Public Transportation Electrification with the Support of Mobile Energy Storage

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

In recent decades, fossil fuels and carbon emissions reduction have become an increasingly popular global phenomenon; therefore, a number of governments worldwide have allocated substantial funds to transportation electrification projects. As a result of its significant positive environmental impact, the electrification of public transportation in particular is becoming increasingly popular. It is important to note, however, that this wide-scale electrification presents a number of challenges: numerous technical challenges arise due to the infancy of the technology, high capital costs associated with the infrastructure and assets involved pose a significant financial barrier, and last but not least, the additional load imposed by the new electric fleets on the electrical distribution system poses a significant electrical barrier. It is for this reason that this thesis is designed to address a series of questions posed by transit agencies as they strive to electrify their fleets and address the many barriers they face along the way.

In order to electrify the public transportation system, the first stage is to determine the appropriate sizing of the necessary assets. Consequently, the first objective of this thesis is the sizing of the fleet and chargers according to the charging technology selected by the transit agency. The developed methodology incorporates detailed route assignment, energy consumption modeling, and charging requirements for electric fleets. The formulation reflects the real-world selection and procurement process, which accounts for the interactions between transit agencies and technology manufacturers or suppliers. After determining which assets are required, a transit agency must determine when they should be purchased. This is addressed by the second objective of this thesis which is the development of a comprehensive fleet transition plan. As key stakeholders in transportation electrification, the perspectives and interests of transit and distribution systems are intertwined and therefore must be accounted for in order to determine when and how to make optimal purchasing decisions. For this reason, the methodology developed has two stages an input stage and a transition stage, where the input stage entails the identification of the optimal depot location depending on the distribution system as well as the operation of the transit system. The results from the input stage are utilized in the next stage; the transition stage, which aims to minimize the net present value of the purchase decisions. Together, these produce an optimal transition plan, based on accurate input models. A transit system consisting of four short-distance routes is studied using two modes of charging: overnight and opportunity. The results demonstrate the effectiveness of the proposed approach in meeting electrification targets while adhering the budget constraints, respecting the limitations of the distribution system, and providing continuity of service to the transit agency through an adaptable and scalable formulation.

Once the transition plan is determined, the transit agencies are ready to electrify their fleets, but there remain a number of barriers preventing their widespread use: whether they are technical, financial, or electrical in nature. The third objective of this thesis is to present Mobile Energy Storage (MES) as a fast, flexible, and holistic solution to the aforementioned barriers. As seen from the transit agency's perspective, a comprehensive optimal sizing, routing, and scheduling problem is developed, which aims to minimize purchase and operation costs simultaneously. The MES is operated to meet Battery Electric Buses (BEBs) on their designated routes, thereby reducing or eliminating the need for on-route charging, or reducing the number of BEBs required to operate a route. The incorporation of MES results in substantial cost savings, as well as a variety of benefits, including reducing driving range anxiety among BEB operators, and reducing stress on the electrical grid as a result of the large sudden load imposed by on-route charging. Additionally, MES offers transit systems resiliency in case of accidents and emergencies, as well as the flexibility needed for the dynamic transportation sector. Hence, this thesis brings together two important players in the e-mobility field: electric buses and mobile energy storage.

In order for the transit system to be able to take full advantage of a powerful tool like MES, it is imperative to study how it can be utilized to its full potential. Due to the added complexity of the mobility factor, a study was designed and presented as the fourth objective to investigate privately-owned stationary energy storage and their interactions with potential customers. Upon completion, the findings of this study along with the previous studies are used to model revenue stream generation of the transit-owned MES. A profit maximization model based on optimization and a profit maximization model based on an integrated auction and optimization are developed to determine which external customers are served by the MES. The results of the final objective presented show the efficacy of the MES in serving its own internal system while utilizing the unused capacity to serve additional customers and generate profit.

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Dedication

To my beloved parents, Youhanna and Dalia, who never doubted me especially when I doubted myself, and dedicated their whole lives to supporting me,

To my dear life partner, David, whose support got me through the hardest days,

To my sunshine, Daniel, you can do anything you set your mind to.

