Evaluating Infrastructure Demand and Optimizing Charging Strategies for Battery Electric Bus Fleet - A Pilot Study on Concordia Shuttle Fleet.

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Evaluating Infrastructure Demand and Optimizing Charging Strategies for Battery Electric Bus Fleet - A Pilot Study on Concordia Shuttle Fleet.

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Abstract

The transition from conventional buses to Battery Electric Buses (BEBs) poses significant challenges for transit agencies in terms of feasibility and in identifying potential operational issues. One of the crucial challenges is accurately determining the charging infrastructure demand for effective fleet management of electric buses. Insufficient infrastructure can result in operational problems, increased costs, and dissatisfied passengers. Additionally, high initial and maintenance costs, as well as compatibility issues, further impede infrastructure development. Evaluating infrastructure demand and the performance of different charging strategies in various route and operational conditions is essential in addressing these challenges. This thesis aims to evaluate the charging infrastructure demand and the effect of different charging strategies for a Battery Electric Bus (BEB) fleet using mathematical formulations and simulation modeling, specifically focusing on three scenarios: Depot charging, Depot & Opportunity charging combined, and Opportunity charging. The impact of these scenarios on fleet operations is analyzed using Discrete Event Simulation, with Arena software employed for simulation purposes. Additionally, the thesis evaluates the daily average charging costs, considering appropriate assumptions.

The results of the simulations indicate that both the Depot & Opportunity charging combined and Opportunity charging alone scenarios outperform the depot charging strategy in achieving low charging costs. The analysis ascertained that a battery capacity of 300 kWh, coupled with a charging power of 100 kW, suffices to maintain a 100% trip success rate for the Concordia University shuttle fleet under the route conditions considered. However, it is worth noting that the depot charging strategy with overnight charging takes advantage of lower energy costs and grid loads during non-peak hours with proper charging schedules. Overall, the proposed work provides valuable insights for decision-makers and transit agencies looking to deploy electric shuttle bus fleets across different route conditions.

Keywords: Battery electric bus, Discrete event simulation, Arena Software, modeling

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- Murali Krishna Vakada.

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List of Acronyms

Acronym	*Description*
BEB(s)	Battery Electric Bus(es)
IPCC	Intergovernmental Panel on Climate Change
EPA	Environmental Protection Agency
OEMs	Original Equipment Manufacturers
WRI	World Resource Institute
DES	Discrete Event Simulation
DoE	Design of Experiments
CDB(s)	Conventional Diesel Bus(es)
ICCT	International Council on Clean Transportation
HEB(s)	Hybrid Electric Bus(es)
TCO	Total Cost of Ownership
IEA	International Energy Agency
WRI	World Resources Institute
PEC	Power Electronic Converter
SoC	State of Charge

CHAPTER 1

INTRODUCTION

"The time is now to confront the urgent global climate crisis head-on."

The recently released Intergovernmental Panel on Climate Change (IPCC) report reaffirms the urgency of transitioning to a sustainable, decarbonized future as global warming poses a severe threat to the planet [1]. Scientists have been warning for decades about the catastrophic consequences of human activities such as pollution and carbon emissions. Consequently, it is imperative to thoroughly examine all sectors contributing to greenhouse gas emissions, with transportation being of utmost importance. By addressing transportation emissions, we can effectively advance greenhouse gas mitigation strategies in numerous countries, given that this sector accounts for the highest energy consumption in 40% of the world's nations and ranks as the second-largest energy-consuming sector in the remaining countries. These variations reflect diverse levels of urbanization, land use patterns, the pace of demographic changes, and socioeconomic development [2].

1.1 Transportation Sector

As of 2019, the movement of passengers and freight in road transport was the largest source of transport emissions (6.1 GtCO_2-eq, 69% of the sector's total) [1]. In 2021, global CO_2 emissions from the transportation sector increased by 8% to nearly 7.7 Gt CO_2 as covid pandemic restrictions were lifted and passenger and cargo movements began to recover after an unprecedented decline in 2020. In order to support the Net Zero Scenario, wherein transport demand is expected to grow, it is essential to reduce emissions in the transport sector by approximately 20% to below 6.0 Gt by 2030 [3]. Figure 1-1, explains the CO_2 emissions in the road transport sector under the growing popularity of the Net Zero Scenario.

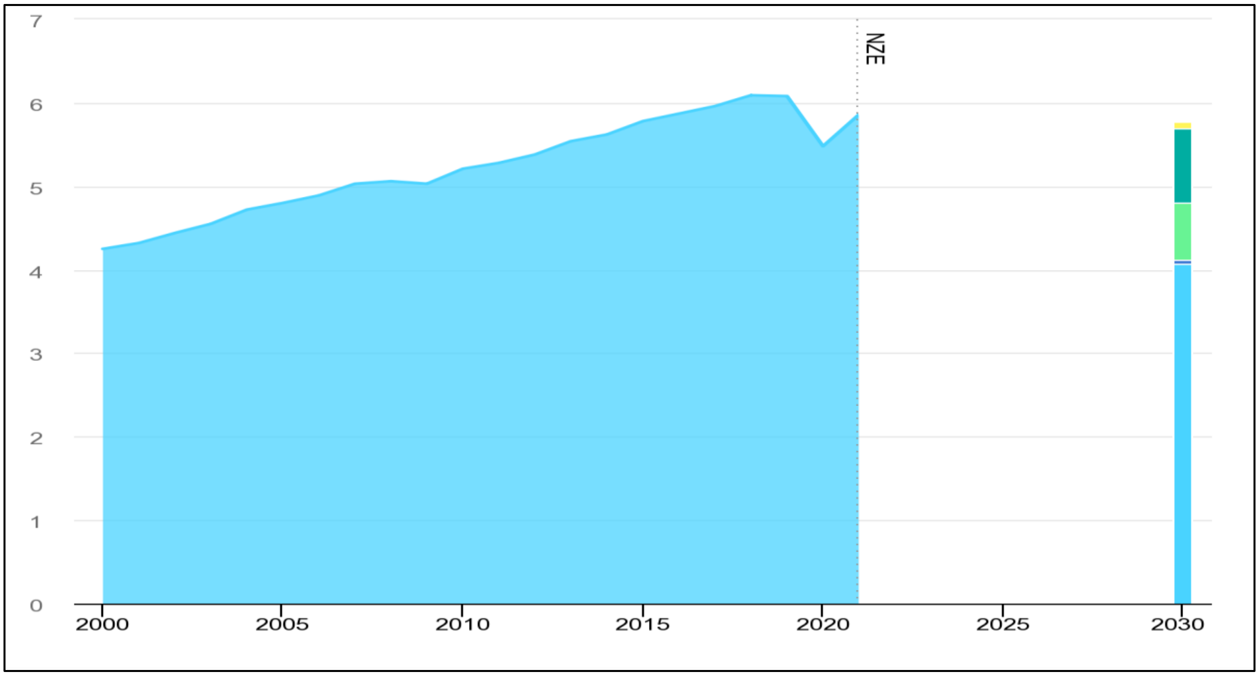


Figure 1-1. Global CO_2 emissions from road transport in Net-Zero scenario [3]

Various solutions have been proposed to tackle the issue of carbon emissions in the transportation sector. One widely used framework to structure policy measures for decarbonizing transport is the "Avoid Shift-Improve" framework [2]. This framework suggests that unnecessary transportation should be "avoided" by improving land-use and reducing trip time, "shifted" to environmentally friendly transport modes by increasing trip efficiency, and "improved" through advancements in existing transportation technology.

The critical aspect of this framework is the need to "shift" towards modes of transport with considerably lower carbon footprints than private passenger vehicles. One effective way to achieve this is by transitioning from private to public transportation, specifically buses. According to the US Environmental Protection Agency (EPA), public transport buses emit 33% less emissions per passenger mile than private cars [4]. This makes developing and promoting zero-emission public transit buses an increasingly crucial focus of transportation strategies for climate action plans across cities and countries worldwide.

In order to achieve the necessary reduction in carbon emissions to promote sustainable mobility, a combination of measures is necessary. These measures include the swift electrification of road vehicles, implementation of operational and technical energy efficiency measures, advancement, and widespread adoption of low-carbon fuels, particularly in the maritime and aviation sub-sectors, and the policies that promote a shift towards low-carbon emission travel options. These collective efforts are crucial for attaining the necessary emissions reduction targets within the transport sector, even in the face of anticipated growth in demand.

1.2 Sustainable Transportation

The importance of transportation in sustainable development was first recognized at the United Nations Earth Summit in the year 1992. Sustainable transportation refers to a transportation system that meets present-day needs while ensuring that future generations can meet them without compromising. It aims to minimize the environmental impact of transportation, promoting socio-equity and economic growth by encompassing various transportation modes and systems that are environmentally friendly and energy efficient, including public transportation, cycling, walking, and electric vehicles. Sustainable mobility intends to reduce greenhouse gas emissions, air pollution, and traffic congestion while improving accessibility and reducing transportation-related expenses. Sustainable transportation is an essential element of sustainable development that helps to achieve a more sustainable future [5], [6].

Studies have shown that public transportation, particularly buses, significantly contributes to sustainable transportation and reduces energy use and emissions. Public transportation also has several other benefits, including reducing the need for parking, promoting social interaction, and improving citizens' overall health and well-being. Public transportation, particularly buses, is an efficient mode of transportation in terms of energy usage, emissions and can reduce traffic congestion, promoting sustainable transportation. In addition, electric buses are becoming increasingly popular as a low-cost means of providing high-capacity, efficient transportation [7]. Thus, investing in public transportation infrastructure and encouraging its use is essential to achieving sustainable transportation goals.

1.3 Review of Electric Public Transit in the World

The global electric bus market is poised for substantial growth in the coming years. Based on a recent report by MarketsandMarkets, the market is expected to witness a remarkable surge, with projections indicating a rise from 112,000 units in 2022 to an astounding 671,000 units by 2027, reflecting an impressive compound annual growth rate of 43.1%. In 2021, Europe observed a notable increase in electric bus registrations, while the United States experienced significant growth in the deployment of zero-emission buses. The Pacific Asia region dominates the electric bus market, with China leading the way. However, the North American region is expected to emerge as the fastest-growing market due to the rising demand for electric mass transit solutions, the presence of renowned original equipment manufacturers (OEMs), and government support. The overall expansion of the electric bus market can be attributed to growing environmental concerns and advancements in electric vehicle technologies [8].

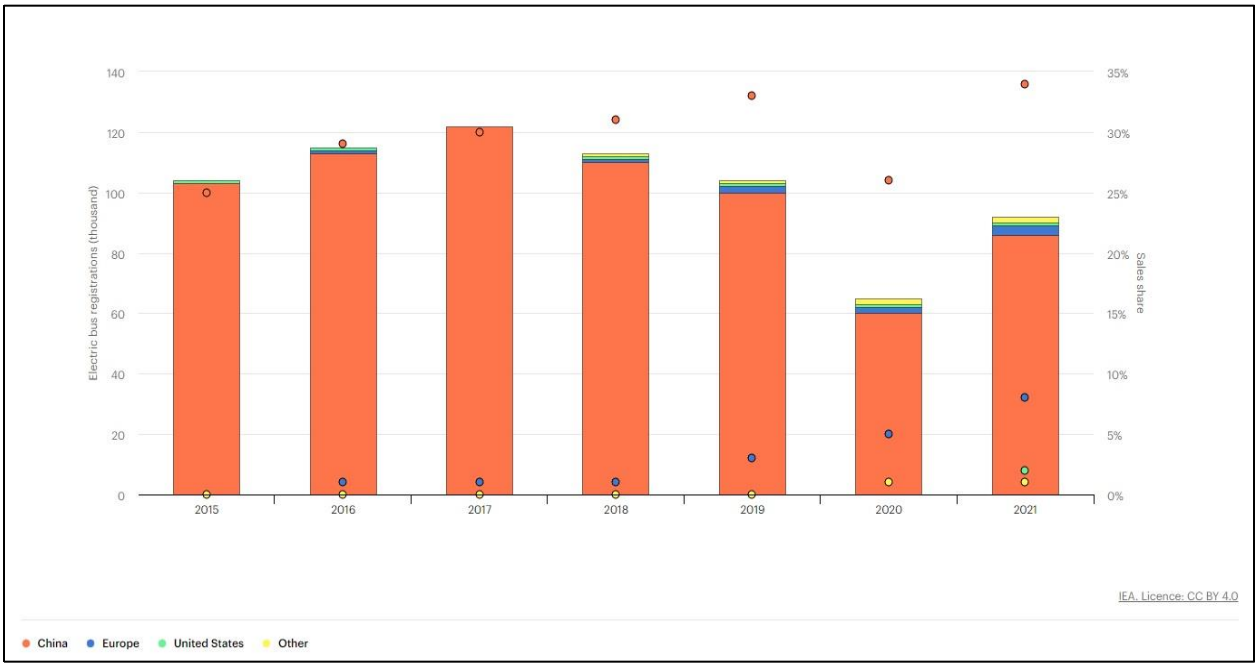


Figure 1-2. Electric bus registrations and sales share by region, 2015-2021 [8]

As per the International Energy Agency, China has emerged as the global leader in adopting battery electric buses (BEBs), encompassing a staggering 99% share of the world's electric bus fleet by 2019. The Netherlands and Germany have taken the lead in Europe, with electric buses constituting

15% and 13% of their respective bus fleets. The statistics above clearly depict the state of electric bus adoption up until 2021 [9].

Despite having a lower carbon footprint, public transportation is still far from being the zero-emission alternative we aspire to achieve. Public transportation contributes more than 7% of transportation emissions, frequently relying on fossil fuels such as diesel. The figure will only rise if we do not promote a switch towards electrifying public transportation as it currently exists. This Emphasizes the importance of conducting research and strategic planning to effectively decarbonize this mode of transportation, with a specific focus on battery-powered electric buses.

1.4 Review of Electric Public Transit in North America.

According to the Mordor intelligence study repot, the North American electric bus market is undergoing a remarkable surge, with a projected CAGR of 5.50%. Despite the challenges faced during covid pandemic, the market is projected to surpass USD 850 million in North America by 2027 [10]. This growth is predominantly attributed to government support, increasing environmental concerns, and the rising demand for sustainable transportation solutions. The graph below shows Canada's projected sales volume and year-over-year growth from 2016-2028, with a compound annual growth rate of 29.36%.

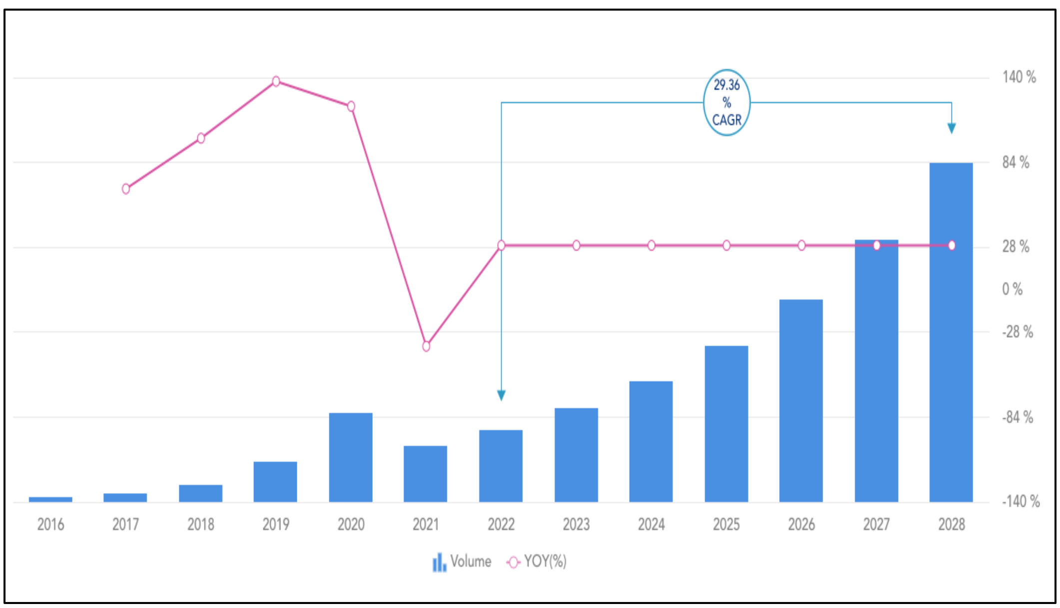


Figure 1-3. Expected North America electric bus market share by Canada.

1.5 Problem Context

Many authors and scientists explained how the widespread implementation of electric buses is vital in reducing emissions and enhancing air quality in cities worldwide. A report from the World Resources Institute (WRI) [11] highlights various obstacles that hinder the extensive adoption of this technology. These barriers are classified into three primary categories - technological, financial, and institutional - referring to the challenges that transcend different aspects within the electric bus industry. Below, table 1-1, presents the barriers that are likely to be encountered by many transit agencies for Battery Electric Buses (BEBs) adoption. Section 2.3.2 provides a detailed description of these barriers.

	General Barriers		
	Technological	***Financial***	***Institutional***
Vehicles and batteries	• Lack of information on the advantages and disadvantages of e-buses. • Range and power limitations of e-buses. • Design flaws in e-buses. • Disjointed or limited e-bus marketplace.	• High up-front capital costs of e-buses. • Lack of financing options.	• Difficulties for manufacturers in engaging with cities. • Lack of a plan to remove current bus stock
Agencies and operators	• Lack of information on how to start. • Lack of operational data.	• Rigid financial management and business models. • Scaling investment past initial pilot programs.	• No enabling policies supporting adoption of e-buses. • Negative public perception • Coordinating maintenance duties • Weak governmental coordination • Informal transit
Grid and charging infrastructure	• Lack of understanding of the requirements to upgrade infrastructure. • Limitations of the charging ports and stations • Grid instability. • Lack of standards and regulations on charging infrastructure	• Large capital expenses for grid infrastructure. • Difficult to determine grid infrastructure responsibilities.	• Lack of space and land to install infrastructure. • Limited planning for long-term implications.

Table 1-1. Barriers to adopting electric buses.

It is essential to recognize that many of these technological challenges stem from a fundamental issue: the lack of relevant information and the absence of suitable modeling tools to facilitate the decision-making and long-term implementation plans for electrifying the bus fleet.

To overcome these challenges, transit agencies must develop more comprehensive planning models incorporating critical factors such as route planning, charging strategies, and electric bus fleet management. These models would enable transit agencies to understand better the long-term costs and benefits of adopting electric buses, leading to operational efficiency, and addressing future technological challenges.

1.6 Thesis Objective

This thesis evaluates different charging strategies (depot and opportunity charging) by exploring the performance measures for a fleet of Battery Electric Buses (BEBs) operating on a specific route considering varied operational conditions. The objective is to develop a comprehensive mathematical formulation and simulation models that can assess various factors, such as chargers demand, charging time, and charging costs, in relation to changes in battery capacity, charging power, and route conditions. To accomplish this, the study utilizes the Discrete Event Simulation (DES) methodology to compare and analyze performance parameters based on the selected inputs. By employing simulation models, as illustrated in figure 1-4, this research investigates different scenarios to gain valuable insights.

Charging Stations at Depot: Depot or overnight charging of BEBs involves charging the buses at charging stations in the depot or garage during the overnight period. The buses reach the depot after finishing their scheduled passenger trips to get to full charge before starting the next day's trips.

Charging Stations at Depot & Terminal: This charging approach involves placing the charging stations at the depot and at the terminal. The buses charge at the terminal during their scheduled stops, taking advantage of the stoppage time to add some charge. After completing their passenger trips, the buses return to the depot for overnight charging, ensuring a full charge for the next day's operations.

Charging Stations at Terminals: In this charging approach, charging stations are strategically placed at the terminals, at the starting and ending points of the route. BEBs take advantage of their regular stoppage time to undergo charging and prepare for their passenger trips. The buses receive a quick charge at the terminals, utilizing the opportunity to replenish their battery levels.

Furthermore, the implemented models provide valuable insights regarding the following aspects:

- Accessing the demand for charging stations considering battery capacity, charging power, and ambient temperature constraints.
- Identifies the optimal charging strategy to employ under different route conditions.
- Evaluating average charging costs under different charging strategies.

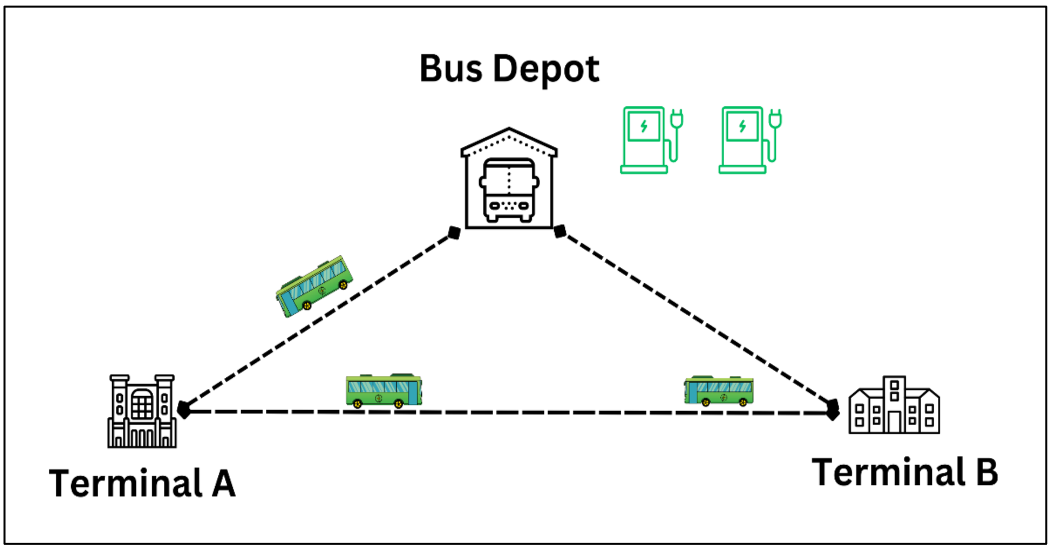


Figure 1-4a. Charging Stations at Depot.

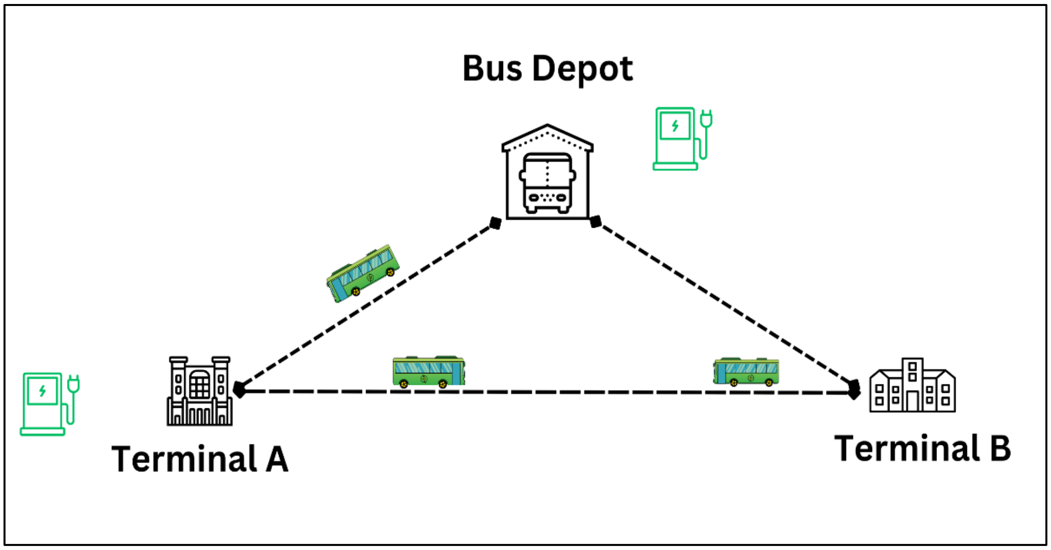


Figure 1-4b. Charging Stations at Depot & Terminal.

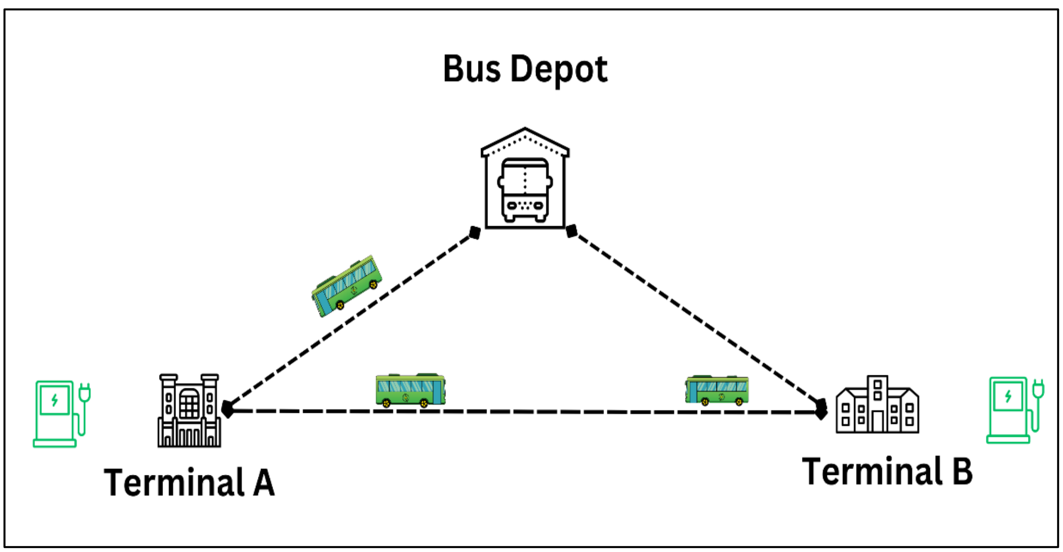


Figure1-4c. Charging stations at Terminals.

Figure 1-4: Charging Scenarios.

1.7 Thesis Organization

The major research contributions of this thesis are as follows:

Chapter 2: Literature Review

This chapter provides an overview of the relevant literature on various topics, including sustainable public transport, battery electric buses, charging strategies, mathematical modeling, and discrete event simulation.

Chapter 3: Solution Approach

In this chapter, the solution approach is presented. It includes a detailed explanation of the discrete event simulation process, the conceptual model, and the step-by-step execution of the simulation model.

Chapter 4: Model Adaptation and Implementation

Chapter 4 focuses on the adaptation and implementation of the model in Arena. It provides all the necessary information on how the model was adapted and executed using the Arena simulation software.

Chapter 5: Results and Discussion

This chapter presents the numerical evaluation of the developed models through the pilot study. It includes design of experiments (DoE), detailed numerical example and finally verification and validation of the model results. Additionally, the sensitivity analysis is conducted to determine the impact of input parameters on the results.

Chapter 6: Conclusion and Future Works

The final chapter presents the conclusions and outlines the potential areas for future exploration.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In this chapter, research available on the chosen topic is reviewed and discussed. Section 2.2 describes how BEBs differ from conventional and hybrid buses concerning sustainability. Section 2.3 discusses more in detail about BEBs and how it is seen as a critical enabler for future public transportation. This section further elaborates on two topics, one being why this transition is needed and the other topic about barriers to this transition. In section 2.4, the research and available information on charging infrastructure and different charging strategies have been vividly detailed. Finally, section 2.5, section 2.6 brings out the literature with respect to mathematical modeling, and discrete event simulation since the approach has been embraced as a methodology and is used to evaluate the objective of our study. Finally, section 2.7, elaborates the scenario representation for the bus network.

2.2 Conventional Vs. Hybrid Vs. Battery Powered Buses Vs. Fuel Cell

Zero-emission buses are gaining momentum worldwide as cities and transit agencies aim to reduce their carbon footprint and improve air quality. BEBs have the most favorable environmental impact and adoption rate [12]. They produce zero tailpipe emissions and significantly reduce particulate matter and carbon dioxide emissions compared to Conventional Diesel Buses (CDBs) and hybrid buses [13]. According to the International Council on Clean Transportation (ICCT), BEBs can reduce particulate matter emissions by up to 89% and oxide emissions by up to 76% compared to CDBs. However, the high upfront costs and the need for charging infrastructure are significant challenges to their adoption [14].

Hybrid Electric Buses (HEBs) are the intermediate option between BEBs and CDBs. They use a combination of a small internal combustion engine and an electric motor, resulting in better fuel efficiency and fewer emissions than CDBs. According to a study conducted by Volvo Group, a fully hybrid bus can reduce carbon dioxide emissions by 25% compared to CDBs. HEBs offering a more affordable option, better fuel efficiency, and lowered maintenance costs offset the higher upfront costs and could be considered the next best alternative to BEBs [15].

