the EN14750:1-2006 standard, the desired setpoint indoor temperature for the C30 falls within the range of 18 to 22 degrees Celsius when the outside temperature is up to 10 degrees Celsius [39]. Therefore, any indoor set-point temperature has to be made in the future in compliance with this standard.

To have a better understanding of the upper and lower limits of the standard, it has been calculated to generate the data set manually in Excel from the standard information. The main methodology that has been followed is to look at the breakpoints for upper and lower limits and assume they are linear over the span and fit a straight line. This relation can be found in Figure 9.

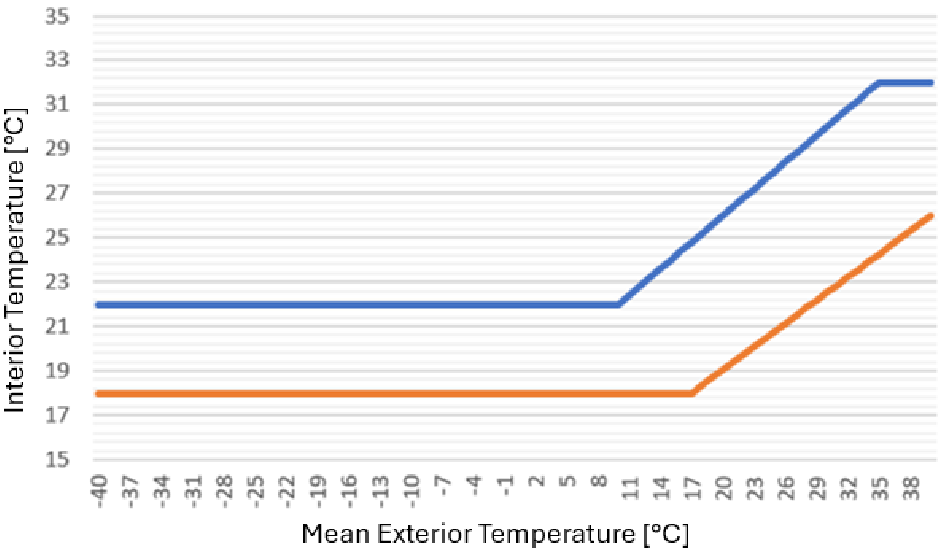

Figure 9: EN14750:1-2006 standard for temperature [39]

From the data interpolation, functions representing the upper and lower limits have been obtained [39]. The functions for obtaining the interior set-point temperature for the upper and lower limits can be found as

$$T_{ic} = \begin{cases} 18, & T_{em} < 10 \\ 0{,}4 \cdot T_{em} + 18, & T_{em} > x \geq 10 \end{cases} \quad (6)$$

$$T_{ic} = \begin{cases} 22, & T_{em} < 17 \\ 0.3478 \cdot T_{em} + 12.09, & 40 > T_{em} \geq 17 \end{cases} \quad (7)$$

Considering the acknowledged limitations and the general understanding of the system, it is imperative to propose optimum interior set-point temperatures for both specific timeframes and months. It would be advantageous to suggest multiple temperature settings for evaluation purposes, aiming to determine which temperature yields the lowest energy usage while maintaining reasonable PMV values. This approach allows for comprehensive assessment and optimization of indoor comfort conditions while minimizing energy consumption. For future iterations, these operations shall be refined for accurate detailing of temperature adjustment suggestions.

EN14750:1-2006 standard for ventilation flow rate

Another aspect contributing to energy consumption is the ventilation of the HVAC system, which also plays a fundamental role in passenger comfort. Therefore, ventilation flow rates have been standardized under EN14750:1-2006.

The current ventilation practice implemented in the C30 by the MTR maintains a constant flow rate of 10 m^3/h/person throughout the year and hours, without adjusting ventilation rates based on passenger occupancy levels. This approach is primarily due to limitations in the existing infrastructure of the HVAC, which cannot modify ventilation flow rates and implement proposed flow rates in the future.

Since the C30 falls under category B, it is worth exploring ventilation flow rates ranging from 8 to 12 m^3/h/person [40]. To enhance the accuracy of energy usage projections, it would be advantageous to adjust ventilation flow rates throughout the day based on passenger occupancy levels. Some of the business cases considering that aspect will be explained in the following chapters qualitatively. The basic logic is that for periods with fewer passengers, the ventilation flow rate can be decreased, whereas, for high passenger numbers during rush hours, higher ventilation flow rates can be implemented. With this logic, unnecessarily high ventilation flow rates would be eliminated during normal passenger occupancy rates, thus decreasing energy consumption.

Furthermore, for a more detailed analysis, it is recommended to propose customized monthly ventilation flow rates for different hours of the day, similar to the approach suggested for temperature adjustments. In future work, conducting quantitative simulations is needed for accuracy.

Comfort of passengers (PMV)

Ensuring passenger satisfaction inside the train throughout the journey is particularly important when evaluating the socio-economic benefits of proposed business cases. Therefore, following a standardized comfort parameter for the rolling stock vehicles is crucial.

A quantifying standard for passenger thermal comfort in rolling track applications has been identified. The PMV method, which predicts the thermal sensation votes of a large group of people on a 7-point scale, is utilized to describe thermal comfort. The range of comfort quantification is between ±3 [40]. The formulations described in the article serve mainly as the quantification tool for this socio-economic behavior. The output of the formulations mainly provides the PMV value within the range. The formulation is primarily derived empirically according to ISO 7730 as stated in the same article.

The PMV equation allows for iterative calculation for different combinations of clothing, air temperature, airspeed, relative humidity, and radiant temperature. The parameters of air temperature, airspeed, and relative humidity (defined by the corresponding partial pressure of water vapor) can be inserted into the equation directly as measurement values or as standard requirements. Additional considerations, however, must be addressed for local radiant temperature.

It is common for some rail operators or PTAs to aim for a PMV scale ranging from -1 to +1 [40]. However, if TF intends to deviate from this span, consideration should be given to what is permissible or not.

The utilization of PMV is particularly beneficial for quantifying the effects of various indoor set-point temperatures and ventilation flow rates. PMV provides detailed, quantifiable outputs for different seasons and months, offering a powerful tool for comprehending the impacts of modifications on the HVAC system and its relation to socio-economic benefits. This analytical approach enhances understanding of how HVAC adjustments influence indoor thermal comfort and energy consumption, aiding in the optimization of system performance and the identification of cost-effective solutions.

Energy consumption calculation

To better understand the methodology of calculating energy, it is crucial to comprehend the formulation of energy as

$$E_{HVAC} = \int_{0}^{t} P_{Aux,HVAC}(t)\, dt \tag{8}$$

This equation serves as the primary function for merging the *HVAC Energy Demand Calculator* and the *HVAC Annual Energy Model*. By integrating the power output at different proposed interior set-point temperatures and ventilation rates over time, the energy usage of that configuration can be calculated.

An aspect that may be subject to debate is the temporal segmentation within the *HVAC Annual Energy Model*. The primary rationale behind dividing time into distinct frames is to differentiate between rush hour and non-rush hour periods, as this variation significantly impacts HVAC energy consumption. Accordingly, the operation time of the C30 has been partitioned into various timeframes, accounting for the normalization of passenger occupancy rates. The proposed work in this thesis divides a weekday into five different timeframes.

Governing equations for power calculation

To better understand the *HVAC Energy Demand Calculator*, it is essential to grasp the heat exchange logic. For this purpose, Erik Vinberg's thesis, "Energy Use in the Operational Cycle of Passenger Rail Vehicles," was referenced, as he conducted a similar study for the commuter trains of Stockholm [36]. His research provides detailed insights into modeling heat exchange between the interior of the train and the external ambient environment. It was found that some heat flows can be bidirectional, with the direction depending on the temperature and humidity differences between the systems.

To evaluate the compatibility of using the model developed in his thesis, several meetings were held with Sidharth and Erik. It was confirmed that the model generated was generic and could be applied to the C30, provided that the parameters in the HVAC Energy Demand Calculator were adjusted according to the C30's technical specifications.

Moreover, in discussions with Erik Vinberg, it was determined that simulating and determining the heat capacity of the Second System, which includes components such as traction motors, bogies, and wheels, presents considerable challenges in prediction. Obtaining such data from Alstom for the C30 would likely be unavailable and pose logistical issues. Consequently, it is suggested that the temperature difference between the First System and the Second System either be assumed to be zero or be subjected to further investigation.

To simulate the overall effect of the above-mentioned factors, the following formulations will be primarily followed. As the HVAC operates both as a heating and cooling source, the formulations of these two functions differ. Depending on the interior set-point temperature of choice, either cooling or heating would be supplied inside the vehicle. For supplying heat and cooling,

$$P_{\text{HVAC,heating}} = \dot{Q}_{She} - \dot{Q}_{Sun} - \dot{Q}_{Win} + \dot{Q}_{V,sen} - \dot{Q}_{pass,sen} - \dot{Q}_{\text{aux}} + \dot{Q}_{S2} \quad (9)$$

$$P_{\text{HVAC,cooling}} = \frac{\dot{Q}_{She} + \dot{Q}_{Sun} + \dot{Q}_{Win} + \dot{Q}_{V,sen} + \dot{Q}_{V,lat} + \dot{Q}_{pass,lat} + \dot{Q}_{pass,sen} + \dot{Q}_{\text{aux}} + \dot{Q}_{S2}}{\text{COP}} \quad (10)$$

will be utilized to calculate the power demand for heating and cooling operations respectively [39]. For the complete simulation of the heating and cooling of the train, it should be noted to include the heating and cooling of the driver's cabin and other auxiliaries as well.

The parameter $P_{\text{Aux,HVAC}}$ corresponds to the overall heating/cooling performance of the HVAC system for the entire train and is the primary parameter for cost and energy consumption calculations annually [36]. The function of the $P_{\text{Aux,HVAC}}$ parameter for heating and cooling is formulated as

$$P_{\text{Aux,HVAC}} = \frac{P_{\text{HVAC,heating}} + P_{\text{Other Aux}} + P_{\text{Driver,heating}}}{n_{\text{Aux}}} \quad (11)$$

$$P_{\text{Aux,HVAC}} = \frac{P_{\text{HVAC,cooling}} + P_{\text{Other Aux}} + P_{\text{Driver,cooling}}}{n_{\text{Aux}}} \quad (12)$$

It should be noted that the *HVAC Energy Demand Calculator* primarily utilizes MATLAB for its implementation, with the input interface integrated into an Excel file. To ensure smooth operation, both the MATLAB file and the Excel file must be in the same folder. To provide insight into the interface, a replica of the input interface has been included within a sheet labeled "*MATLAB Interface*" in the *HVAC Annual Energy Model* Excel tool developed. The user interface is depicted in Figure 10, and the necessary parameters for utilizing this tool can be found in the accompanying figure, along with the data sources for each parameter. The values for parameters are redundant for C30 and are only inserted for demonstration purposes of the filling process of the tool.

HVAC and Auxilliary temperature data			Data sources
T_i [◦C]	20	Indoor temperature	Suggestions depending on the EN14750
T_u [◦C]	5	Outdoor temperature	SMHI
# Passengers	100	Number of passengers in all carbodies	TF
k [W/m^{2}K]	1	Thermal Conductivity of shell	Alstom
A_{shell} [m^2]	1100	Total surface area of car shell	
A_{win} [m^2]	120	Area of windows (one side)	
q [W/m^2]	100	Incident heat flux in sun	SMHI
COP [-]	2	Coefficeint Of Performance of refrigerator system	HVAC provider / Alstom
E_{light} [W]	10000	Electrical lights in the train	TF
E_{aux} [W]	10000	Other auxilliary load(like emergeny door, radio, communication etc)	
E_{driver_heat} [W]	0	Driver cabin heating load	
E_{driver_cool} [W]	1000	Driver cabin cooling load	
Auxiliary efficiency [-]	0,95	Auxilliary power flow efficiency from aux converter to devices	TF / Alstom
Temperature [◦C]	Volume flow rate [m3/h]	Volume flow rate of fresh air at different temperature	
-5	3960	T < -5 [◦C]	Suggestions depending on the EN14750
26	5550	-5 < = T [◦C] <= 26	
26	4400	T > 26 [◦C]	

Figure 10: User interface of HVAC Energy Demand Calculator [36]

In hot conditions, humidity control becomes crucial. As such, an assumption has been made regarding the onset of "hot weather" conditions. In the *HVAC Energy Demand Calculator* tool, this threshold is set at 19 degrees Celsius. Below this threshold, the model does not consider the latent heat flow rate and assumes it to be zero.

Annual energy consumption calculation

In this section, the utilization of the output from the *HVAC Energy Demand Calculator* in the cost model developed in this thesis is explained. The output from the *HVAC Energy Demand Calculator* tool is the power for heating or cooling, depending on the setting of the outdoor temperature. The tool generated is titled *HVAC Annual Energy Model* and mainly calculates the annual energy consumption from the power input from the *HVAC Energy Demand Calculator*. As referenced in the previous section, the energy is calculated through the accumulated power over time.

The accumulated HVAC energy consumption for January is presented as a demonstration and visualization of the energy calculation process as

$$\mathrm{E_{HVAC,January}} = \mathrm{h_1} \cdot \int_{05:00}^{07:00} \mathrm{P(t)\,dt} + \mathrm{h_2} \cdot \int_{07:00}^{09:00} \mathrm{P(t)\,dt} + \mathrm{h_3} \cdot \int_{09:00}^{16:00} \mathrm{P(t)\,dt} + \mathrm{h_4} \cdot \int_{16:00}^{17:00} \mathrm{P(t)\,dt} + \mathrm{h_5} \cdot \int_{17:00}^{01:00} \mathrm{P(t)\,dt} \qquad (13)$$

In this equation, h_1 and the respective “h” values represent the total hours of the respective periods in that month. These values may or may not be subject to change and would require detailed investigation in the TF database. After obtaining the energy usage for each month, it will be accumulated for the whole year by summing up the 12 months, resulting in the annual energy usage as

$$Annual\ Energy\ Consumption = E_{HVAC,annual} = \int_{January}^{December} E_{HVAC}(t)\ dt \qquad (14)$$

Upon acquiring the annual energy usage with the proposed HVAC operation configuration, the annual cost of maintaining such operation will be calculated using

$$Annual\ total\ cost = (Price\ rate\ of electricity) \cdot E_{HVAC,annual} \tag{15}$$

To calculate the cost, the price rate of electricity must be known. This parameter is determined in the contract between the electric grid supplier and TF before each contract and is typically denoted in the unit SEK/kWh.

5.2. Model for ESS Installation

The cost model tool developed for the ESS installation business case outlines the cost parameters associated with such an installation following the general cost model described earlier. This cost model will primarily serve as an example of generating technology-based business cases. To assist decision-makers in utilizing the cost model tool developed for the ESS installation, the model and parameters are explained in detail. This includes specifying the sources of the relevant data and the associated units.

5.2.1. Data Flow Scheme into the ESS Model

The developed cost model will primarily provide two fundamental metrics to decision-makers at the PTAs. Firstly, it will output the NPV of the total ESS business case cost (C_{SS}) in units of SEK. Secondly, it will calculate the cost per kilowatt-hour for the lifetime of the ESS (C_0) in units of SEK/kWh. These two outputs serve as valuable parameters for decision-making, as these are some of the main metrics TF is using actively.

The Excel tool developed for preliminary cost calculations is titled "*ESS LCC Model*," while the spreadsheet including the cost equation is labeled "*ESS Cost*." The parameter details are incorporated and highlighted within this spreadsheet, accompanied by the data sources for each parameter. This organization ensures clarity and accessibility, enabling users to easily navigate and comprehend the cost estimation process. The total model interface can be found in Appendix G.

The "ESS 1 / ESS 2 / ESS 3" represents various potential ESS options under investigation. Consolidating them within the same spreadsheet enables decision-makers to assess their cost aspects concurrently, streamlining the decision-making process with enhanced accuracy for future works.

To facilitate a comprehensive comparison, it is essential to provide details about the maintenance aspect of each ESS implementation. Thus, a set of tables has been included on the right-hand side of the spreadsheet to input maintenance period requirements for each ESS business case. An illustrative example, showcasing 20 years of operation and corresponding replacement periods for three different ESS business cases, has been provided for clarity. It should be noted that the numbers are only for representation purposes without a value. This segment of the spreadsheet is depicted in Figure 11.

O&M Layout

ESS 1

		Maintanence costs		Operation costs
Number of replacement	Years	FC_SS	VC_SS	EC_SS
	1	0		0
	2	0		0
1	3	0	0	0
	4	0		0
	5	0		0
2	6	0	0	0
	7	0		0
	8	0		0
3	9	0	0	0
	10	0		0
	11	0		0
4	12	0	0	0
	13	0		0
	14	0		0
5	15	0	0	0
	16	0		0
	17	0		0
6	18	0	0	0
	19	0		0
	20	0		0

ESS 2

		Maintanence costs		Operation costs
Number of replacement	Years	FC_SS	VC_SS	EC_SS
	1	0		0
	2	0		0
1	3	0	[SEK]	0
	4	0		0
	5	0		0
2	6	0	[SEK]	0
	7	0		0
	8	0		0
3	9	0	[SEK]	0
	10	0		0
	11	0		0
4	12	0	[SEK]	0
	13	0		0
	14	0		0
5	15	0	[SEK]	0
	16	0		0
	17	0		0
6	18	0	[SEK]	0
	19	0		0
	20	0		0

ESS 3

		Maintanence costs		Operation costs
Number of replacement	Years	FC_SS	VC_SS	EC_SS
	1	0		0
	2	0		0
1	3	0	0	0
	4	0		0
	5	0		0
2	6	0	0	0
	7	0		0
	8	0		0
3	9	0	0	0
	10	0		0
	11	0		0
4	12	0	0	0
	13	0		0
	14	0		0
5	15	0	0	0
	16	0		0
	17	0		0
6	18	0	0	0
	19	0		0
	20	0		0

Figure 11: Maintenance period visualization for different applications

As a general user manual for the ESS LCC Model, it is imperative to note that cost parameters and maintenance period details are unique to each ESS installation, necessitating accurate acquisition of data from the respective company of interest. The output generated by the tool includes the *NPV of the total cost of the ESS*, along with the *Cost per kWh* for the lifetime, empowering decision-makers with precise financial insights for the selection of business cases. The following sections explain the required parameters for the development of this preliminary cost model.