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List of Abbreviations

AACO Average annual cost of operation.

BEB Battery Electric Bus.

CBR Charger to Bus Ratio.

CUTRIC Canadian Urban Transit Research and Innovation Consortium.

DNO Distribution Network Operator.

DT Day-time.

EB Electric Bus.

EBEC Electric Bus Energy Consumption.

EMS Energy Management System.

EOR End of Route.

ES Energy Storage.

ESH Energy Storage Hub.

ESMP Energy Storage Management Platform.

EV Electric Vehicle.

FC Fast Charger.

FCS Fast Charging Station.

GAMS General Algebraic Modeling System.

HVAC heating, ventilation, and air conditioning.

IESO Independent Electricity System Operator.

MES Mobile Energy Storage.

MESRSP MES Routing and Scheduling Problem.

MINLP Mixed Integer Non-Linear Programming.

MIP Mixed Integer Programming.

NT Night-time.

OPPC Opportunity Charging.

OVNC Overnight Charging.

PDS Power Distribution System.

PT Public Transportation.

PTE Public Transportation Electrification.

PV Photovoltaic.

RES Renewable Energy Source.

RTO Regional Transmission Organizations.

SC Slow Charger.

SD Short Distance.

SES Stationary Energy Storage.

SOC State of Charge.

TA Transit Agency.

TTC Toronto Transit Commission.

V2G Vehicle-to-Grid.

VCG Vickrey-Clarke-Groves.

List of Symbols

Parameters

$aT_{t,r}$	Binary indicator of trip r being run at time t.
η_b^{ch}	Bus b's battery charging efficiency.
η_b^{dch}	Bus b's battery discharging efficiency.
Δt^{day}	Time step for the day-time operation of buses.
$\mu_{sc/fc}$	Efficiency of slow/fast chargers.
$\mu_m^{dc/c}$	Discharging and charging efficiencies of MES.
ρ_j	Price paid by customer j to MES (\$/kWh).
γ_r	Electrification percentage target.
$AW^{\diamond}$	Capital recovery factor of asset $\diamond$.
$B_{o,p}$	Susceptance of power system line o to p.
Bd_t	Transit agency's annual budget.
BG_t	Bonuses or grants received by the transit agency in period t.
$C^{cap,MES/BEB/ch}$	Annualized capital costs of purchasing MES/ BEBs/ chargers.
$C_{cn}^{ch,cap}$	Capital cost of charger cn.
C_t^{grid}	Cost of purchasing energy from the fris in \$/kWh.
$C_{pb,ro}^{BEB,op}$	Operating cost when running route ro using manufacturer pb's buses.

C^{travel}	MES's cost of travel (\$/km).
$C^{penalty}$	Penalty cost incurred by the MES associated with not providing an energy need.
$C_{pb}^{BEB,cap}$	Capital cost of purchasing BEBs from manufacturer pb.
$C_{k,t}^{B,cap}$	Purchase costs of bus type k in time period t.
$C_{sc/fc,t}^{Sch/Fch,cap}$	Purchase costs of slow/fast charger type sc/fc in time period t.
$C_{k,h,t}^{B,salv}$	Salvage (retirement) cost of bus type k age h at period t.
$C_{k,t}^{B,midlife}$	Midlife cost of operating buses of type k.
$C_{r,t}^{cB/eB,op}$	Annual operating costs incurred when route type r is run using conventional/electric buses.
$C^{chg,s}$	Cost of purchasing energy from energy sellers.
C^{labor}	Cost of labor for operating the MES (\$/hour).
$CC^{BEB,e}$	Energy investment cost of purchasing BEBs (\$/kWh).
$CC^{BEB,p}$	Power investment cost of purchasing BEBs (\$/kVA).
$CC_{k}^{MES,p}$	Power investment cost of purchasing MES in (\$/kVA).
$CC_{k}^{MES,e}$	Capital cost of purchasing MES type k (\$/kWh).
$CC_{h}^{FC,p}$	Capital costs of fast chargers (\$/kW).
$CC_{h}^{SC,p}$	Capital costs of slow chargers (\$/kW).
CC_{h}^{FC}	Installation costs of Fast Chargers (FCs) (\$).
CC_{l}^{SC}	Installation costs of Slow Chargers (SCs) (\$).
$d_{i,j}$	Distance in kilometres between two locations i and j.
df_m	Driver's behavior factor.
dT_{r}^{depot}	Time spent by the buses at the depot to be charged overnight when assigned to run type r.
$D_{l,o}$	Distance between the route starting location l and power system bus o.
D_{r}^{trip}	Distance traveled in kilometers for run type r.