Fuel cell buses are another option for zero-emission public transportation. Battery electric buses use rechargeable batteries and have lower operating costs, while fuel cell buses use hydrogen to generate electricity and offer longer ranges and quicker refueling times. However, fuel cell buses face challenges related to hydrogen production and infrastructure management [16]. The choice between BEBs and fuel cell depends on factors such as driving range requirements, charging infrastructure availability, and overall energy goals.

As stated by International Energy Agency in their 2021 report, government incentives such as subsidies or tax breaks for purchasing clean buses and installing charging infrastructure can help encourage the adoption of clean buses [17]. Table 2-1 summarizes the advantages and disadvantages of different drive technologies, briefed in various research works [16] [12] [18] [19].

Technology	*Advantages*	*Disadvantages*
Conventional buses	- Well-established technology - Widespread refueling infrastructure - Lower upfront costs - Familiarity and ease of maintenance	- High greenhouse gas emissions - Poor air quality due to diesel exhaust - Noise pollution - Dependence on fossil fuels
Hybrid	- Reduced fuel consumption and emissions - Regenerative braking for energy recovery - Improved fuel efficiency - Lower greenhouse gas emissions during idling	- Higher upfront costs - Limited electric-only range - Added weight from dual power systems - More complex maintenance and repair
Plugin hybrid	- Reduced fuel consumption and emissions - Flexibility of dual power sources - Regenerative braking for energy recovery - Extended driving range compared BEBs	- Higher upfront costs compared to CDBs - Limited electric-only range - Dependency on both electricity and fossil fuels - Added weight from dual power systems
Fuel cell	- Zero-emission vehicle - Long driving ranges - Challenges in hydrogen production - Reduced noise pollution	- Limited hydrogen refueling infrastructure - High upfront costs - Quick refueling times - Complexity of hydrogen storage and safety
Battery electric	- Zero-emission vehicle - Lower operating costs - Increasing charging infrastructure - Reduced noise pollution	- Limited driving range per charge - Longer charging times - Limited availability of charging stations - Upfront costs of battery replacements

Table 2-1: Summary of different driving technologies.

2.3 Battery Electric Buses (BEBs)

As a viable option for cities due to their eco-friendliness, reduced noise pollution, and lower operating costs compared to diesel-powered buses, BEBs are gaining popularity worldwide. These buses use a large battery pack to power an electric motor that propels the bus and can be recharged by plugging it into a charging station or by using regenerative braking. With a range of up to 300 miles, they are suitable for many city bus routes, and as they do not emit tailpipe pollutants, they can improve air quality and reduce noise pollution in urban areas. Additionally, BEBs can be more cost-effective in the long run, thanks to lower operating costs, government subsidies, and incentives.

2.3.1 Electrification of Public Transit Buses

Cities worldwide are facing rapid urbanization, leading to increased private car ownership and associated issues like pollution and accidents. As a result, there is a growing recognition of the need for a paradigm shift towards sustainable urban mobility. Most cities are re-evaluating their strategies, emphasizing inclusive public transportation networks to create sustainable and efficient solutions for the expanding urban population [20].

There are multiple reasons why many countries worldwide are promoting the electrification of buses.

- Firstly, electric buses have been shown to have lower emissions than diesel buses under specific circumstances, including passenger load, traffic congestion, heating and air conditioning usage. According to a study published in Energy Journal, electric buses cut 85% of CDBs lifecycle petroleum use and 20–35% of CO_2 emissions [21]. This is due to the fact that electric buses do not emit pollutants directly, and the emissions generated by power plants that supply electricity to these buses are generally lower than those produced by diesel engines.

- Secondly, electric buses are becoming increasingly economically attractive alternatives to diesel buses. A study conducted by Zhou et. al., on urban bus routes in Kielce, Poland, revealed that the Total Cost of Ownership (TCO) of BEBs could be less than that of their diesel counterparts and depends mainly on the routes and schedules they operate [22]. Additionally, if battery costs continue to drop as they have recently, the economic attractiveness of BEBs will only increase.

- Thirdly, switching to electric buses reduces a country's reliance on imported fuel from oil-rich countries, eliminating the risk of price inflation that comes with it, which is especially significant for countries that heavily rely on imported fuel. According to the International Energy Agency (IEA), the transportation sector is responsible for almost two-thirds of global oil demand, most of which comes from the road sector, including buses [17].

- Lastly, some government authorities often control public transport operations, allowing for more accessible support and implementation of electrification policies. Many countries have already started providing subsidies for purchasing and operating electric buses and funds to build the required infrastructure to support it [23]. This support can help accelerate the electrification of buses and other vehicles.

2.3.2 Barriers for Transition to Electric buses

As detailed in a report by the World Resources Institute (WRI) [11] and the conclusions made by many researchers, several barriers are currently preventing this technology's widespread adoption. Some of them are detailed below.

High upfront costs: Electric buses are often more expensive than traditional diesel or natural gas buses. This high upfront cost can be a significant barrier for transit agencies operating on tight budgets.

Limited range and charging infrastructure: Electric buses have a limited range and require regular access to charging infrastructure. Installing and maintaining this infrastructure can be costly when operating on longer routes, and transit agencies may not have the resources to make these investments.

Limited availability and long lead times: Electric bus models may have longer lead times for delivery, and manufacturers may be unable to produce enough buses to meet demand. This can make it challenging for transit agencies to switch to electric buses quickly.

Lack of familiarity with technology: Some transit agencies may not have experience operating electric buses, which can make them hesitant to adopt this technology. There may also be concerns about reliability and performance, which can further discourage adoption.

Regulatory and policy barriers: Certain regulations and policies can limit the adoption of electric buses. For example, restrictions on installing charging infrastructure or incentives for diesel or natural gas buses make it more difficult for transit agencies to switch to electric buses.

Limited technical expertise: Electric buses require specialized knowledge and expertise to maintain and repair. Transit agencies may not have the technical expertise in-house to operate and maintain electric buses, which is another barrier to adoption.

Lack of information & Operational data: Another significant factor affecting the transition to electric buses. Without comprehensive data on electric bus performance, energy consumption, charging patterns, and maintenance requirements, decision-makers face challenges in making informed choices.

Limited understating for long-term planning: Information on operational conditions, technical requirements, and infrastructure planning is necessary for successful long-term adoption. Without a comprehensive understanding of these factors, developing effective long-term strategies for integrating e-buses into transportation systems becomes complicated.

Political barriers: Finally, political barriers can also hinder the adoption of electric buses. There may be resistance from stakeholders invested in the status quo or concerns about the economic impact on local industries. Overcoming these political barriers can be challenging but is essential to the widespread adoption of electric buses.

2.4 Charging Infrastructure for BEBs

In order for BEBs to be widely adopted, it is crucial to establish a robust charging infrastructure. The two most promising charging methods for BEBs are conductive charging and wireless charging. Although battery swapping is another option for recharging vehicles, it is limited by the size and capacity of the batteries, making it impractical for BEBs with large battery packs.

Conductive charging is the most used technique and can be achieved through plug-in systems or by using a pantograph mounted on the roof of the bus or a gantry. On the other hand, wireless charging allows for recharging BEBs while stationary or in motion, using charging pads fixed in the ground. The choice of charging method depends on the specific characteristics and requirements of the bus network in cities, as each method has its advantages and disadvantages.

Figure 2-1 explains the categories of charging methods currently in use and development. [24].

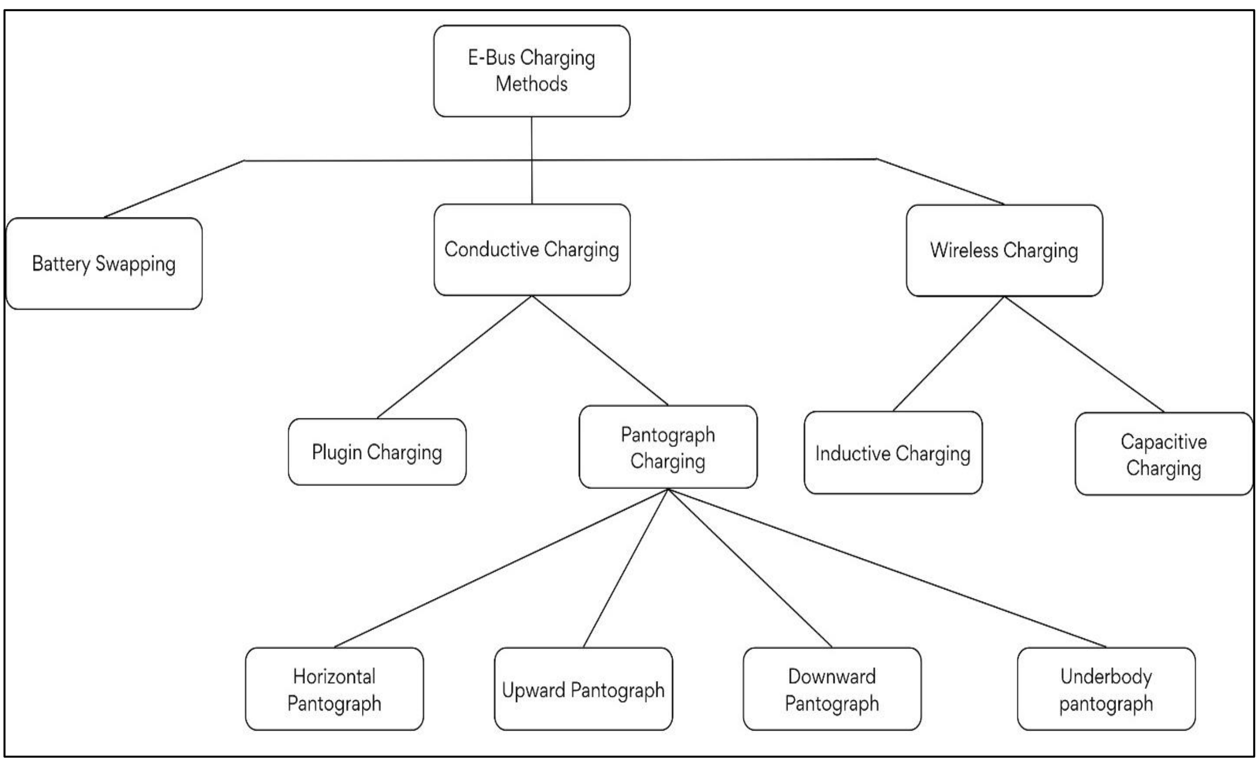


Figure 2-1: E-Bus charging methods.

2.4.1 Charging Strategies

Unlike other electric vehicles, BEBs rely on off-board chargers, meaning the Power Electronic Converter (PEC) responsible for converting three-phase AC power from the grid into DC power is located outside the BEBs [25]. These chargers can allow higher charging power levels since they are not limited to size and weight. Additionally, due to the limited driving range of BEBs, a specific charging concept is necessary to ensure their continuous operation throughout the day. This section provides an overview of the existing charging concepts aiming to deliver reliable and efficient charging operations.

2.4.1.1 Depot Charging

Depot charging is a reliable and widely used method for charging BEBs. It involves the overnight charging of BEBs while they are parked inside the depot or hub. Typically conducted during off-peak hours, depot charging ensures that the buses are fully charged and ready for service the next day. This approach provides ample time for BEBs to recharge their batteries, taking advantage of the longer overnight duration. In cases where BEBs have limited range or require additional daytime charging, depot charging can be supplemented with daytime charging sessions. By utilizing depot charging, transportation operators can efficiently manage their fleet's charging needs, optimize charging schedules, and maintain a reliable and consistent operation of electric buses [25].

2.4.1.2 Opportunity Charging

Opportunity charging, on the other hand, refers to charging BEBs at end terminals or at regular bus stops. BEBs are charged multiple times throughout the day during their regular stoppage times without necessarily needing to be fully charged each time. Opportunity charging uses fast chargers that quickly top up the battery levels during brief stops, ensuring continuous operation without significant downtime. This flexibility extends the range and operational efficiency of BEBs and reduces reliance on long charging periods at depots.

2.4.1.3 On-route Charging

Dynamic wireless charging is a type of on-route charging where BEBs are charged while driving on specific road sections equipped with inductive charging pads. As the BEB drives over these charging pads, the wireless power transfer system transfers energy to the vehicle's battery, replenishing its charge. This approach eliminates the need for the BEB to stop at charging stations or depots, enabling a seamless charging experience while maintaining the bus's operational schedule. Dynamic inductive charging infrastructure is a costly alternative to build and maintain and is currently in development [26].

The typical State of Charge (SoC) evolution of BEBs using depot charging and opportunity charging strategy is detailed below in figure 2-2.

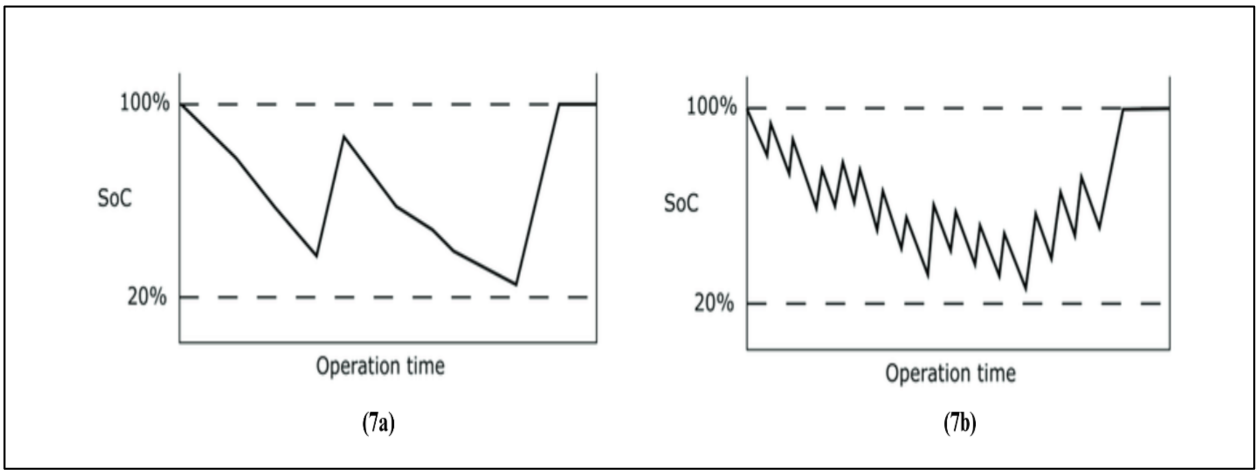


Figure 2-2: SoC profile for (a) depot charging (b) opportunity and dynamic wireless charging.

Below, Table 2-2 explains the power ranges and applications of various worldwide charging technologies currently in use.

Charging Technology	*Power (kW)*	*Installation*
Plug-in	30 - 150	Each depot station is connected to a typical electric grid through a cable for charging.
Pantograph	100 - 700	Charging is performed at the end stop, terminal, or at a dedicated charging point using a post, beam, or gantry.
Induction (Stationary)	100-350	The charging plate is installed beneath the ground, and both the source and receiver (BEBs) remain stationary during charging.
Induction (Dynamic)	100-300	The charging plate is installed beneath the ground, and charging occurs while the BEB is in motion.

Table 2-2: charging power (kW) for different charging technologies.

2.5 Research on BEBs

Recent works has made some advances towards the smooth integration of BEB systems. In reference, Wang et. al., [27] developed a strategy to reduce the cost of charging operations and was based on a static BEB system setup and a predetermined charging period, which was not dynamically optimized. Additionally, the inefficiencies caused by BEBs traveling to charge at the depot were overlooked. Another study, by Teoh et. al., [28] constructed a scenario-dependent scheduling method for BEB transit, focusing on route planning and fleet management, neglecting the transit schedules and routes. Ren Ke et. al., presented an innovative approach to design BEB transit systems with the goal of minimizing infrastructure costs, with the underlying assumption that the number of charging stations are equal to the number of BEBs [29] .

Further research by Yang et. al., [30] introduced an optimal charging strategy for BEBs that uses wireless charging technology, aiming to specifically lower the costs associated with charging procedures. Earlier research, by El-Taweel et. al., explored a mixed integer linear programming approach to develop charging facilities for BEBs considering different charging strategies across various transit networks, taking into account a fixed battery capacity for the buses [31].

Despite these contributions, it has been identified that there are principal limitations in the current research on BEB systems, particularly in two areas:

- *The need for a robust mathematical model to estimate various parameters, including charging infrastructure demand associated with electric bus fleets.*
- *The development of a detailed energy consumption model for BEBs that considers the BEB parameters, impact of route, and climatic conditions.*

2.5.1 Research on Mathematical Modeling

In this context, the successful integration of electric buses into the public transit system requires careful consideration of their distinct features, constraints, and specific infrastructural needs. Therefore, the creation of effective methodologies, models, and resources is crucial in supporting the decisions of policymakers as they move towards the adoption of electric bus fleets. One such crucial factors is the estimation of charging infrastructure needed for successful electric bus fleet operations, and this significance is underpinned by research studies across different electric vehicles (EVs). Previous literature has shown great interest in the deployment of charging facilities for private electric vehicles (PEVs). Regarding e-buses, they have distinct operation characteristics which should be considered when estimating e-bus charging stations. Several studies have dealt with the optimal deployment of charging infrastructures for EVs, with some focusing on the optimal location of charging facilities for heavy – duty vehicles, such as electric buses.

In the realm of this research focus, Uslu et. al., [32] proposes a mixed integer-linear mathematical model to determine the optimal placement and capacity for electric bus charging stations. The study finds that driving ranges, charging durations, number of trips, and service rates are significant factors influencing the capacities of charging stations. Another study by Momenitabar et al., [33] proposed a Queuing based mathematical model addressing the challenges of designing an efficient electric transit network, emphasizing the importance of considering waiting times, charger configurations, service intervals and model parameters in minimizing total costs and optimizing the deployment of charging stations. The study done by Lin et. al., [34] takes into account the distinct operational characteristics of electric buses, such as their charging frequency in estimating the demand for chargers, which depend on factors like the driving range, daily operating range, and safety range. Mathematical formulas are developed, and conclusions highlight the significance of driving range in reducing costs and the robustness of the layout to changes in charging power.

Further important studies comprise the research by He et. al., [35] emphasized energy storage systems as a possible solution for high electricity prices caused by peak loads from fast charging. Rapid charging can result in high electricity demand charges, which undermines the competitiveness of electric buses as a viable alternative to diesel buses. Additionally, the authors highlighted the critical impact of electric vehicle driving range on the selection of fast charging station locations. Recognizing the connection between route operational features and charger placement, Iliopoulou et. al., [36] created and evaluated a thorough route design model for a transit route network solely serviced by an electric bus fleet. The authors devised a bi-level optimization model, simultaneously designing an effective transit route network and determining the necessary charging infrastructure demand and locations. Rogge et. al., [37] explored the technical feasibility of electrifying an existing bus network using fast-charging batteries. The authors investigated the relationship between charging power and battery capacity furthermore discussing the impact of load profiles on electricity grid of charging infrastructure. Xylia et. al., [38] introduced a mixed integer-linear programming model that optimizes the placement of electric bus charging stations, taking into account major public transportation hubs as potential locations for these stations. Elma et. al., [39] focused on emerging ultra-fast charging stations, which can significantly reduce charging times for BEBs, calculating the optimal battery size and ideal route lengths for electric buses.

Clearly, extensive research attention has been devoted to effectively locating charging infrastructures for electric buses, with most studies concentrating on the optimal placement and sizing of electric bus charging stations for BEBs. However, the issue of missed scheduled trips due to bus charging delays has been largely overlooked in the literature. Also, charging delays at terminal stops can disrupt scheduled bus services and cause subsequent delays, leading to discomfort for passengers waiting to board the next bus. Also, Uslu et. al., [32] cited driving range has the highest effect for selecting locations and capacities of charging stations at minimum cost. This study, however, focused on intercity bus services, with charging stations located freely along the route.

The novelty of our proposed study lies in its innovative approach to estimating the demand for charging infrastructure for a specific bus fleet. This approach is distinct because it takes into account a comprehensive set of parameters that other research studies have collectively overlooked. These parameters include not only the operational aspects of the fleet and the conditions of the routes but also key factors such as charging power, battery capacity, and, particularly, ambient temperature—which is a crucial consideration for Battery Electric Bus (BEB) fleet operations, especially operating within the varied Canadian climatic conditions. By integrating these elements, our study aims to provide a more accurate and holistic assessment for the transition from conventional buses to BEBs.

2.6 Discrete Event Simulation (DES)

According to Rossetti [40], simulations can be categorized based on time as static or dynamic, stochastic or deterministic, and discrete or continuous. The author explains that a static system remains constant over time, while a dynamic system evolves over time. Additionally, a system is considered stochastic if it is random in nature and deterministic if it is not. From a temporal perspective, Rossetti clarifies that discrete systems undergo state changes at specific points in time, whereas continuous systems experience continuous state changes.

In terms of simulation methodology, Rossetti further elaborates that discrete event simulations collect observations at the moment when a specific change occurs in the system. In contrast, continuous event simulations continuously collect observations throughout a given period. In this thesis, the emphasis will be on a deterministic approach within the discrete event simulation model.

Also, Discrete Event Simulation provides the opportunity to assess operational performance prior to implementing an actual system. Companies can conduct what-if analyses using these models, which assist in making efficient decisions. Moreover, these models allow for identifying various operational alternatives without disrupting existing systems, facilitating better policy decision-making [41].

2.6.1 Why DES methodology

Discrete event simulation (DES) is favored for modeling electric bus networks because of its event-driven approach to accurately capturing real-time behaviors like bus schedules, charging, and route networks. By incorporating various charging strategies, DES can evaluate how different charging patterns, power allocation schemes, and charging station placements impact the overall performance of electric bus networks. With DES, decision-makers can make informed choices and optimize charging strategies to ensure the successful deployment and operation of electric bus networks reliably and sustainably. Some of the research studies that used DES methodology has been discussed below.

In a study conducted by Lebeau et. al.,[42] DES methodology is implemented to model the operations of an urban distribution center and to evaluate the impact of introducing electric vehicles in place of conventional trucks. The study validated the model by comparing the simulation results with the real operations of the center and highlighted the impact of introducing electric vehicles considering battery and operational aspects. Additionally, the study addresses the need for further research to integrate cost aspects with operational considerations to assess the price-performance ratio of electric vehicles. According to Lebeau, DES is particularly useful for modeling operational problems with a high degree of detail, making it the most appropriate approach for understanding the impact of electric vehicles.

Lopez et. al.,[43] discussed an improved model for simulating electric vehicle (EV) charging demand using discrete event simulation (DES) by modeling of individual EV user characteristics, including the availability of electric vehicle supply equipment (EVSE) outside homes and the charging threshold of each EV user. This approach facilitated the estimation of hourly charging demand and the impact of increasing EVSE availability on charging behavior. The study demonstrated that DES methodology provided a structured and effective approach for modeling and analyzing EV charging demand, offering valuable insights for policymakers and stakeholders involved in electric vehicle charging infrastructure and policy development.

Sebastiani et. al.,[44] studied integrating battery electric buses into Curitiba's Transit system using discrete event simulation, aiming to optimize charging station placement, and reducing extra recharging time. A bi-objective genetic algorithm was used to find solutions, balancing station count and recharging time. Results provided insights into station count's impact on routes, energy consumption, and round-trip times. The study also assessed solution robustness against changes in full charge times and effects of using multiple battery packs. These findings aid decision-making in electric bus deployment and charging infrastructure planning, advancing sustainable public transportation. The discrete event simulation accurately estimated energy consumption and evaluated the practicality of integrating battery electric buses into a real Transit system.

Maizi et. al.,[45] established a reliable urban public EV charging infrastructure using robust optimization and discrete event simulation, determining optimal charging station locations and sizes, integrating real traffic flows and power grid simulation modeling. This allowed for improved recommendations for deploying fast chargers and setting up charging stations. The study considered uncertain traffic intensity, speed, and on-route charging demand. The authors concluded that combining simulation modeling with optimization methods offers more accurate system performance analysis, capturing the dynamic and complex nature of traffic flows and charging demands, ultimately enhancing the public EV charging infrastructure's reliability and effectiveness. With regards to the study's choice of methodology, discrete event simulation, or DES, has been widely used in previous electric vehicle studies. The primary areas of application were in the modeling of electric vehicle energy demand [45], [46], [47], cost of ownership [48], optimal charging infrastructure planning [48], [49].

Considering the research on university electric bus shuttle fleets, Hulagu et. al., [50] developed a multi-objective formulation aimed at minimizing operational costs by optimizing the route selection for cost-effectiveness within the university's fleet. In another study, Filippo et. al., [51] at Ohio State University constructed a simulation model in MATLAB to examine the impact of charger type and infrastructure demand, with the goal of maintaining reasonable service frequencies. Zaneti et. al.,[52] at the University of Campinas, conducted research that concluded the integration of photovoltaic panels can lead to substantial reductions in operational costs. Their study involved estimating the optimal timing, duration, and power levels for charging to maximize efficiency. The research by Korsesthakarn et al. [53]stands out as the study in the field of electric shuttle fleet management that employed discrete event simulation using Arena software. This study addressed the bus scheduling challenge with the objective of minimizing passenger wait times.

The analysis findings indicate that simulation is the most flexible and appropriate approach for the study on electric vehicles. Remarkably, no previous studies have incorporated both mathematical modeling and simulations together. Additionally, very limited research studies are available on electric bus shuttle fleets that operate without intermediate stops, and none have applied a discrete event simulation framework to determine the factors that we considered affecting fleet operations. Hence, this thesis has employed discrete event simulation in conjunction with mathematical modeling to support the considered performance parameters.

2.7 Simulation Study Scenarios

To develop a comprehensive set of scenarios to perform discrete event simulation of a university electric bus fleet, various configurations that could be possible by varying charging infrastructure locations and operational strategies that potentially influence the performance and sustainability of the electric bus fleet are discussed. Listed below are the possible scenarios based on insights gained from the various research articles.

i. Overnight Depot Charging

Depot charging is a traditional approach that involves charging the entire bus fleet overnight at a central depot. Studies on grid load management and electric bus charging infrastructure indicate that overnight charging takes advantage of lower energy costs during non-peak hours with proper charging schedules. Additionally, it minimizes the impact on the power grid, allowing for a smoother integration of electric buses into the existing infrastructure [54]. However, the drawbacks include the need for a significant number of charging stations at the central depot, results in high initial infrastructure costs, and the potential for a concentrated demand on the power grid during overnight hours [55].

ii. Mixed Charging with Depot & Opportunity charging

Introducing an opportunity charging station at one terminal supplement the overnight depot charging strategy. Opportunity charging, supported by research on its benefits, extends the operational range of buses by reducing total downtime for charging. This scenario aims to strike a balance by maintaining a level of the traditional depot charging approach while providing flexibility through opportunity charging. Economic analyses of EV charging infrastructure deployment indicate the potential for cost savings with charging station at terminal, making it an economically viable option [56], [57].

iii. Distributed Opportunity Charging at Terminals

Placing charging stations at terminals anticipates a more balanced use of charging resources. Studies on the optimization of charging station placement highlight the potential for improved operational efficiency and reliability when buses can be topped up at either end of their routes. This scenario aligns with research emphasizing improved battery life and efficiency with frequent, shorter charging cycles. It promotes a resilient and reliable charging infrastructure that can adapt to various operational demands [58].

iv. On-route Charging at Intermediate Stops

This scenario explores the feasibility and benefits of dynamic charging at selected stops along the bus route. Assessments of dynamic inductive charging technology suggest that this approach allows buses to receive power during brief stops, eliminating the need for extended charging breaks. Continuous operation without significant downtime enhances the overall efficiency of the bus fleet, making it a potential solution for routes with frequent stops [59]

v. Flexible Charging Strategy with Mobile Charging Units

Mobile charging units offer flexibility in providing charging capabilities where needed. Innovation studies on mobile EV charging solutions highlight their potential to reduce reliance on extensive fixed infrastructure. This strategy particularly beneficial in situations where fixed charging stations are impractical or economically unfeasible, allowing for adaptability in meeting the charging needs of the bus fleet. Managing a fleet of mobile charging units introduces logistical challenges in terms of tracking demand, optimizing deployment routes, and ensuring timely response to charging needs, leading to passengers' discomfort [60].

vi. Demand-Responsive Charging Allocation

Adapting charging schedules based on real-time data and demand is a forward-thinking approach supported by research on smart grids and EV integration with real-time demand response. This scenario enhances fleet operation efficiency by aligning charging activities with demand patterns, optimizing energy consumption, and potentially reducing overall operational costs [61], [62].

vii. Solar-Powered Charging Stations

Exploring solar-powered charging stations aims to leverage renewable energy sources. Studies on the integration of renewable energy sources with EV charging infrastructure suggest that solar power can reduce operating costs and decrease the carbon footprint of the bus fleet [63]. However, energy storage becomes critical to address solar intermittency, ensuring continuous service during periods of low sunlight. Also, initial setup costs for solar-powered stations are higher than traditional grids, ongoing reductions due to technological progress and increased adoption are expected, narrowing the cost disparity over time [64].

viii. Battery Swapping Stations at Terminals

Battery swapping technology, as indicated by research, can significantly reduce recharge time. This scenario involves replacing depleted batteries with fully charged ones at designated terminals, minimizing downtime, and enhancing the efficiency of the bus fleet [65]. It addresses the challenge of prolonged charging times, ensuring continuous operation of the buses. However, challenges to implementing battery swapping include high setup costs and the need for extensive storage space for both discharged and fully charged batteries.

ix. Varying Fleet Composition with Hybrid Buses

Incorporating hybrid buses as part of the fleet composition offers a transitional strategy toward full electrification. Comparative studies on electric vs. hybrid bus performance and sustainability indicate that hybrid buses can serve as an intermediate solution. A full shift from the existing diesel fleet to BEBs is both expensive and time intensive. Consequently, an interim solution involves a blend of diesel, hybrid, and BEBs. A planning framework is needed to concurrently address the interconnected aspects of transit electrification mainly charging infrastructure, fleet configuration, and scheduling [66].