5.2.2. Parameter Details

Initial Acquisition Cost

The acquisition pricing is very much related to the power and energy requirements of the systems. Thus, knowing these two, you are much more able to calculate the cost of acquisition of the ESS pack. It is a combination of Energy Related Costs and Power Related Costs.

"For a battery storage system, there are two main cost categories namely the initial costs and O&M costs" [27]. "Initial costs include the costs of purchasing battery cells and packs, hardware costs (such as inverters), soft costs (such as industry education, licensing fees, and labor costs, and the engineering, procurement, and construction (EPC) costs)." [27]. The motivation for the estimation of cost calculation concerning the energy and power parameters [27] is calculated using

$$IC_{SS} = C_e \cdot E_{SS} + C_p \cdot N_{SS} \tag{16}$$

After that, a rough estimate of the price of the battery pack to be acquired [30]. IC_{SS} represents the initial investment cost of battery storage, measured in Swedish Krona (SEK). C_e is the energy cost of battery storage (SEK/kWh). This is a product-specific range that can be referenced from other articles. A lower value within this range serves as a distinguishing factor for a high-quality product. E_{SS} is the energy capacity of battery storage (kWh). This information can be obtained from the product's technical sheet. C_p is the power cost of battery storage (SEK/kW). This is a product-specific range that can be referenced from other articles. A lower value within this range serves as a distinguishing factor for a high-quality product. N_{SS} is the nominal output power of battery storage (kW). This information can be obtained from the product's technical sheet, with adjustments made according to the required duration of charge/discharge.

The parameter values are listed in some articles for Specific Energy Costs and Specific Power Costs. These values typically differ from the technology used inside the ESS and should be taken from the supplier for detailed cost calculation.

The parameter values for Specific Energy Cost and Specific Power Cost are listed in several articles [30], [41]. These values typically vary depending on the technology used within the ESS and should be obtained from the supplier for a detailed cost calculation.

To understand the required sizing of the ESS, the following parameters need to be investigated. The primary objective of the ESS is to cover the energy or power requirements at any given moment. However, it should be noted that these requirements are more complex than they initially appear; therefore, the proposed calculation method generated in this thesis should only act as a brief introduction to capacity sizing. In the cost model, the parameters listed below are sufficient, but they cannot be used as the general energy and power requirements of the grid. Typically, these requirements also include the charging and discharging speeds of the ESS, which are crucial considerations.

Therefore, the suggested function below should be used for the initial assessment of the ESS acquisition cost. Both parameters will be decided during joint meetings between stakeholders. The initial sizing of the ESS will use

$$E_{req} = Required\ energy\ capacity\ [kWh]$$

$$N_{req} = Required\ power\ capacity\ [kW]$$

$$Required\ number\ of\ ESS\ modules\ = n = Maximum\ of \begin{cases} \frac{E_{req}}{E_{SS}} \\ \frac{N_{req}}{N_{SS}} \end{cases} \quad (17)$$

$$C_{acq} = C_{oth} + n \cdot IC_{SS} \quad (18)$$

by calculating the number of ESS requirements and the acquisition cost respectively. C_{oth} represents the cost of acquiring inverters or other necessary equipment, measured in Swedish Krona (SEK). C_{acq} represents the total acquisition cost of the ESS pack, also measured in Swedish Krona (SEK). With this logic, it will be possible to calculate the required number of ESS modules to be acquired.

Soft & EPC Cost

As the soft and EPC costs are closely tied to the contracts negotiated between the ESS suppliers and the PTAs, a thorough investigation is necessary to delineate the sub-elements of these costs.

$$C_{epc} = Soft\ and\ EPC\ costs\ [SEK]$$

Fixed and Variable Maintenance Costs

The Fixed Maintenance cost recurs annually, while the Variable Maintenance cost typically arises every 4-5 years, depending on the acquired technology. Hence, it is crucial to compile a comprehensive list of items replaced during both maintenance periods, along with their associated costs, sourced from the agreed-upon ESS company [30]. For the representation of the fixed maintenance cost, it will be formulated as

$$FC_{SS} = IC_{SS} \cdot m \cdot x_2 \tag{19}$$

FC_{SS} represents the annual fixed maintenance cost, measured in Swedish Krona (SEK). m denotes the fraction of the annual O&M cost to the total initial investment, expressed as a percentage. Typically, this fraction falls between 0.5% to 1% of the total investment cost, depending on the chosen technology [30]. x_2 represents the mean annual O&M cost inflation rate, expressed as a percentage. This information can be obtained from the energy supplier to the grid [30].

Moreover, the variable maintenance cost of the ESS for each maintenance instance is denoted as VC_{SS}. This primarily includes the costs of parts to be replaced, the cost of stopping the operation, and labor and construction costs [30]. The equation representing these relationships is provided as

$$VC_{SS} = C_{part} + C_{stop} + C_{lbr} \tag{20}$$

Operations Costs

In terms of KPI notation, this item would typically be clustered under Recovered energy cost, rather than Operation Cost, as it represents a potential revenue gain from not expending energy in the Brake Resistors.

In traditional braking systems, when a vehicle decelerates, kinetic energy is converted into heat energy using brake resistors, which dissipate this energy as heat. However, with the implementation of an ESS, such as regenerative braking systems used in electric vehicles, this kinetic energy is not wasted. Instead of being dissipated as heat, the energy is captured and stored in the ESS for later use. This process enhances energy efficiency by recycling and repurposing the energy that would otherwise be lost, thereby reducing energy consumption, and increasing overall system efficiency. The representation of the recovered energy in monetary values is

$$EC_{SS} = \varepsilon \frac{E_{total}}{\eta_{SS}} c_1 x_1 \tag{21}$$

EC_{SS} represents the annual recovered energy costs, measured in Swedish Krona (SEK). This cost may be considered a cash inflow since the energy is not drawn from the grid but rather saved from being dissipated in the brake resistors [30].

ε denotes the energy demand ratio covered directly by the ESS, expressed as a percentage. This can be determined by TF for the peak shaving demand daily and annually. In the absence of precise data, self-assigned values can be used. Moreover, from the Tableau Reader, it is named as %EACBRR/ EAC_Tot and typically falls between 25-30% if more precise data is needed for C30.

E_{total} denotes the annual energy demand of the local electricity network, measured in kilowatt-hours (kWh). From the Tableau Reader, it is named as EAC_Tot. η_{SS} represents the energy transformation efficiency of the ESS, expressed as a percentage. This information can be obtained from the product technical sheet of the ESS. C_1 denotes the specific input energy cost, measured in Swedish Krona per kilowatt-hour (SEK/kWh). This information can be obtained from the energy supplier to the grid. x_1 is the mean annual escalation rate of the input energy price, expressed as a percentage. This information can be obtained from the energy supplier to the grid.

Phase Out Cost

The phase-out costs for the ESS align primarily with the general cost model and encompass two key cost items: the Environmental Cost of Decommissioning and the Residual Value. These cost elements are denoted as C_{env} and C_{res} respectively, with the units for both items being SEK.

Final Cost Calculation

To recap, the total cost attributed to the storage system installation and operation after 'n' years, expressed in NPV, can be estimated using

$$C_{SS} = C_{acq} + C_{epc} + NPV(FC_{SS}) + NPV(VC_{SS}) - NPV(EC_{SS}) + NPV(C_{env}) - NPV(C_{res}) \qquad (22)$$

where C_{SS} is the NPV of the total cost of the ESS in SEK [30]. For the next step of evaluating the financial feasibility, one may express the present value of the recovered electricity or Cost per kWh for the lifetime of the ESS by dividing the total cost of the installation during the n-year service period by the total energy recovered during the same period, taking into consideration the expected recovered electricity price escalation rate “x4” [30]. The Cost per kWh for a lifetime is denoted as C_0. The lower the C_0, the better it gets [30]. Therefore, the corresponding Cost per kWh for a lifetime is given as

$$C_0 = \frac{C_{SS}}{\varepsilon E_{total} x_4} \qquad (23)$$

6. Results and Discussion

Up to this section, the methodology for constructing a preliminary decision-making model, the generation of the decision-making model, and the details of the parameters have been explained. Additionally, individual cost models for preliminary technology and operation-based business cases, specifically ESS installation and HVAC modification, have been presented, all of which have been developed in this thesis.

The general takeaway from the current applications deducted from the literature review can be summarized as follows: having a structured approach is particularly important for dealing with such a complex system in this thesis. This approach ensures the accuracy and reliability of the tools and algorithms proposed for decision-making. To achieve this, the first step was to examine the decision-making process by researching system-level papers. These articles and projects mainly highlighted the methodology for structuring and identifying the KPIs necessary to overcome bottlenecks in energy efficiency for urban rail transport systems. The main KPIs identified were cost, percentage decrease in energy usage, and the type of improvements, whether hardware (technology) based, or operation-based. It was found that technology-based solutions require higher installation costs but offer substantial energy savings, whereas operation-based solutions provide moderate energy savings at lower to moderate costs.

Upon understanding the general methodology for the decision-making process, the next step was to investigate how other municipalities have addressed the energy efficiency task and the technological details of these measures. Therefore, papers from various municipalities were examined to identify and analyze the convergence of solutions. It was found that municipalities implement a range of measures, which broadly fall into two categories: technology-based and operation-based solutions.

Given this diversity, it was beneficial to develop cost models for both types of measures. Different municipalities may follow different approaches depending on their specific needs and contexts. By having cost models for both technology-based and operation-based measures, the thesis aimed to cover a comprehensive range of potential solutions available in the market. These models will serve as primary tools for future installation options, allowing stakeholders to adapt and modify the generated tools to suit their specific requirements. This dual approach ensures that the thesis provides versatile and robust tools for enhancing energy efficiency in urban rail transport systems.

To better understand cost model creation, a paper on LCC analysis was reviewed to understand the nature and dynamics of generating such a tool. The review highlighted three main aspects of LCC model generation: initial acquisition, maintenance and operation, and phase-out. These insights form the backbone for creating cost tools and incorporating the financial aspects of business cases into the decision-making model.

Further in this chapter, detailed qualitative comments for the business cases on ESS installation and HVAC modifications will be covered. Subsequently, it will outline the utilization of the decision-making model generated, accompanied by a representative simulation, incorporating the proposed business cases. It is important to note that both the business case proposals and the decision-making proposals will be presented in a qualitative aspect and would necessitate further elaboration for consideration by the TF. This outcome is primarily due to the project's limited timeframe and data availability. Although the cost models and decision-making models were developed quantitatively, the qualitative nature of the proposals is a result of these limitations.

6.1. HVAC Modifications for In-Service Mode

Regarding the current temperature setting of the C30, data provided by the MTR indicates that the optimal indoor temperature is set at 20 degrees Celsius year-round, with a permissible deviation of ±3 degrees Celsius controlled by the central system without requiring additional adjustments by the driver for C30 trains. This information was directly obtained from the personnel at MTR.

Ventilation is supplied through a single unit equipped with integrated heating and cooling functionalities, HVAC. Ventilation can be performed independently of heating or cooling, with air conditioning activated only when the temperature deviates from the setpoint. In instances where cooling is required due to cooler external temperatures, increased fresh air intake (known as free cooling) may be sufficient. However, if external temperatures are warmer, the cooling compressor initiates operation.

6.1.1. Proposed Solutions

For general comparison purposes, the current ventilation flow rate is set at 10m^3/h/person and the indoor setpoint temperature is maintained at 20 degrees Celsius throughout the year by MTR. The Annual Total Cost of this configuration must be inputted into the model namely as a reference value for comparing proposed settings of interior setpoint temperature and ventilation flow rate. Subtracting the Annual Total Cost of each setting from the reference value will provide the cost difference for each setting, clarifying the benefits of each proposed setting. After subtracting all proposed settings, the best one can be determined by comparing them to the reference value.

After a comprehensive review of all configurable parameters within the *HVAC Annual Energy Model*, it has been determined that adjustments to business cases can be made primarily through two main parameters: Interior set-point temperature *and* ventilation flow rate *adjustments*. Each of these parameters leads to a variety of business cases with distinct characteristics.

In terms of interior set-point temperature adjustment modifications, three main options have been identified, each with detailed sub-options. The first option involves maintaining a fixed interior set-point temperature throughout the year as it is now.

The second option involves proposing and modifying the temperature through monthly adjustments for each month. This approach has generalized temperature settings for the entire month based on the respective outdoor temperatures, which constitutes the primary drawback of this business case. The average monthly outdoor temperatures have been extracted and prepared from the averaged 5-year data from SMHI. In total, there would be 12 indoor setpoint temperature inputs to the HVAC per year from the central control system. While this implementation is relatively straightforward and is unlikely to require significant operational changes or include human error, its drawback lies in the lack of granularity and responsiveness to dynamic environmental conditions throughout the month.

The third option involves detailed time-period indoor temperature adjustments, which expands upon the generalization of the Monthly indoor temperature adjustments business case to achieve further energy-saving potential. Under this plan, daily operation settings are proposed for either a 5-time frame or 4-time frame-specific periods for each month, targeting the indoor setpoint temperature.

For the 5-time frame option, the time frames include 05:00-07:00, 07:00-09:00, 09:00-16:00, 16:00-17:00, and 17:00-01:00. This translates to 5 temperature inputs to be entered into the system for every day of the month, with variations across months. In total, it results in 60 temperature inputs for a year.

Alternatively, the 4-time frame option clusters the time frames as 05:00-07:00, 07:00-09:00=16:00-17:00, 09:00-16:00, and 17:00-01:00. The simplification is that approaching the morning and evening rush hours as the same in terms passenger occupancy rates. This simplification is primarily based on framing rush hours for the sake of simplicity, leveraging passenger occupancy rates for generalization purposes. This translates to 4 temperature inputs to be entered into the system for every day of the month, with variations across months. In total, it results in 48 temperature inputs for a year. However, it should be further analyzed as this simplification is based on the passenger occupancy rates. By evaluating the PMV values after this generalization, it should also be considered for passenger comfort, as this may not be a valid assumption to be made, although the passenger occupancy rates are similar, they are not identical.

In terms of ventilation flow rate modifications, two main options have been identified, each with detailed sub-options. The first option involves maintaining a fixed ventilation flow rate throughout the year as it is now.

The second option involves dynamic adjustments of the ventilation flow rate. The proposal suggests a 4-time frame option, utilizing time frames as 05:00-07:00, 07:00-09:00=16:00-17:00, 09:00-16:00, and 17:00-01:00, employing the same simplification of time frames used for temperature adjustments. This simplification is primarily based on framing rush hours for the sake of simplicity, leveraging passenger occupancy rates for generalization purposes. However, further analysis is required as this simplification relies on passenger occupancy rates. Evaluating the PMV values after this generalization is crucial to consider passenger comfort, as this assumption may not be entirely valid; while passenger occupancy rates may be similar, they are not identical.

To accurately evaluate the modifications, it's essential to acknowledge certain limitations. Feedback from MTR personnel on the general business cases for HVAC highlighted several points. One key limitation is the dynamic nature of readjusting indoor set-point temperatures based on individual outdoor temperatures, which poses challenges for effective tracking. Currently, operators manually input the interior set-point temperature, making it more practical to adhere to a fixed indoor set-point temperature for each month or timeframe rather than adjusting it for every outdoor temperature variation, primarily due to the manual input aspect. This constraint influenced the decision to utilize yearly/monthly time framing for generating business cases from the outset. Additionally, modifications to control and adjust indoor temperatures are manually made in the remote-controlled room by operators using software interfaces. There's no automated functionality within the software for temperature adjustments, necessitating manual input of suggestions for changes in the interior setpoint temperature.

However, it's important to note that the following business cases assume a consistent hourly passenger occupancy rate trend daily throughout each month, mainly from the unavailability of data. To further clarify, this assumption must be verified through data investigation for each month and ideally extended to analyze trends for upcoming years. After considering these parameters and drawbacks, several potential implementation methods were concluded before proposing business cases in detail.

The first implementation involves hiring a full-time employee to manually input modifications for temperature and ventilation flow rates using the current manual interface at the central control room. The handbook will include interior set-point temperature values and ventilation flow rate values, depending on the resolution of the timeframe: 5 timeframes per day, 4 timeframes per day, or monthly.

The outline of the manual or handbook would be as follows, presented in Figure 12, Figure 13, and Figure 14. The employee will primarily look at the monthly timeframe of operation, and then input the suggested optimum indoor temperature and ventilation flow rate into the HVAC system. The Excel file is titled *"In-service Implementation Interface for HVAC.xlsx"*. Regarding Figure 13 and Figure 14, only the timeframe from January to May is presented. The list for both cases follows the same structure for the January-December period.