DC_t	Monthly demand charge rate in (\$/kW).
DOD_m	MES's depth of discharge.
$e_{i,j,m}$	Energy required to travel from location i to j.
$e_{sc/fc}$	Number of chargers of type sc/fc previously owned by the transit agency.
eB_m	Capacity of MES m.
$eB_k^{rat,MES}$	Energy rating of MES (kWh).
$ec_{k,t}$	Average energy consumption per kilometer of BEB type k (kWh/km).
et_m^{sd}	MES's earliest departure time from the depot.
E_l^B	Energy consumption rate (kWh/km) of buses departing from location l.
$E_b^{bat,cap}$	Bus battery energy capacity.
$G_{o,p}$	Conductance of power system line o to p.
H_{MES}	Operating hours of the MES.
i, i', in	Nominal interest, effective interest and inflation rates.
K_{ro}	Route topology factor.
LC_m	MES cycle life.
lt_m^{sd}	MES's latest return time to the depot.
N_l^B	Number of buses departing from location l.
$N_{b/pb/ro}$	Number of buses b / procurement bids pb / routes ro.
$n_{k,t,r}^{trips}$	Number of trips that can be run by a bus of type k, running run type r, in year t.
$P_{sc/fc}$	Power consumption ratings of slow/fast chargers (kW).
P^{ch}	Power rating of selected charger.
$P_{cn}^{ch,rat}$	Power rating of charger cn.
$P_{ch}^{depotch,rat}$	Power rating of charger ch installed at the depot.
$P_{o,t}^L$	Active power demand at power system bus o at time t.

$P_{t,r}^{rdch,profile}$	Power consumed along trip r at time t.
PgF_t	Net present value conversion factor for year t.
sB_k	MES's rated apparent power in kVA.
SOC^{depart}	Minimum required SOC upon departure from the depot.
$SOC0_b$	Bus b's initial SOC.
st_i	Customer service time.
$st_i^{early/late}$	Earliest/ latest service time requested at customer i.
T_{ga}	Target years.
$T_{b,t}^{conn/dconn}$	MES connection/ disconnection time.
$T_{b,t}^{leaving}$	Binary indicator of the time t at which bus b leaves the depot in the morning.
T^{depot}	Average number of hours spent by the buses at the depot overnight.
$\diamond^{max}$	Maximum (upper) limit of the variable $\diamond$.
$\diamond^{min}$	Minimum (lower) limit of the variable $\diamond$.

Variables

$\alpha_{k,h,t}^{B}$	Number of buses of type k, age h, available in the transit system's inventory at time t.
$\alpha_{sc/fc,t}^{Sch/Fch}$	Number of available slow/ fast chargers of type sc/fc in period t.
$\beta_{k,t,r}$	Number of buses of type k assigned to run trips of type r, during period t.
$\delta_{t,o}$	Voltage angle of power system bus o at time t.
$\Delta P_o^{depotch}$	Additional load imposed on power system bus o by the depot.
$\psi_{k,h,t}$	Number of buses of type k, age h, salvaged during period t.