Each scenario represents a nuanced exploration of different aspects of bus fleet management and charging strategies, highlighting the intricate trade-offs and interactions that need to be considered.

In our current study the exploration of BEB fleet management and charging strategies through Scenarios i, ii, and iii that presents a methodical progression from conventional to advanced approaches, encapsulating a range of considerations from cost-efficiency to operational flexibility. Scenario 1 centers on traditional centralized overnight charging, offering a straightforward and foundational perspective. Scenario 2, with the introduction of distributed charging infrastructure between depot and terminals marks a shift toward more complex BEBs system. Finally, Scenario 3 delves into opportunity charging, a cutting-edge strategy that embodies the move to dynamic and resilient fleet operations. These scenarios collectively chart the trajectory of electric bus fleet operations for transit agencies planning to introduce BEBs in place of conventional buses. Serving as a critical framework for ongoing research and simulation-based studies aiming efficient existing fleet management practices with current trends in electric bus infrastructure development.

CHAPTER 3

SOLUTION APPROACH

3.1 Simulation steps

The goal of the simulation study is not just to replicate real-world situations. It is a powerful tool for accurately representing a system and its complex interconnections as they evolve over time [40]. The primary objective of this study is to create a flexible simulation model of the actual physical system and its interconnected components, which can then be modified and validated using various scenarios until the desired results are achieved. Figure 3-1 illustrates a process flow chart detailed in Chapter 3 for achieving the problems' objective.

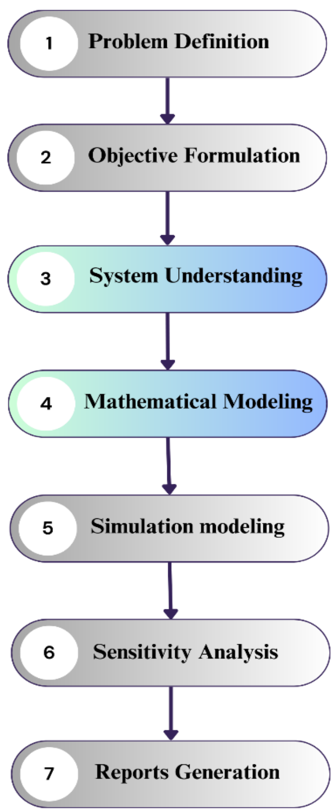


Figure 3-1: Process flow diagram.

The initial step in simulation is to grasp the problem and to determine its scope. In Chapter 1, Sections 1.5 and 1.6 elaborate on these initial two steps of our study. Steps 3 & 4 involve thoroughly understanding the system and making informed decisions to establish a model to address the identified problems effectively. Sections 3.2 and 3.3 provide a more detailed explanation of the decision-making process, including the assumptions made. Step 5 encompasses the actual simulation process, an iterative approach depicted in figure 3-2. The process comprises of four stages: Model Conceptualization, Numerical Analysis, Model Implementation, and Model Execution.

Model Conceptualization

Before implementing the model, a UML design is created to establish clear system definitions with respect to the inputs and outputs that need to be considered. A case diagram is constructed to understand how entities such as BEBs interact with other elements within the system. The system's activity flow becomes apparent through the creation of case diagrams, which are then evaluated against the crucial requirements for addressing the defined problem. Section 3.6 elucidates how the flow is represented in three specific scenarios that are being discussed.

Numerical Analysis

A numerical analysis is conducted to assess the conceptualized model's theoretical validity. Mathematical equations are formulated to understand different outputs, such as average charging time, chargers demand, and average charging costs. An Excel spreadsheet is utilized to verify how these outputs change when the fleet size and route parameters are modified. Through mathematical calculations, values are generated to enable the validation of the model results. Appendix A4 provides a visual representation of the spreadsheet, showcasing the mathematical calculations performed prior to the execution of the model.

Model Implementation

The process of adapting the actual system to the Arena simulation model is carried out using the model concept and the numerical analysis sheet, ensuring the level of detail in the simulation closely aligns with the planned concepts and the inputs designed from the numerical analysis. Before implementing the model in Arena Simulation, various elements such as variables, attributes, events, queues, and schedules are identified based on the actual operations at the bus depot, charging stations, and the behavior of BEBs during transit. These parameters are derived from the logic that needs to be modeled, as determined during the model conceptualization phase.

Model Execution

Next, the developed model is executed using various input values under different charging strategies. This execution aims to analyze crucial factors such as average charging time, total charging costs, and the success rate of trips.

Model Evaluation

This process aims to ensure that the model is comprehensive in all intended aspects and that the generated outputs closely align with the results from the numerical analysis sheet. This process involves two primary steps: setting up initial values and observing output variations. The primary objective of this step is to determine whether the model accurately represents the planned, logical structure when the inputs are appropriately configured. Evaluation is conducted by analyzing statistical outputs generated by the model, which helps verify its accuracy. Additionally, input controls are varied systematically to cover all scenarios.

Model Validation

The model validation phase ensures that the model closely represents the real-world system. During this phase, a sensitivity analysis is performed on the BEB network, focusing on parameters, entities, and resource operations relevant to the bus transit environment. By identifying and varying the respective controls, the outputs are carefully observed. Multiple trials are executed using the process analyzer tool, and the results are thoroughly analyzed compared to the actual system. This iterative approach allows for fine-tuning the model, ensuring its accurate representation of the real-world system.

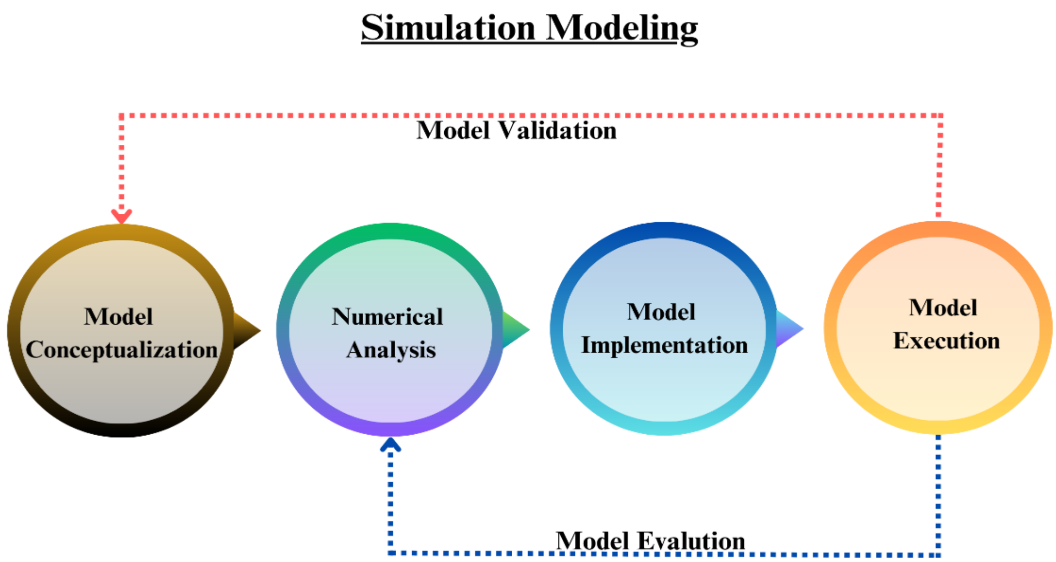


Figure 3-2: Steps in simulation modeling.

3.2 Model Characteristics

The bus characteristics which should be considered in the model depend on the charging facility locations. In a typical bus operation, buses depart from the depot and reach the initial stop, where their journey starts, followed by sequential stops, and then the final stop. In our case, we considered Concordia University's shuttle bus fleet that transits between initial and final stops without any intermediate stops. For charging facility planning, depot, and terminal stops are considered.

3.2.1 Charging Infrastructure Planning Model

The on-route charging technology, as discussed in section 2.4.1.3, results in high electricity power demand because of its rapid charging technology, and it may also increase electricity energy charges due to charging during peak hours. Considering the potential additional costs of operating high-speed inductive chargers, the depot and terminal stations with plugin charging stations seem appropriate and considered for this study.

For the depot charging scenario, buses can only be charged at the depot after completing the scheduled trips. They cannot be charged en-route while in operation, which is the main difference between on-route and depot charging behavior for e-buses. This study considers three potential charging station locations: bus depot, initial stop, and final stop (the initial stop becomes the final stop in the reverse direction), which are the potential origins of bus charging trips. Buses can travel directly from the initial stop to charging stations at the depot or from the final stop after the passenger transport trips are finished. These characteristics do not apply to other electric vehicles, such as taxis and private cars, because they usually do not start the charging trips from fixed points, unlike a BEB that always starts from fixed points.

A BEB has various charging options available. The first one is to charge when they are not in operation, even if the battery has adequate power. The second approach is to charge them when the power is low. Since most large-scale bus charging stations are not located at bus terminals, it takes time to travel to the depot for charging operations. Transit agencies with a small fleet of BEBs usually adopt the first strategy to successfully fulfill the scheduled passenger trips of the day. Companies with large fleets implement the latter strategy to decrease the number of charging trips, and buses undergo a full charge each time they go to charging stations. In this study, we considered a BEB charge at the depot under two conditions, either after finishing scheduled daily trips or when the battery capacity is below the threshold safety level (which is considered 25% of battery capacity).

3.3 Mathematical Modeling

In this section, mathematical formulations are developed to understand, analyze, and predict the behavior of the electric bus fleet operations under different conditions and scenarios. Relevant variables, relationships, and assumptions are identified and translated into mathematical equations to capture and describe real-world e-buses transit operations. Table 3-1, summarizes the notations used in the study.

Parameters

d_i	distance between terminals in a bus line i. (km)
d_t	distance travelled at any given time (km)
OP_h	bus operating hours per day in bus line *i*. (hrs)
Sh_{ti}	total scheduled round trips per day in a bus line i.
Sh_{tbi}	total scheduled round trips per bus per day in a bus line i.
DR	driving range (km)
SR	safety range (km)
SF_T	safety threshold level (%)
OR	operating range of a BEB in a bus line i per day (km)
$R_{Consump}$	rate of consumption $\left({}^{kWh}/_{km}\right)$
X_i	charging frequency (E-buses go for charging every X day(s) in a bus line i).
N_i	the fleet size operating on the bus line i
t_i	charging time (hrs).
C	rated battery capacity of e-buses (kWh)
$C_{avail(t)}$	battery capacity left at given time (kWh)
$C_{consumed(t)}$	battery capacity consumed at any given time (kWh)
H	charging power (kW)
Y_i	daily charging demand in a bus line i (per day)
SoC	state of charge (%)
$SoC_{avail(t)}$	state of charge available at given time (%)

$SoC_{desired}$	state of charge desired (%)
η	charger efficiency (%)
$temp$	battery temperature (^{0}C)
age	battery age
T	ambient temperature (^{0}C)
R_e	cost of electric usage $\left(\$/_{hr}\right)$
C_{bi}	avg cost of charging per bus per charge for a bus line i $\left(\$/_{bus}\right)$
C_{di}	avg cost of charging per day for bus line i $\left(\$/_{day}\right)$
C_{T}	total cost of charging ($)
Ch_t	daily charger's operating hours (hrs)
D_i	the demand for chargers in bus line i
C_{bi}	avg cost of charging per bus per charge operating in i ($) $per\ charge$
C_{di}	avg cost of charging per day operating in bus line i $^{(\$)}/_{day}$

Table 3-1: Parameters considered in the study.

Driving Range $(\boldsymbol{DR})$

Driving range for a BEB refers to the distance that an electric bus can travel on a single charge of its batteries before it needs to be recharged. According to data collected by the Dutch company Viricity in 2019, the focus of the e-bus test, a 12-meter bus in optimal conditions consumes around 0.8 kWh per kilometer [67]. Also, they stated that this figure could be affected by factors such as temperature and driving skills. A skilled driver can achieve this level of consumption during a typical day with a temperature of 20 ^{0}C and in less traffic conditions. However, when the temperature drops to -10 ^{0}C with electric heating turned on in the winter, consumption can increase to 2.3-2.5 kWh per kilometer. Diesel heating, on the other hand, could result in a consumption of 1.5 kWh per kilometer.

The driving range (DR) of a bus mainly depends on battery capacity and energy consumption/ rate of consumption. Equation i, describes the relationship between them.

$$Driving\ Range\ (DR) = \frac{Battery\ Capacity\ (kWh)}{Consumption\ rate\ \left({}^{kWh}/_{km}\right)}$$

$$DR = \frac{C}{R_{consump}} \qquad (i)$$

<u>Energy Consumption</u> $(R_{consump})$

The study on energy consumption of electric buses in cold climates in Tampere, Finland by Vehviläinen et al. [68], reveals that ambient temperature significantly impacts energy efficiency of a BEB. The author performed a case study and analyzed data from four electric buses over a period from 2019 to 2021. The study found that energy consumption increased significantly during winter, with an average of 2.1 kWh/km to up to 2.5 kWh/km compared to 1.1-1.35 kWh/km in summer, largely due to heating demands.

The energy consumption equation developed by the authors is a piecewise function that models the electrical energy consumption of electric buses as a function of temperature (T) in Tampere with an average annual temperature of 3.7 ^{0}C with lowest average temperature is −8.2 ^{0}C in February, and the average temperature is 16.0 ^{0}C in July. This temperature profile perfectly fits with our study area Montreal, Canada with a lowest average temperature corresponding to -8 ^{0}C to -9 ^{0}C in the months of January and February and +14 ^{0}C to +21 ^{0}C in the months of June, July [69] and is considered in our study.

For T ≥ 0 ^{0}C:

$$R_{consump} = (5.4 * 10^{-5} * T^3) - (2.7 * 10^{-4} * T^2) - (0.05 * T) + 1.6 \qquad (ii)$$

For T < 0 ^{0}C:

$$R_{consump} = (-0.04 * T) + 1.6 \qquad (iii)$$

Using this model, the energy consumption rates at –25 ^{0}C, 0 ^{0}C, and +25 ^{0}C have been estimated at 2.6 kWh/km, 1.6 kWh/km, and 1.025 kWh/km, respectively. Given a battery capacity of 400 kWh, the corresponding driving ranges at these temperatures are calculated to be 153.85 km, 250 km, and 390.25 km, in that order. Considering the average winter temperature of -7 ^{0}C in our study area, Montreal, the driving range can be 212.76 km with a consumption rate of 1.88 kWh/km. These values indicate how temperature variations can significantly affect the efficiency and range of electric buses.

<u>Operating Range</u> $(\boldsymbol{OR})$

The operating range of a bus refers to the maximum distance or range that a bus travels to perform its passenger trips within a single day of operation in a bus line i.

$$Operating\ Range\ (OR) = 2 * (distance\ between\ terminals) * (Scheduled\ round\ trips\ per\ bus\ per\ day\ in\ line\ i)$$

$$OR = 2 * d_i * Sh_{tbi} \qquad (iv)$$

The scheduled number of round trips for a BEB per day in a particular line i (Sh_{tbi}) can be calculated by dividing the total scheduled round trips per day in the route i (Sh_{ti}) with fleet size (N_i). Which can be calculated using operating hours and the frequency of buses per hour.

$$Sh_{tbi} = \frac{Sh_{ti}}{N_i}$$

By substituting(Sh_{tbi}) in the above equation (iv), we get,

$$OR = 2 * d_i * \frac{Sh_{ti}}{N_i} \qquad (v)$$

Charging frequency $(\boldsymbol{X_i})$

The charging frequency of a BEB refers to how often the bus needs to be charged in order to maintain its power level enough to carry out scheduled trips. The charging frequency depends on several factors, including the battery capacity of the bus, the distance it travels, and the driving conditions, such as terrain and route characteristics that could impact the energy consumption of the bus. For instance, hilly routes or frequent stops can increase energy consumption and reduce the driving range of the bus, resulting in a need for more frequent charging.

Consider e-buses go for charging every X day(s) on the route i [34].

$$X_i = \left(\frac{Driving\ range - Safety\ range}{Operating\ range}\right) * f(driving\ conditions) \qquad (vi)$$

For the simplicity of our study, we considered that driving conditions does not affect the charging frequency of a BEB; rather, it depends on driving, safety, and operating ranges. In a study conducted by Xing et. al.,[70] the optimal charge and discharge threshold of a BEB in a particular study route is found to be 25% & 85% respectively. Considering the safety threshold level (SF_T) of 25% of battery capacity for our study, meaning the BEB cannot operate passenger trip tasks when the remaining SoC is below 25%. An SoC of 25% can support a safety range (SR) of 53.19 km journey for a BEB with 400kWh at a 1.88kWh/km consumption rate.

$$X_i = \left(\frac{DR - SR}{OR}\right) \text{ days}$$

$$X_i = \left(\frac{\left(\frac{C}{R_{consump}} - SR\right)}{OR}\right) * 24 \text{ hrs.} \qquad (vii)$$

Daily Charging demand $(\boldsymbol{Y_i})$

Daily charging demand refers to the average number of buses from a specific fleet size (N_i) that require charging on a daily basis. This metric takes into account the charging needs of buses in a particular bus line *i* and is used to estimate the demand for charging infrastructure required to keep the fleet operational. Daily charging demand can vary depending on factors such as fleet size, traffic congestion, distance, frequency of buses, and the charging technology used.

Traffic congestion is one of the factors not considered in our study, which can impact the charging frequency of e-buses. When buses are stuck in traffic, they consume more energy and may need to be charged more frequently than buses that operate on less congested routes. Additionally, traffic congestion can cause delays and disruptions in the bus schedule, which may require buses to be charged more frequently to maintain their schedule and meet the demands of the passengers.

From the observations by the authors Lin et. al.,[34] the average number of buses to be charged from a fleet size of (N_i) in bus line i per day.

$$Y_i = \left(\frac{N_i}{X}\right) * \ f(traffic\ congesation)$$

$$Y_i = \left(\frac{N_i}{X}\right)$$

$$Y_i = \frac{N_i * OR}{\left(\frac{C}{R_{consump}} - SR\right)} \qquad (viii)$$

<u>State of Charge</u> (SoC)

The state of charge (SoC) for a battery represents the available battery capacity at any given time relative to its rated capacity. SoC ranges from 0% to 100%, with a SoC of 100% indicating a fully charged cell and a SoC of 0% signifying a completely discharged battery. The primary factors that effect the SoC are the energy consumption rate, which varies with driving conditions, driving behavior such as acceleration and deceleration patterns, and cruising speed. The state of charge at any given time [71] is given as

$$SoC_{avail(t)} = \frac{C_{avail(t)}}{C} * \ 100\ [\%]$$

$$SoC_{avail(t)} = \frac{(C - C_{consumed(t)})}{C} * \ 100\ [\%] \qquad (ix)$$

The total energy consumed by the BEB during its journey at any point of time is obtained by multiplying the distance traveled (d_t) by the energy consumption rate ($R_{consump}$).

$$C_{consumed(t)} = d_t * R_{consump}$$

$$SoC_{avail(t)} = \frac{(C-(d_t * R_{consump}))}{C} * 100\ [\%] \qquad (x)$$

Charging Time (t)

The charging time t of an e-bus mainly depends on charging power H , battery capacity C, state of charge SoC, and charger efficiency η [34]. The other factors $\mathrm{f}(battery\ temp, age, Ch_{type})$, that adjusts for other considerations such as battery temperature, battery age, and charging method, which are neglected in our study. The average charging time can be determined as [72]

$$t = \frac{C * \frac{(\mathrm{SoC}_{desired} - SoC_{avail})}{100}}{\eta * H * \mathrm{f}(temp, age, Ch_{type})} \qquad (xi)$$

For a BEB to get fully charged to 100% ($\mathrm{SoC}_{desired}$) from any available SoC $\left(C_{avail(t)}\right)$, the charging time can be modeled as

$$t = \frac{C * \frac{\left(100 - \left(\frac{C_{avail(t)}}{C} * 100\right)\right)}{100}}{\eta * H} \qquad (xii)$$

Simplifying the above equation (xii)

$$t = \frac{C - C_{avail(t)}}{\eta * H}$$

$$t = \frac{d_t * R_{consump}}{\eta * H} \qquad (xiii)$$

The first part of the formula $\{d_t * R_{consump}\}$ represents the amount of energy consumed that needs to be charged at any given time, considering the distance traveled and battery's state of charge. The second part of the formula $\{\eta * H\}$ represents the rate at which the battery can be charged.

Charger efficiency can vary based on many factors like the specific charger technology, the state of charge of the battery, temperature conditions, and the charging infrastructure. Generally, modern DC fast chargers can achieve efficiencies in the range of 85-93%. Research by Trentadue et. al., [73] from Europe indicated an efficiency of 93% under standard +25ºC ambient temperature conditions. Likewise, a study conducted by Genovese et. al., [74] in Korea showed that the total efficiency of charging varied between 85% and 89%.

<u>Charging Cost</u> $(\boldsymbol{C})$

Various factors influence the charging costs of an electric bus. Some critical factors considered are the battery capacity, charging power, electricity tariffs, including time of day, and local electricity rate plan. Due to their larger battery size, electric buses typically have higher charging costs than electric cars. The charging power can also impact the cost; fast charging typically costs more than slow charging. On the other hand, the electricity rate plan can also affect the charging costs, with some plans offering cheaper electricity during off-peak hours.

Therefore, it is essential to consider all these factors when calculating the charging costs of an electric bus to ensure the most cost-effective and efficient charging solutions. Since we are estimating the charging costs, some factors are neglected, and the cost of charging per day is given as [75].

$$Avg\ cost\ of\ charging\ per\ bus\ per\ charge\ (C_{bi}) = (charging\ time\ in\ hours) * (cost\ per\ hour)$$

$$C_{bi} = t * R_e \tag{xiv}$$

$$Avg\ cost\ of\ charging\ per\ day\ (C_{di}) = (Daily\ charging\ demand) * (cost\ per\ bus\ per\ charge)$$

$$C_{di} = \frac{N_i}{X} * t * R_e \tag{xv}$$

Charging Infrastructure Demand $(\boldsymbol{D_i})$

The demand for charging infrastructure, or chargers demand on bus line i, refers to the number of chargers required to meet the daily charging needs of the buses in a specific bus line. This includes the number and type of charging stations needed, as well as the power and energy requirements for each station. The demand for charging infrastructure of bus line i is influenced by several factors, such as the size and composition of the bus fleet, the length and frequency of bus routes, and the charging technology used. Accurately estimating the demand for charging infrastructure is critical to ensure the efficient operation of electric bus networks. Insufficient charging infrastructure can result in service disruptions, increased costs, and reduced reliability [34].

The demand for charging infrastructure of bus line i is estimated as

$$Chargers\ demand = \frac{(Daily\ charging\ demand * charging\ time)}{Daily\ chargers\ operating\ hours}$$

$$D_i = \frac{(Y_i * t)}{Ch_t} \tag{xvi}$$

Substituting the above equations (vi), (viii) in (xi)

$$D_i = \frac{(N_i * t)}{X * Ch_t} \tag{xvii}$$

3.4 Summary of Devised Numerical Equations.

$$DR = \frac{C}{R_{consump}}$$

For $T \geq 0\ ^0C$ $\quad R_{consump} = (5.4 * 10^{-5} * T^3) - (2.7 * 10^{-4} * T^2) - (0.05 * T) + 1.6$

For $T < 0\ ^0C$ $\quad R_{consump} = (-0.04 * T) + 1.6$

$$OR = 2 * d_i * \frac{Sh_{ti}}{N_i}$$

$$SR = SF_T * DR$$

$$X_i = \left(\frac{DR - SR}{OR}\right)$$

$$Y_i = \left(\frac{N_i}{X}\right)$$

$$SoC_{avail(t)} = \frac{C_{avail(t)}}{C} * 100\ (\%)$$

$$t = \frac{C - C_{avail(t)}}{\eta * H}$$

$$C_{bi} = t * R_e$$

$$C_{di} = \frac{N_i}{X} * t * R_e$$

$$D_i = \frac{(N_i * t)}{X * Ch_t}$$

3.5 Sample Calculation

A sample numerical calculation is illustrated by inputting the values detailed in table 3-2 to summarize the above equations. The supporting excel calculations sheet is provided in the appendix A1.

<u>Assumptions</u>

- Below are calculations performed for the operation of fleet size N_i each with homogeneous battery and an identical driving range in a route i, for 30 operational days.
- The rate of consumption depends ambient temperature which was assumed to be -7 ^{0}C, corresponding to the average winter temperature for the Montreal region [69].
- Factors like battery temperature, battery age, and charging method do not affect the charging time; rather, it depends on charging power H, battery capacity C, state of charge SoC, and charger efficiency η.
- Charging time and costs remains the same for every one percent increment from 0-100% and are set to be 36.87 $^{\$}/_{hr}$ irrespective of the hour of the day, which in reality varies [76].
- Charging stations with the same charging power with charger efficiency of 89% considered [74].
- In practice, the time required for charging varies depending on the available battery level, specifically for the ranges of 0-50%, 50-80%, and 80-100%, which is assumed to be constant.
- The energy consumed during charging process is directly proportional to the amount of time spent by BEB at charging station.

Input Values

Parameter	***Value***	***Units***	***Description***
Fleet size (N_i)	4		corresponds to Concordia's existing fleet size
Total scheduled round trips per day (Sh_{ti})	38		corresponds to Concordia's existing fleet operations [77]
Rate of consumption $(R_{Consump})$	1.88	kWh/km	considering Montreal's avg winter temp -7 ^{0}C (eq. iii)
Battery capacity (C)	400	kWh	
Safety threshold level (SF_T)	25	%	For a battery capacity of 400 kWh, BEBs does not perform trips after reaching 100 kWh capacity
Charging power (H)	100	kW	
Charger Efficiency (η)	89	%	DC fast chargers' efficiency range of 85-93%. [74]
distance between terminals in a bus line i. (d_i)	10	km	originally 8 km for Concordia's shuttle, but estimated to 10 giving us a room for service route disruptions
Chargers working time (Ch_t)	10	hrs	Assumed charging stations are available to charge between 10.00 PM-8.00 AM at the depot
Cost of electric usage (R_e)	36.87	$\$/_{hr}$	Corresponding to 100 kW fast charger by Hydro Quebec [76]

Table 3-2: Input values for the sample calculation.

Outputs

Parameter	***Value***	***Units***	***Description***
scheduled round trips per bus per day (Sh_{tbi})	9.5 ≈ 10		Each BEB to perform at 9/10 trips to fulfil the daily scheduled trips.
driving range (DR)	213	km	Range a BEB can cover with rated battery capacity
operating range (OR_i)	190	km/day	Distance each BEB covers per day
safety range (SR)	53.19	km	Corresponds to 400kWh battery at 1.88 kWh/km $R_{Consump}$ with 25 % of (SF_T)
Charging frequency (X_i)	20.157	hrs	For every 17.78 hrs, the BEB needs to charge
Avg Charging time per charge (t_i)	4.01	hrs	Time spent by each BEB at charging station to get fully charged.
Daily charging demand for line $\boldsymbol{i}$ (Y_i)	4.76	buses	Corresponds to 1428.8 kWh energy consumed by fleet of 4 with 25% safety threshold per day.
Demand of chargers (D_i)	1.92 ≈ 2		Charging stations required to meet the charging demand in the bus route i
Cost of charging per BEB per charge (C_{bi})	147.98	$/bus/charge	Charing costs on single charge
Charging cost per day	704.77	$/day	Charing costs per day for fleet size of 4
Total Cost of Charging (C)	21142.97	$	Charging costs per month (30 days)

Table 3-3: Outputs for sample calculation.

Based on the above outputs from the mathematical formulations, the demand for chargers is estimated to be 1.92 ≈ 2 corresponding to which base simulation model was built to check its correctness. Various scenarios were also considered, which are discussed below in section 3.7.