Months	***Optimum indoor temperature [C]***	***Ventilation Flow rate [m3/h/passenger]***
January		
February		
March		
April		
May		
June		
July		
August		
September		
October		
November		
December		

Figure 12: Implementation interface for HVAC on the monthly resolution

Months	Operation hour intervals	Optimum indoor temperature [C]	Ventilation Flow rate [m3/h/passenger]
January	05:00-07:00		
	07:00-09:00		
	09:00-16:00		
	16:00-17:00		
	17:00-01:00		
February	05:00-07:00		
	07:00-09:00		
	09:00-16:00		
	16:00-17:00		
	17:00-01:00		
March	05:00-07:00		
	07:00-09:00		
	09:00-16:00		
	16:00-17:00		
	17:00-01:00		
April	05:00-07:00		
	07:00-09:00		
	09:00-16:00		
	16:00-17:00		
	17:00-01:00		
May	05:00-07:00		
	07:00-09:00		
	09:00-16:00		
	16:00-17:00		
	17:00-01:00		

Figure 13: Implementation interface for HVAC on 4-time frame per day resolution

Months	Operation hour intervals	Optimum indoor temperature [C]	Ventilation Flow rate [m3/h/passenger]
January	05:00-07:00		
	07:00-09:00		
	09:00-16:00		
	16:00-17:00		
	17:00-01:00		
February	05:00-07:00		
	07:00-09:00		
	09:00-16:00		
	16:00-17:00		
	17:00-01:00		
March	05:00-07:00		
	07:00-09:00		
	09:00-16:00		
	16:00-17:00		
	17:00-01:00		
April	05:00-07:00		
	07:00-09:00		
	09:00-16:00		
	16:00-17:00		
	17:00-01:00		
May	05:00-07:00		
	07:00-09:00		
	09:00-16:00		
	16:00-17:00		
	17:00-01:00		

Figure 14: Implementation interface for HVAC on 5-time frame per day resolution

While straightforward to generate, this handbook would require updating for any future modifications to the optimum indoor set-point temperature. Additionally, if changes to the ventilation flow rate are decided, this would add further tasks for the employee and increase the potential for human error in data input.

To mitigate the risk of errors, a safety mechanism algorithm would be necessary. This could involve providing an overview of the inputs to the employees before they are sent to the HVAC units. This additional step can help reduce the likelihood of errors and ensure the accuracy of the inputs.

One significant risk of human error is the potential deviation of energy consumption from the optimal level and the discomfort it may cause for passengers. Moreover, incorrect input to the system could trigger an electrical load, leading to an overload on the system. Therefore, it is crucial to include a safety mechanism algorithm to mitigate such risks when making inputs. One approach could be to provide an overview of the inputs to the employee in a pop-up page before they are sent to the HVAC units, allowing for verification and correction if necessary.

The second implementation involves developing software capable of automatically monitoring the timeframe, month, optimum indoor set-point temperatures, and suggested ventilation flow rates for the respective slot, then automatically inputting them into the HVAC system. The data sheet that the software will receive as input will be structured similarly to the figures explained above. This solution offers the advantages of future modification availability and automation. However, since there is currently no such system employed in the Stockholm Metro, developing, testing, and installing new software would be necessary.

After the revision of the above-mentioned parameters, limitations, and implementation methods, 8 business cases were concluded and listed below.

- Fixed Setpoint Temperature with Fixed Ventilation Flow Rate
- Fixed Setpoint Temperature with Dynamic Ventilation Flow Rate
- Monthly Temperature Adjustments with Fixed Ventilation Flow Rate
- Monthly Temperature Adjustments with Dynamic Ventilation Flow Rate
- Detailed (5 Adjustments / Day) Time-Period Temperature Adjustments with Fixed Ventilation Flow Rate
- Detailed (5 Adjustments / Day) Time-Period Temperature Adjustments with Dynamic Ventilation Flow Rate
- Detailed (4 Adjustments / Day) Time-Period Temperature Adjustments with Fixed Ventilation Flow Rate
- Detailed (4 Adjustments / Day) Time-Period Temperature Adjustments with Dynamic Ventilation Flow Rate

While scenarios involving fixed setpoint temperatures and adjusted ventilation flow rates may be easier to implement initially, those incorporating monthly or detailed time-period temperature adjustments may require the development of new software and testing before integration with the HVAC control system as well as acquirement of new HVAC units. Each scenario offers different levels of optimization and energy efficiency, necessitating careful consideration based on available resources and desired outcomes.

The general conclusion is that the proposed business cases need thorough evaluation using the *HVAC Annual Energy Model* and *HVAC Energy Demand Calculator* to assess their impact on energy consumption and associated costs. Since changes to ventilation flow rates and hourly set-point temperatures through software integration may involve additional expenses, it's crucial to conduct a cost-benefit analysis to determine the economic viability of each approach. This holistic evaluation will ensure that the chosen strategy optimizes HVAC performance while aligning with budgetary constraints and overall project goals.

6.2. HVAC Modifications for Depot Mode

After the meeting with personnel from MTR, it was understood that the C30 trains are housed inside a closed area where ambient heating systems are operated. Although detailed storage information could not be collected due to data availability constraints, it was assumed to approach the environment solely in terms of temperature. Therefore, the consideration for the depot condition focuses solely on ambient temperature in this thesis. The modifications proposed in this thesis mainly target the HVAC unit mounted in the C30 trains. While this may not be the current application, any future scenario requiring such an operation can refer to this thesis for guidance.

Navigating this challenge is complex due to the unknown ambient air conditions in the depot. As such, there emerge two primary data sources for the outdoor temperature column in the *HVAC Annual Energy Model*. Assuming the C30 trains are kept outside during depot hours, the following statement could be made: Given the availability of outdoor temperature data collected hourly from 2019 to 2023, an alternative approach is suggested. The proposed time frame for assessing depot conditions spans from 01:00 to 05:00 on weekdays throughout the year. Instead of focusing solely on this timeframe, which would require significant effort, data clustered within the 00:00 to 09:00 period could be leveraged for simplicity.

The methodology and data flow employed in evaluating business cases for depot conditions mirror those utilized in the In-Service mode. To establish a comparison point, essential parameters such as indoor set-point temperature and ventilation flow rate during depot conditions must be collected from MTR sources. Only upon acquiring this data can the energy and cost-effectiveness of the proposed business cases for depot conditions be comprehensively evaluated.

Due to the redundancy of passenger occupancy rates in depot conditions, utilizing a singular ventilation flow rate is preferable. However, a notable limitation arises regarding the maintenance of a minimum temperature within the car body. Before advancing business cases, it would be required to consider four primary limiting factors while investigating future business cases.

Firstly, ensuring the prevention of humidity condensation must be investigated to obtain the minimum temperature requirement. Yijing and Jimmy conducted a study on this issue for the Pendeltag [38], [42]. Comparable restrictions must be gathered, and similar experimentation needs to be conducted on the C30 train to ascertain the minimum indoor temperature if not provided by MTR. This becomes important particularly, if MTR specifies humidity percentage as a limit rather than the indoor temperature itself, as energy calculations are temperature-dependent based on the proposed *HVAC Annual Energy Model* and *HVAC Energy Demand Calculator*.

The second limiting factor pertains to preparing the train body for regular in-service conditions before operations commence for the day. Yijing and Jimmy's thesis categorizes this operational phase as a transition stage [38], [42]. A significant constraint arises if the temperature gap between the depot and in-service condition is substantial, as this would necessitate higher power to achieve the desired in-service condition due to the time required to heat the interior. Therefore, proposing excessively low interior set-point temperatures for depot conditions is not pragmatic. Consequently, a detailed investigation into this transient stage of depot conditions is required.

The third limiting factor considered regarding the temperature modification proposals is humidity and its condensation inside the car body during depot times, as suggested in Jimmy's thesis [38]. If condensation occurs, there is a risk of electrical shorts in the interior's electrical infrastructure, posing a potential safety hazard. Therefore, further analysis following Jimmy's thesis would be beneficial to identify suitable time intervals and propose interior set-point temperatures for each timeframe.

The last limiting factor concerns secondary activities conducted during depot time, such as cleaning the train's interior. Typically, technicians or similar personnel are assigned to perform these tasks. A minimum temperature must likely be maintained to ensure a safe working environment for these technicians. Given that cold weather poses a greater challenge in Stockholm, obtaining data on the minimum working temperature for technicians for each month would be required.

6.2.1. Proposed Solutions

After a comprehensive review of all configurable parameters, it has been determined that adjustments to business cases can be made primarily through two main parameters same as the In-Service operation: interior set-point temperature and ventilation flow adjustments. Each of these parameters leads to a variety of business cases with distinct characteristics.

In terms of interior set-point temperature adjustment modifications, three main options have been identified, each with detailed sub-options. The first option involves maintaining a fixed interior set-point temperature throughout the year as it is now.

The second option involves proposing and modifying the temperature through monthly adjustments for each month. This approach has generalized temperature settings for the entire month based on the respective outdoor temperatures. The average monthly outdoor temperatures have been extracted and prepared from the averaged 5-year data from SMHI. In total, there would be 12 indoor setpoint temperature inputs to the HVAC per year from the central control system. While this implementation is relatively straightforward and is unlikely to require significant operational changes or include human error, its drawback lies in the lack of granularity and responsiveness to dynamic environmental conditions throughout the month.

The third option proposes detailed time-period indoor temperature adjustments, expanding upon the generalization of the Monthly indoor temperature adjustments business case to achieve further energy-saving potential. A similar approach has been proposed in Jimmy's thesis regarding the transient division of the depot time interval [38]. While the exact operation regimes for the C30 in the depot time interval are not known, the proposed logic involves identifying the timeframes of the depot times to achieve smooth temperature fluctuations inside the train, thereby reducing energy usage. This strategy aims to preserve the current temperature inside the train car and require less heat supplied, contributing to energy efficiency.

In terms of ventilation flow rate modifications, two main options have been identified, each with detailed sub-options. The first option involves maintaining a fixed ventilation flow rate throughout the year.

The second option involves dynamic adjustments of the ventilation flow rate. However, similar to the temperature setting data, the exact depot conditions for ventilation settings are not known. Therefore, the following details represent a logical proposal. If it is determined that dynamic ventilation could be utilized to decrease CO_2 concentration inside the car body or reduce humidity levels, implementing dynamic ventilation regimes within the car body throughout the proposed time frames may require less energy. Consequently, further detailed analysis is necessary to assess the feasibility of using dynamic ventilation in depot conditions for the C30, considering the factors outlined.

After the revision of the above-mentioned parameters, limitations, and implementation methods, 6 business cases were concluded and listed below.

- Fixed Setpoint Temperature and Fixed Ventilation Flow Rate
- Fixed Setpoint Temperature and Dynamic Ventilation Flow Rate
- Monthly Temperature Adjustments and Fixed Ventilation Flow Rate
- Monthly Temperature Adjustments and Dynamic Ventilation Flow Rate
- Detailed Time-Period Temperature Adjustment and Fixed Ventilation Flow Rate
- Detailed Time-Period Temperature Adjustment and Dynamic Ventilation Flow Rate

In general conclusion, the proposed solutions are deemed more suitable for C30 or any urban rail transport, whether stored outdoors or indoors. The focus lies on modifications solely to be made on the HVAC system mounted on the rail vehicle itself.

6.3. ESS Installation

The primary rationale behind ESS installation is to ensure continuous train operations by providing support during energy or power supply shortages. Without this support, trains may face challenges with acceleration or movement. However, integrating an ESS into the existing infrastructure is a complex project that demands a comprehensive analysis.

After examining existing applications and relevant literature, two main alternatives have emerged: On-board ESS and Wayside ESS. The following sections will provide qualitative analysis based on their limitations and potential.

6.3.1. On-Board ESS

Installing On-board ESS for trains eliminates the need for additional infrastructure on the electric grid. This simplifies the installation process and reduces costs by eliminating the requirement for external equipment or connections beyond the existing on-board systems. By integrating the ESS directly into the train, the need for external infrastructure such as charging stations or grid connections is eliminated, streamlining the deployment process, and reducing overall project complexity. This approach not only reduces upfront capital expenditures but also minimizes ongoing operational costs associated with maintaining and managing additional infrastructure.

Moreover, the electric connection interface for On-board ESS is likely to be simpler compared to Wayside ESS installations. Since the ESS is integrated directly into the train, the connection process can be simpler. This simplification can lead to easier installation and maintenance procedures, as well as potentially reducing the complexity of electrical connections required for interfacing with the train's existing systems.

On-board ESS can potentially provide faster response times for charging and discharging, which are crucial for maintaining operational efficiency and determining the type of ESS to be installed. This responsiveness is particularly advantageous in scenarios where rapid energy storage or release is needed, such as during acceleration or regenerative braking events with two 2 trains instantly.

In addition, in the event of a grid failure, On-board ESS can serve as a reliable safety energy supply, ensuring uninterrupted service and passenger safety during emergencies. This capability enables trains to continue operating and safely carry passengers to the next station, mitigating disruptions and enhancing overall system resilience.

Maintaining On-board ESS poses logistical challenges, potentially disrupting train operations. Typically, maintenance occurs during designated depot times specified by PTAs to minimize service disruptions. However, careful consideration of maintenance scheduling remains necessary to mitigate operational impacts. Collaborating with ESS suppliers to ascertain maintenance durations enables proactive planning, ensuring minimal disruption to service. By coordinating maintenance activities in advance, PTAs can optimize train availability and minimize service disruptions, enhancing overall system reliability.

Deploying a dedicated ESS for each train presents a significant financial investment, raising concerns about cost-effectiveness. Determining the optimal number of trains requiring ESS installation is essential to balance operational requirements with cost considerations. Conducting a thorough cost-benefit analysis can help evaluate the feasibility and economic viability of this approach together with the electrical model developed. Moreover, exploring alternative deployment options, such as shared ESS installations across multiple trains or selective deployment based on route characteristics, may offer cost-saving opportunities while ensuring operational efficiency.

Ensuring safety is one of the most important factors when implementing On-board ESS due to their proximity to passengers and exposure to various environmental conditions. Comprehensive safety assessments must be conducted to identify and mitigate potential hazards, including fire risks and other safety concerns. Implementing robust safety measures, such as fire suppression systems, thermal insulation, and protective enclosures, can help minimize risks associated with ESS installations on trains. Additionally, adherence to industry standards and regulations, along with testing and certification processes, would be essential to guarantee the reliability and safety of On-board ESS deployments. If these tests have been done by the ESS manufacturer, researching and analyzing these test results is advised.

Evaluating the space availability and suitability for On-board ESS on trains is crucial for ensuring successful implementation. Factors such as the dimensions, weight, and configuration of ESS modules must be considered concerning available on-board space. Additionally, accessibility for installation, maintenance, and potential future upgrades should be considered to facilitate integration and operation.

Analyzing vibrations on trains and their potential impact on ESS is also crucial for ensuring system reliability and longevity. Vibrations experienced during train operation can induce mechanical stress and fatigue in ESS components, potentially leading to premature wear or damage. Therefore, conducting a comprehensive vibration analysis involves identifying and evaluating factors such as the frequency, magnitude, and duration of vibrations experienced during train operation. This analysis helps identify resonance frequencies that may coincide with critical frequencies of ESS components, increasing the risk of structural resonance and potential damage. Mitigation strategies, such as damping systems or structural reinforcements, may be utilized to minimize vibration-induced risks and maintain ESS integrity.

On-board ESS types typically have smaller energy and power capacities compared to Wayside ESS installations. This limitation arises from the smaller volume of the On-board ESS packages. As a result, On-board ESS usually have limited capacity to store and deliver energy, which can affect their effectiveness in providing auxiliary power or mitigating peak energy demands. Therefore, careful consideration of energy and power requirements is essential when implementing On-board ESS to ensure they align with operational demands and performance expectations. Having a detailed electrical model of the train would enable the balance between size and requirements.

One limitation of the On-board ESS is that its peak shaving and load balancing benefits are exclusive to the train on which the system is installed. Unlike Wayside ESS installations, which can serve multiple trains through the grid, the On-board ESS can only be utilized by the specific train it is integrated with. This restriction reduces the potential impact of the ESS on overall energy efficiency across the metro network, as its benefits are limited to individual trains rather than being distributed electricity network-wide. Therefore, while the On-board ESS provides localized advantages in energy management and performance optimization, its inability to benefit other trains through the grid decreases its overall effectiveness in generating system-wide efficiency.

The weight of On-board ESS presents a significant challenge due to its potential impact on train operation. Increased payload weight affects the traction system's power consumption, potentially leading to higher energy usage and rendering the ESS redundant. To address this issue, detailed simulation models are essential to assess the system dynamics accurately. These models can help quantify the additional energy requirements of the traction system when the ESS is installed and evaluate whether the supplied energy from the ESS is sufficient to justify its implementation. Understanding the complex interplay between payload weight, energy consumption, and ESS functionality is crucial for making informed decisions about its deployment.

6.3.2. Wayside ESS

One of the primary advantages of Wayside ESS over On-board ESS is its higher capacity in both energy storage and power output. This increased capacity allows Wayside ESS to store larger amounts of energy and deliver it at a higher rate, making them suitable for applications with greater energy demands. However, it's essential to note that discharge times may vary, and careful evaluation is required to determine the optimal discharge characteristics for specific use cases.