$\omega_{sc/fc,t}^{Sch/Fch}$	Number of slow chargers/fast chargers of type sc/fc purchased during period t.
$\zeta_{k,t}$	Number of buses of type k purchased in period t.
$a_{b,r}$	Assignment of bus b to trip r.
$a_{b,cn}^{charger}$	Assignment of bus b to charger cn.
$AACO$	Annualized average cost of operating the transit system with MES.
B_{MES}	Number of MES.
$bP_{b,t,r}^{dch,profile}$	Power consumed by bus b running trip r at time t.
$C_{pb,ro,b}^{ann}$	Annualized capital cost of purchasing and operating bus b from manufacturer pb on route ro.
C^{cap}	Annualized capital cost of transit system purchases with MES incorporation.
C^{op}	Annual operational cost of the transit system with MES incorporation.
$C^{op,MES}$	Cost of operating MES.
$C^{op,ch,day}$	Annual cost of day-time charging of buses from the grid.
C^{deg}	Degradation cost of the MES ($/kWh).
$C_t^{Trans,ann}$	Transit system's purchase and operating costs for year t.
$Cost^{Trans}$	Net present value of the total capital cost of purchasing and operating a transit system.
D_i	Demand of MES customer i.
$ec_{i,m}$	State of energy of MES m, upon departure from location i (kWh).
f_k	Binary indicator of whether MES of rating k is selected.
g_k	Number of MES of type k purchased.
IN	MES's income from serving external customers.
$inR_{b,t,r}$	Binary indicator of bus b running trip r at time t.
$iU_{b,cn,t}$	Binary indicator if charger cn is in use by bus b at time t.

$m_{ch,o}^{depotch}$	Binary indicator of charger type ch installed at depot.
$n_{ch,o}^{depotch}$	Number of chargers of type ch installed at depot.
$P_{b,t}^{dch}$	Power consumed by bus b at time t.
$P_{o,t}^{G}$	Active power generated at power system bus o at time t.
$P_{t}^{L,depotch}$	Active power load caused by buses charging at the depot.
$P^{depot,max}$	Maximum permissible active power load that can be installed at the depot.
P_i^f	Customer i's final payment in clinching auction.
$Profit$	MES's profit from serving external customers.
$SOC_{b,t}^{day/night}$	The SOC of bus b at time t during the day/night-time.
$sw_{b,t}^{on}$	Binary indicator of the time instant t at which bus b begins charging.
$sw_{b,t}^{off}$	Binary indicator of the time instant t at which bus b stops charging.
$swM_{b,t}^{conn}$	Binary indicator of the time instant t at which bus b begins charging from the MES.
$swM_{b,t}^{dconn}$	Binary indicator of the time instant t at which bus b stops charging from the MES.
$t_{j,m}^{arr}$	Arrival time of MES m at location j.
$t_{i,j}^{tr}$	Travel time from location i to j.
UBd_t	Transit agency's unused annual budget during period t.
$V_{t,o}$	Voltage at power system bus o at time t.
$x_{i,j,m}$	Binary indicator if MES m travels from location i to j.
$x_{b,t}^{ch,depot}$	Binary indicator of bus b charging at the depot at time t.
$x_{b,t}^{ch}$	Binary indicator of bus b charging at time t.
$x_{b,t}^{dch}$	Binary indicator of bus b discharging at time t.
$xc_{t,c}^{day,cus}$	Binary indicator of customer c charging at the depot at time t.
$xc_{t,m}^{day,MES}$	Binary indicator of MES m charging at the depot at time t.

xns_j	Binary indicator if customer location j is not served.
$z_o^{depotch}$	Binary indicator of power system bus o at which the depot is located.

Chapter 1

Introduction

1.1 Introduction and Motivation

Climate change has become a major subject of concern worldwide, with efforts to reduce greenhouse gas emissions being seen as the most effective way to combat this issue. In the last decade, over one hundred and ninety countries signed a climate change agreement "*recognizing the need for an effective and progressive response to the urgent threat of climate change on the basis of the best available scientific knowledge*" [1]. In light of this agreement, many nations began looking to modify their transportation sector as a whole. The transportation sector as it is today depends heavily on fossil fuels, which are among the world's fastest depleting resources as well as the greatest source of carbon dioxide emissions. For example, in Canada, the transportation sector is the second largest contributor to greenhouse gases, producing 23% of the nation's carbon dioxide emissions [2]. From an environmental perspective, as all the world's nations aim to reduce their carbon footprints, leaning away from the excessive use of fossil fuels is a major direction.