3.6 Model Conceptualization

Model conceptualization involves defining the key components of the model. This includes identifying the system to be simulated, determining the variables and parameters to be included, and outlining the relationships and interactions between these elements. Data is meticulously gathered from the current conventional bus fleet operated by Concordia University [77] to scrutinize a range of performance indicators. The current simulation model developed on these empirical insights, alongside a set of critical assumptions, to closely resemble Concordia University's fleet operations. Below is a refined comparative analysis of the actual fleet against the simulation model, coupled with a detailed account of the assumptions underpinning the model's development.

Feature	Concordia University Fleet	For Simulation Model
Fleet Size	4	4
Stops & Terminals	2 terminals with no Intermediate stops	2 terminals with no Intermediate stops
Travel Time	Approximately 30 minutes	Uniform distribution between 25 and 35 minutes
Trips Starting Time	7.20 AM (Monday – Thursday) & 7.45 AM on Friday	7.30 AM (Monday – Friday)
Trips Ending Time	11.05 PM (Monday – Thursday) & 7.45 PM on Friday	11.00 PM (Monday – Friday)
Total Number of Trips per Day	38	38

Table 3-4: Simulation model assumptions against Concordia fleet operations.

3.6.1 Critical Assumptions for Simulation Model Development

- The fleet consists of 4 homogeneous battery electric buses (BEBs), each with an identical driving range.
- The route does not include intermediate stations; only terminal stops are considered.
- The energy consumed during charging is directly proportional to the amount of time spent charging.
- BEBs adhere to the pre-established Concordia shuttle fleet schedule for operations and operate between 7.30 AM to 11.00 PM.

- Rate of consumption remains same through out the discharge state irrespective of State of charge and correlates directly with the distance traveled and ambient temperature.

- The Bus depot is situated at a significant distance away from the terminals that buses travel to reach depot after finishing scheduled trips.

- The charging stations for overnight depot charging are available for limited hours daily, allowing Battery Electric Buses (BEBs) to charge from 11:30 PM to 7:00 AM.

- After being plugged into the charger, a Battery Electric Bus (BEB) commences its passenger trips only after getting fully charged to 100% if charged at the depot. However, if the charging station is located at the terminal, the bus chargers during its stoppage time before commencing its next trip only if SoC is below 80%.

- In practice, the time required for charging varies depending on the battery level, specifically for the ranges of 0-50%, 50-80%, and 80-100%. However, for the purpose of this simulation study, we assumed a constant charging time for each percentage increment.

- The cost of electricity is assumed to remains the same 36.87 $^{\$}/_{hr}$ irrespective of the charging power and hour of the day, which in reality varies [76].

- Charging stations with the same charging power and uniformly distributed charger efficiency (85%, 93%) is positioned at different locations to evaluate the performance over different scenarios [74].

Below explained the base simulation model and the scenarios considered for our study.

3.7 Base Model: Charging Stations at Depot.

In this case, we considered the locations of charging stations at Bus Depot. The BEB charge over night and reach terminal A to initiate their passenger trips. The situation is illustrated in figure 3-3, which showcases the bus depot situated away from the terminals with buses (BEBs) returning to the charging stations under three conditions:

i. ***Battery capacity below safety threshold:*** If the battery capacity of a bus falls below the safety threshold, set at 25% of its total capacity

ii. ***Completion of Scheduled Trips:*** After completing the scheduled trips for the day i.e 38, the buses are directed to return to the depot.

iii. ***Time-Based Trigger:*** BEBs return to the depot if the current time surpasses 11:00 PM.

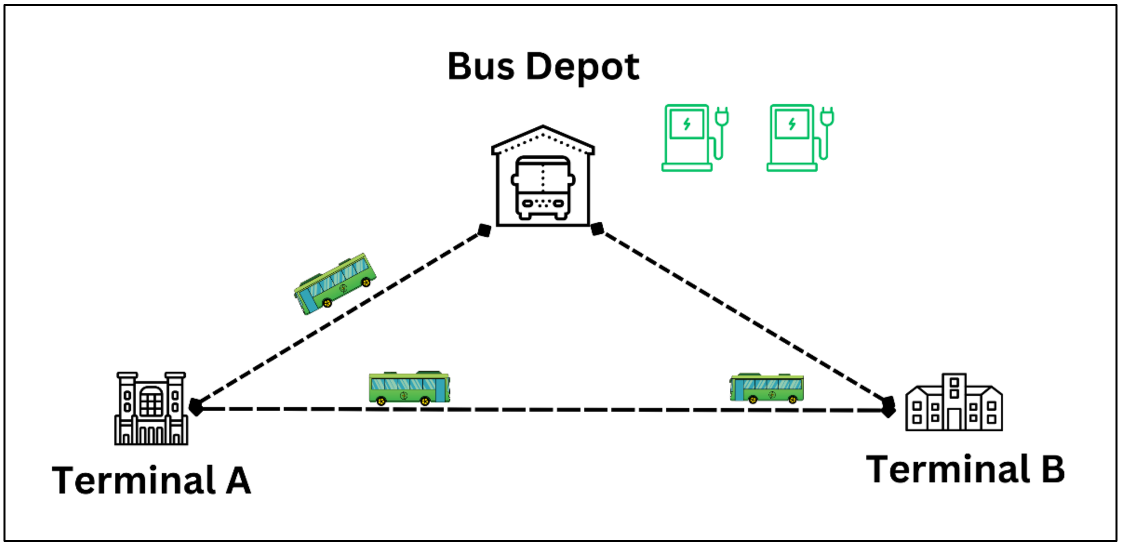


Figure 3-3: Base model illustration.

Figure 3-4 provides an overview of the developed simulation model, which incorporates a network system comprising terminals A, and B, the bus depot, and two charging stations. Based on the comprehensive flow outlined, an EV bus (BEB) commences its journey from the Bus Depot, checking its battery capacity before embarking on the scheduled trips from terminal A to terminal B. At each stage, the BEB assesses its battery capacity, and if the state of charge (SoC) falls below the safety level, the BEB returns to the Bus Depot for recharging. Additionally, upon completing the assigned trips, the BEB returns to the depot for recharging.

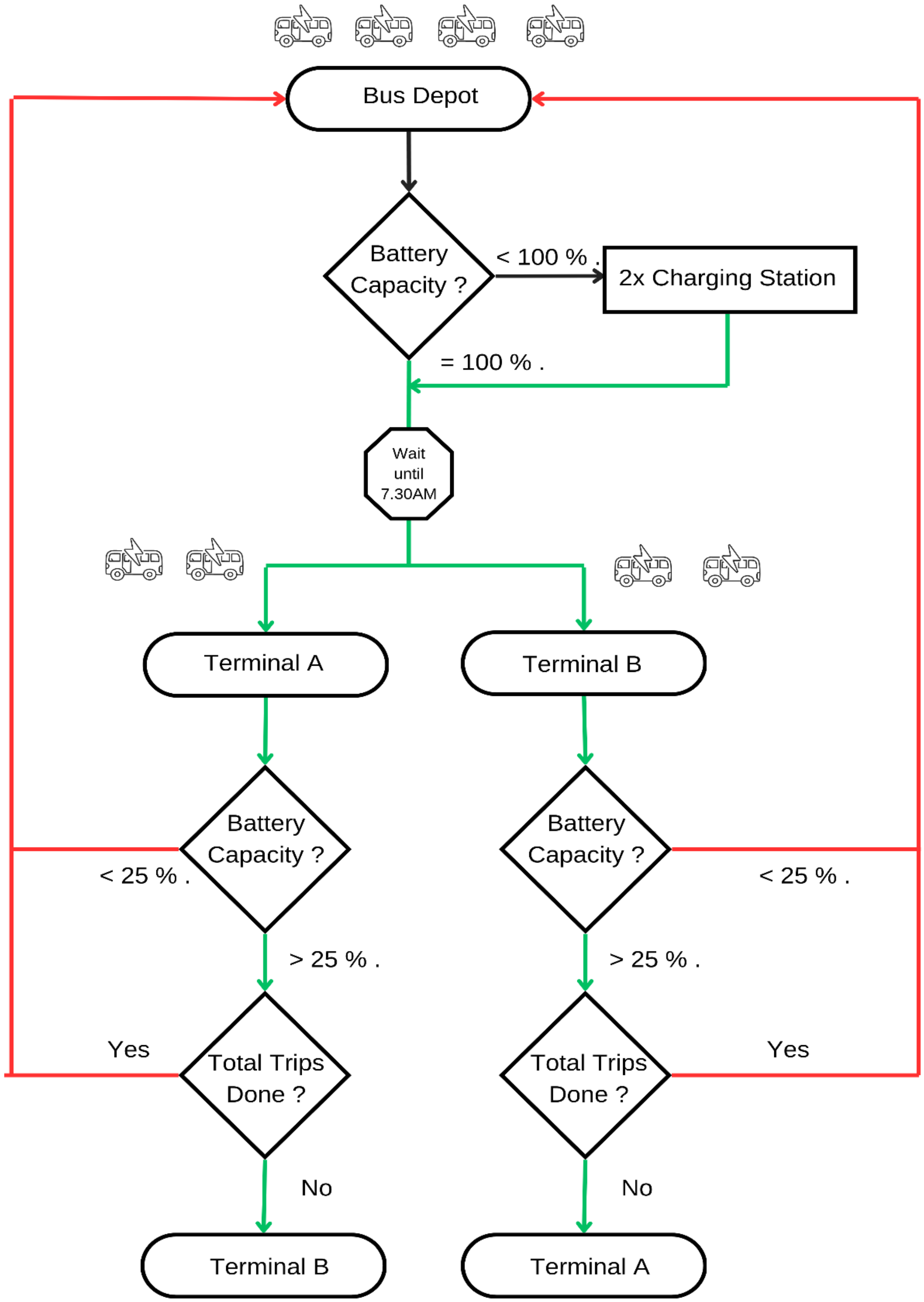


Figure 3-4: Flow diagram - Base model.

The performance evaluation of the fleet, which maintains the same battery capacity, depends on the service level achieved. A 100% service level indicates the successful completion of all scheduled passenger trips without any failures. Other parameters, such as average charging time, average daily charging costs, are evaluated to estimate the approximate expenses incurred over the simulation run time.

3.7.1 Scenario 1: Charging Stations at Depot and Terminal

In this situation, Terminal A is equipped with one charging station, and another is available at the Bus Depot. The buses employ two distinct charging strategies: opportunity charging at Terminal A, which takes advantage of stoppage time between scheduled trips to charge, and depot charging at the Bus Depot. This approach reduces the charging time required at the depot as the buses continuously undergo the charging process at Terminal A.

After completing the scheduled trips, the BEBs return to the Bus depot and gets to full charge before starting the following day's trips. Figure 3-5 illustrates this situation with one charging station at terminal A and the other at Bus Depot.

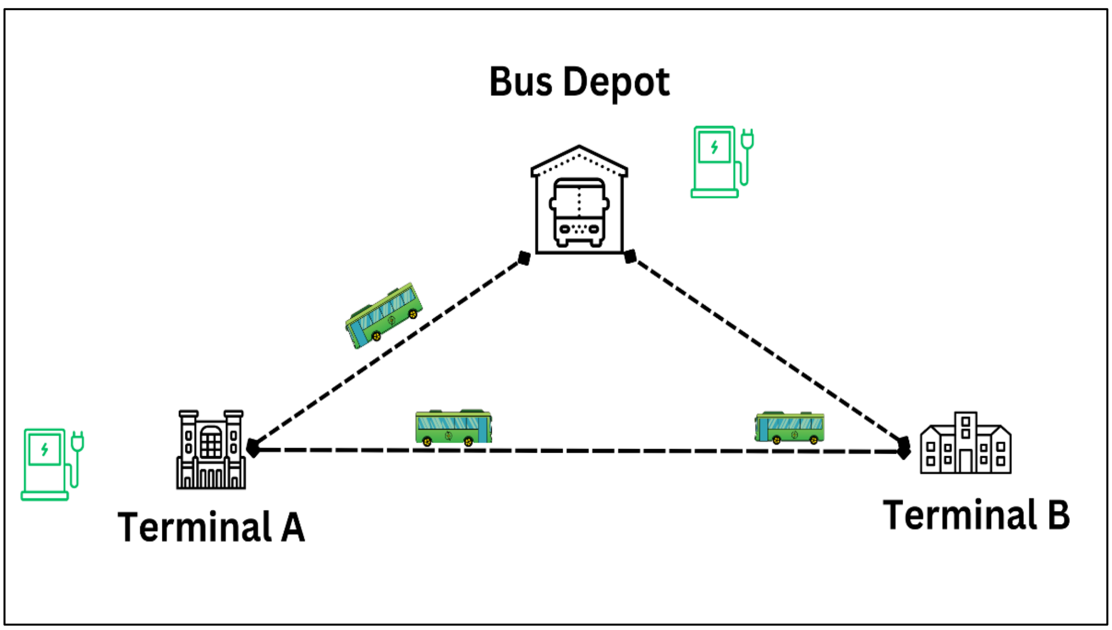


Figure 3-5: Scenario 1 illustration.

The below figure explains the flow diagram for scenario 1.

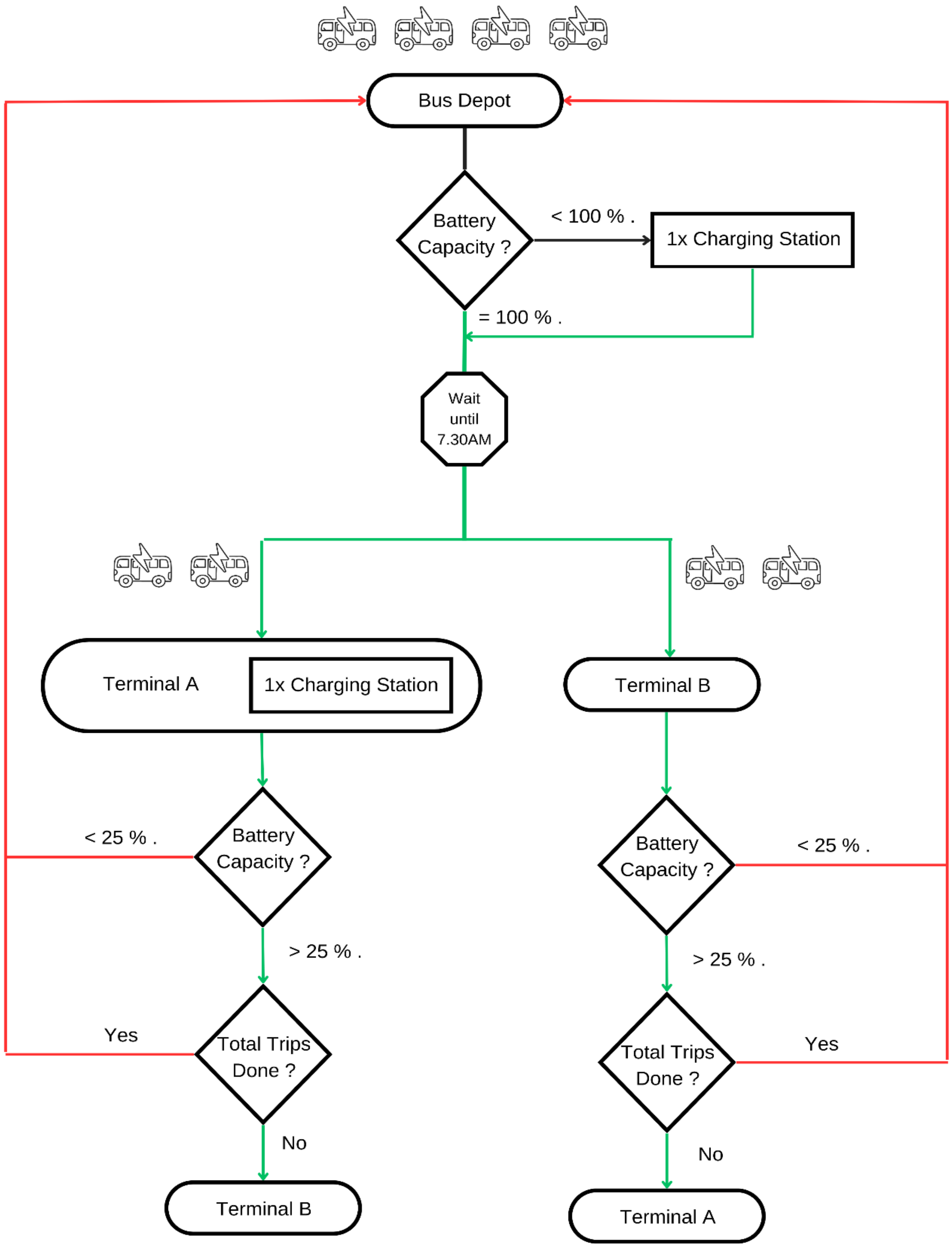


Figure 3-6: Flow diagram – Scenario 1.

3.7.2 Scenario 2: Charging Stations at Terminal A & Terminal B

In this specific scenario, we have considered charging station locations, each at Terminal A and Terminal B. The BEBs use an opportunity charging strategy at the terminal stations taking advantage of the halt times. Unlike the base model and scenario 1, there will not be any charging process taking place at the bus depot. If in-case the battery level goes below the threshold safety level, the bus uses the nearest charging station to get to full charge. Figure 3-7 describes the charging station locations considered for scenario 2.

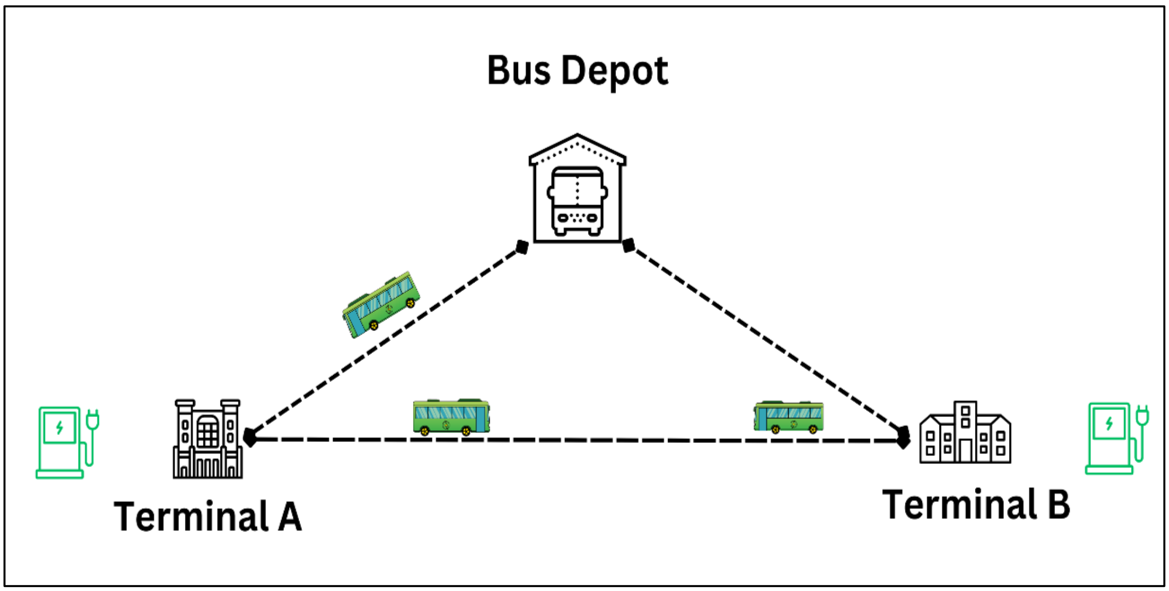


Figure 3-7: Scenario 2 illustration.

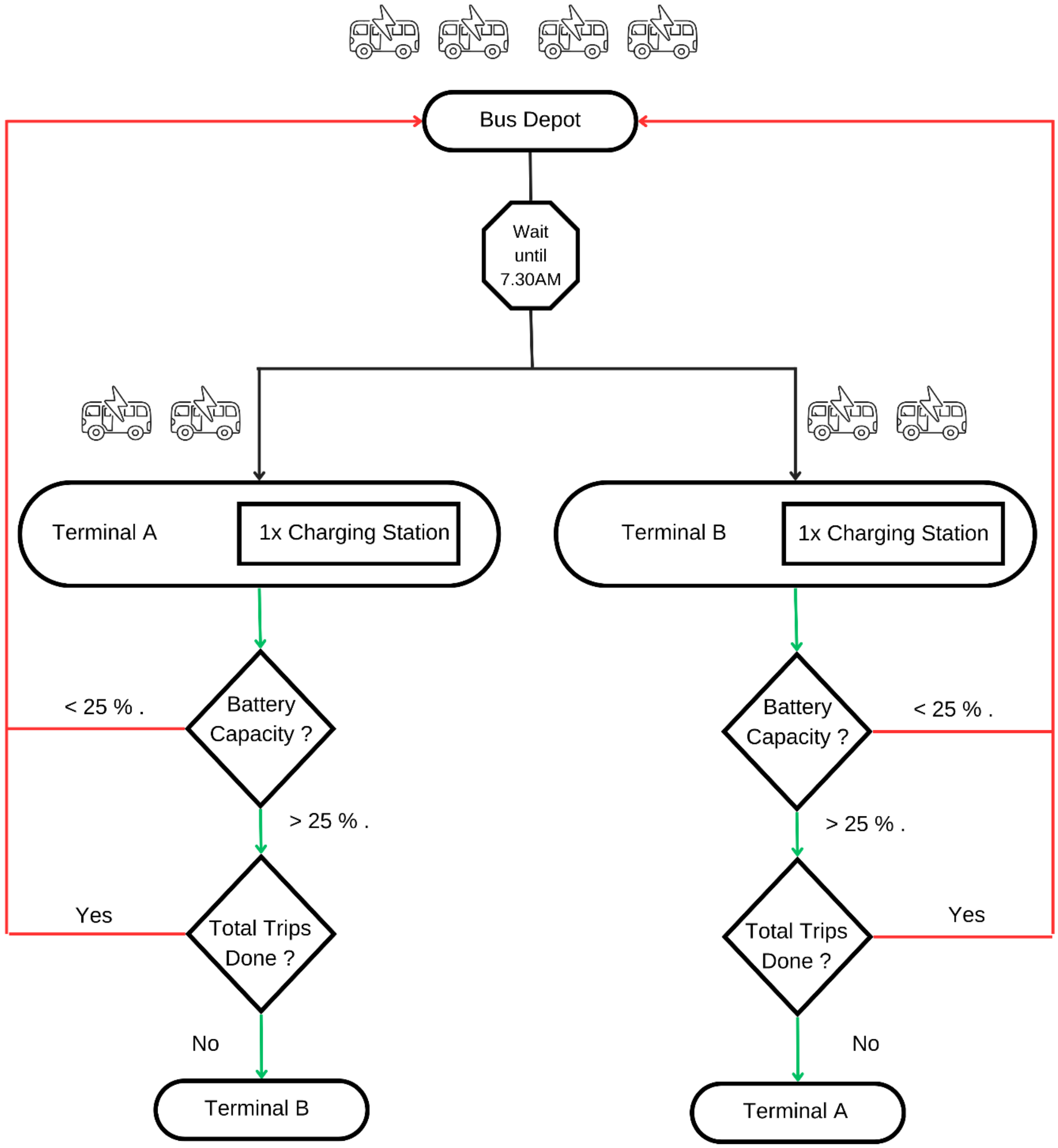


Figure 3-8: Flow diagram – Scenario 2.

CHAPTER 4

MODEL ADAPTATION AND IMPLEMENTATION

The scenarios explained in the preceding chapter are converted into Arena simulation models to be implemented. This chapter summarizes the components of Discrete Event Simulation (DES), the basic simulation concept of the BEB network, and how it is translated into the Arena models. Figure 16 showcases the Arena Software version used in this thesis. All figures and discussions pertaining to the Arena tool in this document will conform to this particular version and revision.

Figure 4-1: Arena 2022, version: 16.20.00000.

4.1 Elements of the Simulation Model

Computer simulation is a highly strategic tool for simulating mathematical models, as it allows multiple executions to assess the model's reliability with the added advantage of providing a visual representation of simulation models. Arena is a software that employs SIMAN processing language for discrete event simulations. This thesis uses Arena simulation to develop and conduct experiments on BEB network. The system description is elaborated below, along with its components, to facilitate a comprehensive understanding and analysis of the model. Additionally, terms associated with the Arena software are explained below in detail to improve transparency.

4.1.1 System

A system is a collection of objects grouped to interact or coordinate interdependently to achieve a common objective. To effectively model a system, it is crucial to understand the underlying concepts and establish the system boundaries. The system consists of components, such as entities, variables, and attributes, that collaborate toward a defined objective. In the context of the present discussion, the system in focus is the battery electric bus (BEB) network with some key components, including the BEB itself, the depot, terminals, the charging process, and their respective operations.

Figure 4-2, shoes the new project tab in the Arena Software, allowing for further simulation and analysis. The project title, required statistics, and other parameters can also be modified at any stage of the project.

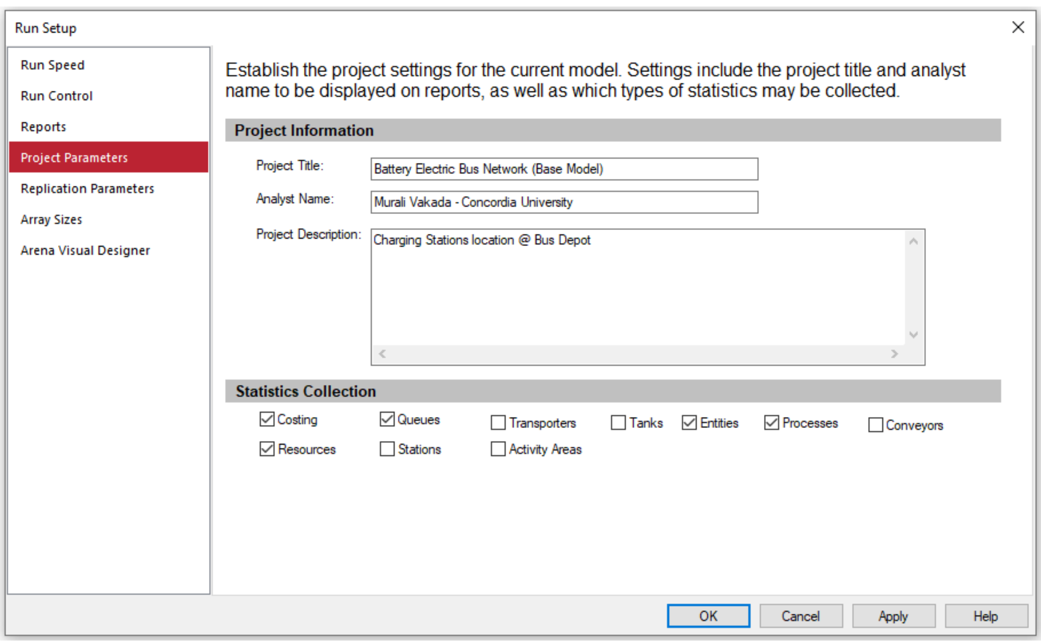


Figure 4-2: New project parameters tab.

4.1.2 Events

Systems undergo changes over time, and in modeling, events are utilized to replicate these system transformations. In simulation, additional logics are employed beyond the initial events to recreate the necessary actions that lead to a change in the system's state. In Arena, there are various methods for creating events, and some of the critical events utilized in the models include the creation of BEB/entities, routes, setting up schedules for BEB and the charging process, introducing delays, and holding entities in queues, among others. The primary modules employed in this study encompass the Create, Process, and Delay modules, which belong to the discrete processing block, while the Hold and Decide modules belong to the decisions block.

4.1.2.1 Events - Entity Creation

Entities hold significant importance and are integral components of the system. They enter the system, traverse through, and, depending on predetermined end conditions, either remain within the system or exit once the simulation run time concludes. In our simulation model, the primary entity is an “EV BUS,” which follows the model's flow based on the defined logic; various events, such as charging and passenger trips. The other entities created in the model are the logic entities, also called dummies, that control the scheduled daily trips and track the running hours.

Adjusting the fleet size is a straightforward process achieved by modifying the value of "Entities per Arrival." Once this block is executed, all buses seamlessly enter the simulation environment. Users have the flexibility to customize the entity name, type, and expression through the Create dialogue box.

Entity Information

The study model uses three entities, and are as follows:

- EV BUS- that enters and flows through the system.
- Logic Entity 1 – that sets the schedule for passenger trips with an interval of 25 minutes.
- Logic Entity 2- to start the scheduled passenger trips count at the beginning of the day.
- Logic Entity 3- that ends the scheduled passenger trips count at the end of the day.

Figure 4-3, below represents how the entities mentioned above are configured and used to build the model.