Wayside ESS offers higher capacity in energy and power compared to On-board ESS, making them suitable for applications requiring greater energy storage and discharge capabilities. Additionally, since they are not installed on the train itself, the current traction models can still be utilized. This aspect simplifies simulation processes and ensures that the performance and efficiency provided by Alstom's systems remain effective.

Maintenance for Wayside ESS is typically easier compared to on-board systems. Since they are connected to the main electric supply grid rather than being integrated directly into the train, maintenance can generally be performed without interrupting train operations. This aspect simplifies maintenance procedures and ensures minimal disruption to service.

Scaling up the capacity of Wayside ESS is typically easier compared to on-board systems. Since Wayside ESS is installed at the station, there are fewer restrictions related to space and volume compared to on-board installations. This means that expanding the capacity of the system to meet increasing demand can be achieved more easily.

One significant advantage of Wayside ESS is its ability to provide peak shaving and load balancing benefits to every train in the grid. By strategically distributing energy stored in the ESS among trains as needed, it can effectively reduce peak demand periods and ensure a more stable and efficient operation of the entire metro infrastructure. This capability is particularly advantageous during rush hour times of high energy demand. Additionally, the centralized nature of Wayside ESS facilitates easier monitoring, control, and coordination of energy distribution across multiple trains and stations, enhancing overall system flexibility.

One potential drawback of Wayside ESS is that its response time could be slower compared to On-board ESS. This delay in response may directly impact the effectiveness of the ESS, particularly in situations requiring rapid energy storage or release. Slower response times could potentially limit the ESS's ability to quickly address fluctuations in energy demand or supply, leading to suboptimal performance in managing peak loads or balancing energy consumption. Therefore, careful consideration of response time requirements and operational needs is essential when evaluating the suitability of Wayside ESS for a metro system.

Another potential drawback of Wayside ESS is that the installation interface may require more complex work, leading to higher installation costs compared to On-board ESS. This complexity may arise from the need to integrate the ESS with existing infrastructure at the station, such as power distribution systems and control mechanisms. Additionally, factors like site preparation, transportation of equipment, and coordination with other station activities could contribute to increased installation expenses. Therefore, thorough cost analysis and careful planning are necessary to assess the feasibility of implementing Wayside ESS and to mitigate potential cost overruns during the installation process.

6.3.3. Aspect for Both

Considering the residual value at the end of their service life, both types of ESS can find utility in less critical applications. These could include powering less frequently used sections of the lines or serving different parts of the grid where train operation isn't necessary. One innovative business case involves repurposing decommissioned ESS systems to power platform lighting during nighttime. This not only extends the lifespan of the ESS but also contributes to sustainable energy practices by utilizing stored energy from Photo Voltaic cells. Such use cases demonstrate a holistic approach to infrastructure sustainability and resource optimization.

Considering the environmental cost of decommissioning, particularly for ESS systems predominantly comprising chemical battery packs, adherence to appropriate disposal methods is imperative. With the global surge in battery pack usage due to the electrification trend, the disposal of these packs must be carefully considered. Establishing decommissioning facilities or partnering with specialized companies can be integral to the business planning of ESS implementation. By incorporating this aspect into the business plan, Stockholm can emerge as a role model for other PTAs, showcasing responsible and sustainable infrastructure management practices.

Expanding passenger capacity through ESS installation presents an opportunity to adjust train frequency according to demand, particularly during peak hours. By leveraging voltage management strategies, the system can accommodate more frequent trains, addressing high-demand periods effectively. Evaluating this business case necessitates the development of a comprehensive multi-train model to understand the energy and power requirements accurately. Only with such insights can the cost implications of ESS implementation be properly assessed. The *ESS LCC Model* developed in this thesis can serve as a valuable tool for analyzing the financial aspects of this scenario, enabling informed decision-making regarding capacity enhancement initiatives. This business case can later be detailed further through a comprehensive investigation and classified under timetable optimization as a separate business case for more precise analysis and implementation planning.

Assessing the TRL of ESS applications involves considering factors such as technological maturity, performance characteristics, cost-effectiveness, regulatory frameworks, and market acceptance to determine the suitability of different storage solutions for specific use cases. In one study, the TRL level is compared through the Commercial Maturity and the Cost Certainty [43]. This methodology would be logical to follow. With such a comparison to be made on the decision point of the technology that the ESS holds, the TF should conduct such a study to ensure financial certainty of the ESS installation of choice.

The general conclusion is that the ESS selection process requires a highly technical investigation of both the system requirements and the suitability of the signaling system. Moreover, as ESS systems potentially offer greater performance, it would be beneficial to insert another train to increase the frequency of trains or to change the driving regimes. The cost tool generated in this thesis *ESS LCC Model* could be utilized as an initial assessment of the sizing decision as well as cost estimation. However, it should be noted that further investigation of ESS business cases is required, involving stakeholders in the process.

6.4. Decision-Making Tool

As discussed earlier, the decision-making tool offers a visual representation for decision-makers. Therefore, it would be beneficial for decision-makers to have an illustrative example in this thesis. This section will simulate how a hypothetical decision-making process at a preliminary level would unfold through the utilization of the Decision-Making Tool generated in this thesis. Consequently, this section shall serve as a user manual on how to utilize the proposed decision-making tool, rather than focusing on the data and outcomes presented.

The initial step to utilize the decision-making tool is to list the promising business cases in the Business Cases column. For this instructional simulation, decision-makers have identified nine sets of business cases worth investigating. These business cases have been proposed in sections 6.1, 6.2, and 6.3. The set of hypothetically decided business cases is inserted into the interface of the *Decision Making Tool* and illustrated in Figure 15.

Business Clusters	***Business Cases***
In service HVAC	*Fixed Setpoint Temperature with Dynamic Ventilation Flow Rate*
	Monthly Temperature Adjustments with Dynamic Ventilation Flow Rate
	Detailed (5 Adjustments / Day) Time-Period Temperature Adjustments with Dynamic Ventilation Flow Rate
	Detailed (4 Adjustments / Day) Time-Period Temperature Adjustments with Dynamic Ventilation Flow Rate
Depot HVAC	*Fixed Setpoint Temperature and Dynamic Ventilation Flow Rate*
	Monthly Temperature Adjustments and Dynamic Ventilation Flow Rate
	Detailed Time-Period Temperature Adjustment and Dynamic Ventilation Flow Rate
ESS	*On-Board ESS*
	Wayside ESS

Figure 15: Hypothetical business cases to be evaluated in the simulation

The next step is to insert KPI weights to facilitate the decision-making process by decreasing the number of available business cases. In this simulation, any KPI weight of 3 or below is assumed to be non-priority on a scale of 1-5, with 5 being the highest. The assigned weights of the KPIs can be found in Figure 16.

List of clusters
Costs
Benefits
Others

	Weight level
Most important	5
Least important	1

Clusters	*Factors*	*KPIs*	*Weight of KPIs*	*Comments*
Costs	*Initial costs*	Initial acquisition	4	
		Soft&EPC	2	
	O&M costs	Fixed maintenance costs	3	
		Variale maintenance costs	2	
		Operation costs	2	
	Phase out costs	Environmental cost of decommissioning	2	
		Residual Value	2	
Benefits	*TF perspective*	Energy usage decrease	5	
		Capacity increase	3	
		Sustainability	2	
	Passenger perspective	Frequency increase	2	
		Travel comfort	2	
Others	*Risks*	Complexity	2	
		TRL	4	
	Availability of future customization	Availability of future customization	3	

Figure 16: Assigned weights for the KPIs

Ideally, the process of filling the relevant KPI cells with values should be conducted through detailed investigation and modeling. However, given the scope of this thesis, which primarily focuses on describing the process, the values assigned to each cell are purely random. In this simulation, the decision maker is assumed to assign random prioritization for the KPIs, thus assigning weight values. They serve only to demonstrate the utilization of the tool. While a general understanding of comments made on possible solutions was referenced when generating these random outputs, it should be noted that these numbers should be decided after careful investigation of business cases. No deductions about business cases shall be made from this simulation.

As discussed earlier, some KPIs are challenging to quantify precisely. Therefore, in this simulation, assigning numbers from a 1-5 scale was chosen. For Sustainability, TRL, and Availability of Future Customization, higher numbers would indicate positive attributes, while a higher number for Complexity would signify a negative aspect for the business case of interest. Regarding the Cost per kWh, it is trivial to estimate without any model and investigation. Therefore, that KPI column is left unfilled, as the weight of that KPI already makes it redundant to evaluate in this simulation.

In Appendix H, each business case is depicted with quantities assigned to respective KPIs in their corresponding cells. These business cases are explained qualitatively in depth in the following sections. It is important to note that these numbers are solely illustrative and have been inputted randomly for demonstrational purposes of the usage of the decision-making tool. While the specific values may not reflect actual data, they serve to exemplify the functionality and layout of the tool, highlighting its capability to handle diverse inputs and streamline the decision-making process.

As of now, the KPI values for each business case have been filled in the Decision Matrix spreadsheet, and the business cases are ready to be evaluated. As proposed in Chapter 4, the decision-selection process initially evaluates the Best Individual row for the assessment of the best business cases for each KPI. Therefore, the next step is to examine the Best Individual row at the bottom of the spreadsheet to identify which business cases perform best for each KPI. Given the high number of business cases, the previously assigned weights will help narrow down the options by focusing only on the important KPIs. This process involves considering the weights assigned to each KPI and filtering out the less significant ones based on the priorities of the decision-maker.

By considering the KPI weight values equal to or greater than 3, the highly prioritized KPIs can be listed as Initial Acquisition Cost, Fixed Maintenance Costs, NPV of Total Costs, Energy Usage Decrease, Capacity Increase, TRL, and Availability of Future Customization. This filtering process is crucial, and a detailed investigation must be conducted by decision-makers on the weights assigned to each KPI. The best individual business cases for each KPI can be found in Appendix I. By examining the Best Individual row and identifying the resulting best business case for the identified priority KPIs, the business cases are now reduced to:

- Fixed Setpoint Temperature with Dynamic Ventilation Flow Rate (Service)
- Wayside ESS
- Detailed (5 Adjustments/Day) Time-Period Temperature Adjustments with Dynamic Ventilation Flow Rate
- Fixed Setpoint Temperature and Dynamic Ventilation Flow Rate (Depot)

One risk of utilizing the decision-making tool is the absence of KPI data for some business cases, which may complicate the decision-making process. As an example, regarding the Capacity Increase KPI, the Fixed Setpoint Temperature with Dynamic Ventilation Flow Rate (Service) and Detailed (5 Adjustments / Day) Time-Period Temperature Adjustments with Dynamic Ventilation Flow Rate business cases result as *Not Applicable*. This implies that this KPI shall not be included for these two business cases upon evaluation. Instead, the evaluation shall proceed with the rest of the KPIs.

The utilization of radar charts is required for further decision-making. Hence, visualizing the performance of the chosen business cases regarding these priority KPIs is crucial for comparison. Initially, individual radar charts were constructed for each priority KPI, incorporating the performance of the four promising business cases. This approach allows stakeholders to visually compare the performance of the business cases and facilitates data interpretation through visualization. Following this, another radar chart was created to compare the cost KPI cluster, representing the performance of all four business cases regarding cost-related KPIs within the same figure. This primarily enables decision-makers to comprehensively evaluate the business cases by comparing them more thoroughly. All these figures are detailed in Appendix J. Regarding the visualization of the figures, the current results may not be optimal in terms of readability. The primary reason for this is the random data inputted into the cells. As more detailed models and estimations are developed in the future, the figures will present more accurate results, thus making them easier to understand by all stakeholders.

With the performance of individual business cases for each KPI and the comparison between business cases, the decision-making process aims to be as comprehensive as possible. The resulting figures and values will serve as an initial step for decision-making, as the tool is designed to be as generic as possible while enabling the comparison of different business cases simultaneously. The tool can be used for a brief understanding of various business cases and how they converge for the urban rail system of choice to be implemented. As detailed investigations are conducted in the future, the model will enable further modifications and offer a more detailed comparison and decision-making tool.

To effectively utilize the *Decision Making Tool* and other quantification tools for energy and cost calculations, thorough and detailed investigations were imperative. Once completed, the cost and decision-making tools developed in this thesis will facilitate a robust decision-making process backed by highly quantifiable data. Moreover, the visualization aspect of the model generated in this thesis will facilitate decision-making by presenting the data in a visual format, as not every stakeholder involved in the decision-making process may understand the data directly. Therefore, it enables an inclusive approach for every stakeholder.

7. Conclusion and Future Works

Recalling the research question, “How can a quantifiable decision-making algorithm be generated for business case comparison to be utilized by decision-makers?”. To generate a quantifiable decision-making algorithm for business case comparison, the thesis developed a Decision-Making Tool that uses quantifiable KPIs for objective analysis. This tool employs radar charts to visually represent data, reducing biases and facilitating informed discussions among decision-makers. Additionally, the HVAC Annual Energy Model and ESS LCC Model provide detailed cost and energy output data for integration into the tool. Future work involves expanding stakeholder inclusion, refining cost models, and accurately assigning KPI weights to enhance the tool's effectiveness in urban rail transport decision-making.

The current applications of energy-saving measures are primarily divided into two main methods. The first method involves technological modifications, such as the installation of ESS. The second option covers operational modifications, such as adjustments.

The application of ESS is divided into two categories: On-board and Wayside ESS. Both options offer a similar energy-saving potential, ranging from 10% to 35%, as indicated by the literature reviewed. Therefore, the primary consideration for choosing between them revolves around factors such as energy and power capacity, as well as practicality. On-board ESS provides the advantage of easy integration with the train's electric infrastructure. However, it suffers from limitations in energy and power capacity, as well as space constraints on the train. In contrast, Wayside ESS offers greater capacity for energy and power, aligning with the primary objective of installation. Additionally, it facilitates scalability for future expansions of metro lines. Nonetheless, challenges include managing the charge/discharge rate and addressing the complexity of infrastructure connections.

The operational regime of urban rail transport is divided into in-service and depot conditions. HVAC modifications for these conditions primarily involve adjustments to temperature and ventilation flow rates. A significant challenge lies in automating data insertion into the central control unit of the HVAC systems across the train fleet. Detailed business cases, such as implementing 4-5 adjustments per day, would likely require the development of new software. However, monthly adjustments may not necessitate such software development. While these suggestions promise enhanced operational precision and greater energy-saving potential, the development of automation software entails high initial and EPC costs, necessitating thorough investigation. Despite the costly installation, such software would facilitate automation and enable future modifications, thus requiring detailed research by the TF for long-term strategic planning.

The Excel file titled *Decision Making Tool*, generated within this thesis, serves to support the decision-making process for the TF. The novelty of this tool lies in its objective to quantify KPIs, allowing for a quantitative comparison of proposed business cases. Additionally, the utilization of radar charts aims to enhance decision-making by providing visual representations of data, thereby mitigating biases. This visualization facilitates productive discussion sessions among decision-makers from diverse backgrounds, ultimately leading to informed and effective decisions regarding urban rail transport systems. Moreover, the tools titled *HVAC Annual Energy Model* and *ESS LCC Model* have been developed to facilitate the evaluation of business cases in terms of cost modeling. These tools are designed to generate cost and energy output data, which can then be integrated into the *Decision Making Tool* for the analysis of relevant business case proposals.

In terms of future work, several key areas emerge. Firstly, expanding the inclusion of stakeholders and their respective KPIs within the *Decision Making Tool* is crucial. In this thesis, only the TF and passengers were considered stakeholders, necessitating the incorporation of additional relevant stakeholders. Additionally, the cost models developed for ESS and HVAC modifications require further refinement. Limited data availability during the development phase underscores the need for enhanced detail to ensure the accuracy of these models in the future. Another critical aspect is the assignment of KPI weights, which must be determined to facilitate precise decision-making. Furthermore, as identified in the literature review, various business cases such as eco-driving, reversible substations, and timetable optimization demonstrate promising energy-saving potentials. The development of the cost models of these cases into the developed decision-making framework would enrich its utility and effectiveness.