To further support the significance of the impact of the transportation sector on carbon emissions, a recent study concluded that as a direct result of the pandemic shutdowns, greenhouse gas emissions dropped in China by 8.8% with the majority of these deductions resulting from the decreased use of ground transportation [3]. The interest in fossil fuel as well as carbon emission reduction in the transportation sector is a popular global phenomenon; hence transportation electrification is viewed as one of the most important ways to move towards a cleaner environment and a more sustainable future with electrification projects being allocated large funds by several governments worldwide.

Electrification of the public transportation sector in particular has gained increasing traction in recent years due to its positive impact on climate change and greenhouse gas emissions. Some countries already operate large electric bus fleets, while others require electric bus conversions by a specific date in the next twenty years, meaning that the transition to electric buses is inevitable. As an example, Toronto and California plan to have their entire fleets converted to zero-emission vehicles by 2040 and 2050, respectively. While electric bus penetration is still relatively low worldwide, it is estimated to increase significantly by 2030, reaching 80% in some areas [4]. Additionally, when observed through an economic lens, numerous studies have shown that the transition to a more electrified transportation system could appreciably improve global economies, and consequently populations' national security. Hence, the transition to electric fleets is no longer a question of if, but rather when.

Implementing an electrified fleet, which is still in its infancy, does not come without challenges. These obstacles must be overcome to allow for a smooth transition to electrified Public Transportation (PT) and, subsequently, for climate change objectives to be achieved. BEB deployment is hindered by three major barriers; technological barriers, financial barriers, and electrical network barriers, a summary of which is presented in Fog. 1.1 [5, 6]. There are two major technological barriers: driving range anxiety and battery performance anxiety where major stakeholders are reluctant to transition to Battery Electric Buses (BEBs) because of their limited driving ranges as well as a lack of knowledge and understanding of BEBs, their manufacturing, operation, and maintenance. Further, the electrification of PT poses multiple financial challenges due to the high capital costs associated with the purchase of BEBs and the necessary charging infrastructure. Additionally, the installation of the required infrastructure may require a large amount of space, resulting in the need for land purchase. Lastly, electrical network barriers are primarily caused by a lack of knowledge, standards, and regulations regarding charging infrastructure. Additionally, permits and approvals are very time consuming procedures. Further, grid instability poses another serious issue, particularly as electrification expands.

The aforementioned barriers have significantly slowed down the adoption of BEBs in spite of their numerous advantages, therefore, multiple research works as well as industry innovations present solutions to encourage BEB adoption. As a means of overcoming the aforementioned technological challenges, several transit agencies have opted to utilize hybrid electric buses as a first step, in an effort to gain a better understanding of the concept of electrification to ease into the transit to BEBs [7]. Further, the placement of Fast Charging Stations (FCSs) along bus routes is an important research area, aimed at reducing drivers' range anxiety by allowing buses to recharge along the route [8]. Additionally, researchers have studied optimal purchase decisions as well as optimal charging schedules