	Name	Entity Type	Type	Value	Units	Entities per Arrival	Max Arrivals	First Creation
1	Create Buses	EV Bus	Constant	1	Hours	4	1	0.0
2	Logic Entity 2	Logic 2	Constant	24	Hours	1	30	5
3	Logic Entity 1	Logic 1	Constant	25	Minutes	1	Infinite	0.0
4	Logic Entity 3	Logic 3	Constant	24	Hours	1	Infinite	23

Figure 4-3: Entity information.

4.1.2.2 Events – Station and Route Setup

Our foundational model is designed as a depot charging system, operating without intermediate stops. The key stations in this model include the Bus depot, Terminal A (SGW Campus), and Terminal B (LYL Campus). To facilitate the movement of entities between these stations, specific route modules have been established.

Typically situated at a distance from the terminals, the route time between the Bus depot and Terminal A, as well as Terminal B, and vice versa, is assumed to be uniform in this study, lasting 15 to 25 minutes. On the other hand, the route time between Terminal A and Terminal B is considered as a variable (referred to as Route Time Btwn Terminals), accounting for various operational factors one such is traffic congestion, which is further elaborated in the section 4.1.4. Figure 4-4, presents the stations and route data utilized in the development of the base simulation model.

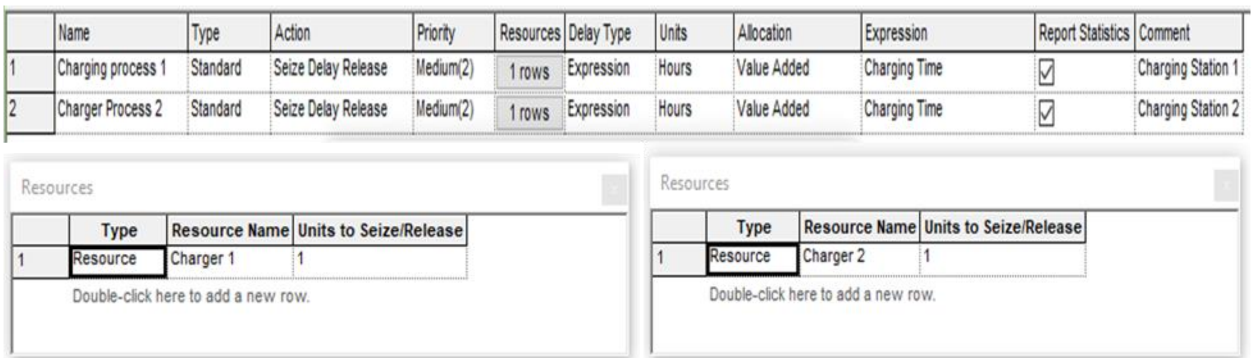
	Name	Station Type	Station Name	Parent Activity Area	Associated Intersection	Report Statistics	Comment
1	Bus Depot	Station	BusDepot			☑	To Gather the Buses
2	SGW Campus	Station	SGW			☑	Terminal A
3	LYL Campus	Station	LYL			☑	Terminal B

	Name	Route Time	Units	Destination Type	Station Name	Comment
1	Route SGW to LYL	Route Time Btwn Terminals	Minutes	Station	LYL	To send buses to Terminal B (LYL)
2	SGW to Depot	UNIF(15 , 25)	Minutes	Station	BusDepot	To send buses to Depot from Terminal A (SGW)
3	Route LYL to SGW	Route Time Btwn Terminals	Minutes	Station	SGW	To send buses to Terminal A (SGW)
4	Depot To SGW	UNIF(15 , 25)	Minutes	Station	SGW	Bus Depot To Terminal A (SGW)
5	LYL to Bus Depot	UNIF(15 , 25)	Minutes	Station	BusDepot	To send buses to Depot from Terminal B (LYL)
6	Depot To LYL	UNIF(15 , 25)	Minutes	Station	LYL	Bus Depot To Terminal B (LYL)

Figure 4-4: Stations & Routes information.

4.1.2.3 Events- Process Module

The Arena software's process module facilitates the modeling and analysis of specific actions or activities within a system. One notable activity in our study is the overnight charging process at the depot. Entities, represented as EV Bus, undergo a full charging cycle over a specific duration (charging time), which varies based on the individual Bus's State of Charge (SoC). In alignment with mathematical modeling, two charging stations are designated as resources. Each charging station caters to one Bus at a time, and buses awaiting charging are organized in a queue associated with the hold module.



	Name	Type	Action	Priority	Resources	Delay Type	Units	Allocation	Expression	Report Statistics	Comment
1	Charging process 1	Standard	Seize Delay Release	Medium(2)	1 rows	Expression	Hours	Value Added	Charging Time	☑	Charging Station 1
2	Charger Process 2	Standard	Seize Delay Release	Medium(2)	1 rows	Expression	Hours	Value Added	Charging Time	☑	Charging Station 2

Resources

	Type	Resource Name	Units to Seize/Release
1	Resource	Charger 1	1

Double-click here to add a new row.

Resources

	Type	Resource Name	Units to Seize/Release
1	Resource	Charger 2	1

Double-click here to add a new row.

Figure 4-5: Process module & Resource information.

4.1.2.4 Events- Hold module

The Hold module serves as a crucial component for managing entity flow and introducing delays within the simulation model. In the base model, four distinct hold modules, each outlined below, are employed to mimic the bus operations in a real-world system.

Hold 1: "Depot Charging with Type Scan for Condition" scrutinizes the process module (charging process) to determine its occupancy status. It triggers the dispatch of entity (EV Bus) to the charging station when the module is unoccupied.

Hold 2: "Sending Buses to Terminals with Type Scan for Condition" assesses bus numbers and directs them to their respective terminals (Terminal A and Terminal B) before commencing daily operations. Given the consideration of four BEBs, two are routed to Terminal A, and the remaining two are directed to Terminal B. This synchronization ensures that all BEBs initiate their operations simultaneously at 7:30 AM without any delays.

Hold 3: "Bus Leaves SGW with Type Wait for Signal" provides buses with sufficient stoppage time, adhering to the schedule. It is set to allow a EV Bus to depart from SGW terminal every 25 minutes.

Hold 4: "Bus Leaves LYL with Type Wait for Signal" ensures buses adhere to the schedule by incorporating ample stoppage time at Terminal B, which is set at 25 minutes.

	Name	Type	Wait for Value	Limit	Condition	Queue Type	Queue Name
1	DepotCharging	Scan for Condition	1		Charging process 1.WIP == 0 || Charger Process 2.WIP == 0	Queue	DepotCharging.Queue
2	Bus Leave LYL	Wait for Signal	2	1		Queue	Bus Leave LYL.Queue
3	Sending Buses to Terminals	Scan for Condition	1		MR(SGWExits) == 1 && MR(LYLExits) == 2	Queue	Sending Buses to Terminals.Queue
4	Bus Leave SGW	Wait for Signal	1	1		Queue	Bus Leave SGW.Queue

Figure 4-6: Hold modules information.

4.1.3 Attributes

Attributes in Arena Simulation are the properties associated with entities in the simulation model. They provide additional information for data collection, decision-making, and customization. Common attributes include name, type, location, state, capacity, processing time, arrival time, and priority. These attributes define and control the behavior of entities, allowing for accurate and flexible modeling of complex systems and processes.

In the developed model of the BEB network, key attributes were established to characterize the properties of entities. These attributes include,

i. BusID: which identifies a specific bus within a fleet of size Ni. With 4 BEBs each given identifier from 1 to 4.
ii. Direction: which specifies the movement of BEBs between terminals A and B, as well as B and A.
iii. Charging Time: determines the time required for entities (EV Bus) to get fully charged based on their available SoC (SoC_{avail}), which is equivalent to derived mathematical equation xi.

iv. Distance between Terminals: determines the distance between terminal A and terminal B, which is set at 10km.

v. Current Time: reads the present time within the simulation model facilitating the collection of time-related statistics.

	Name	Rows	Columns	Data Type
1	Direction			Real
2	BusID			Real
3	Charging Time			Real
4	Current Time			Real
5	Distance btwn Terminals			Real

Figure 4-7: Attribute information.

4.1.4 Variables

variables are placeholders used to store and manipulate data during the simulation run. They represent quantities or values that can change over time or based on specific conditions. Variables are crucial in capturing and updating information, performing calculations, making decisions, and controlling the behavior of entities and processes within the simulation model. Variables could be scalar or an array. The current models developed have used both scalar and 1D arrays, which are described below.

Variables used in our study are:

i. BusNumber: A scalar utilized for tracking the number of incoming entities (EV Bus).

ii. BusChargeLevel: A 1D array that represents the remaining charge level in a EV Bus based on its unique identity (BusID).

iii. MaxBatteryCapacity: The maximum rated capacity of the bus battery.

iv. ChargingPower: The power at which the charging operation occurs.

v. ChargingEfficiency: denotes the percentage measure of how effectively electrical energy from a power source is converted and delivered to a battery during the charging process considering the impact of temperature and other factors on the overall energy transfer.

vi. ChargingProcessCount: A scalar that counts the occurrences of the charging operation.

vii. TotalDepotCharged: Keeps track of the number of buses undergoing the charging process at the depot.

viii. TripCount: A scalar that tallies the number of successful trips occurring in a day. This count resets to 0 at the commencement of each new day.

ix. TotalTrips: Counts the overall number of successful trips at any point during the simulation run.

x. Rate of Consumption: determines the amount of energy (kWh) consumed per km considering operational and route conditions

xi. Route Time between Terminals: refers to the duration it takes for an entity to travel from one terminal to another, which is set to be uniformly distributed with a range of 25 to 35 minutes to commute between terminals.

	Name	Rows	Columns	Data Type	Clear Option	File Name
1	BusChargeLevel			Real	System	
2	BusNumber			Real	System	
3	ChargingProcessCount			Real	System	
4	TripCount			Real	System	
5	TotalDepotCharged			Real	System	
6	Route Time Btwn Terminals			Real	System	
7	MaxBatteryCapacity			Real	System	
8	ChargingPower			Real	System	
9	TotalTrips			Real	System	
10	ChargerEfficiency			Real	System	
11 ▶	Rate of Consumption			Real	System	

Figure 4-8: Variable information.

4.2 Base Model Explanation

The Arena simulation model developed for this study is unique by exploring various parameters related to implementing Battery Electric Buses (BEBs) on a specific route by replacing the conventional buses. The construction of these models is based on insights gained from lectures (INDU 6311- Discrete Event Simulations) and practical examples provided by Arena Rockwell Automation and Rossetti, 2021 [40].

The foundation of this study is a base model that represents a scenario where charging stations are located at the bus depot, which is situated away from the terminal stations. This section aims to provide a contextual background for the base model, which is divided into four parts: setting up trip schedules, the Bus Depot, Terminal A, and Terminal B. Figure 4-10, explains the arena simulation model for depot charging strategy.

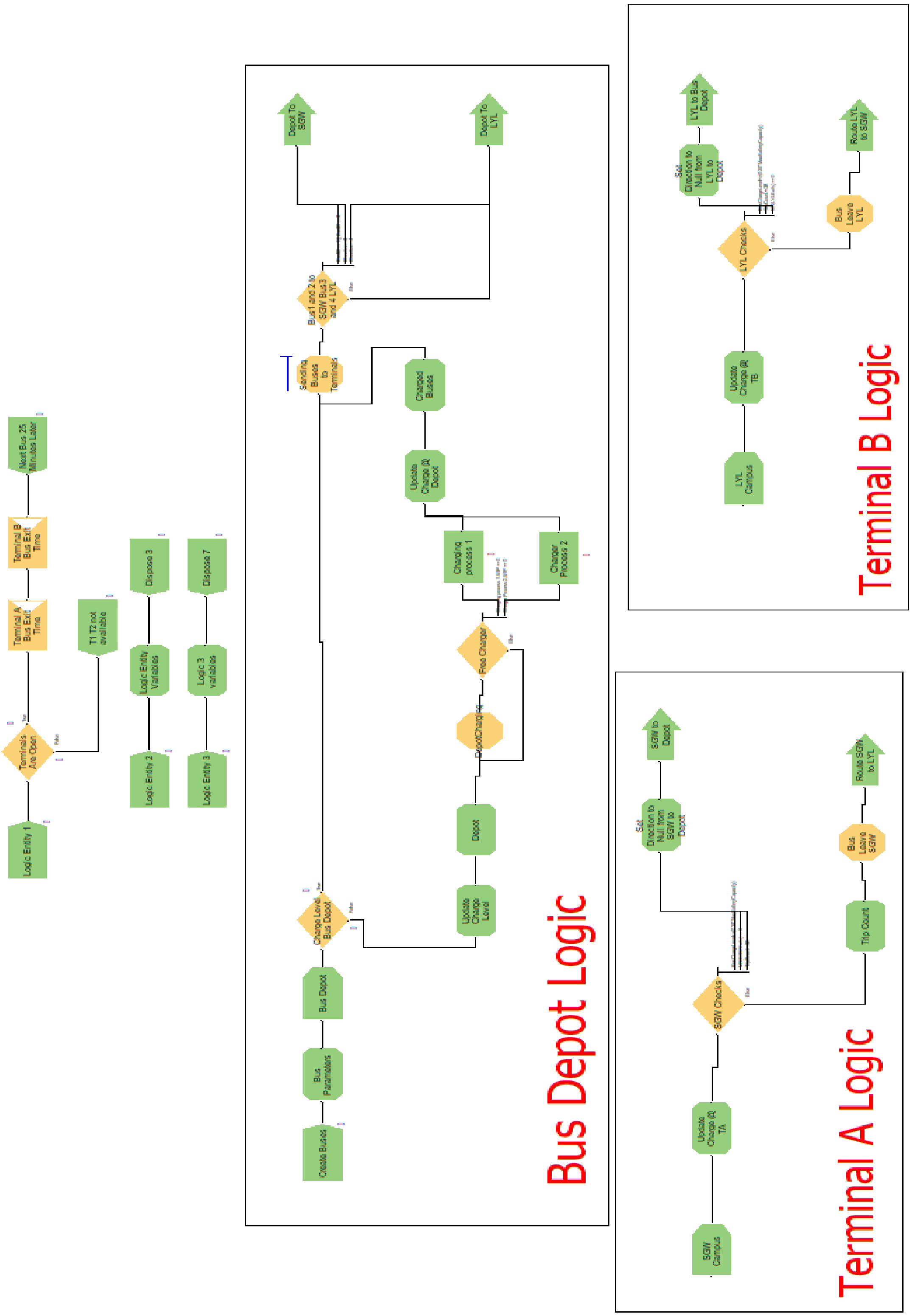


Figure 4-10: Base model Scenario.

4.2.1 Setting up the Trip Schedules

The logic developed below is the initial decision-making point of the simulation model, serving as the trigger for trip initiation. Logic entity 1, which is a dummy entity, operates by assessing whether the terminals are open or not. If the terminals are open which is set at 7.30AM, the model progresses to evaluate the exit times which is set at 11.00PM at Terminal A, followed by Terminal B, and then accounts for the scheduling of the next bus, which is set to depart 25 minutes later. Conversely, if the terminals are closed, the model bypasses the exit time evaluations and instead acknowledges that Terminal A and Terminal B are not available, thereby holding the BEBs at the depot. The operation of Logic Entity 1 is crucial as it determines the flow of BEBs through the entire simulation.

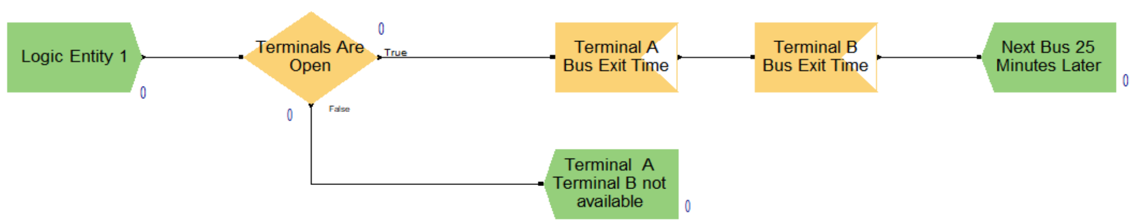


Figure 4-11: Trip scheduling logic.

4.2.2 Bus Depot Logic

The described logic handles the arrival of entities (EV buses) once they have completed their scheduled passenger trips. Upon entering the Bus Depot, each entity undergoes a series of condition checks, including evaluating the available SoC. Based on the charge percentage left, each entity is directed to a charging station dock on a first-come, first-served basis, where it remains until it reaches a full charge of 100%. Once fully charged, the EV BUs leave the depot to commence their scheduled trips from their allotted terminal stations.

The initial action involves creating an entity (EV Bus) using the 'create' block to begin the model creation. The mean time between arrivals for this entity is set to a constant value, determined by the desired fleet size for a specific route. Any fleet size can be generated within the model by specifying the number of entities per arrival. In our case, a fleet size of 4 is considered, and it remains constant in the system throughout the simulation runtime.

After their creation, attributes such as Bus ID and variables like BusNumber and MaxBatteryCapacity etc . were assigned to the entities (EV Buses), which are then directed to the Depot Station. Subsequently, the first decision module assesses the remaining battery charge percentage and determines whether the entities should be sent to the charging stations dock for recharging or to terminals. The primary objective of this logic is to efficiently manage the reception and routing of BEBs based on their charge levels, ensuring they are appropriately directed either to the charging stations dock or to terminals to perform passenger trips.

Figure 4-12 represents this flow as developed in Arena.

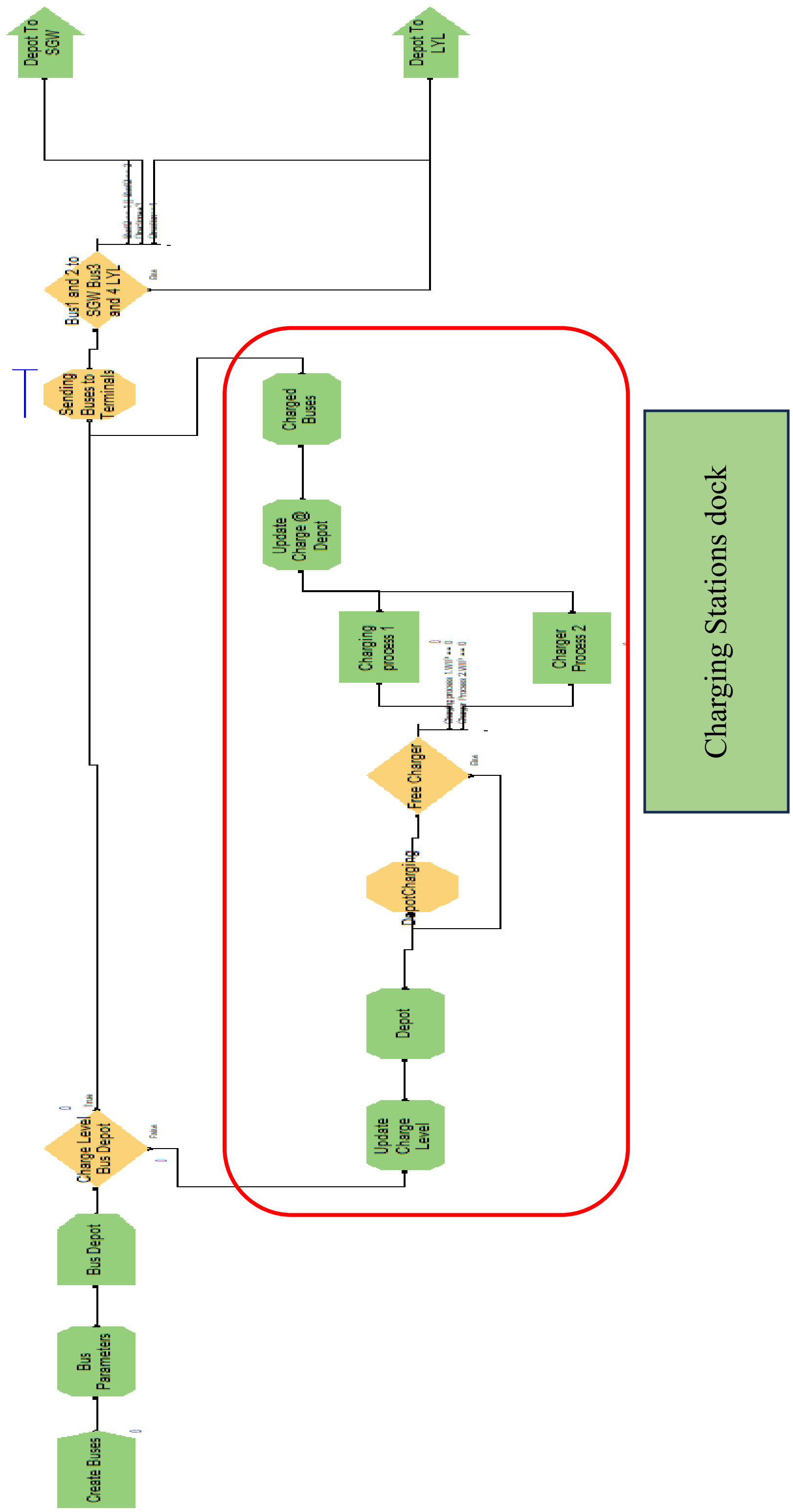


Figure 4-12: Bus depot logic.

4.2.2.1 Charging Stations Dock

Upon arrival at the charging dock, the entities are assigned with attributes and variables to gather statistics related to the charging process, including the charging process count. One of these attributes is the charging time, which is determined by a mathematical expression that specifies the duration for the entities to remain connected to a charger. In the flow, a designated Hold and Decide module enables the BEBs to check for the availability of a free charger periodically. Once a charger becomes available, the module selects the next EV Bus in the queue and assigns it to the charger. The charging process itself is defined by process modules utilizing chargers as resources. For the purposes of our study, we have considered two chargers to accommodate a fleet size of 4. Once the charging process is finished, the battery level is updated to its maximum capacity, and the BEBs are directed to the bus depot exits.

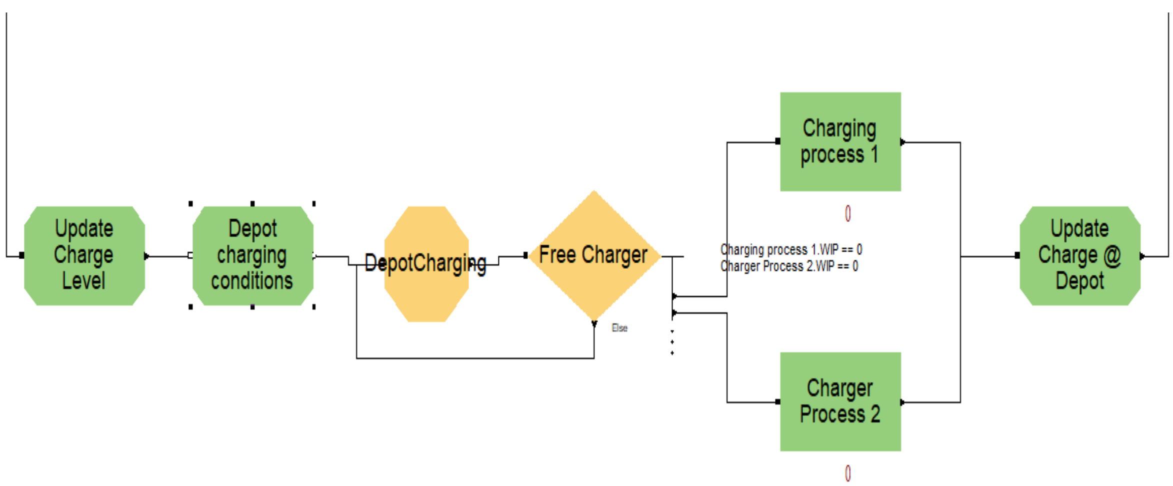


Figure 4-13: Charging stations logic.

4.2.3 Terminal A Logic

The entities arrive at terminal A from the depot, where an assigned module is utilized to allocate attributes and variables, initiating their scheduled trips according to the schedule. A Decide module within the flow determines whether the bus should be redirected to terminal B or returned to the bus depot based on specified conditions. The BEBs will only return to the bus depot if their battery capacity drops below the threshold safety level (SFT), or they have completed their daily scheduled round trips $i.e$ 38. In our base model, the safety threshold is set at 25%, and the BEBs with a battery capacity (C) of 400 kWh with rate of consumption ($R_{Consump}$) of 1.88 kWh per kilometer operating at -7 ^{0}C are considered.

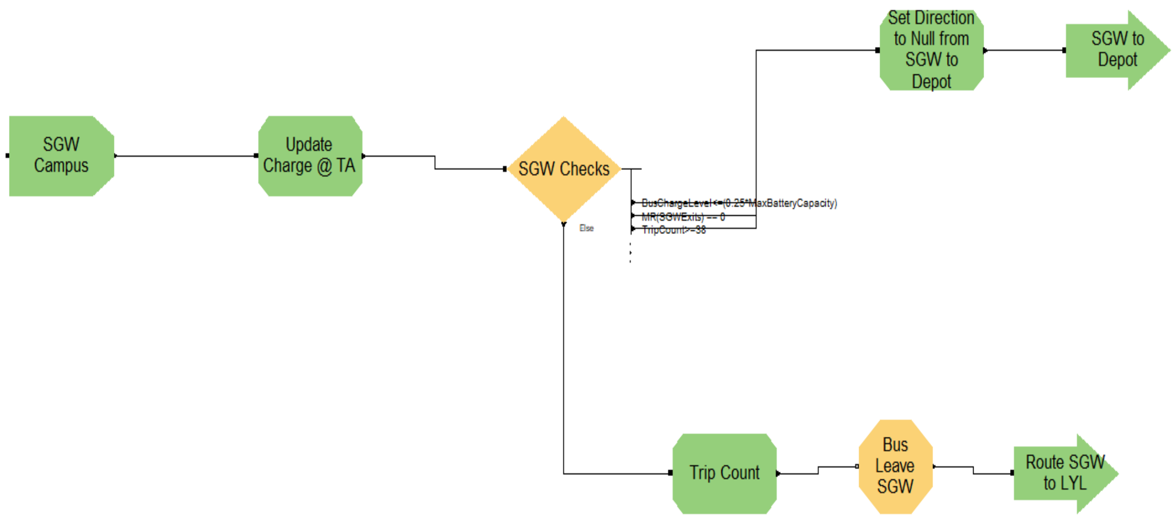


Figure 4-14: Terminal A logic.

4.2.4 Terminal B Logic

With SoC greater than 25 %, the entities arrive at terminal B within the specified timeframe of 25-35 minutes, as defined in the route module. Following the station module, an assign module updates the battery level and assigns the "direction" attribute, allowing the EV Bus entity to travel in the reverse direction. Before commencing its trip from terminal B, the bus undergoes a series of checks, including evaluating the remaining battery capacity and the number of scheduled trips. If the battery level falls significantly below the safety threshold, the bus is directed to the depot regardless of scheduled trips. Subsequently, a hold module is used to halt the buses at terminal B for a predetermined duration, which in our case is 25 minutes. The diagram below illustrates the simulation flow at Terminal B.

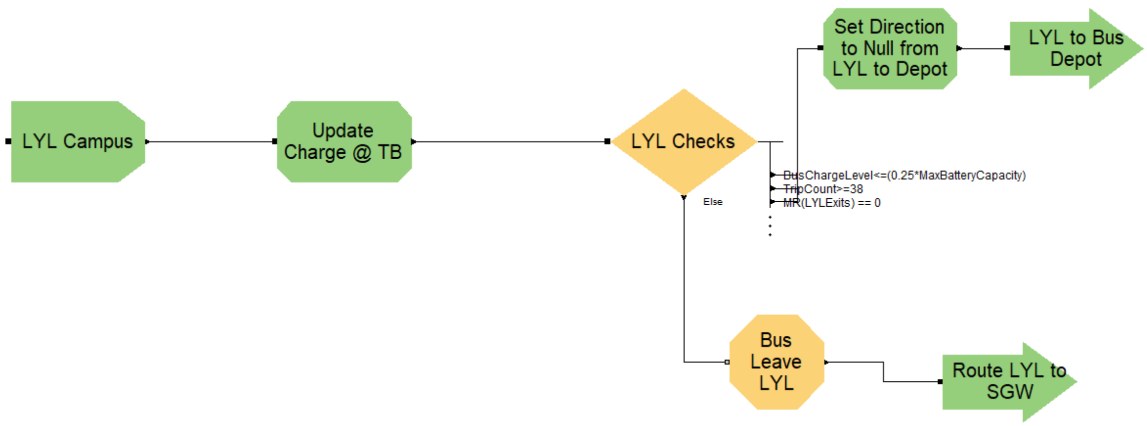


Figure 4-15: Terminal B logic.

4.3 Replication Parameters

After creating a project in the Arena environment, the next important step is configuring the "Replication parameters," including the replication number and the replication length that determines the number of iterations and the duration for which the simulation should run to obtain meaningful results.