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Appendix A

Decision Matrix

	Clusters	Costs									Benefits					Others		
	KPIs	*Initial acquisition*	*Soft&EPC*	*Fixed maintenance costs*	*Variale maintenance costs*	*Operation costs*	*Environmental cost of decommissioning*	*Residual Value*	*NPV of total cost*	*Cost per kWh*	*Energy usage decrease*	*Capacity increase*	*Sustainability*	*Frequency increase*	*Travel comfort*	*Complexity*	*TRL*	*Availability of future customization*
	Units	*[SEK]*	*[SEK]*	*[SEK]*	*[SEK]*	*[SEK]*	*[SEK]*	*[SEK]*	*[SEK]*	*[SEK/kWh]*	*[%]*	*[%]*	-	*[%]*	*PMV*	-	-	-
Business Cases	**Weight of KPIs**																	
Business case 1																		
Business case 2																		
Business case 3																		
Business case 4																		
Business case 5																		
Business case 6																		
Business case 7																		
Best individual		#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

Appendix B

HVAC Energy Demand Calculator Matlab codes

HVAC Energy Demand Calculator

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Based on: 'Energy use in the operational cycle of passenger rail vehicles' MSc thesis - Erik Vinberg

URL: https://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-234853

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                   %
hvac.input_data_brake = readmatrix('Energy_calculation - Test.xlsx','sheet','HVAC_Auxiliary');
hvac.T_i = hvac.input_data_brake(1,2);                  % Indoor temperature in degree Celsius
hvac.T_u = hvac.input_data_brake(2,2);                  % Outdoor temperature in degree Celsius
hvac.n_passenger = hvac.input_data_brake(3,2);          % Number of passengers
hvac.k_shell = hvac.input_data_brake(4,2);              % Shell thermal conductivity
hvac.A_shell = hvac.input_data_brake(5,2);              % Total Shell area in meters square
hvac.A_win = hvac.input_data_brake(6,2);                % One side window area in meters square
hvac.q_sun = hvac.input_data_brake(7,2);                % heat flux from sun in W/m2
hvac.COP = hvac.input_data_brake(8,2);                  % Refrigerant cycle COP
hvac.V_array = [hvac.input_data_brake(16,2),hvac.input_data_brake(17,2),hvac.input_data_brake(18,2)]./3600;  % Volume flow rate of fresh air in m3/s
hvac.T_u_array = [hvac.input_data_brake(16,1),hvac.input_data_brake(17,1)];         % Outdoor temperature to decide volume flow rate in above array
                         % below 1st temperature, its the
                         % first value of flow rate,
hvac.P_lights = hvac.input_data_brake(9,2);             % lightning load
hvac.Other_auxiliary = hvac.input_data_brake(10,2);
hvac.driver_heat = hvac.input_data_brake(11,2);
hvac.driver_cool = hvac.input_data_brake(12,2);
hvac.aux_efficiency = hvac.input_data_brake(13,2);
[hvac.h,hvac.c] = HVAC(hvac.T_i,hvac.T_u,hvac.T_u_array,hvac.V_array,hvac.n_passenger,hvac.k_shell,hvac.A_shell,hvac.A_win,hvac.q_sun,hvac.P_lights,hvac.COP);
if hvac.T_u > 20
  hvac.Aux_power_electrical = (hvac.c + hvac.Other_auxiliary + hvac.driver_cool)./hvac.aux_efficiency;
else
  hvac.Aux_power_electrical = (hvac.h + hvac.Other_auxiliary + hvac.driver_heat)./hvac.aux_efficiency;
end
function [electrical_heating_power,electrical_cooling_power] = HVAC(T_i,T_u,T_u_array,V_array,n_passenger,k_shell,A_shell,A_win,q_sun,P_lights,COP)
rho_air = 1.225;                   % kg/m3 density of air
c_p = 1002;                        % J/K.kg specific heat of air
h_w = 2260*1000;                      % J/kg latent heat of vaporization of water
eps_shell = 0.3;                   % absorption factor of shell of metal surfaces
eps_win = 0.67;                    % transmission factor of the window
shading_factor = 0.5;                 % radiation constantly varies due to continuous changing sun orientation
K_s2 = 1.73e4;                     % For X55 train in W/K Heat transfer coefficient including the area for the secondary thermal system. For X61 its 5.17e3
A_side = 0.25*A_shell;                % Fraction of shell area exposed to sunlight
A_roof = 0.25*A_shell;                % Area of roof
x_i_max = 10/1000;                    % EN standard for maximum water vapor fraction
% Fresh air m3/h for T = [-5C,-5 < T_o < 26C, T_o > 26]
if T_u < T_u_array(1)
  V = V_array(1);
elseif T_i > T_u_array(2)
```