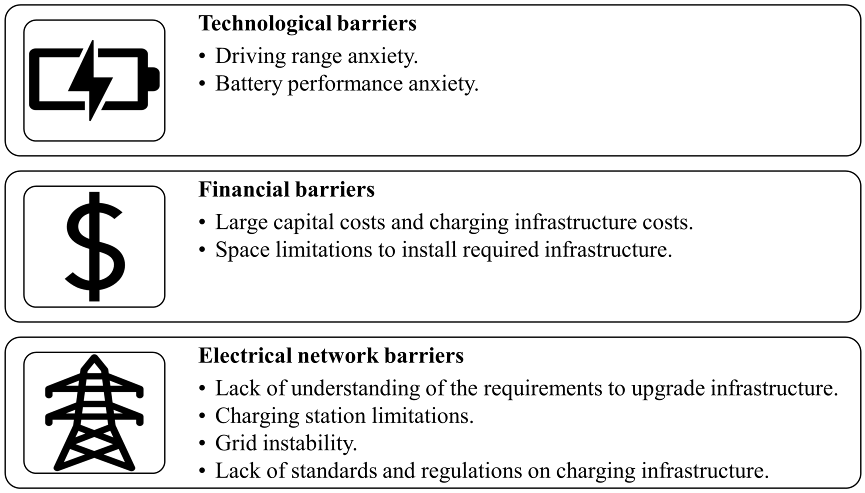


Figure 1.1: Summary of barriers to BEB deployment.

to minimize capital and operating costs. Finally, to tackle some of the barriers related to the electrical network a commonly presented solution entails placing Stationary Energy Storage (SES) at FCSs to offset power peaks caused by buses' Fast Chargers (FCs) along the routes [9–11]. Hence, it can be seen that the barriers to BEB deployment are addressed individually rather than holistically, resulting in slow global BEB deployment.

Further, once installed, the electrified transit system does not have the resiliency to withstand rare or emergency events. For example, an on-route fast charger operated by Foothill Transit in the US caught fire as a result of a thermal event in the spring of 2020, leaving the charger out of service without backup, thus causing serious interruptions to that route, forcing the operators to return to using conventional fleets to run the routes [12]. Furthermore, when power system failures or blackouts occur, the conventional fleet is not affected, but an electrified fleet may have to completely cease operations. Additionally, in the event of an emergency that leaves a bus stranded for an extended period of time, gas can be transported to refuel conventional fleets; however, an electric bus would have difficulty refueling. In light of the infancy of the BEB and charging technology, and the lack of experience, these concerns remain as concerns, rarely addressed by practical solutions or implementations. For all these reasons, public fleet electrification is concerning to many transit agencies as they are unable to guarantee the resiliency of their transportation system and while they want to meet electrification targets, they remain concerned about continuity of service [13].

1.2 Objectives

In an era where e-mobility is taking over the world, being a constant subject of discussion, research, and innovation, this thesis offers to integrate, plan, and operate two very important players in the e-mobility field: electrified public transportation and mobile energy storage. The primary objective of this thesis is to create a comprehensive overview of the many factors that go into electrifying a large fleet like the public transportation sector, while presenting MES as a technology that can facilitate smooth and flexible electrification and a reliable transportation system, while generating revenue. Hence, an overview of the thesis can be seen in Fig. 1.2, and the objectives of this thesis are as follows:

- Develop an operational-planning fleet and charger resource allocation methodology that incorporates detailed energy consumption and optimal route assignment in order to ensure smooth and reliable transportation for the Transit Agency (TA). The methodology should be representative of the real-life process of selecting and procuring assets accounting for the cooperation among TAs and technology manufacturers.

- Propose a novel, realistic, comprehensive fleet transition plan that generates timely decisions while adhering to budgetary, spatial, and operational constraints amongst others. For completeness, the optimal depot location should also be determined, and the Charger to Bus Ratio (CBR) should be studied.

- Introduce Mobile Energy Storage (MES) as a fast, flexible and holistic solution to tackling the electric fleet deployment barriers. A novel problem of mobile energy storage sizing, routing, and scheduling is to be developed for modeling in-depth MES operations as it travels from one location to another. In order to allow easy application by any owner of MES, the proposed model should be designed in a generic manner.

- Model the interactions between the owner of an Energy Storage (ES) module and their customers. A cooperative and a non-cooperative game-theoretic approach are to be explored in order to develop insights into energy storage owners' and customers' behaviors.