4.3.1 Replication Number

The estimation of the number of replications is a pivotal process that ensures the statistical validity and precision of the results. This section outlines some of the methodologies for estimating the number of replications [78].

Method 1: Initial Approach

The initial approach involves the determination of an acceptable half-width (β) for the 95% confidence interval. A pilot test simulation to be conducted with a preliminary number of replications (n_0) to ascertain the standard deviation ($S(n)$) of the sample mean. This standard deviation is instrumental in calculating the number of replications needed to achieve the desired half-width, thereby ensuring the results fall within an acceptable range of precision.

$$n \cong \left(t_{n-1,\ \frac{\alpha}{2}} \frac{S(n)}{\beta}\right)^2$$

Method 2: Alternative Estimation

Method 3 presents an alternative estimation technique. Similar to the previous methods, it begins with the establishment of an acceptable half-width (β). A pilot test simulation with n_0 replications is run to find a preliminary half-width ($\beta 0$). This preliminary half-width is then used to adjust the number of replications to meet the desired precision level.

$$n \cong n_0 \frac{{\beta_0}^2}{\beta^2}$$

For to estimate the number of replications for our study we followed both the methodologies by conducting a pilot test on Base model running 20 replications with the inputs from table 3-2 to gather the data and the replication number is estimated to be 56 corresponding to 95% confidence interval and supporting calculations are displayed in appendix A2.

4.3.2 Replication Length

- The chosen replication length for our study is 720 hours, corresponding to 30 operational days, with 24 hours per day.
- As the simulations automatically stop after reaching the replication length, there is no need to include a terminating condition explicitly.

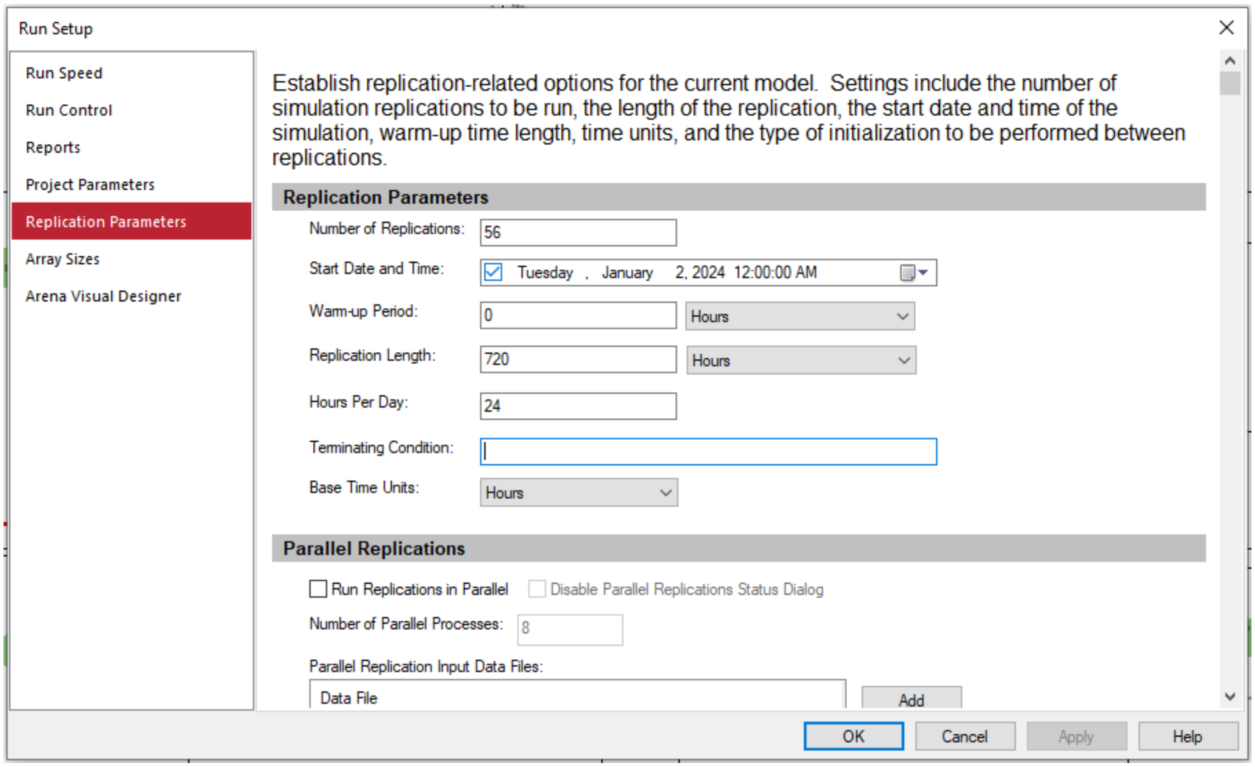


Figure 4-16: Run Setup – Replication Parameters Tab

4.4 Statistics Collection

As previously stated, the simulation was conducted for 720 hours, gathering multiple statistics. These included the success rate of trips, the total number of BEBs charged during the simulation period, and the average charging time for each bus. Moreover, an estimation of the total charging costs per bus, the daily cost of charging, and the overall charging cost for the entire simulation duration is done, considering an electricity usage cost of $36.87 per hour.

Furthermore, graphs depicting the State of Charge (SoC) were generated to observe the battery percentage fluctuations during bus operations. Each graph displays the SoC curve for individual EV Bus within the fleet.

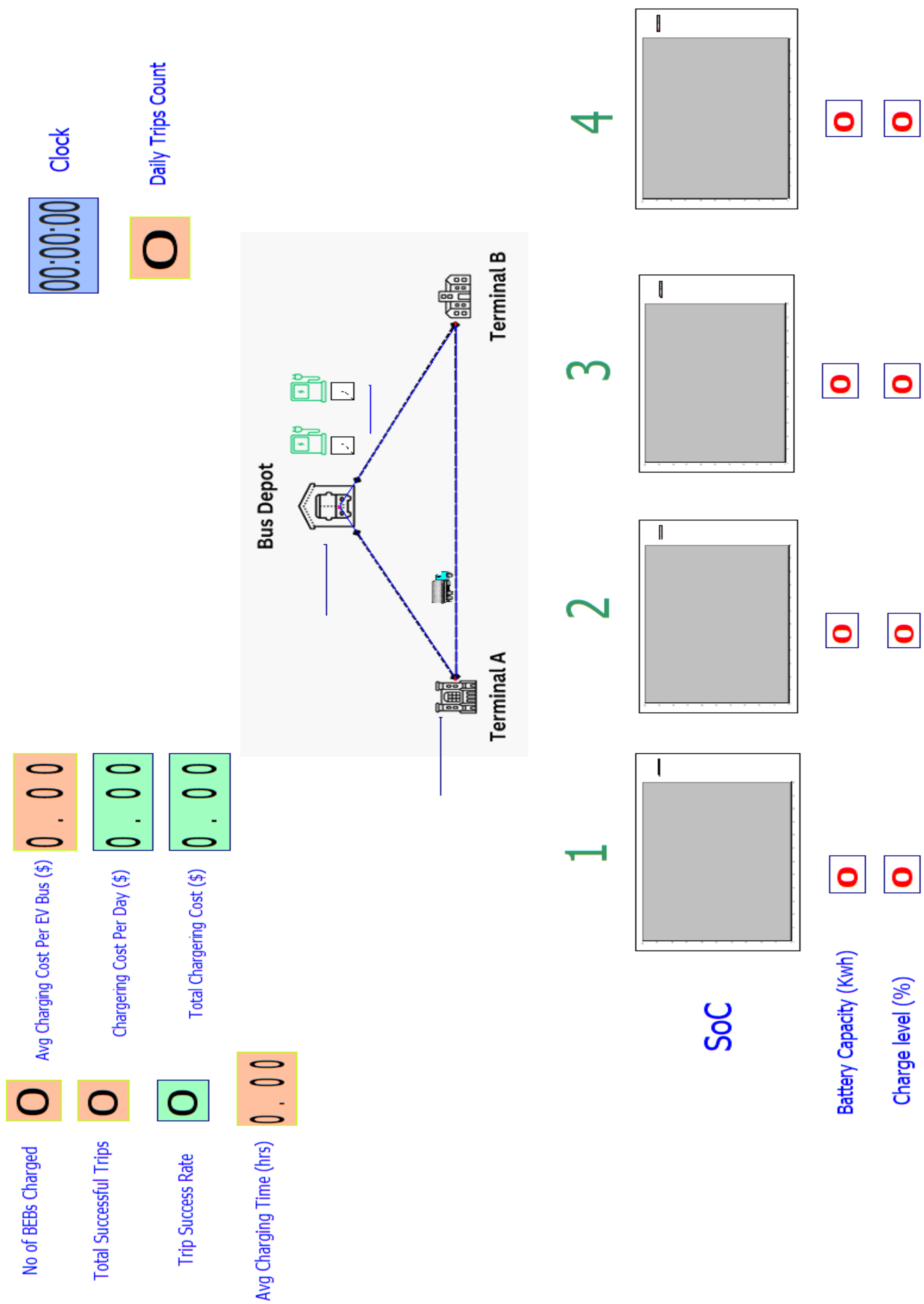


Figure 4-17: statistics collection tab.

4.5 Scenario 1: Charging Stations at Depot and Terminal

As detailed in section 3.7.1, one charging station is installed at Terminal A and another at the Bus Depot in this scenario. The BEBs use the opportunity charging strategy at Terminal A and charge overnight at Depot.

4.5.1 Bus Depot Logic

The flow diagram remains unchanged from the base model, as explained in section 4.2.2, except for the number of chargers present at the Bus Depot, which is adjusted accordingly. The diagram below illustrates the logic at the Bus Depot with a single Charging Station.

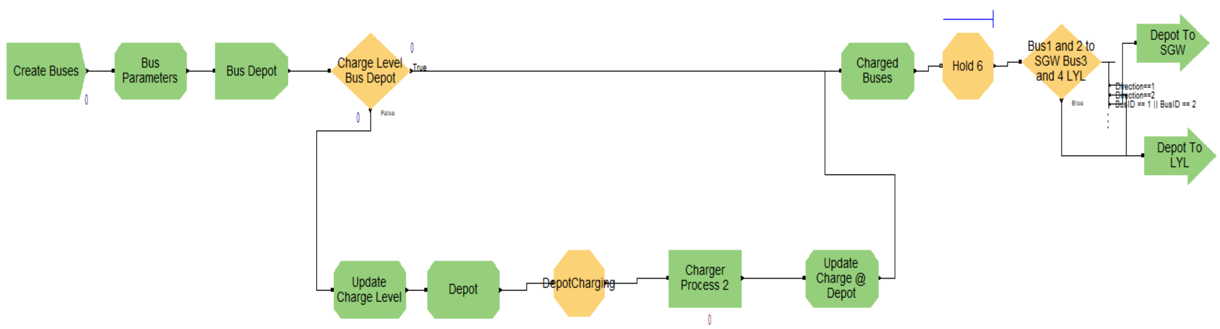


Figure 4-18: Scenario 1, Bus depot logic.

4.5.2 Terminal A Logic

Upon arrival from depot, the entities charging status is updated, and a direction attribute is assigned using the Assign module to guide the buses toward terminal B. Before proceeding, the BEBs undergo specific checks using the decision module accessing the state of charge (SoC) and the trips count.

In figure 4-19, the highlighted section enables the returning BEBs from Terminal B to undergo the charging process if the available SoC is less than 80%, while they wait at Terminal A. The Assign module is responsible for configuring the necessary variables and attributes to update the battery capacity and charging time. Once disconnected from the charger, the BEBs undergo the above checks before embarking on their journey to Terminal B or the Bus Depot. Figure 4-21 visually represents the logical flow, featuring a single charging station situated at Terminal A.

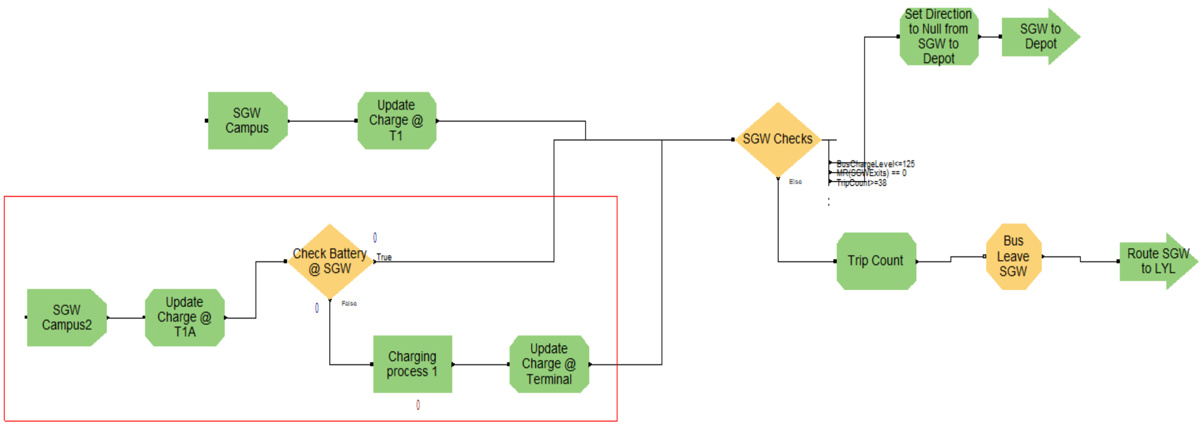


Figure 4-19: Scenario 1, Terminal A logic.

4.5.3 Terminal B Logic

The logic at terminal B remains unchanged from the Base model, as the operations remain the same. Below figure 4-20 defines the logic used.

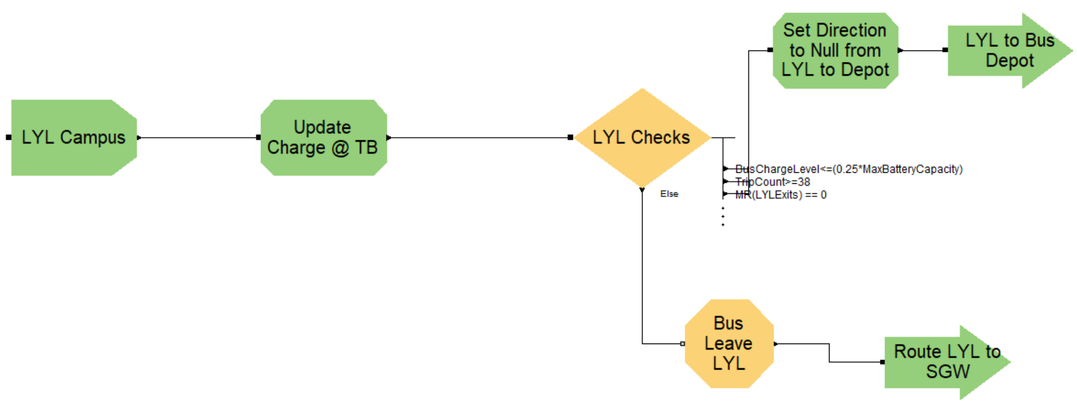


Figure 4-20: Scenario 1, Terminal B Logic.

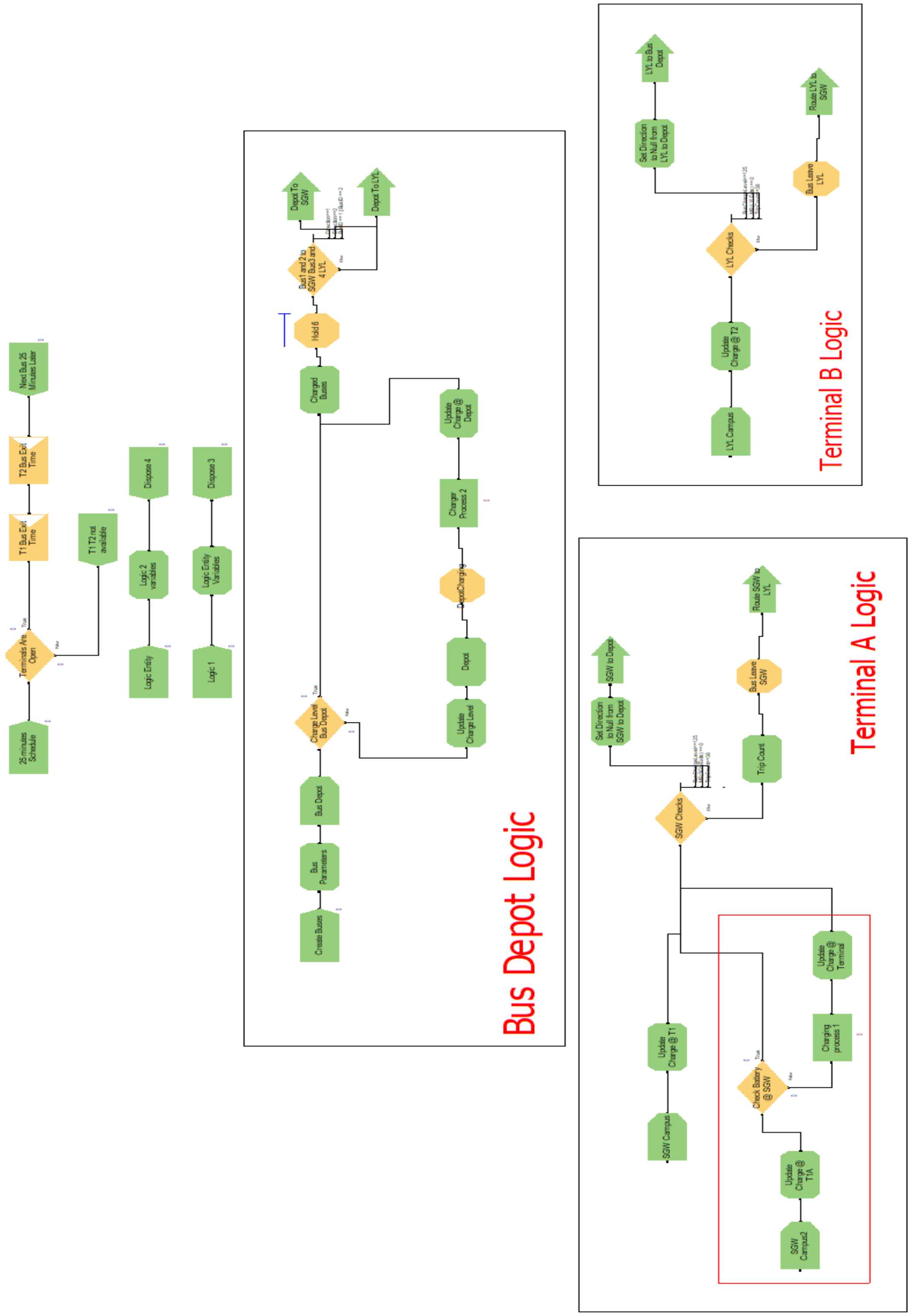


Figure 4-21: Scenario 1, Charging stations at Depot and Terminal.

4.6 Scenario 2: Charging Stations at Terminals.

In this particular scenario, we have considered the existence of charging stations at both Terminal A and Terminal B. The vehicles use the opportunity charging strategy by charging at both terminals during the waiting times. This approach allows for the efficient utilization of charging opportunities. As with the base model and scenario 1, the BEBs are stationed at the bus depot during their non-operational periods, ensuring their readiness for the next day's operations.

4.6.1 Bus Depot Logic

The logic utilized to establish the bus depot is simple and straightforward. The creation of entities is achieved through the implementation of a create module. Following this, attributes and variables are assigned to the BEBs using an Assign module. Once these preparations are complete, the BEBs depart from the depot to commence their trips according to the predefined schedule depicted in figure 4-22.

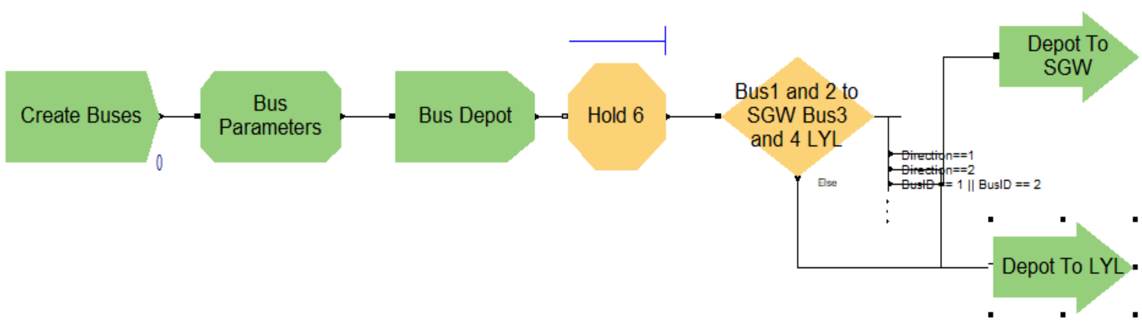


Figure 4-22: Scenario 2, Bus depot logic.

4.6.2 Terminal A Logic

The operational logic at terminal A remains consistent with scenario 1, where a single charging station is used. The assign and process modules manage the opportunity charging process for the buses returning from terminal B. These modules ensure that the returning buses are efficiently charged and prepared for their subsequent trips.

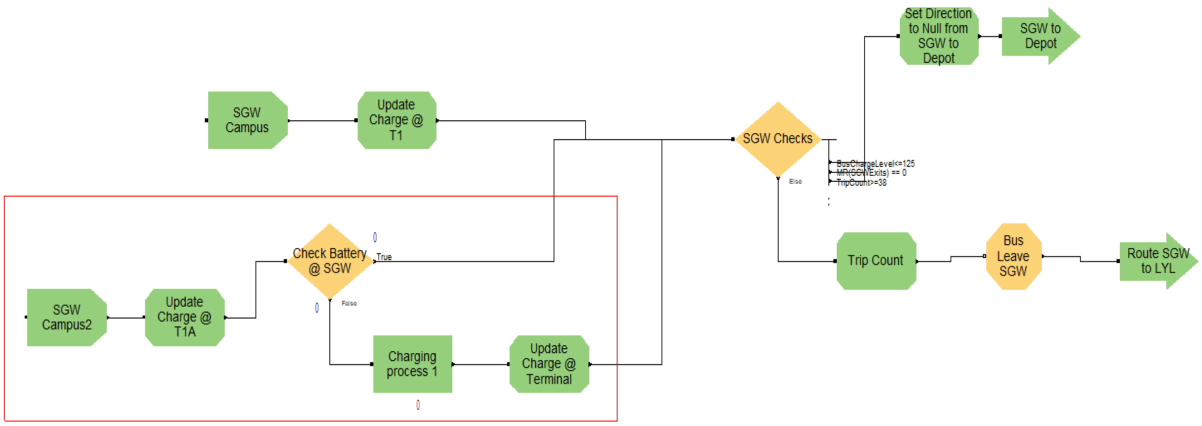


Figure 4-23: Scenario 2, Terminal A logic.

4.6.3 Terminal B Logic

In contrast to the previous scenarios, terminal B is equipped with a fast-charging station, enabling the buses to recharge quickly during their stopovers. Once a bus arrives at terminal B, an assign module updates its battery charge and sets the reverse direction attribute. A hold module is used to hold the bus temporarily after the charging process to ensure adherence to the schedule. Before departing from terminal B, checks are conducted to assess the State of Charge (SoC) and trip count. Based on this assessment, the BEBs are sent to terminal A or the Depot.

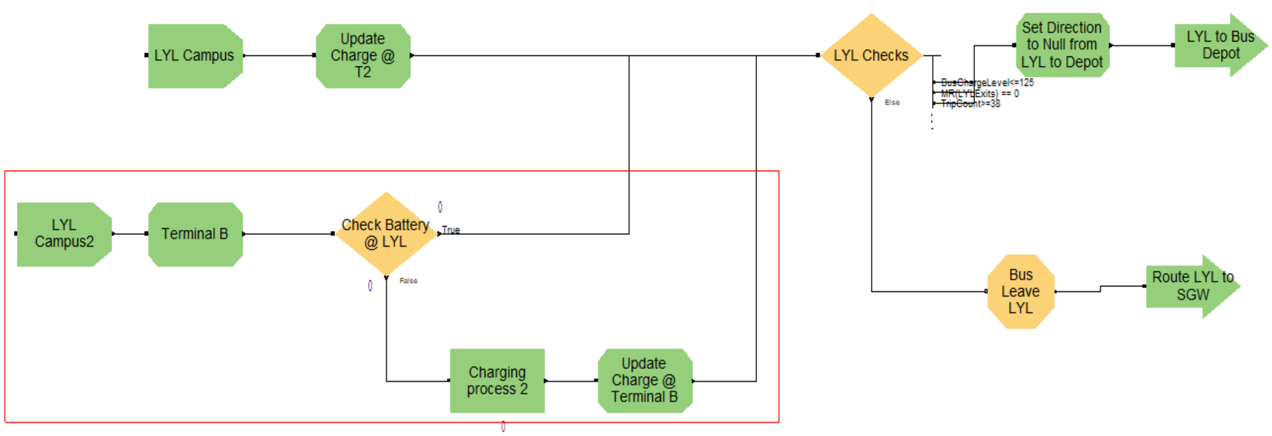


Figure 4-24: Scenario 2, Terminal B logic.

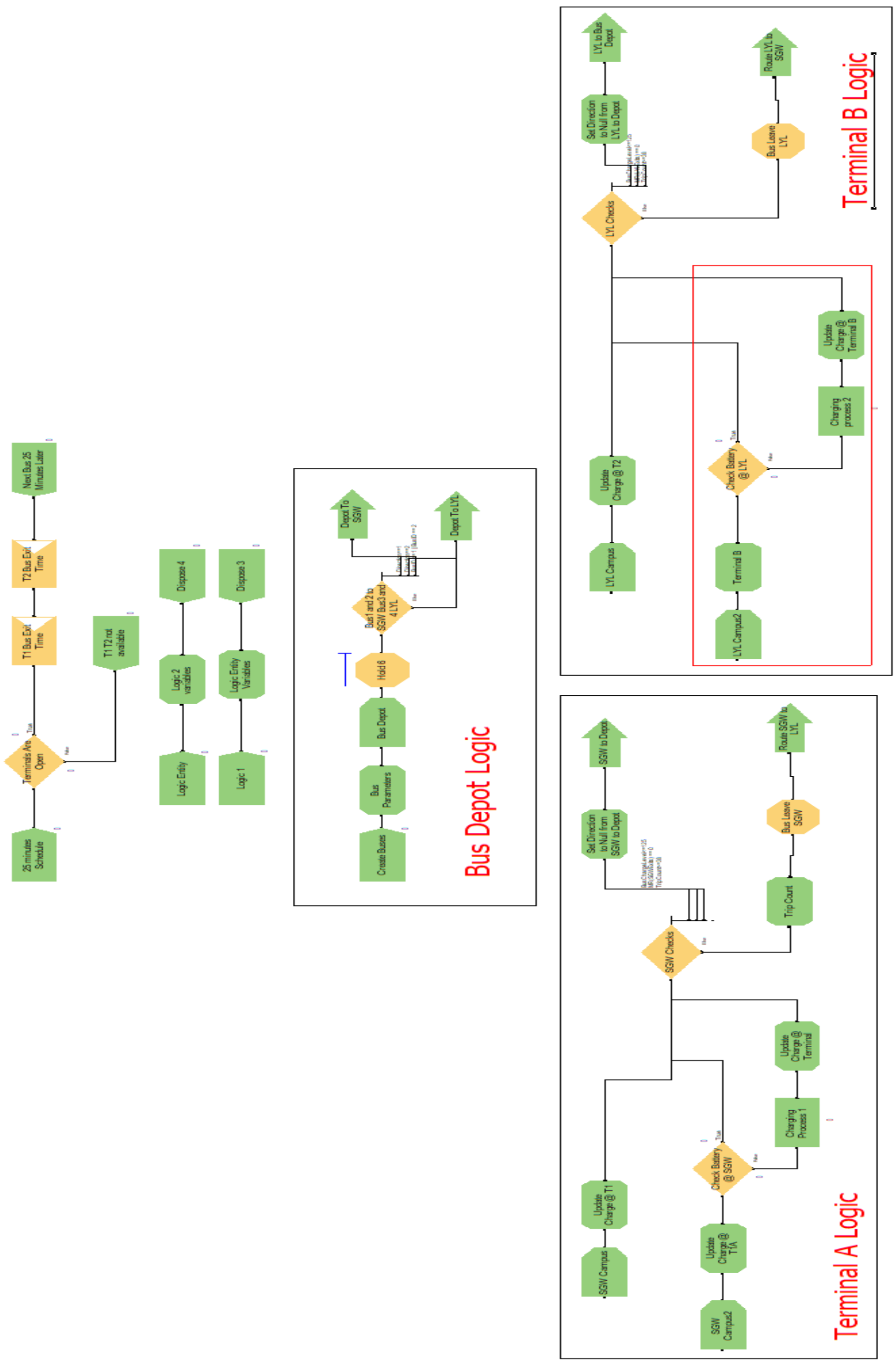


Figure 4-25: Scenario 2, Charging stations at terminals.