```
   V = V_array(1);
else
   V = V_array(2);
end
x_u = 15/1000; % inlet humidity
if T_u < 19
    T_i = T_i + 0;
    Q_lat_vent = 0; %More to the humidity control. It is latent heat of ventilation. Humidity occurs in high temperatures.
 else
    T_i = 20 + 0.25*(T_u - 19);
    Q_lat_vent = rho_air*h_w*V*(x_u - x_i_max);    %In hot conditions, we need to control the humidity.
 end
T_s2 = T_i - 3; % (Assume Zero!!) Secondary themal system i.e. the thermal mass below the car body
 assumed to be 3 degrees difference the car body
Q_shell = k_shell*A_shell*abs(T_i - T_u); % Heat loss from the car body shell
Q_sun = shading_factor*eps_shell*q_sun*(cosd(30)*(A_side - A_win) + sind(30)*A_roof); % Sun's heat entering into the car body from shell
Q_win = shading_factor*eps_win*q_sun*cosd(30)*A_win; % Sun's heat entering into the car body from window at an average incident angle at 30 deg
Q_sens_vent = rho_air*c_p*V*abs(T_i - T_u); % Sensible heating requirement for outdoor air
Q_sens_pass = (98.6 - (T_i - 18)*3.56)*n_passenger; % latent heat from passengers from EN 13129
Q_lat_pass = (23.5 - (T_i - 18)*2.98)*n_passenger; % sensible & latent heat from passengers from EN 13129
Q_aux = 0.98*P_lights; % Heat generated due to lights
Q_s2 = K_s2*(T_i - T_s2); % Secondary thermal system that tries to reach T_i temperature while gaining or losing heat from carbody
electrical_heating_power = (Q_shell - Q_sun - Q_win + Q_sens_vent - Q_sens_pass - Q_aux + Q_s2);
electrical_cooling_power = (Q_shell + Q_sun + Q_win + Q_sens_vent + Q_lat_vent + Q_lat_pass + Q_sens_pass + Q_aux + Q_s2)/(COP);
end
```

Appendix C

HVAC Annual Energy Model interface for In-service operations

Week period	Weekdays	
Condition	In Service	
Cost/kWh		[SEK]
Annual Energy consumed	0	[kWh]
Annual Total Cost	0	[SEK]

Months	***Data Sources***	Data from SMHI	EN 14750, propose several	Data from TF	EN 14750, propose several	ISO 7730	Sidharth's model	Data from TF	
	Operation hour intervals	***Outdoor Temperature [C]***	***Optimum indoor temperature [C]***	***Number of passangers [#]***	***Ventilation Flow rate [m3/h/passenger]***	***PMV value***	***Power Required [kW]***	***Annual hours in this condition [h]***	***Annual Energy consumed per timeframe [kWh]***
January	05:00-07:00								0
	07:00-09:00								0
	09:00-16:00								0
	16:00-17:00								0
	17:00-01:00								0
February	05:00-07:00								0
	07:00-09:00								0
	09:00-16:00								0
	16:00-17:00								0
	17:00-01:00								0
March	05:00-07:00								0
	07:00-09:00								0
	09:00-16:00								0
	16:00-17:00								0
	17:00-01:00								0
April	05:00-07:00								0
	07:00-09:00								0
	09:00-16:00								0
	16:00-17:00								0
	17:00-01:00								0
May	05:00-07:00								0
	07:00-09:00								0
	09:00-16:00								0
	16:00-17:00								0
	17:00-01:00								0
June	05:00-07:00								0
	07:00-09:00								0
	09:00-16:00								0
	16:00-17:00								0
	17:00-01:00								0
July	05:00-07:00								0
	07:00-09:00								0
	09:00-16:00								0
	16:00-17:00								0
	17:00-01:00								0
August	05:00-07:00								0
	07:00-09:00								0
	09:00-16:00								0
	16:00-17:00								0
	17:00-01:00								0
September	05:00-07:00								0
	07:00-09:00								0
	09:00:00-16:00								0
	09:00-16:00								0
	17:00-01:00								0
October	05:00-07:00								0
	07:00-09:00								0
	09:00-16:00								0
	16:00-17:00								0
	17:00-01:00								0
November	05:00-07:00								0
	07:00-09:00								0
	09:00-16:00								0
	16:00-17:00								0
	17:00-01:00								0
December	05:00-07:00								0
	07:00-09:00								0
	09:00-16:00								0
	16:00-17:00								0
	17:00-01:00								0

Appendix D

HVAC Annual Energy Model interface for Depot operations

Week period	Weekdays	
Condition	Depot	
Cost/kWh		[SEK]
Annual Energy consumed	0	[kWh]
Annual Total Cost	0	[SEK]

Months	***Data Sources***	Data from SMHI	EN 14750, propose several	EN 14750, propose several	Sidharth's model	Data from TF	
	Operation hour intervals	***Outdoor Temperature [C]***	***Optimum indoor temperature [C]***	***Ventilation Flow rate [m3/h/passenger]***	***Power Required [kW]***	***Annual hours in this condition [h]***	***Annual Energy consumed per timeframe [kWh]***
January	01:00-05:00						0
February	01:00-05:00						0
March	01:00-05:00						0
April	01:00-05:00						0
May	01:00-05:00						0
June	01:00-05:00						0
July	01:00-05:00						0
August	01:00-05:00						0
September	01:00-05:00						0
October	01:00-05:00						0
November	01:00-05:00						0
December	01:00-05:00						0

Appendix E

Passenger occupancy rate distributions throughout stations

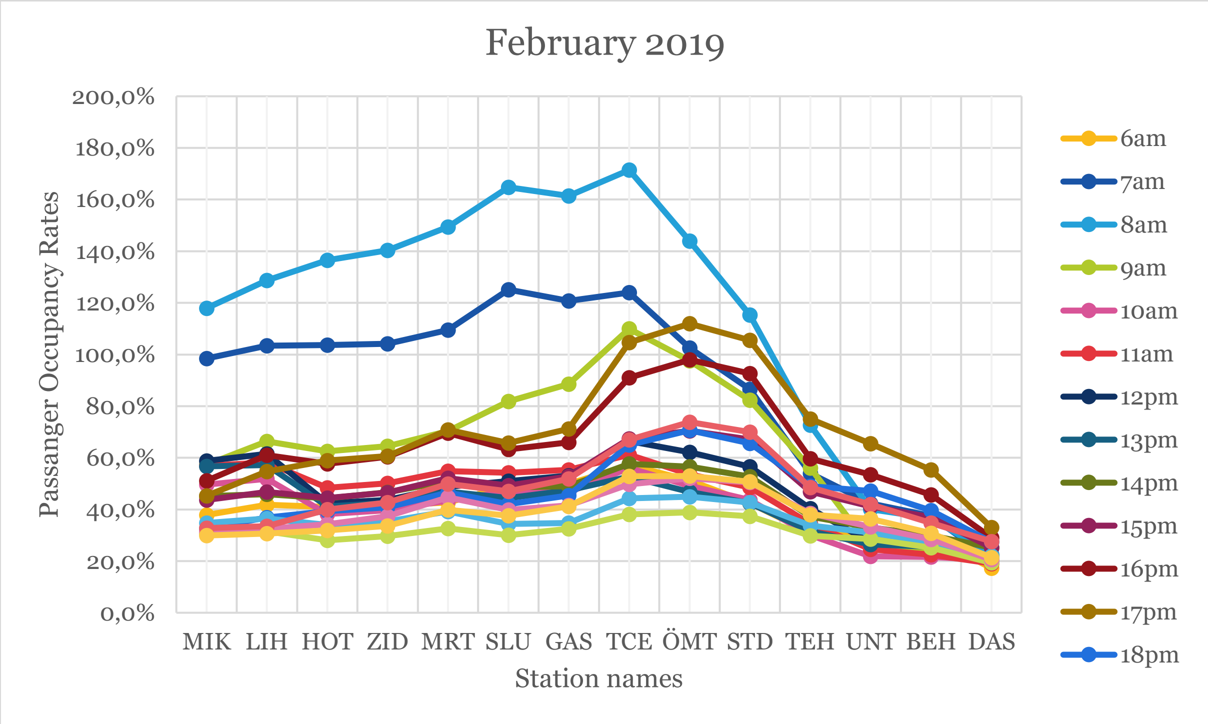

Figure E.1: February 2019 passenger occupancy rates for line 14 from N-S direction

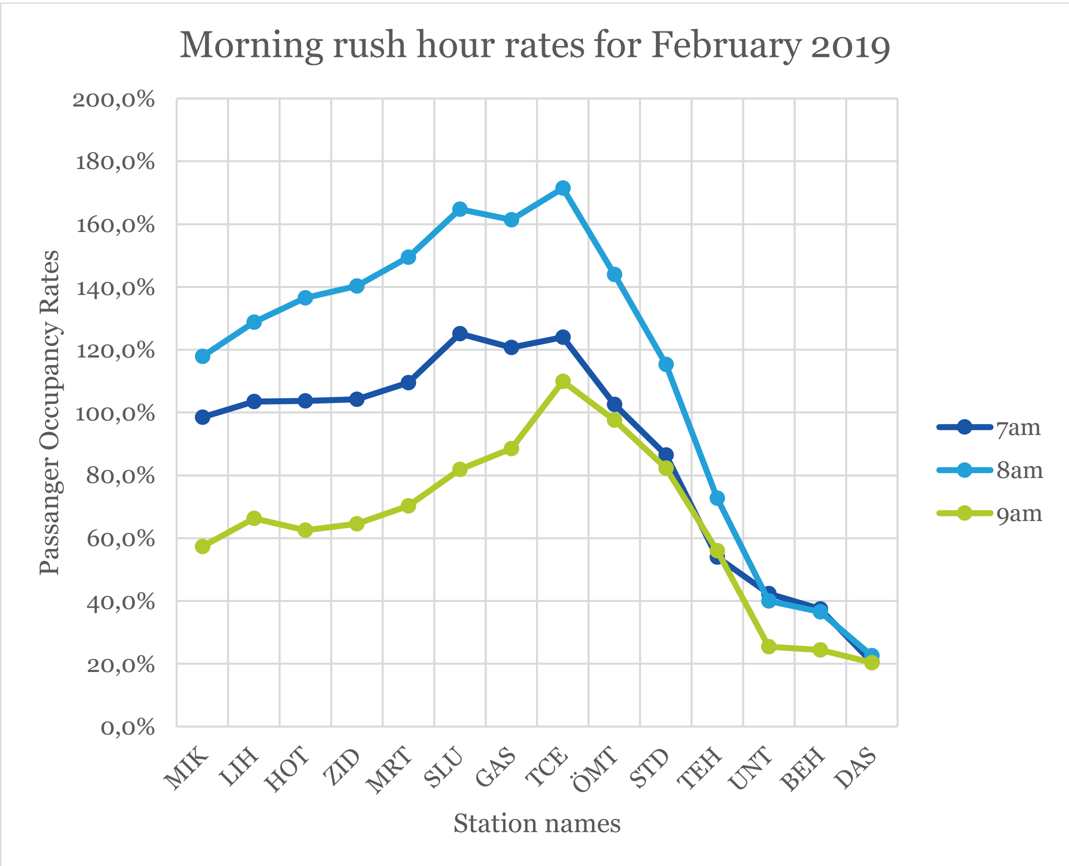

Figure E.2: February 2019 morning rush hour passenger occupancy rates for line 14 from N-S direction

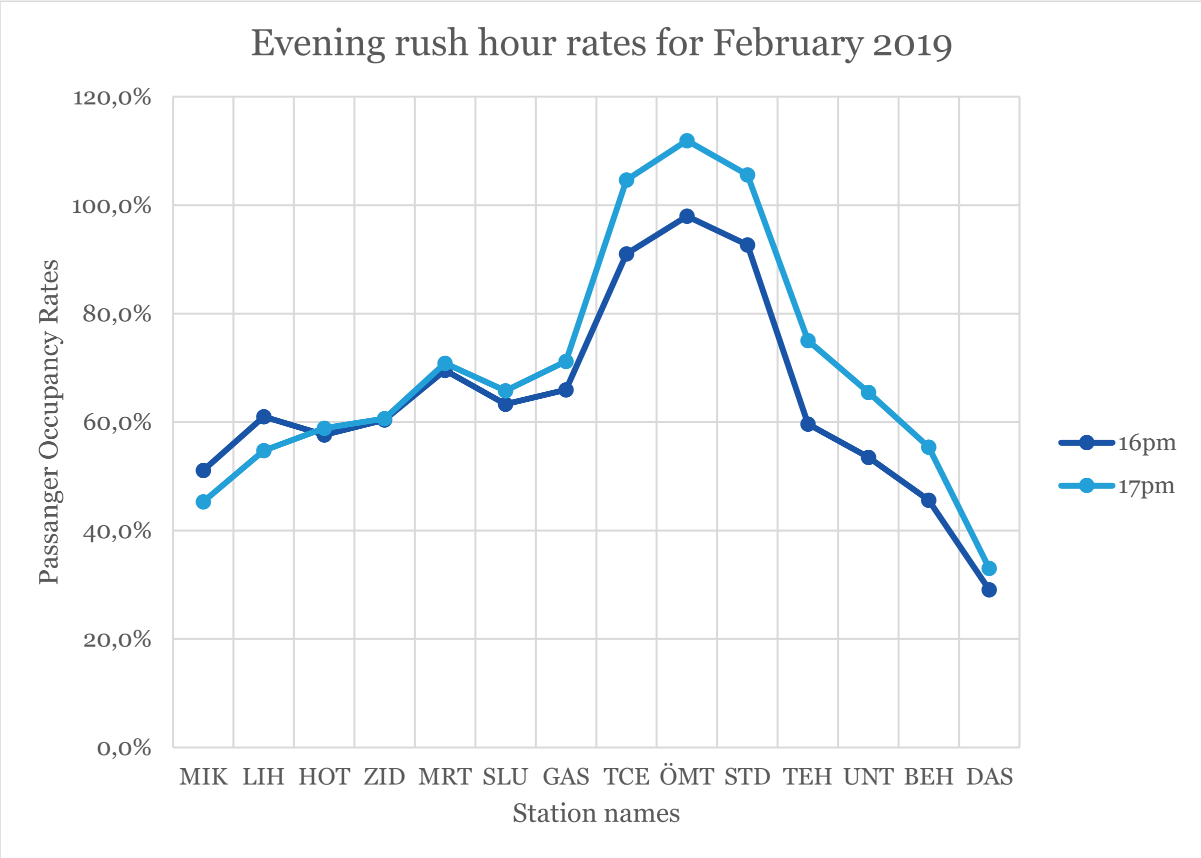

Figure E.3: February 2019 evening rush hour passenger occupancy rates for line 14 from N-S direction

Appendix F

Outdoor temperature distribution data obtained from SMHI

		Years					
Months	***Hour periods***	2019	2020	2021	2022	2023	***Average of 5 years***
January	00:00-09:00	-2,1	3,7	-1,3	0,1	0,9	0,3
	09:00-19:00	-1,4	4,6	-1,0	0,8	1,4	0,9
	19:00-00:00	-1,6	4,0	-1,4	0,4	1,0	0,5
	Monthly Average	-1,7	4,2	-1,2	0,5	1,1	0,6
February	00:00-09:00	1,0	2,1	-3,4	0,0	-0,4	-0,1
	09:00-19:00	2,7	3,7	-0,9	1,7	1,3	1,7
	19:00-00:00	1,7	2,7	-1,9	0,7	0,1	0,7
	Monthly Average	1,9	2,9	-2,0	0,8	0,4	0,8
March	00:00-09:00	1,2	2,0	1,9	1,4	-0,8	1,2
	09:00-19:00	4,0	5,0	4,9	6,4	1,9	4,4
	19:00-00:00	2,4	3,0	2,9	2,8	0,2	2,3
	Monthly Average	2,6	3,5	3,4	3,8	0,5	2,7
April	00:00-09:00	5,1	4,9	3,3	3,4	3,4	4,0