4.7 Process Analyzer Output

The Process Analyzer tool is utilized when multiple experiments need to be conducted with a specific number of replications. This tool serves two primary purposes in the generated models: first, to validate the generated model, and second, to perform sensitivity analysis. Arena provides the Process Analyzer tool and allows for examining multiple scenarios. The tool consists of three main areas: the section for specifying project properties, the region for executing experiments, and the area where charts are displayed. Figure 4-26, illustrates the Process Analyzer tool in Arena.

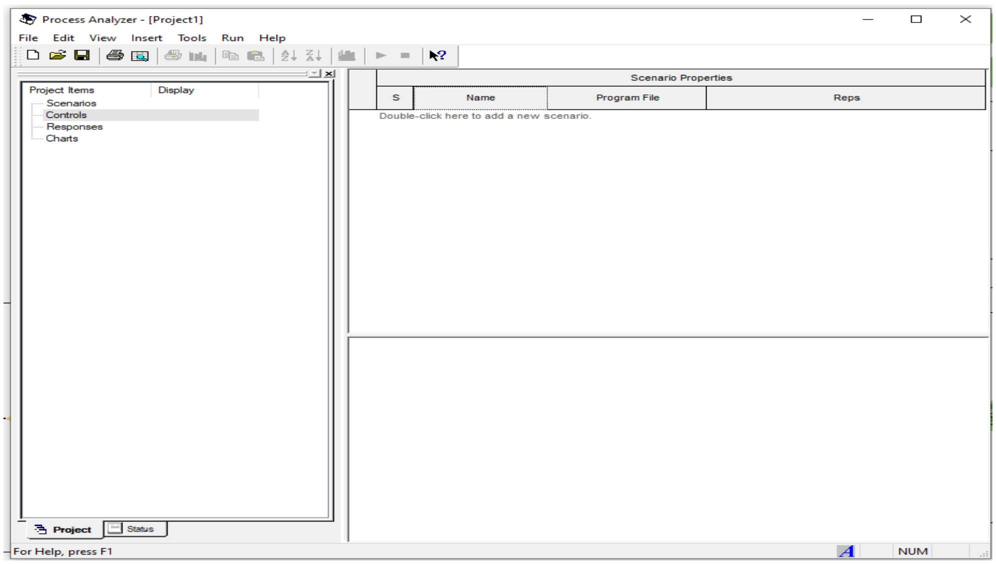


Figure 4-26: Process Analyzer tab.

For the models' verification and validation, four different situations were considered for the base model described in section 5.2.2. The Process Analyzer's controls play a vital role in enabling the specification and adjustment of input parameters, such as variables, distributions, and levels of factors, to explore various situations within a model. In our study, these controls primarily revolved around the factors such as battery capacity, charging power, and electricity rate. The resulting output responses, such as the total number of successful trips and charging costs, were observed by modifying these inputs. Figure 4-26 illustrates how the controls were configured and the corresponding response obtained after executing the experiments. Leveraging the Process Analyzer empowers us to gain insights into the model's behavior, optimize processes, and make informed decisions to enhance overall performance.

CHAPTER 5

RESULTS AND DISCUSSION

This chapter presents the utilization of discrete event simulation models to showcase various scenarios of a Battery Electric Bus (BEB) fleet network. We start by considering a simple scenario based on the existing fleet operations of Concordia University.

To ensure the accuracy and reliability of the model, an experimental design was initially conducted to analyze the model's acceptance and estimate the optimal parameters. This was followed by a numerical analysis for verification and validation purposes. Subsequently, the outputs from the mathematical formulations and the base simulation model, using the optimal parameters, were compared. The purpose of this step was to verify the consistency and correctness of the model's predictions. Further validation of the model was achieved by testing the output of the base model with various controls as part of a sensitivity analysis, which included altering the charging power of the BEBs and observing the resultant outcomes.

5.1 Design of Experiments (DOE)

Design of Experiments (DOE) is a systematic and efficient method employed to investigate the intricate relationship between various input variables, often referred to as factors, and essential output variables, known as responses. DOE serves multiple purposes, including determining the impact of a single factor or a combination of factors on the response by assessing interactions between factors, and to understand the behavior of the response in relation to the factors, and ultimately optimizing the response for desired outcomes.

It's essential for optimizing processes and to estimate the intensity of input factors on responses which is critical in our study on modeling the university's electric bus fleet. We considered three factors: battery capacity (C), charging power (H), and ambient temperature (T) due to their significant influence on electric bus fleet efficiency and optimization. The output responses examined are trip success rate, total charging costs, and total time buses spent at charging stations.

We considered Battery Capacity with three levels (300, 400, and 500 kWh) to explore its effect on range and downtime. Charging Power is being varied at 50, 75, and 100 kW to evaluate charging speed and efficiency. Ambient Temperature is considered at -25°C, 0°C, and +25°C to assess their impact on battery depletion and fleet operations.

Factor	**Levels**	**Response**
Battery Capacity (C) kWh	300 400 500	Trip Success Rate Total Charging Costs Total Charging Time
Charging Power (H) kW	50 75 100	
Ambient Temperature (T) ^{0}C	-25 0 +25	

Table 5-1: List of Inputs & Levels used in full factorial design.

A full factorial design is developed involving all possible combinations of the different levels assigned to each factor. To determine the total number of scenario experiments, one needs to multiply the number of levels for each factor. For our study with three levels for each of the three factors, the calculation would be 3 x 3 x 3, resulting in a total of 27 scenario experiments. Two-level factorial and fractional factorial designs can yield misleading results due to the non-monotonic nature of simulation responses concerning factor levels [79].

The entire set of 27 experimental scenarios is executed, and the corresponding output responses are accurately documented, as explained in appendix A3. By using Minitab software, a comprehensive full factorial analysis is conducted to determine the specific input parameters that exert a significant impact on the resulting output responses. This analytical approach allows us for a systematic evaluation of the influential factors, aiding in the identification and understanding of the key elements that contribute to the observed outcomes.

5.1.1 Output Responses

Trip Success Rate:

The below main effects plot exhibits an upward trend in battery capacity, charging power, and ambient temperature all correspond to an increase in the mean trip success rate. However, the Pareto Chart reveals that ambient temperature as one of the top factors, marking it as a statistically more significant contributor to trip success rate.

The behavior of the residuals for the regression model is shown in figure 5-2, determining that the model is reasonably acceptable based on the residual plots for the trip success rate. The normal probability plot indicates that residuals are approximately normally distributed, which aligns with the assumption of normality for the residuals in regression analysis. The histogram supports this observation, showing a relatively symmetrical distribution. The versus fits plot does not exhibit a strong pattern, affirming that residuals are fairly evenly distributed across the range of fitted values.

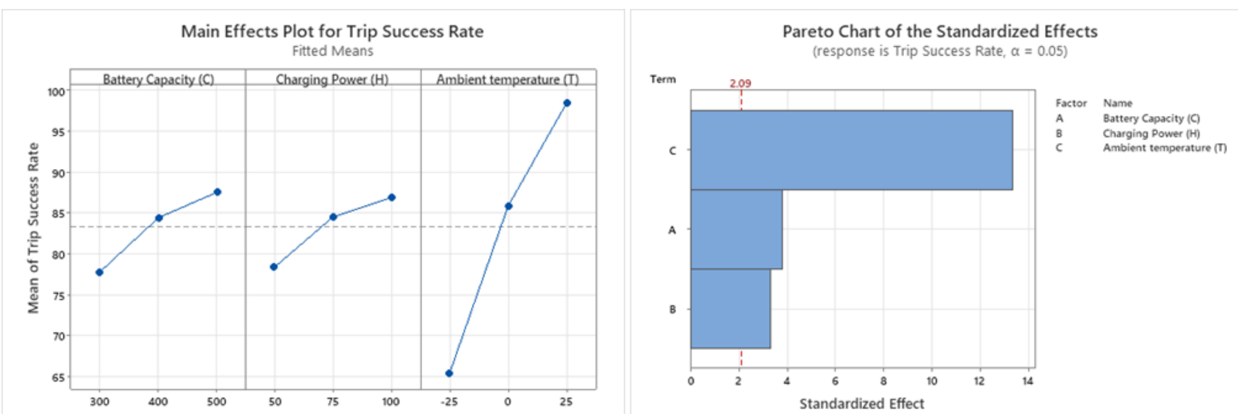


Figure 5-1: Pareto chart and main effects plot (response is Trip Success Rate, α = 0.05)

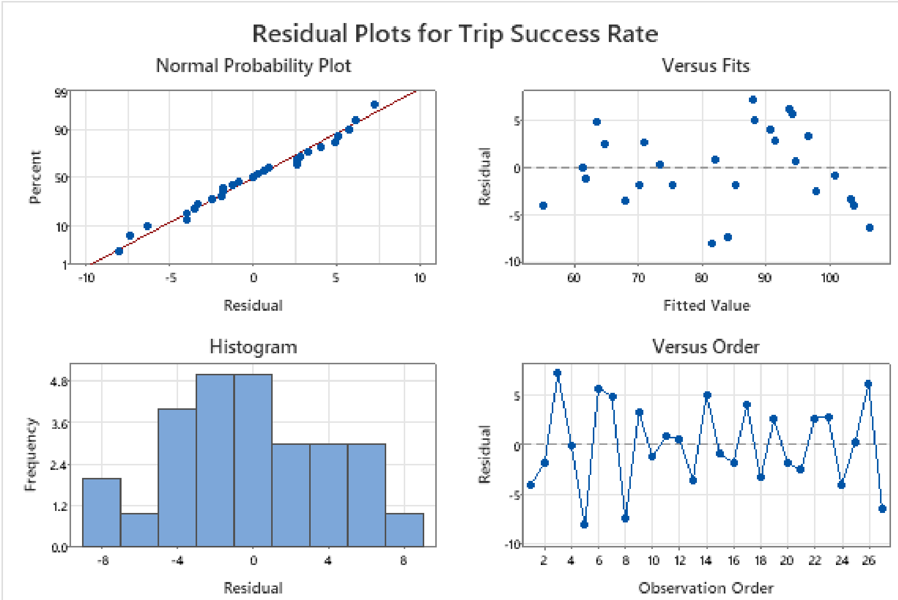


Figure 5-2: Residual plots (response is Trip Success Rate, α = 0.05)

Total Charging Time (T)

Total charging time indicates the total time BEBs spent at the charging stations. The main effects plot indicates that increases in charging power, and ambient temperature are associated with a decrease in total charging time, whereas an increase in battery capacity leads to increase in charging time. The Pareto Chart explains that charging power, and ambient temperature exceed the threshold, suggesting their effects on total charging costs are statistically significant, while battery capacity does not have a standardized effect making it statistically insignificant, concluding that charger power and charger efficiency are the most critical factor in reducing total charging costs.

The residual analysis of total charging time data reveals that residuals closely follow a linear pattern in the normal probability plot, suggesting that the errors are normally distributed, providing credibility to the model's results. The histogram of residuals further supports the assumption of normality, displaying a distribution that is approximately bell-shaped. Additionally, the 'Versus Order' plot, which depicts residuals against the observation order, does not reveal any obvious trends or cyclic patterns indicating that the residuals are independent, satisfying the condition of independence. Taken together, these residual plots, as shown in Figure 5-4, indicate that the model is well-suited to the data.

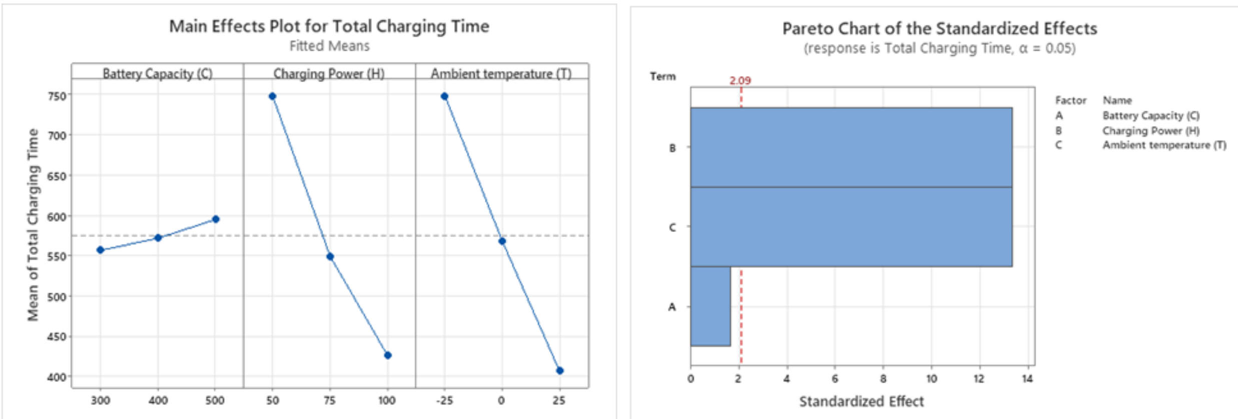


Figure 5-3: Pareto chart and main effects plot (response is Total Charging Time, α = 0.05)

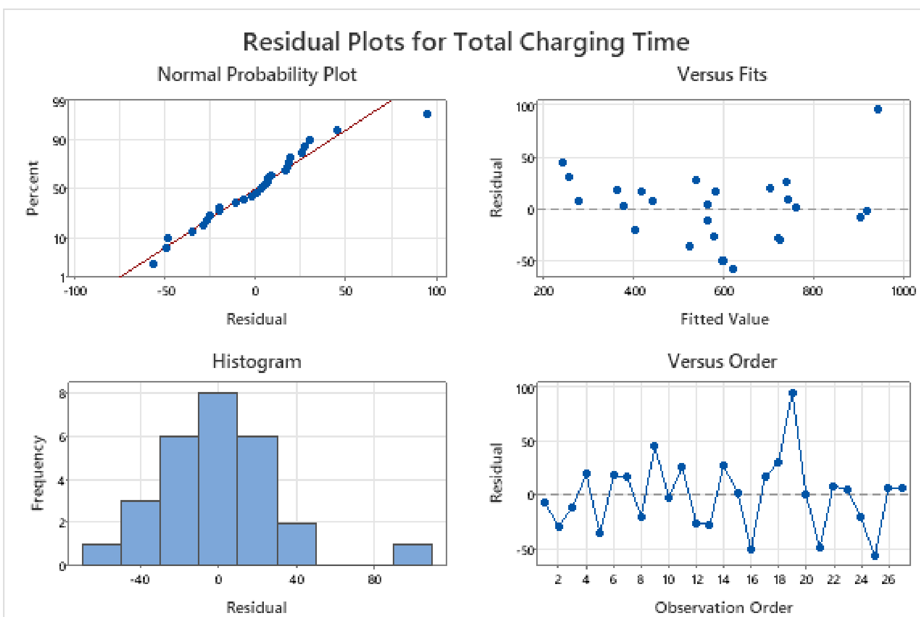


Figure 5-4: Residual plots (response is Charging Time, α = 0.05)

Charging Costs:

The factors battery capacity (C), charging power (H), and ambient temperature (T) have a similar effect on total charging costs as total charging time. As charging time is directly proportional to charging costs irrespective of the state of charge, which is assumed constant in our study.

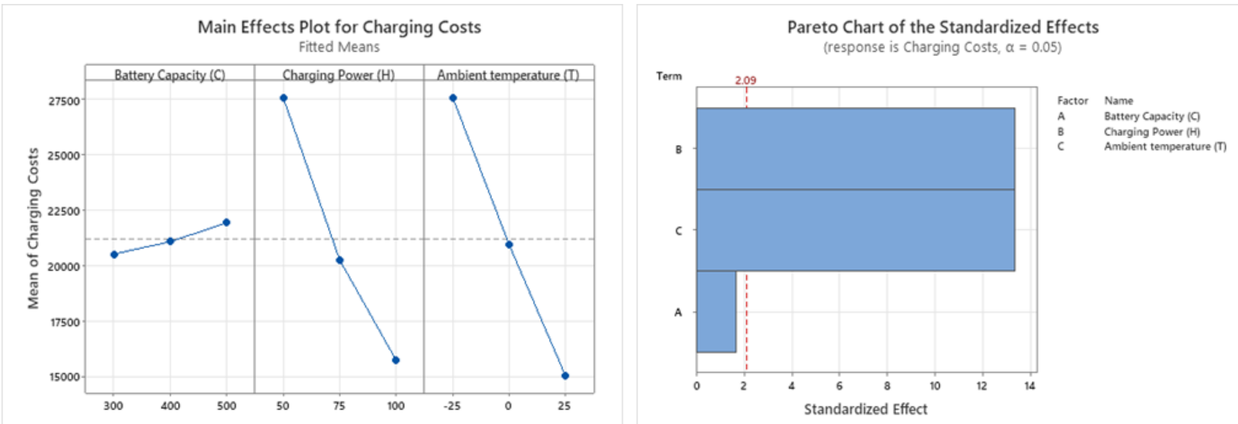


Figure 5-5: Pareto chart and main effects plots (response is Total Charging Costs, α = 0.05)

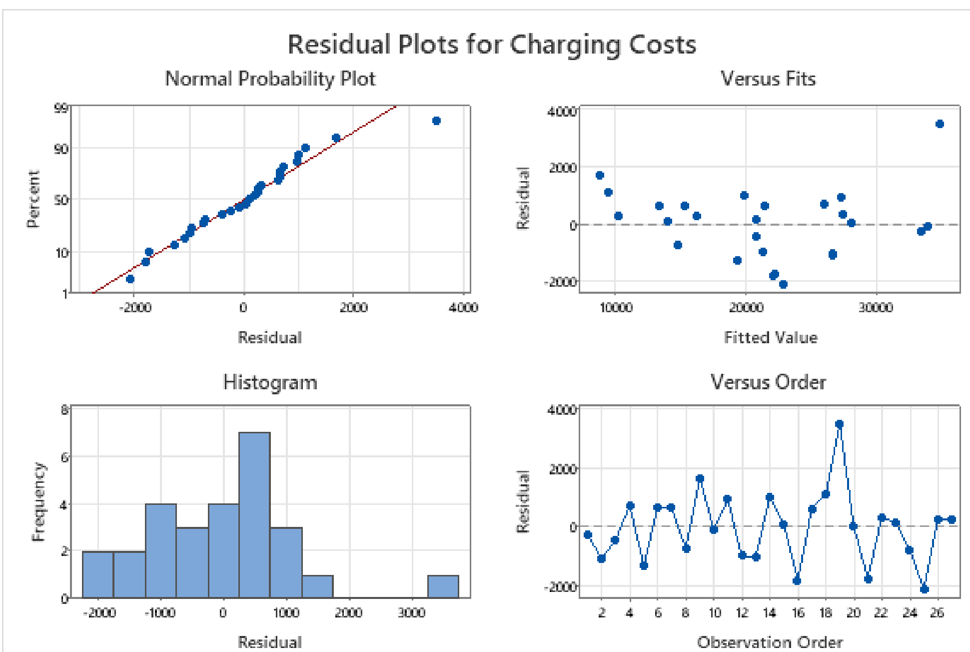


Figure 5-6: Residual plots (response is Charging Costs, α = 0.05)

5.1.2 Response Optimization

From the above factorial plots, we conclude that battery capacity has less effect on total charging time and total charging costs, compared to charging power, and ambient temperature that highly influences the trip success rate. In order to determine the optimal inputs for our simulation model we used the response optimizer based on the goals we set for each response.

Parameters

Response	Goal	Lower	Target	Upper	Weight	Importance
Charging Costs	Minimum		10563.6	38269.8	1	1
Total Charging Time	Minimum		286.5	1038.0	1	1
Trip Success Rate	Target	95	99.9	100.0	1	1

Multiple Response Prediction

Variable	Setting
Battery Capacity (C)	300
Charging Power (H)	100
Ambient temperature (T)	25

Response	Fit	SE Fit	95% CI	95% PI
Charging Costs	8885	692	(7441, 10329)	(5703, 12068)
Total Charging Time	240.9	18.9	(201.6, 280.2)	(154.2, 327.6)
Trip Success Rate	96.64	2.44	(91.56, 101.72)	(85.44, 107.85)

Figure 5-7: Response optimizer tab.

The parameter optimization analysis with the objective of minimizing charging costs and total charging time while aiming for a trip success rate of 100%, indicates that a battery capacity of 300kWh, charging power of 100kW, and an ambient temperature of +25 ^{0}C are the key variables for achieving the desired outcomes.

5.2 Model evaluation – A case study on the Concordia Shuttle Fleet

To ensure the accuracy and effectiveness of the model, an evaluation process was conducted to assess the correctness of the executed logic and the proximity of the generated values to the expected results. The base model was verified using the same inputs from response optimizer and assumptions made which are described in table 5-2, and the outputs derived (appendix A4) were compared to the simulation results. The purpose was to determine the level of correspondence between the mathematical and simulation model illustrated in table 5-4, facilitating a comprehensive understanding of the verification process.

Input Values

Parameter	***Value***	***Units***	***Description***
Fleet size (N_i)	4		corresponds to Concordia's existing fleet size
Total scheduled round trips per day (Sh_{ti})	38		corresponds to Concordia's existing fleet operations
Operating hours per day in the bus line i. (OP_h)	15.5	hrs	trips start at 7.30 AM until 11.00 PM
Rate of consumption $(R_{Consump})$	1.025	kWh/km	Corresponds to +25 ^{0}C (eq. iii)
Battery capacity (C)	300	kWh	From response optimiser
Safety threshold level (SF_T)	25	%	For a battery capacity of 400 kWh, BEBs does not perform trips after reaching 100 kWh capacity
Charging power (H)	100	kW	
Charger Efficiency (η)	89	%	DC fast chargers' efficiency range of 85-93%.
distance between terminals in a bus line i. (d_i)	10	km	originally 8 km but estimated to 10 giving us a room for service route disruptions
Chargers working time (Ch_t)	8	hrs	Assumed charging stations are available to charge between 11.00 PM-7.00 AM at the depot
Cost of electric usage (R_e)	36.87	$\$/_{hr}$	Corresponding to 100 kW fast charger by Hydro Quebec
Replication number	56		Output analysis considering 95% confidence interval, appendix A2

Table 5-2: Input values for the sample calculation.

Outputs

Parameter	***Value***	***Units***	***Description***
scheduled round trips per bus per day (Sh_{tbi})	9.5 ≈ 10		Each BEB to perform at 9/10 trips to fulfil the daily scheduled trips.
driving range (DR)	293	Km	Range a BEB can cover with rated battery capacity
operating range (OR_i)	190	Km/day	Distance each BEB covers per day
safety range (SR)	73.17	Km	
Charging frequency (X_i)	27.157	hrs	For every 17.78 hrs, the BEB needs to charged
Avg Charging time per charge (t_i)	2.19	hrs	Time spent by each BEB at charging station to get fully charged.
Daily charging demand for line ***i*** (Y_i)	3.46	buses	Corresponds to 1428.8 kWh energy consumed by fleet of 4 with 25% safety threshold per day.
Demand of chargers (D_i)	1.2 ≈ 2		Charging stations required to meet the charging demand in the bus route i
Cost of charging per BEB per charge (C_{bi})	80.68	$/bus/charge	
Charging cost per day(C_{di})	279.33	$/day	Charing costs per day for fleet size of 4
Total Cost of Charging (C)	8379.86	$	Charging costs per month (30 days)

Table 5-3: Outputs for sample calculation.

Output Parameters	***Mathematical***	***Simulation***	***Units***
Avg Charging time per charge (t)	2.19	2.37	hrs.
Charging cost per day (C_{di})	279.33	350.24	$/day
Total Cost of Charging for 30 days (C_{T})	8379.36	10157.06	$

Table 5-4: Output results comparison – Mathematical Vs Simulation.

The comparison between the mathematical model and the simulation results shows a reasonable degree of similarity in the output parameters. Despite the differences in cost estimations, which stem from the variance in actual infrastructure demand calculated from mathematical equations and translation to simulation model. The overall trends and magnitudes of the parameters are in the same ballpark, suggesting that both the mathematical model and the simulation results have captured the underlying dynamics to a similar extent. The slight variances observed are attributed to model-specific assumptions and simplifications that are common in comparing theoretical models with more dynamic simulation environments.

5.3 Model Validation

Validation is carried out to ensure that the model accurately reflects the real-world bus transit system. A sensitivity analysis is performed graphically and by using the Arena process analyzer tool, focusing on parameters and resource operations relevant to the bus transit environment. The resulting outputs are carefully examined and compared to the actual system to ensure its exact representation of the real-world bus transit system.

5.3.1 Graphical Analysis

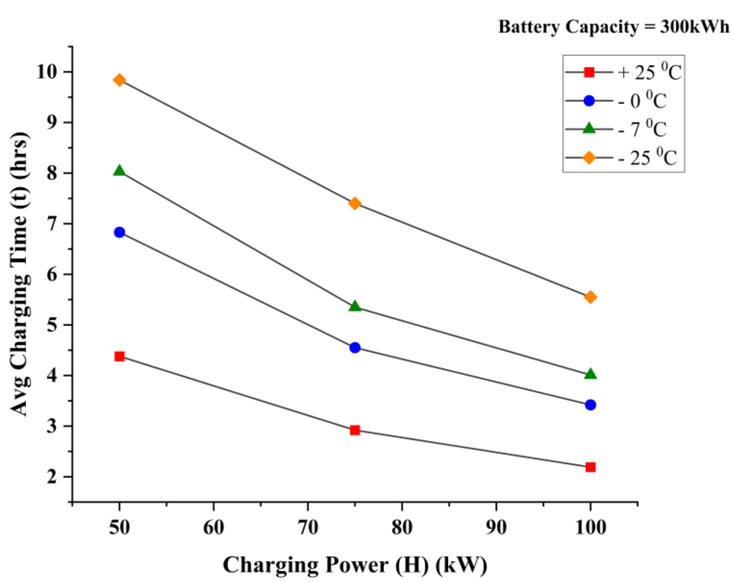


Figure 5-8: Avg charging time Vs. Charging Power.

The graphical analysis was performed using OriginPro, a scientific graphing and data analysis software. Figure 5-8 illustrates a 2D graph showing the relationship between the average charging time (t) and varying charging power (H) for a 300kWh battery at different ambient temperatures (T). The findings indicate a clear correlation, where the average charging time increases as the ambient temperatures decreases and power decreases. The average charging time for a 300kWh battery with a 100kWh charger was found to be 2.19 hrs.

5.3.2 Process Analyzer

The process analyzer is chosen as the best tool to conduct sensitivity analysis and to validate the simulation model. This tool allows us to examine the robustness of the model and understand its response to different control values. By executing the analysis as a batch, allows us to consider multiple factors simultaneously, leading to more conclusive outcomes for the obtained outputs. The process analyzer's output, displayed in figure 5-9, demonstrates that the responses closely align with the graphical analysis for an ambient temperature of +25 ^{0}C corresponds to 1.025kWh/km rate of consumption.

	Scenario Properties				Controls			Responses		
	S	Name	Program File	Reps	Rate of Consumption	MaxBatteryCapacity	ChargingPower	Trip Success Rate	Avg Charging Time	Total Charging
1		Base Model	Depot Charging	56	1.0250	300.0000	100.0000	100.000	2.377	10168.183
2		Scenario 1	Depot Charging	56	1.0250	300.0000	75.0000	100.000	3.170	13557.577
3		Scenario 2	Depot Charging	56	1.0250	300.0000	75.0000	95.956	4.593	19643.346

Figure 5-9: Process Analyzer output.

The model is repeated for 56 iterations at a replication length of 720 hours (equivalent to 30 days). This iterative approach involves running the model with various charging power values at $36.87 /hr electricity rates for detailed comprehensive model validation.

Without seeing the actual results, it is logical that when the charging power increases and charging time decreases as revealed from graphical analysis. Additionally, the average charging time for BEBs tends to increase as the ambient temperature falls, aligning with the greater battery drain associated with the use of heating systems during winter. Processor analyzer results corroborate these observations, demonstrating that charging costs increase when charging power decreases, *since BEBs require longer periods to achieve to full charge. This is under the study assumption that electricity costs per hour remain constant, regardless of the charging power used.*

5.4 Simulation Results

The output results of the three scenarios and the State of Charge (SoC) curves are displayed below. In the base model, where charging stations are located only at the depot, the Battery Electric Buses (BEBs) tend to use up most of their battery capacity before arriving for overnight charging. However, when charging stations are available at the depot and terminal, enabling regular charging for the BEBs, the battery capacity remains comfortably above 50% before reaching the depot. Finally, in the third scenario, where charging stations are present at both terminals, the BEBs manage to recharge their batteries significantly during the trips, resulting in a longer duration before the battery level completely depletes.

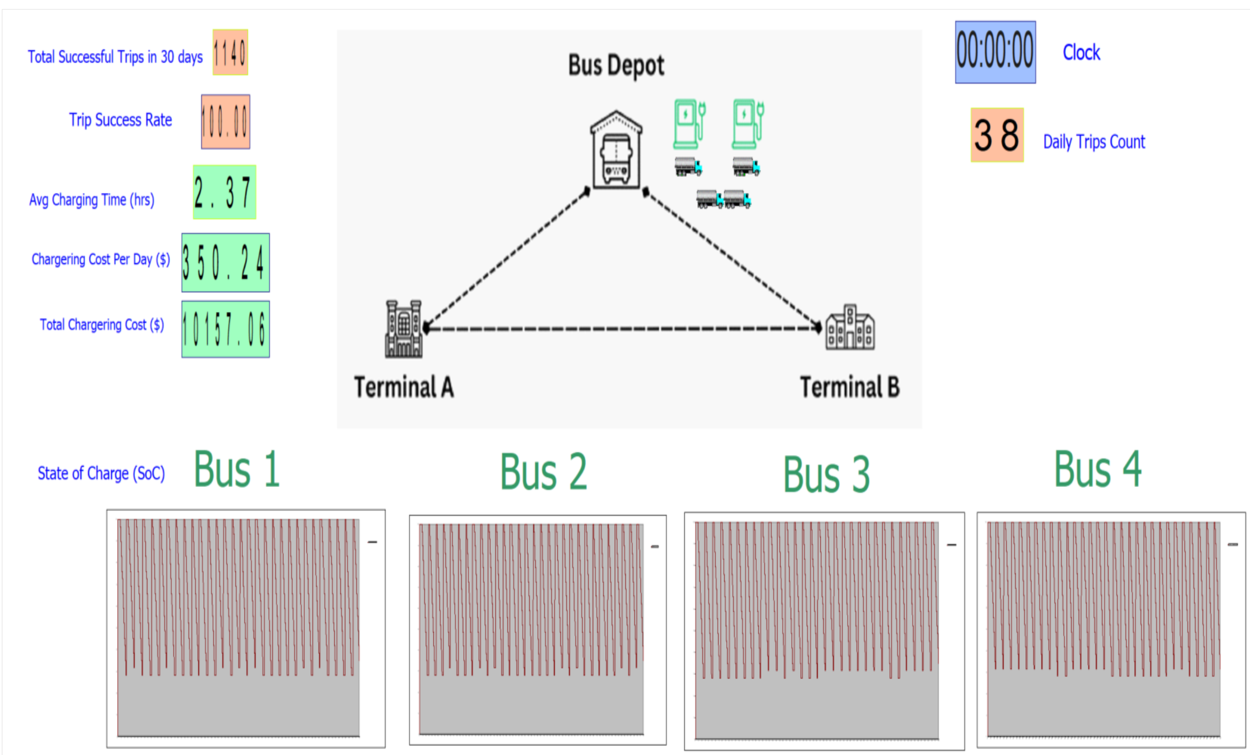


Figure 5-10: Base model, results tab.

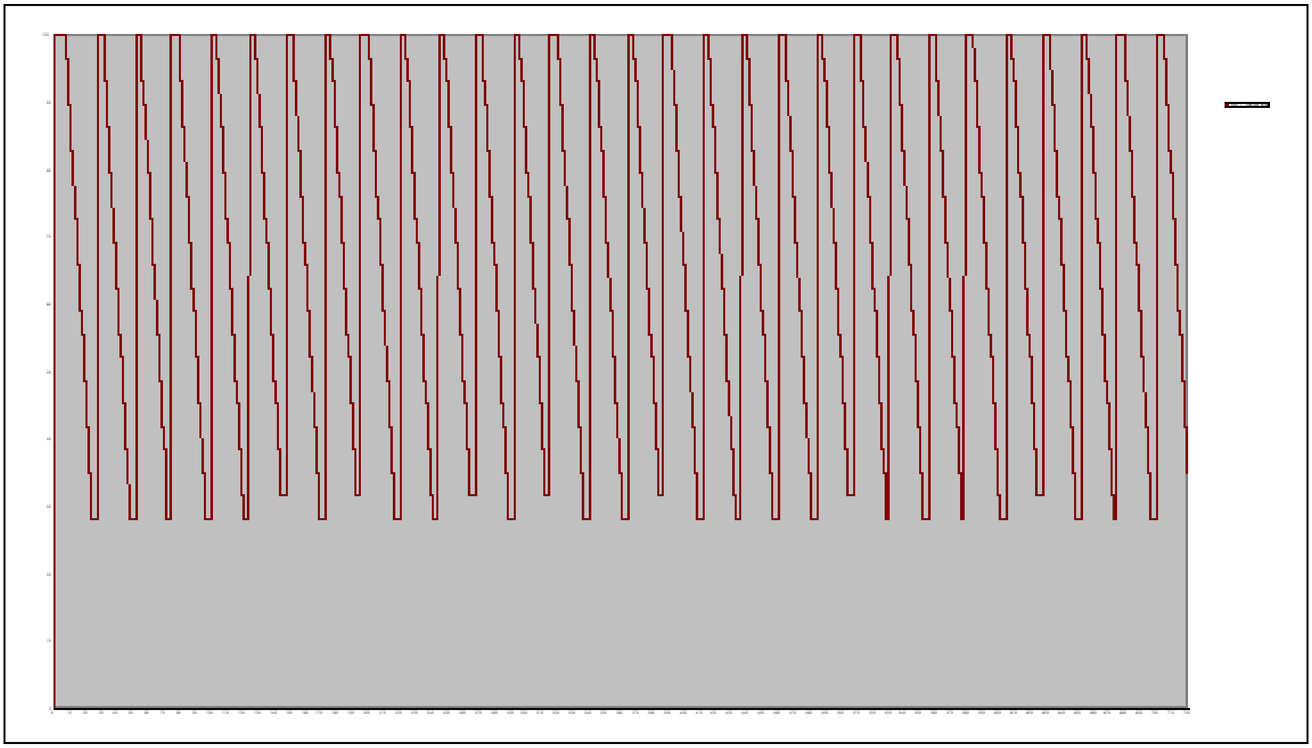


Figure 5-11: Base model, SoC curve of EV Bus.

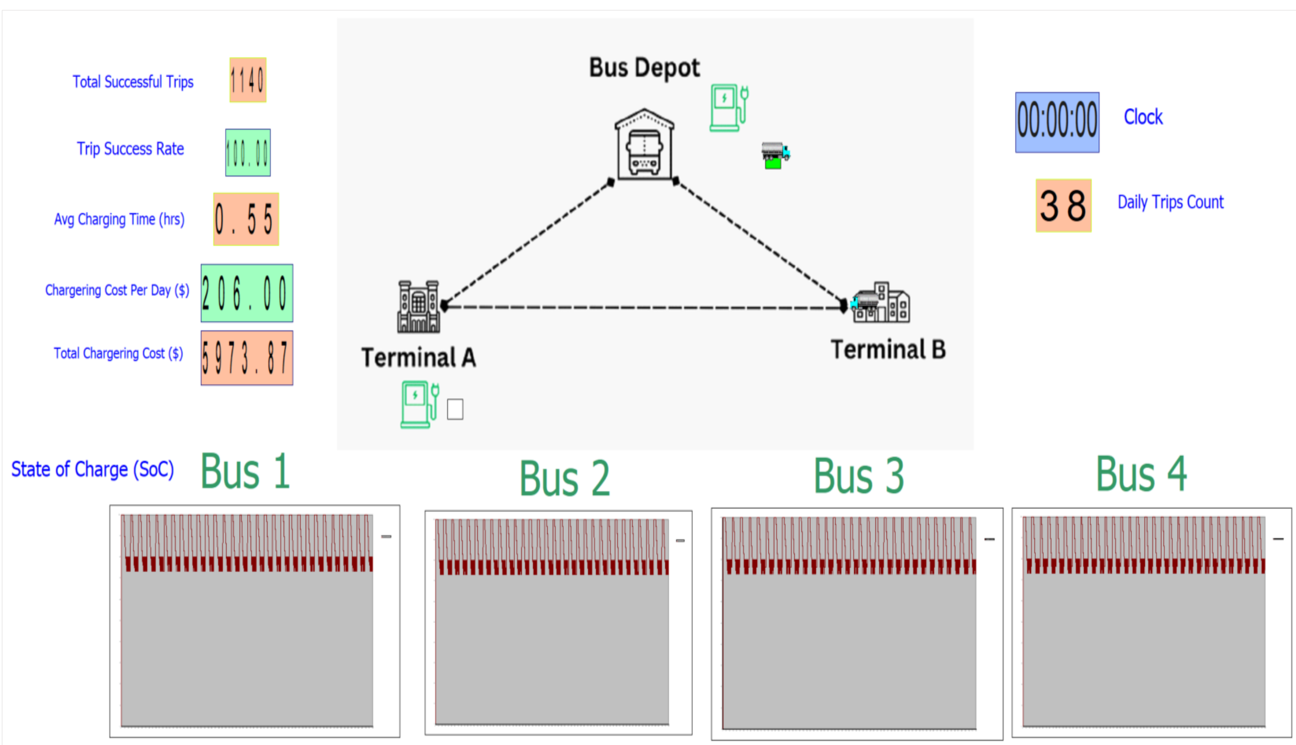


Figure 5-12: Scenario 1, results tab.

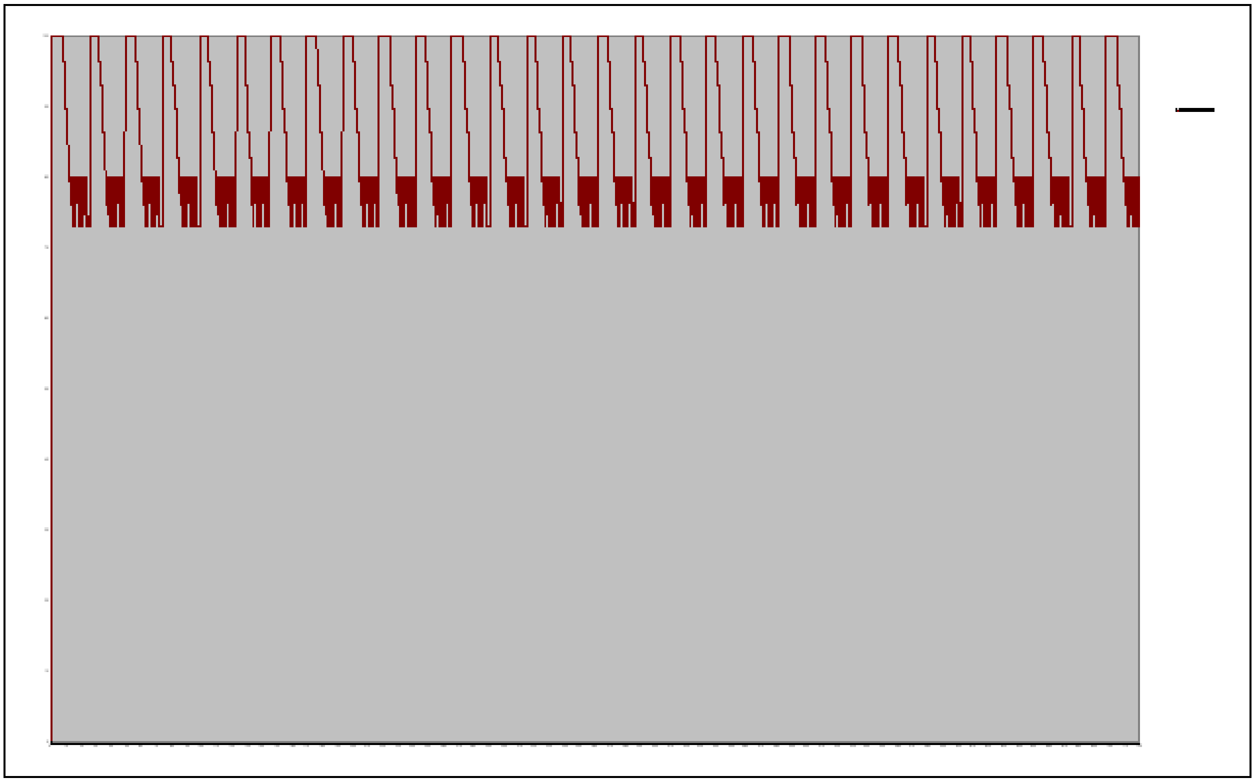


Figure 5-13: Scenario 1, SoC curve for EV Bus.

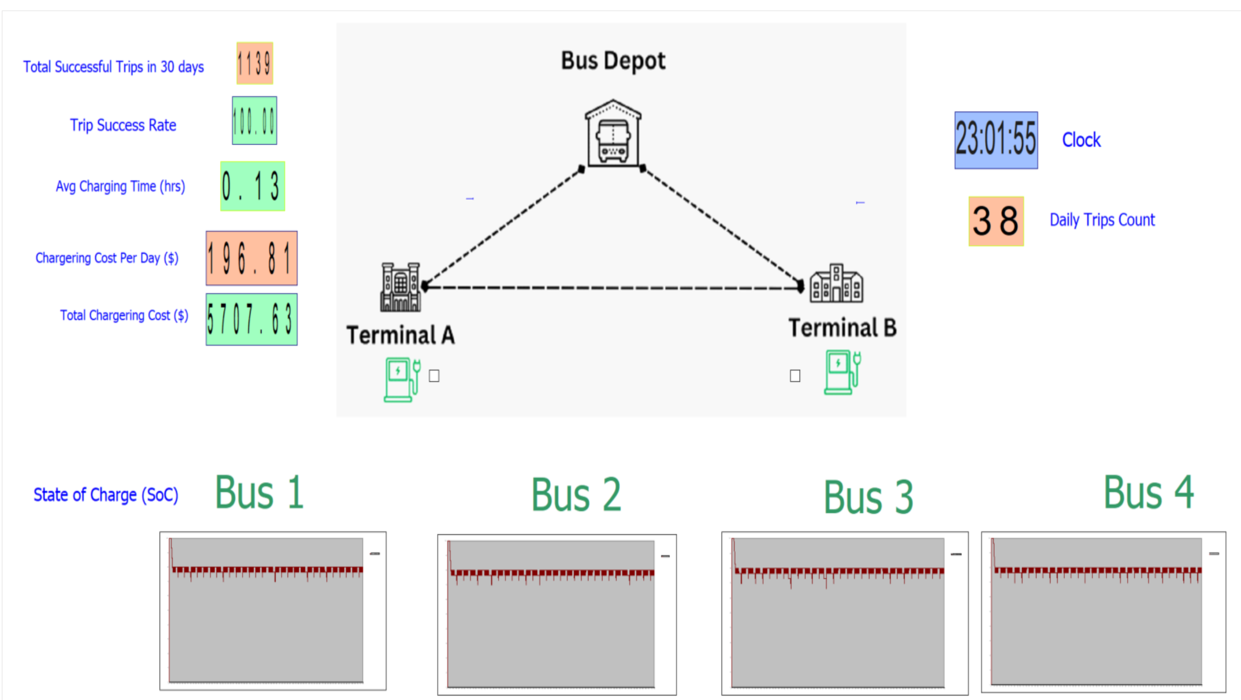


Figure 5-14: Scenario 2, results tab.

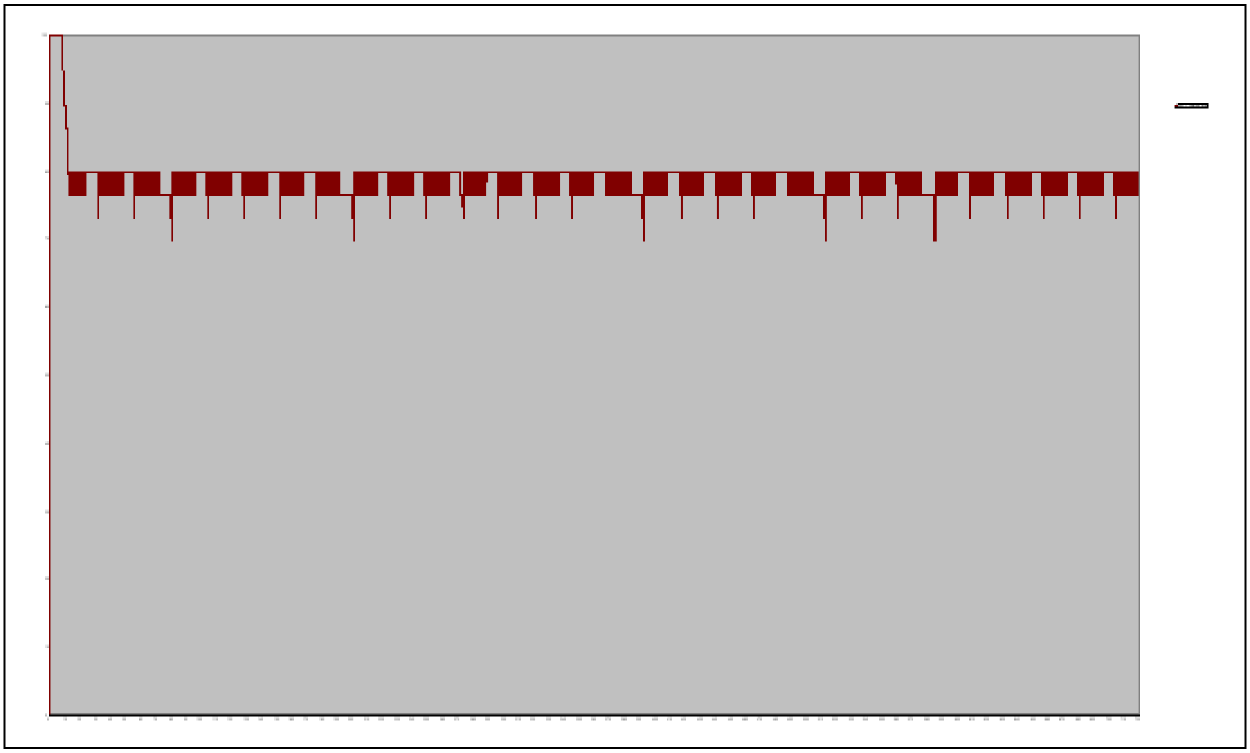


Figure 5-15: Scenario 2, SoC curve for EV Bus.

5.5 Results Comparison across Scenarios

Now, that the base simulation model has been verified and validated across various relationships. Corresponding the same inputs, scenario 1 with charging station at depot and charging station at terminal, scenario 2 with charging stations each at terminal stations were modeled. The output results from it are consolidated, as shown in table 5-5. The charging stations at the depot scenario is kept as the base and compared with the other two systems.

Output Parameter	**Charging Strategies**		
	Depot Charging (Base Model)	***Depot & Opportunity (Scenario 1)***	***Opportunity Charging (Scenario 2)***
Avg Charging time per charge (hrs)	2.37	0.55	0.13
Trips Success Rate (%)	100	100	100
Charging cost per day ($/day)	350.24	206.00	196.81
Total Cost of Charging ($)	10157.06	5973.87	5707.63

Table 5-5: Simulation Scenarios - results comparison.

In summary, each charging strategy guarantees operational success; however, Opportunity Charging (Scenario 2), which incorporates charging stations at terminals, emerges as the most time- and cost-efficient approach. It offers the shortest average charging time and the lowest total cost for charging, while preserving a 100% trip success rate. This strategy enables buses to sustain higher battery levels, thereby enhancing operational efficiency. For organizations evaluating these strategies, Opportunity Charging is likely to be the most economically beneficial option, presuming that the electricity rates per hour remain constant during peak and off-peak periods though, in practice, these rates typically vary.

CHAPTER 6

CONCLUSIONS AND FUTURE WORKS

6.1 Conclusions

In conclusion, this thesis has demonstrated the implementation of different charging strategies for the university electric bus fleet. Performance factors, such as trip success rate and charging costs, were evaluated on a small fleet of four buses with a constant battery capacity of 300kWh and charging power of 100kW operating at an ambient temperature of +25 ^{0}C. Three scenarios were considered: depot and opportunity charging, opportunity charging alone, and the base model with depot charging alone by varying the charging station's locations.

The results suggest that ambient temperature has a considerable impact on the trip success rate of electric buses, implying that fleet operations must be optimized for varying regional temperature conditions. It was observed that BEB operating in positive temperature conditions exhibit lower kWh/km consumption rate allowing BEB to gain maximum driving range thus leading to higher operational efficiency. The analysis ascertained that a battery capacity of 300 kWh, coupled with a charging power of 100 kW, suffices to maintain a 100% trip success rate for the university fleet under the route conditions contemplated. The comparison results revealed that all three scenarios achieved a 100% trip success rate.

This research lays the groundwork for estimating the charging infrastructure demand by using mathematical formulations and for the execution of cost assessments across varied operating conditions. By strategizing proper charging schedules and efficient trip management, transit agencies can opt for slower charging stations, leading to reduced operational costs. This study serves as a crucial initial step toward enhancing the understanding of electric bus fleet management and lays the groundwork for future advancements in sustainable transit technologies. Nevertheless, further research and analysis is necessary to investigate additional variables that affect fleet operations and to pinpoint the most suitable charging strategies for expansion to larger fleets.

6.2 Future Works

The potential extensions for the proposed research are outlined below:

- The current thesis models do not account for intermediate stations between terminals. Incorporating intermediate stops in the simulation would lead to more accurate results for planning larger transit fleets.
- The study assumes a uniform charging rate from 0 to 100%, which differs in reality. Further elaboration and consideration of different charging rates would enhance the study's accuracy.
- Investigating models with high-speed inductive charging at intermediate stops can lead to more precise transit networks.
- Crucial factors like battery temperature and age that significantly impact charging and discharging rate can be integrated into the models for a more comprehensive analysis.
- Lastly, the same methodology can be applied to model larger fleets of Battery Electric Buses (BEBs) with varying battery capacities operating in both urban and suburban regions, providing valuable insights for fleet planning and management.
- The cost of charging can be accurately estimated by taking into account the varying rates of electricity consumption that occur when charging during peak or off-peak hours.

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APPENDIX A

A1. Sample calculation Excel sheet.

INPUT PARAMETER		VALUE	UNITS
Distance beteen Terminals	D	10	km
Daily scheduled trips	Shti	38	
fleet size	Ni	4	
Consumption Rate	Rcomp	1.88	kWh/km
Battery capacity	C	400	kWh
Charging Power	H	100	kW
Chargers avaliable time	Cht	10	hrs
electricity rate	Re	36.87	$/hr
Ambient Temperature	T	-7	degC
charger efficiency	n	0.89	
Thershold Level	SF(T)	25	%

OUTPUT		VALUE	UNITS
scheduled round Trips per bus	Shb	9.5	per day
driving range	DR	213	Km
operating range	OR	190	Km/day
safety range	SR	53.19	Km
Charging frequency	X	20.157	hrs
Daily charging demand	Yi	4.76	buses
Charging time	t	4.01	hrs
Demand for Chargers	Di	1.92	
Cost of charging per Bus per charge	Cb	147.98	$/bus/charge
Charging cost per day	Cd	704.77	$/Ni/day
Total Cost of Charging	TC	21142.97	$

A2. Number of replications at 95% confidence interval.

Number of Replications

Base model with 2 Charging Stations at Depot for a battery capacity of 400kWh, 100kW charger, and for a fleet of 4 at -7 ^{0}C ambient temperature.

Output: Total Charging Costs

Desired number of replications $(n) \cong \left(t_{n-1,\frac{\alpha}{2}} \frac{S(n)}{\beta}\right)^2$

Avg $(\bar{x})$ = 10135.26

Half-width (β) = 125

confidence level is 95%, which corresponds to α = 0.05 in the two-tailed t table.

Size of 95 % CI = Upper bound - Lower bound = $\left(\bar{x} + t_{n-1,\frac{\alpha}{2}} \frac{S(n)}{\sqrt{n}}\right) - \left(\bar{x} - t_{n-1,\frac{\alpha}{2}} \frac{S(n)}{\sqrt{n}}\right) =$ $2^* \, t_{n-1,\frac{\alpha}{2}} \frac{S(n)}{\sqrt{n}}$ = (2* 125) = 250

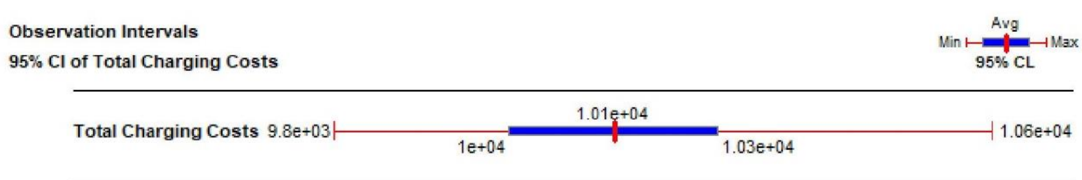
Desired Size of CI = Assuming 60% of 95% CI = 0.6*250 = 150

New desired size of Half-width = 150/2 = 75

Desired number of replications (n) =

$\left(t_{n-1,\frac{\alpha}{2}} \frac{S(n)}{\beta}\right)^2 = \left(t_{19,\ \frac{0.05}{2}} \frac{268}{75}\right)^2 = \left(2.093 * \frac{268}{75}\right)^2 =$

55.8 ≅ **56 replications**



Classical C.I. Intervals Summary
95% CI of Total Charging Costs

IDENTIFIER	AVERAGE	STANDARD DEVIATION	0.950 C.I. HALF-WIDTH	MINIMUM VALUE	MAXIMUM VALUE	NUMBER OF OBS.
Total Charging Costs	1.01e+04	268	125	9.8e+03	1.06e+04	20

Method 2:

Desired number of replications $(n) \cong n_0 \frac{{\beta_0}^2}{\beta^2}$

For $n_0 = 20, \beta_0 = 125$

Desired Size of CI = Assuming 60% of 95% CI = 0.6*250 = 150

New desired size of Half-width = 150/2 = 75

Desired number of replications $(n) = n_0 \frac{{\beta_0}^2}{\beta^2}$

$= 20 * \frac{125^2}{75^2}$ = 55.55 ≅ **56 replications**

A3. DOE scenario experiments.

	Battery Capacity (C)	Charging Power (H)	Ambient temperature (T)	Trip Success Rate	Charging Costs	Total Charging Time
	Kw	Kwh	Deg C	%	$	%
1	300	50	-25	51.14	33087.9	897.42
2	300	50	0	73.68	25621.33	694.91
3	300	50	25	95.35	20349.06	551.91
4	300	75	-25	61.23	26739.51	725.24
5	300	75	0	73.68	18074.82	490.23
6	300	75	25	100	14084.86	382.01
7	300	100	-25	68.6	22129.63	600.21
8	300	100	0	76.67	14108.3	382.65
9	300	100	25	100	10563.65	286.51
10	400	50	-25	60.53	33828.17	917.5
11	400	50	0	83.07	28202.79	764.93
12	400	50	25	95.35	20349.06	551.91
13	400	75	-25	64.39	25573.02	693.6
14	400	75	0	93.42	20927.77	567.61
15	400	75	25	100	14084.86	382.01
16	400	100	-25	68.51	20234.09	548.8
17	400	100	0	94.74	16013.33	434.32
18	400	100	25	100	10563.65	286.51
19	500	50	-25	67.46	38269.8	1037.97
20	500	50	0	83.42	28133.77	763.05
21	500	50	25	95.35	20439.06	551.91
22	500	75	-25	73.68	27756.45	752.82
23	500	75	0	94.3	20955.38	568.36
24	500	75	25	100	14084.86	382.01
25	500	100	-25	73.68	20817.33	564.61
26	500	100	0	100	16510.3	447.8
27	500	100	25	100	10563.65	286.51

A4. Model evaluation excel sheet.

INPUT PARAMETER		VALUE	UNITS
Distance beteen Terminals	D	10	km
Daily scheduled trips	Shti	38	
fleet size	Ni	4	
Consumption Rate	Rcomp	1.025	kWh/km
Battery capacity	C	300	kWh
Charging Power	H	100	kW
Chargers avaliable time	Cht	8	hrs
electricity rate	Re	36.87	$/hr
Ambient Temperature	T	25	degC
charger efficiency	n	0.89	
Thershold Level	SF(T)	25	%

OUTPUT		VALUE	UNITS
scheduled round Trips per bus	Shb	9.5	per day
driviing range	DR	293	Km
operating range	OR	190	Km/day
safety range	SR	73.17	Km
Charging frequency	X	27.728	hrs
Daily charging demand	Yi	3.46	buses
Charging time	t	2.19	hrs
Demand for Chargers	Di	1.20	
Cost of charging per Bus per charge	Cb	80.68	$/bus/charge
Charging cost per day	Cd	279.33	$/Ni/day
Total Cost of Charging	TC	8379.86	$