	09:00-19:00	9,9	9,5	7,4	7,8	8,2	8,6
	19:00-00:00	5,7	6,0	4,3	4,3	4,3	4,9
	Monthly Average	7,2	7,0	5,2	5,4	5,6	6,1
May	00:00-09:00	8,9	8,0	8,8	9,3	10,0	9,0
	09:00-19:00	13,1	12,3	12,7	13,8	15,3	13,5
	19:00-00:00	9,4	8,4	9,2	9,8	10,5	9,5
	Monthly Average	10,8	9,9	10,5	11,3	12,3	11,0
June	00:00-09:00	16,0	16,2	16,9	15,7	15,8	16,1
	09:00-19:00	21,1	21,4	22,1	20,8	21,6	21,4
	19:00-00:00	17,2	16,8	17,7	16,5	16,5	16,9
	Monthly Average	18,4	18,5	19,2	18,0	18,4	18,5
July	00:00-09:00	15,7	14,9	19,0	16,6	15,6	16,3
	09:00-19:00	20,0	19,2	24,0	20,5	19,6	20,7
	19:00-00:00	16,1	15,7	19,5	17,1	16,1	16,9
	Monthly Average	17,6	16,9	21,2	18,3	17,4	18,3
August	00:00-09:00	15,9	16,7	14,4	17,4	15,4	16,0
	09:00-19:00	20,3	21,9	17,7	22,4	18,5	20,2
	19:00-00:00	16,7	17,4	14,9	18,0	15,8	16,5
	Monthly Average	17,9	19,0	15,9	19,6	16,8	17,8
September	00:00-09:00	11,6	12,1	11,1	10,5	14,1	11,9
	09:00-19:00	14,7	15,9	14,2	13,6	17,4	15,1
	19:00-00:00	11,9	13,1	11,8	11,0	14,6	12,5
	Monthly Average	12,9	13,9	12,5	11,9	15,6	13,4
October	00:00-09:00	6,3	8,5	8,3	8,9	5,9	7,6
	09:00-19:00	8,2	10,2	10,3	11,2	7,7	9,5
	19:00-00:00	6,8	9,0	9,0	9,6	6,4	8,2
	Monthly Average	7,2	9,3	9,3	10,0	6,7	8,5
November	00:00-09:00	3,7	6,4	3,2	5,3	1,6	4,0
	09:00-19:00	4,3	7,4	4,3	5,8	2,0	4,7
	19:00-00:00	4,0	6,6	3,3	5,3	1,5	4,1
	Monthly Average	4,0	6,8	3,7	5,5	1,7	4,4
December	00:00-09:00	2,7	3,9	-2,1	-1,8	-2,1	0,1
	09:00-19:00	3,2	4,0	-1,1	-1,2	-1,5	0,7
	19:00-00:00	3,0	4,0	-1,6	-1,6	-1,6	0,4
	Monthly Average	3,0	4,0	-1,6	-1,5	-1,7	0,4

Figure F.1: 5-year outdoor temperature distributions per timeframes

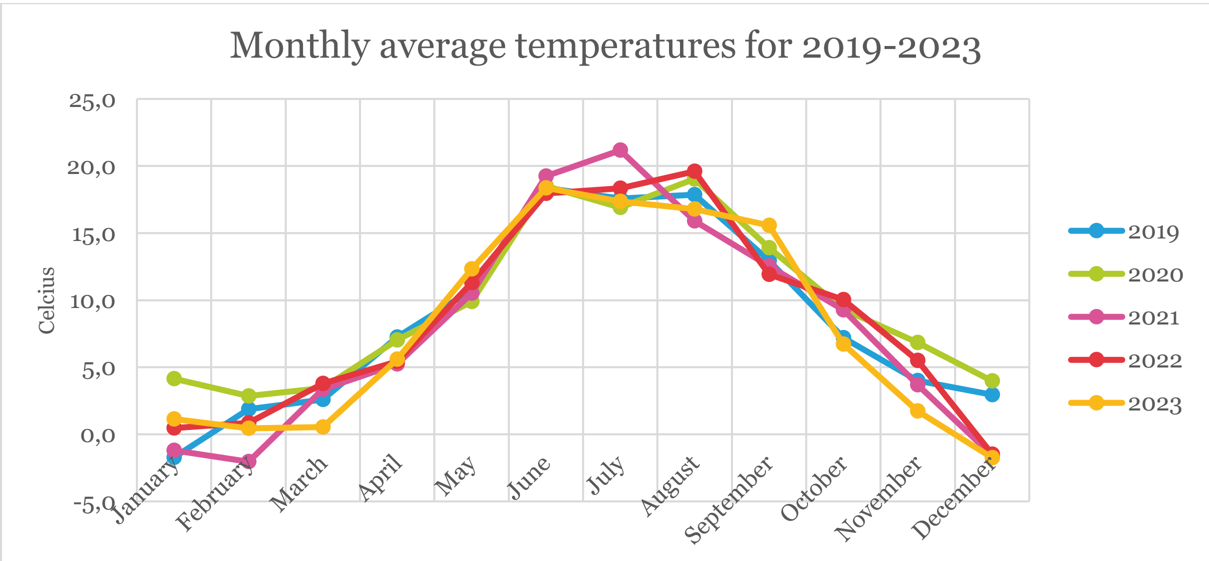

Figure F.2: Monthly average outdoor temperatures for the 2019-2023 period

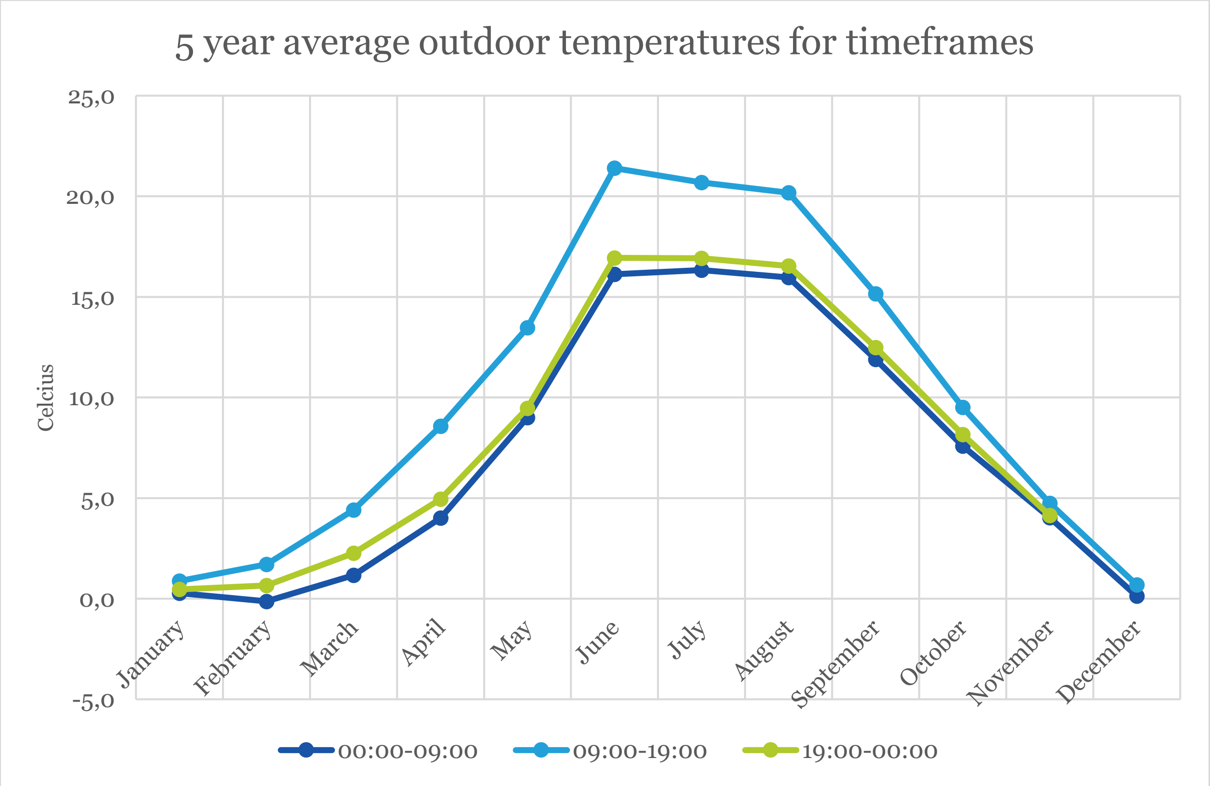

Figure F.3: 5-year average outdoor temperatures for timeframes

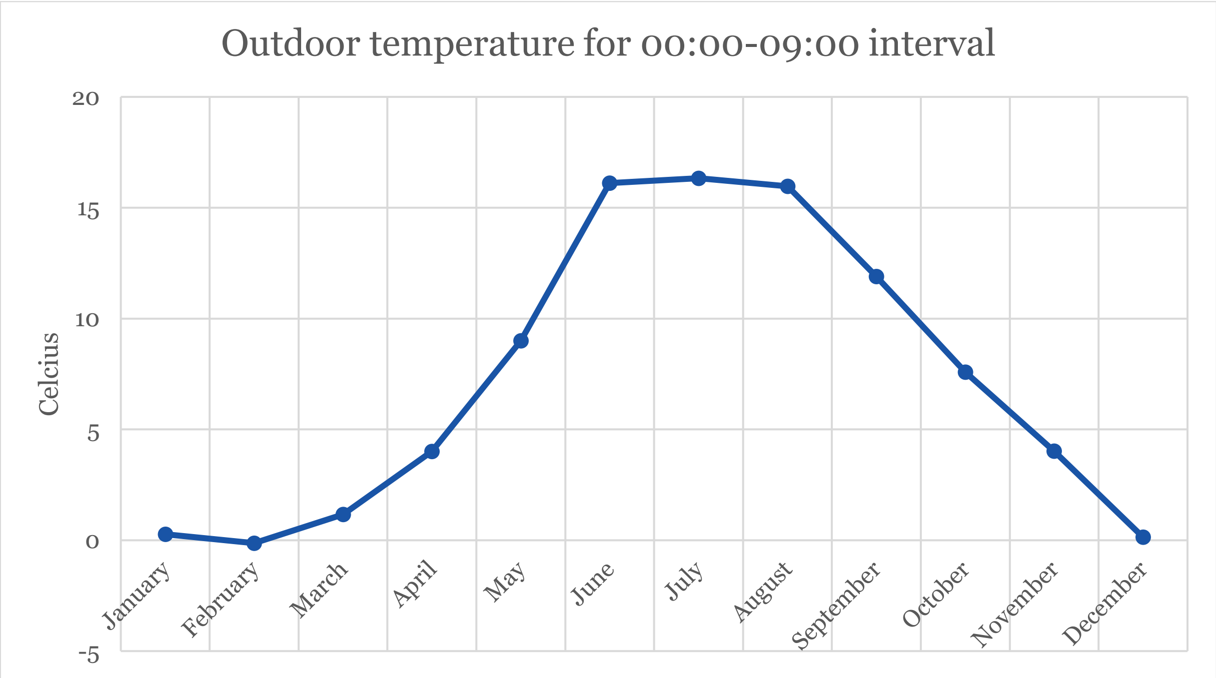

Figure F.4: 5-year averaged outdoor temperature for 00:00-09:00 intervals through months

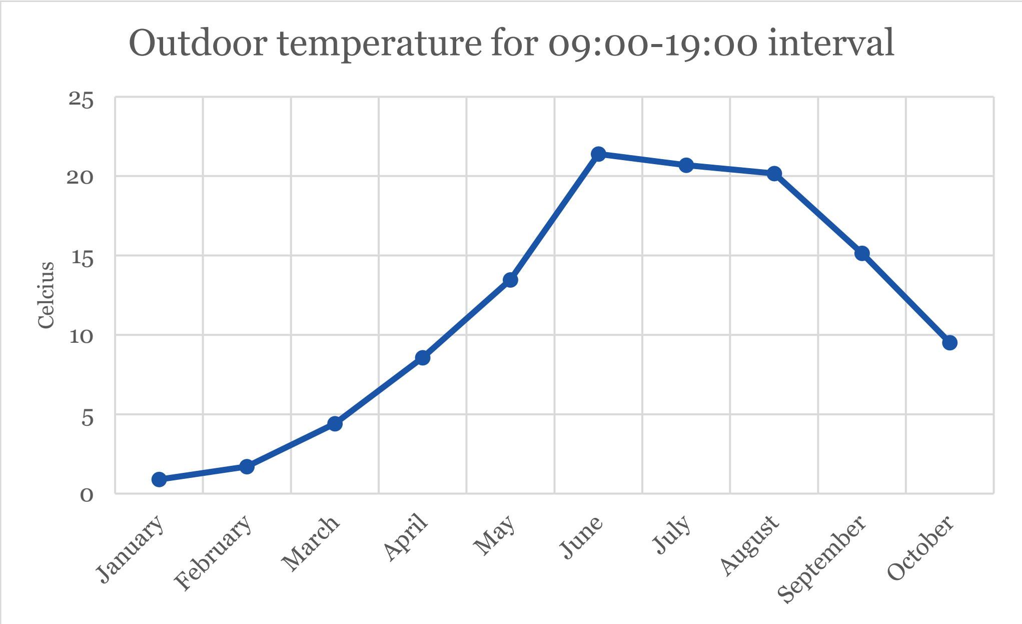

Figure F.5: 5-year averaged outdoor temperature for 09:00-19:00 intervals through months

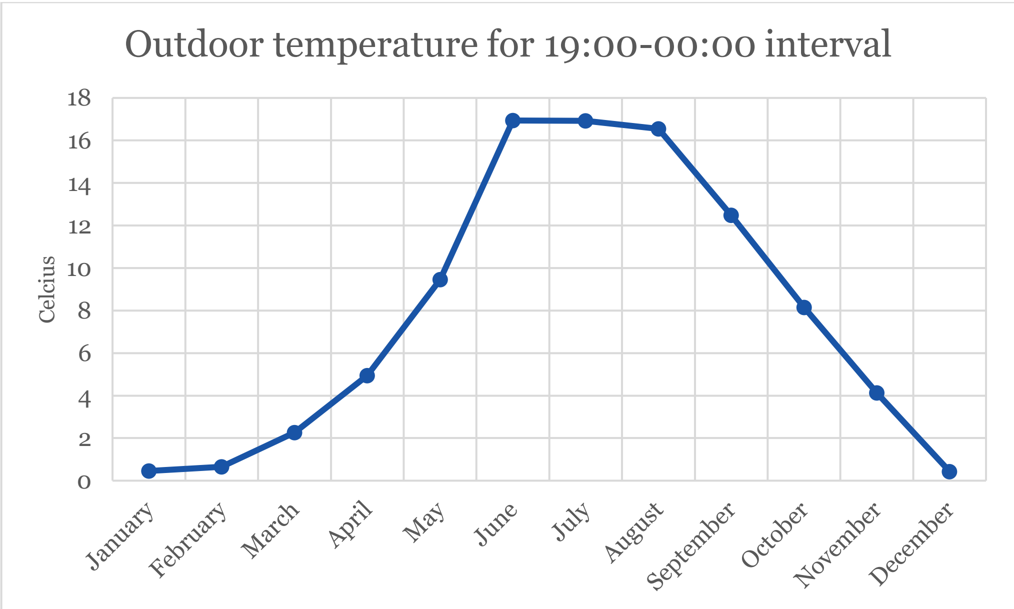

Figure F.6: 5-year averaged outdoor temperature for 19:00-00:00 intervals through months

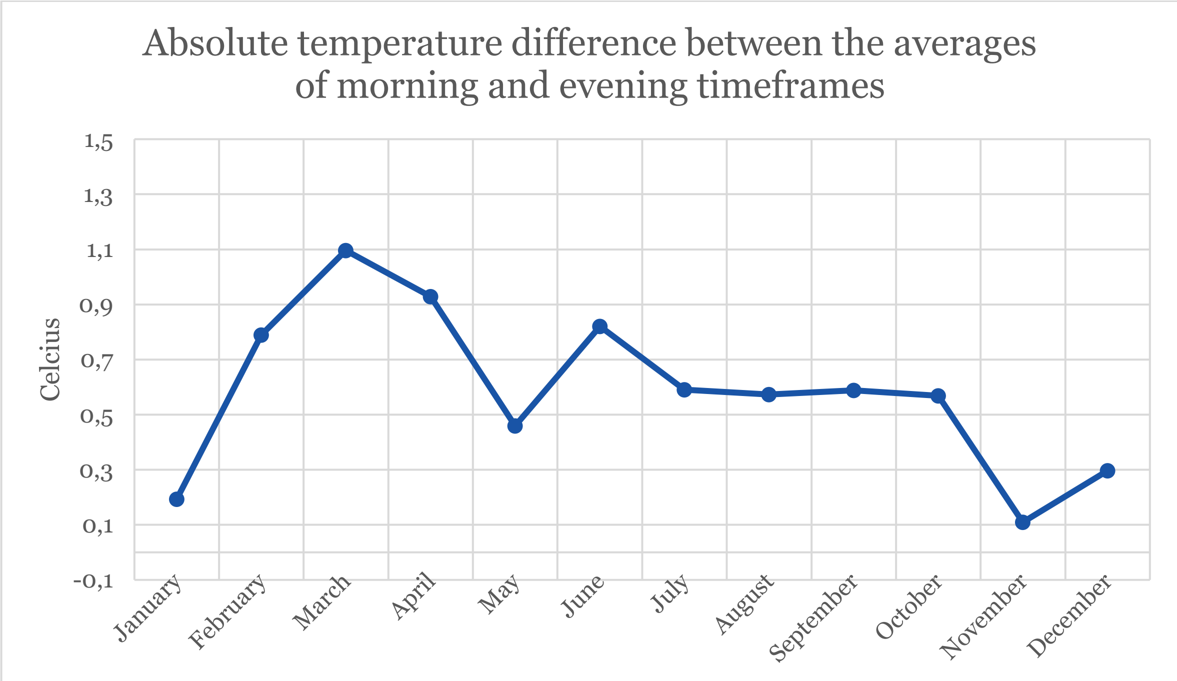

Figure F.7: Temperature differences for each month during the morning and evening timeframes

Appendix G

ESS LCC Model interface

LCC Calculation tool for ESS

Initial Acquisition cost (+)

			ESS 1	ESS 2	ESS 3	Unit
Initial investment cost of battery storage	IC_SS					[SEK]
Specific energy cost of battery storage	C_e					[SEK/kWh]
Energy capacity of battery storage	E_SS					[kWh]
Specific power cost of battery storage	C_p					[SEK/kW]
Nominal output power of battery storage	N_SS					[kW]
Required energy capacity	E_req	Only as a portion: EAC_Tot*ε				[kWh]
Required output power capacity	N_req					[kW]
# of battery units required	n		#DIV/0!			[number]
Other hardware costs	C_oth					[SEK]
Total acquisition cost of ESS pack	C_acq		#DIV/0!			[SEK]

Soft&EPC costs (+)

			ESS 1	ESS 2	ESS 3	Unit
Licensing fee						[SEK]
Operator education						[SEK]
Does the operation needs to be stooped for installation?						[yes/no]
Cost rate for operation stopping						[SEK/hour]
Mean time to Install (MTTI)						[hours]
Cost of stopping the operation	C_stop		0			[SEK]
Labour & construction cost						[SEK]
Total soft&EPC costs	C_epc		0			[SEK]

Maintenance costs (+)

			ESS 1	ESS 2	ESS 3	Unit
Total NPV of Fixed maintenance costs	NPV_FC_SS		0			[SEK]
Fraction of annual M&O cost to the total initial investment	m					[%]
Mean annual M&O cost inflation rate	x_2					[%]
Fixed maintenance cost [Annual]	FC_SS		0			[SEK]
Total NPV of Variable maintenance costs	NPV_VC_SS		0			[SEK]
Years of operation for the proposed configuration	n		20			[year]
Lifetime of energy storage system's major parts to be replaced	n_k		3			[year]
Number of big replacements required throughout the whole life			6			[number]
Cost of part to be replaced	C_part					[SEK]
Does the operation needs to be stooped for installation?						[yes/no]
Cost rate for operation stopping						[SEK/hour]
Mean time to Install (MTTI)						[hours]
Cost of stopping the operation	C_stop		0			[SEK]
Labour & construction cost	C_lbr					[SEK]
Total individual cost of part replacement	VC_SS		0			[SEK]

Recovered energy costs (-)

			ESS 1	ESS 2	ESS 3	Unit
Total NPV of annual Recovered energy costs			0			[SEK]
Annual energy demand of the local electricity network	E_total	EAC_Tot				[kWh/year]
Energy demand ratio covered directly by the ESS	ε	%EACBRR/EAC_Tot				[%]
Energy transformation efficiency of the ESS	η_SS		95			[%]
Specific input energy cost	C_1					[SEK/kWh]
Mean annual escalation rate of the input Energy price	x_1					[%]
Annual Recovered energy costs	EC_SS		0			[SEK/year]

Environmental Cost (+)

			ESS 1	ESS 2	ESS 3	Unit
Total NPV of the environmental cost of decomissioning	C_env					[SEK]
Environmental cost of decomissioning						[SEK]

Residual value at the end of service life (-)

			ESS 1	ESS 2	ESS 3	Unit
Total NPV of the residual value at the end of service life	C_res					[SEK]
Residual value at the end of service life						[SEK]

Final results

			ESS 1	ESS 2	ESS 3	Unit
Cost per kWh for lifetime	C_0		#DIV/0!			[SEK/kWh]
NPV of total cost of the ESS	C_SS		#DIV/0!			[SEK]
Annual energy demand of the local electricity network	E_total	EAC_Tot				[kWh/year]
Energy demand ratio covered directly by the ESS	ε	%EACBRR/EAC_Tot				[%]
Mean annual escalation rate of electricity price	x_4					[%]

Appendix H

Decision-making tool filled with hypothetical KPI values for simulation purposes

		Clusters	Costs									Benefits					Others		
		KPIs	Initial acquisition	Soft&EPC	Fixed maintenance costs	Variale maintenance costs	Operation costs	Environmental cost of decommissioning	Residual Value	NPV of total cost	Cost per kWh	Energy usage decrease	Capacity increase	Sustainability	Frequency increase	Travel comfort	Complexity	TRL	Availability of future customization
		Units	[SEK]	[SEK]	[SEK]	[SEK]	[SEK]	[SEK]	[SEK]	[SEK]	[SEK/kWh]	[%]	[%]	-	[%]	PMV	-	-	-
Business Clusters	Business Cases	Weight of KPIs	4	2	3	2	2	2	2	5	2	5	3	2	2	2	2	4	3
In service HVAC	Fixed Setpoint Temperature with Dynamic Ventilation Flow Rate (Service)		100 000	50 000	10 000	15 000	35 000	50 000	NA	350 000	-	1	NA	1	NA	-1	1	5	1
	Monthly Temperature Adjustments with Dynamic Ventilation Flow Rate (Service)		100 000	100 000	10 000	15 000	50 000	50 000	NA	400 000	-	3	NA	3	NA	1	2	5	1
	Detailed (5 Adjustments / Day) Time-Period Temperature Adjustments with Dynamic Ventilation Flow Rate		750 000	100 000	20 000	35 000	70 000	50 000	NA	1 300 000	-	5	NA	5	NA	3	3	3	5
	Detailed (4 Adjustments / Day) Time-Period Temperature Adjustments with Dynamic Ventilation Flow Rate		600 000	100 000	20 000	35 000	60 000	50 000	NA	1 100 000	-	4	NA	4	NA	2	3	3	5
Depot HVAC	Fixed Setpoint Temperature and Dynamic Ventilation Flow Rate (Depot)		100 000	50 000	10 000	15 000	20 000	50 000	NA	330 000	-	1	NA	1	NA	-1	1	5	1
	Monthly Temperature Adjustments and Dynamic Ventilation Flow Rate (Depot)		100 000	100 000	10 000	15 000	25 000	50 000	NA	400 000	-	2	NA	2	NA	NA	2	5	1
	Detailed Time-Period Temperature Adjustment and Dynamic Ventilation Flow Rate (Depot)		500 000	100 000	20 000	35 000	30 000	50 000	NA	900 000	-	3	NA	3	NA	NA	3	3	5
ESS	On-Board ESS		2 200 000	350 000	60 000	110 000	100 000	100 000	300 000	8 000 000	-	10	2	3	1	NA	4	3	2
	Wayside ESS		1 100 000	300 000	45 000	90 000	110 000	100 000	400 000	7 000 000	-	15	4	3	3	NA	4	5	3

Appendix I

Utilization of the best individual row in the hypothetical decision-making process

		Clusters	Costs									Benefits					Others		
		KPIs	Initial acquisition	Soft&EPC	Fixed maintenance costs	Variale maintenance costs	Operation costs	Environmental cost of decommissioning	Residual Value	NPV of total cost	Cost per kWh	Energy usage decrease	Capacity increase	Sustainability	Frequency increase	Travel comfort	Complexity	TRL	Availability of future customization
		Units	[SEK]	[SEK]	[SEK]	[SEK]	[SEK]	[SEK]	[SEK]	[SEK]	[SEK/kWh]	[%]	[%]	-	[%]	PMV	-	-	-
Business Clusters	**Business Cases**	**Weight of KPIs**	4	2	3	2	2	2	2	5	2	5	3	2	2	2	2	4	3
In service HVAC	*Fixed Setpoint Temperature with Dynamic Ventilation Flow Rate (Service)*		100 000	50 000	10 000	15 000	35 000	50 000	NA	350 000	-	1	NA	1	NA	-1	1	5	1
	Monthly Temperature Adjustments with Dynamic Ventilation Flow Rate (Service)		100 000	100 000	10 000	15 000	50 000	50 000	NA	400 000	-	3	NA	3	NA	1	2	5	1
	Detailed (5 Adjustments / Day) Time-Period Temperature Adjustments with Dynamic Ventilation Flow Rate		750 000	100 000	20 000	35 000	70 000	50 000	NA	1 300 000	-	5	NA	5	NA	3	3	3	5
	Detailed (4 Adjustments / Day) Time-Period Temperature Adjustments with Dynamic Ventilation Flow Rate		600 000	100 000	20 000	35 000	60 000	50 000	NA	1 100 000	-	4	NA	4	NA	2	3	3	5
Depot HVAC	*Fixed Setpoint Temperature and Dynamic Ventilation Flow Rate (Depot)*		100 000	50 000	10 000	15 000	20 000	50 000	NA	330 000	-	1	NA	1	NA	-1	1	5	1
	Monthly Temperature Adjustments and Dynamic Ventilation Flow Rate (Depot)		100 000	100 000	10 000	15 000	25 000	50 000	NA	400 000	-	2	NA	2	NA	NA	2	5	1
	Detailed Time-Period Temperature Adjustment and Dynamic Ventilation Flow Rate (Depot)		500 000	100 000	20 000	35 000	30 000	50 000	NA	900 000	-	3	NA	3	NA	NA	3	3	5
ESS	*On-Board ESS*		2 200 000	350 000	60 000	110 000	100 000	100 000	300 000	8 000 000	-	10	2	3	1	NA	4	3	2
	Wayside ESS		1 100 000	300 000	45 000	90 000	110 000	100 000	400 000	7 000 000	-	15	4	3	3	NA	4	5	3
	Best individual		Fixed Setpoint Temperature with Dynamic Ventilation Flow Rate (Service)	Fixed Setpoint Temperature with Dynamic Ventilation Flow Rate (Service)	Fixed Setpoint Temperature with Dynamic Ventilation Flow Rate (Service)	Fixed Setpoint Temperature with Dynamic Ventilation Flow Rate (Service)	Fixed Setpoint Temperature and Dynamic Ventilation Flow Rate (Depot)	Fixed Setpoint Temperature with Dynamic Ventilation Flow Rate (Service)	On-Board ESS	Fixed Setpoint Temperature and Dynamic Ventilation Flow Rate (Depot)	#N/A	Wayside ESS	Wayside ESS	Detailed (5 Adjustments / Day) Time-Period Temperature Adjustments with Dynamic Ventilation Flow Rate	Wayside ESS	Detailed (5 Adjustments / Day) Time-Period Temperature Adjustments with Dynamic Ventilation Flow Rate	On-Board ESS	Fixed Setpoint Temperature with Dynamic Ventilation Flow Rate (Service)	Detailed (5 Adjustments / Day) Time-Period Temperature Adjustments with Dynamic Ventilation Flow Rate

Appendix J

Radar chart visualizations of the selected business cases for further comparison

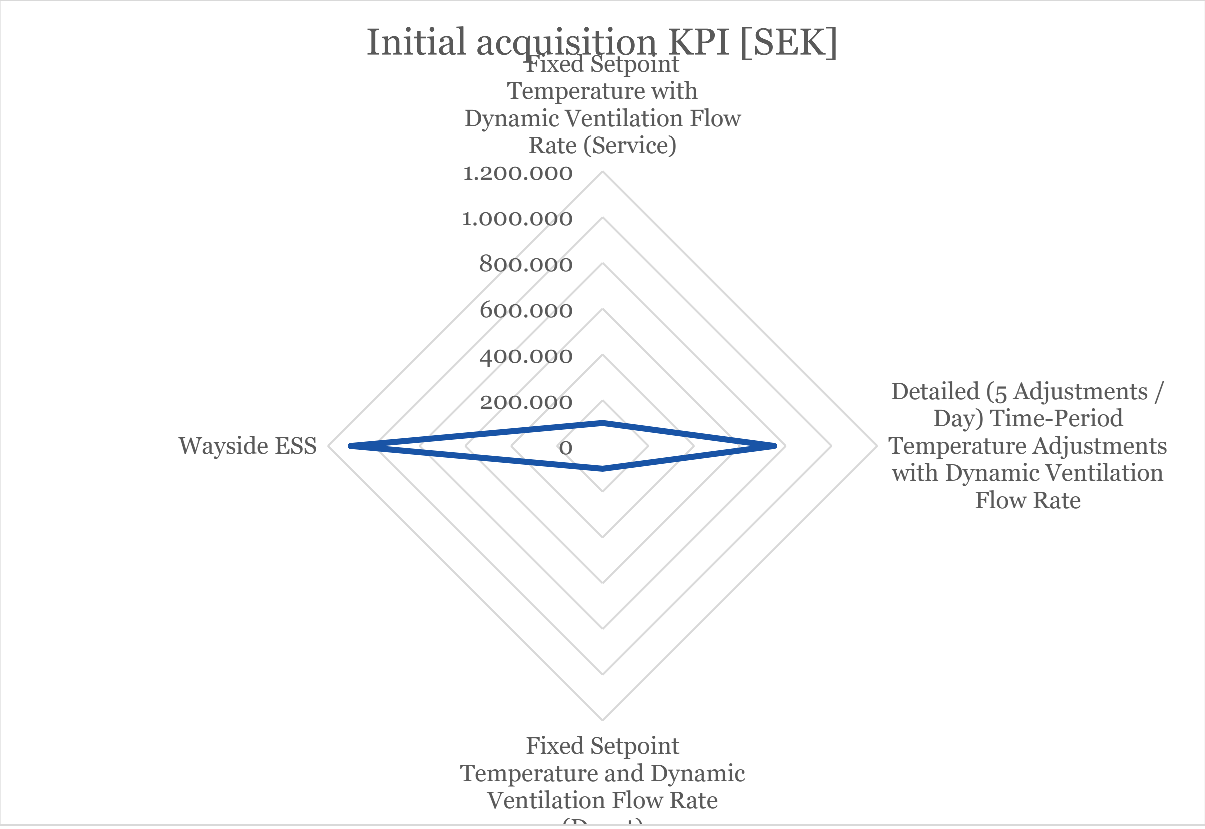

Figure J.1: Initial acquisition KPI results of filtered business cases

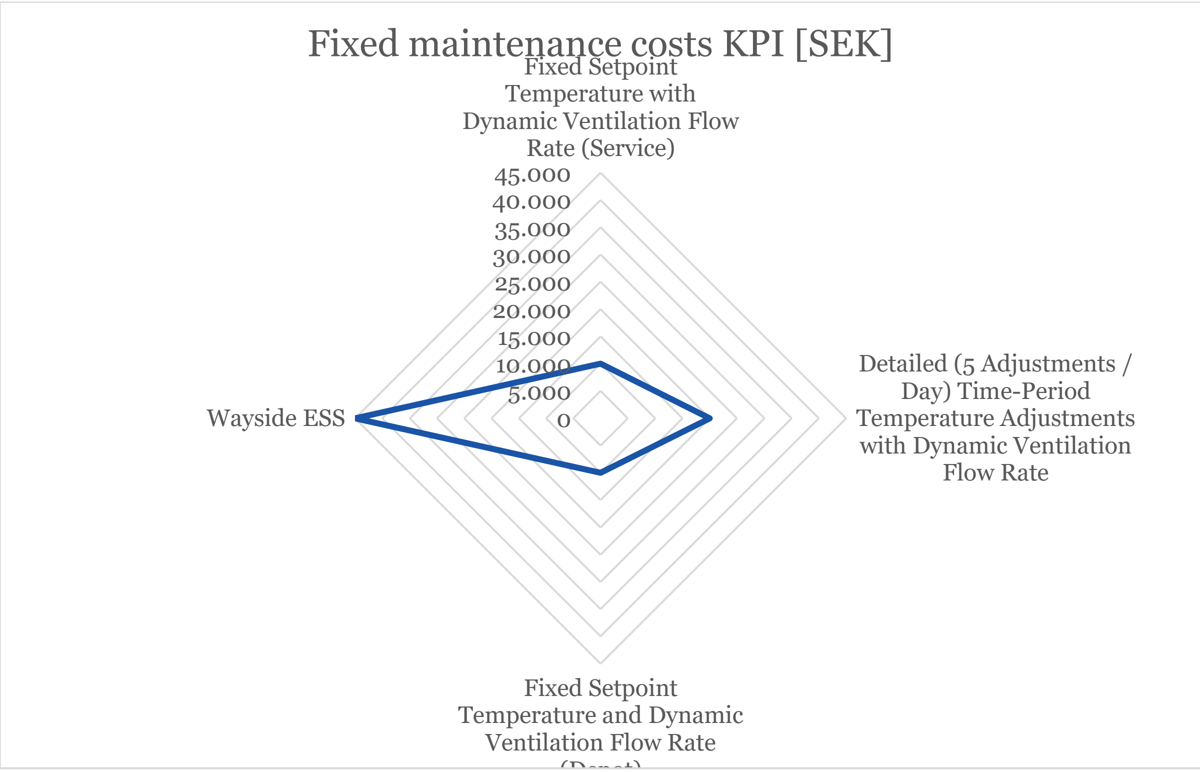

Figure J.2: Fixed maintenance costs KPI results of filtered business cases

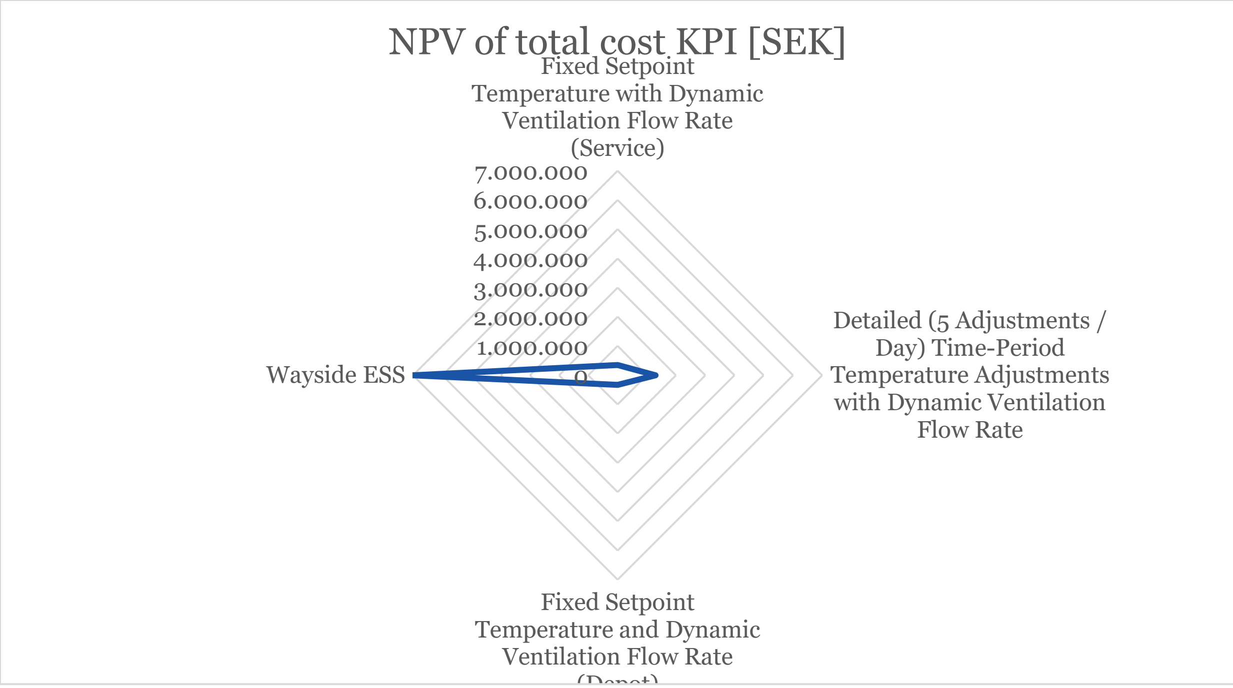

Figure J.3: NPV of total cost KPI results of filtered business cases

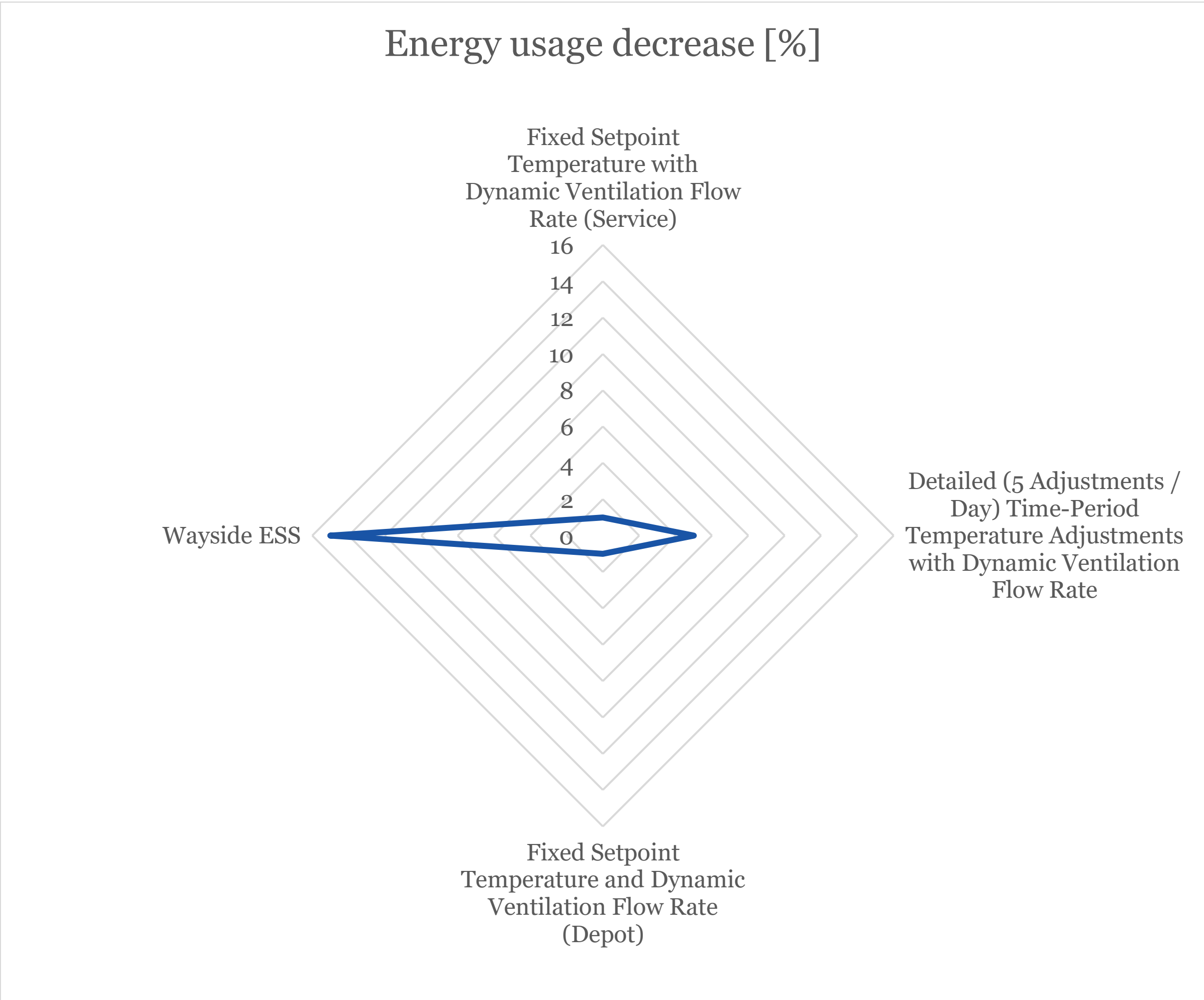

Figure J.4: Energy usage decrease KPI results of filtered business cases

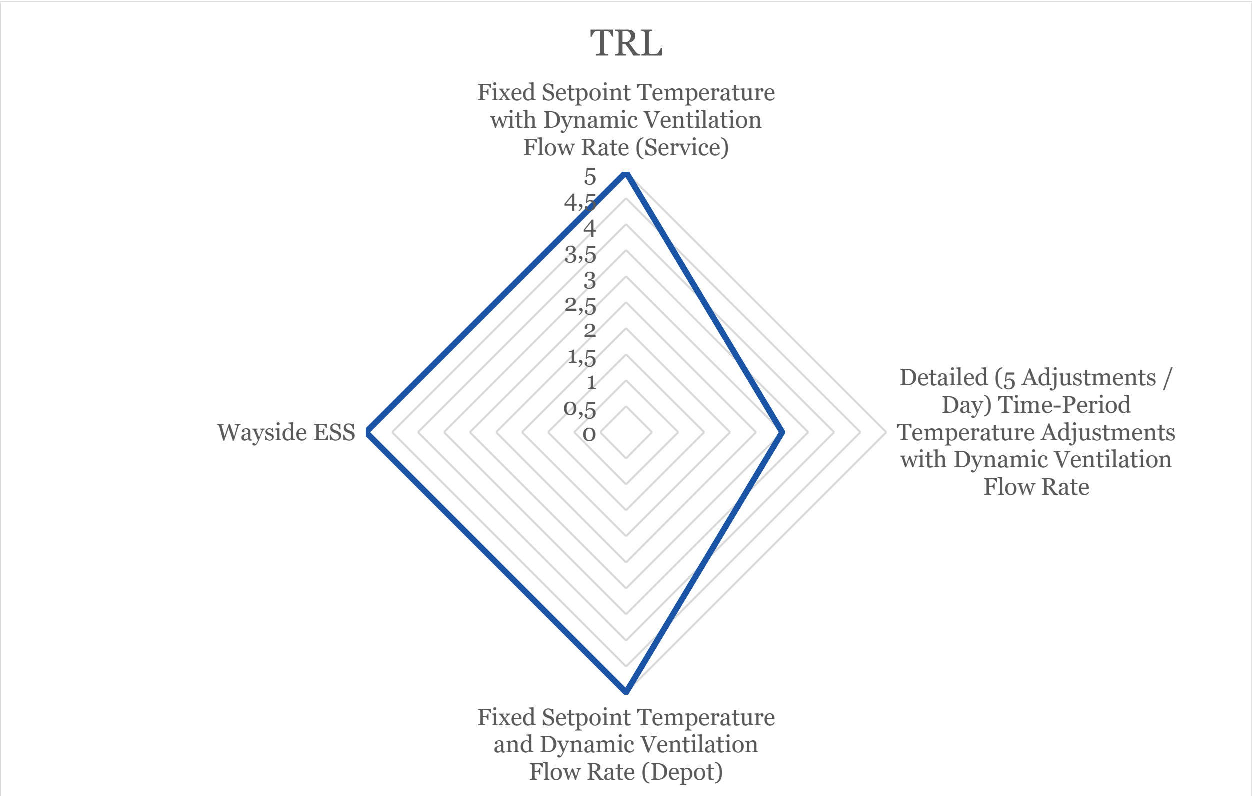

Figure J.5: Technology Readiness Level KPI results of filtered business cases

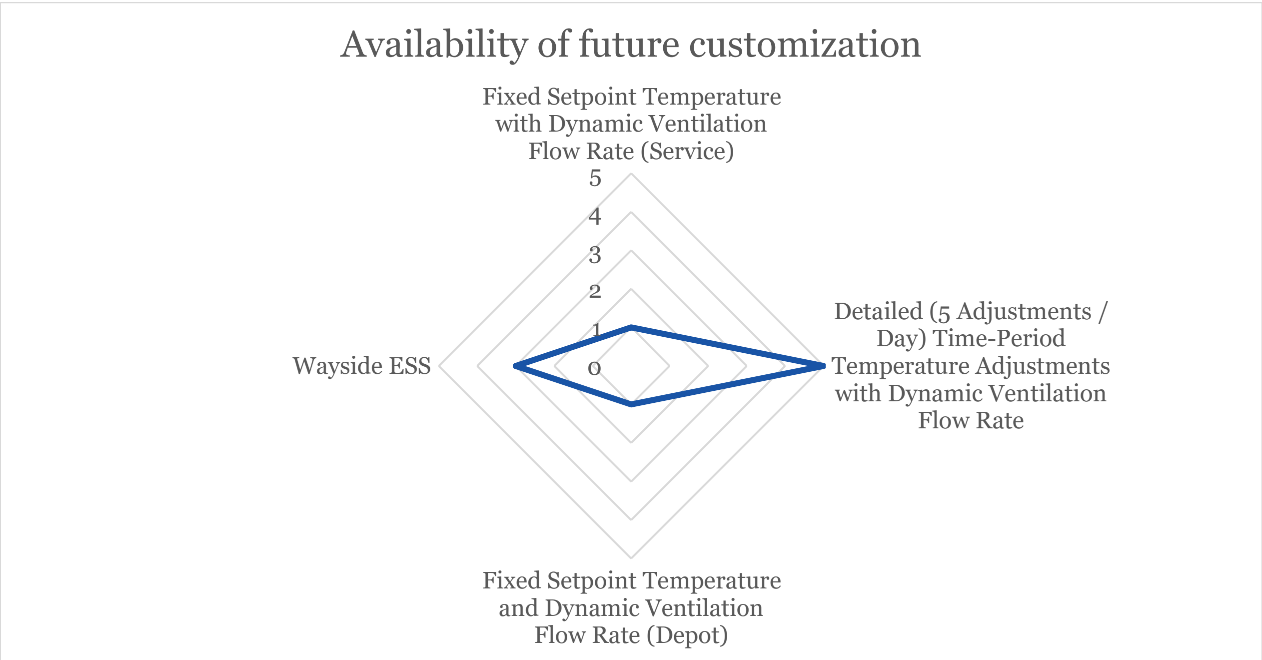

Figure J.6: Availability of future customization KPI results of filtered business cases

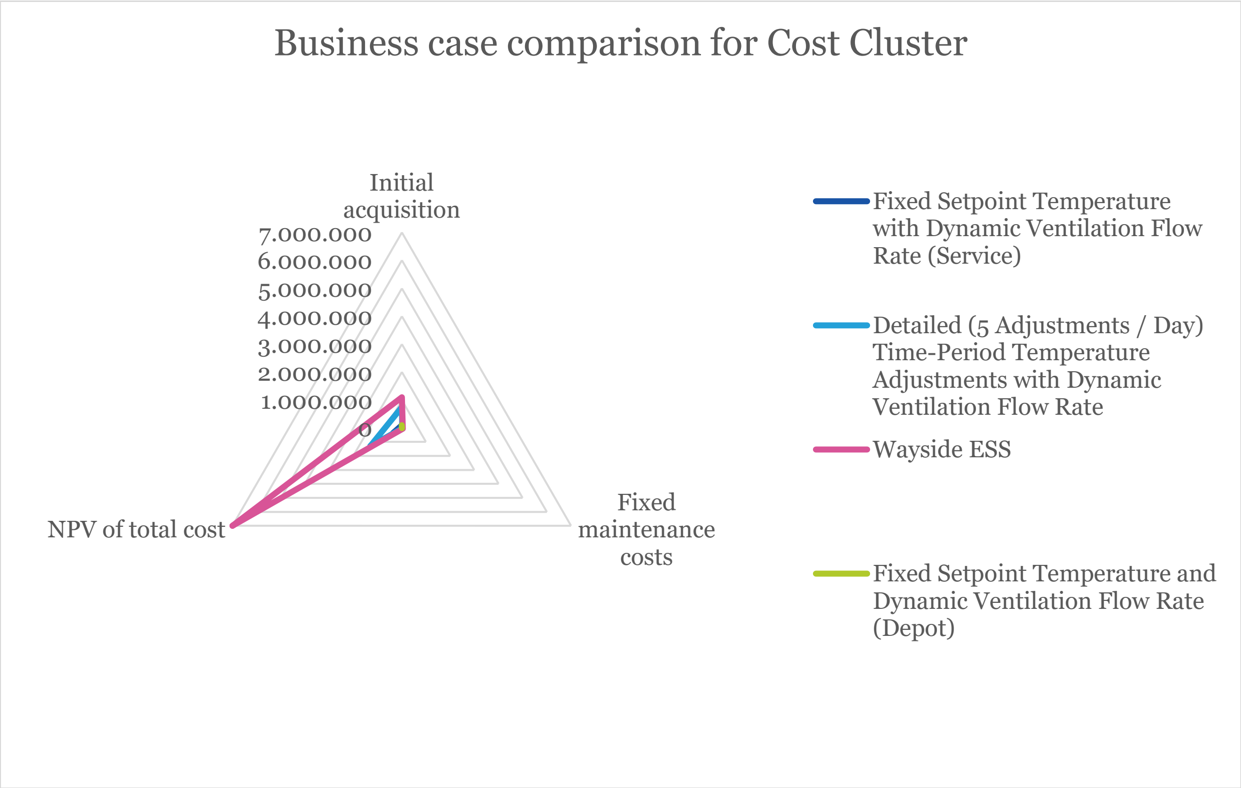

Figure J.7: Business case comparisons for cost cluster KPIs