- Propose optimization-based and integrated auction and optimization-based models for transit-owned MES to sell remaining unused energy capacity to external customers in order to generate multiple revenue streams. A modified MES routing and scheduling problem is to be modeled with the complete formulation being generic

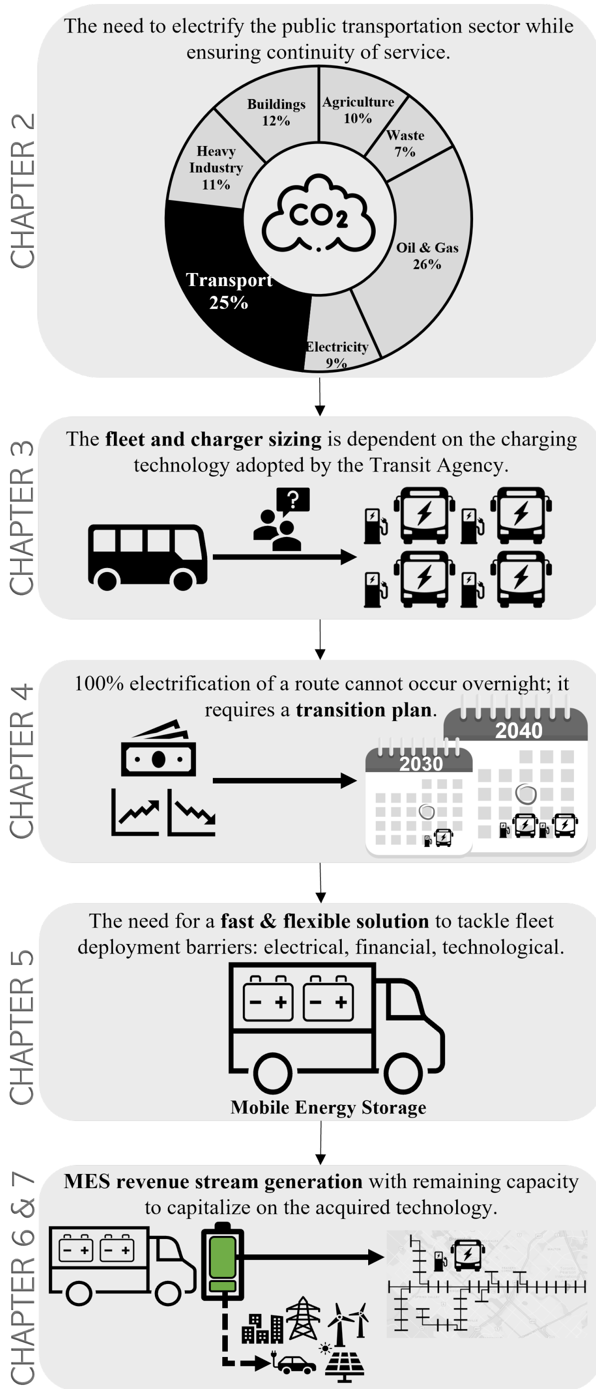


Figure 1.2: Thesis flowchart.

and scalable and can be applied by any MES owner looking to serve internal and external customers.

Meeting the first two objectives will lead to a comprehensive analysis that can be used by TAs to answer why, then how, and then when to electrify their fleets. As a result of deploying electric fleets, a transit agency may encounter some, if not all, of the following obstacles: financial, electrical, and technological. By utilizing MES, the third objective aims to overcome the aforementioned barriers. It is now necessary to study this new technology once it has been acquired. Thus, the fourth objective of the study aims to analyze the interaction between an ES seller and their customers, and the final objective of the study is to generate additional revenue for the transit agency by utilizing surplus MES capacity. In order to demonstrate the efficacy of the proposed models, four short-distance routes and four long-distance routes will be electrified. The characteristics and specifications of these routes correspond to those of real-world Canadian transit routes.

1.3 Thesis Outline

The rest of this thesis is organized as follows:

- *Chapter 2* presents a detailed background and literature review of all the technology and components utilized in the following chapters.
- *Chapter 3* entails an operational-planning fleet and charger sizing methodology to be utilized by transit agencies when electrifying their routes.
- *Chapter 4* develops a transition plan that explains when fleet and charger purchase decisions can be made to meet target electrification deadlines and adhere to budgets.
- *Chapter 5* introduces MES as a holistic, fast and flexible solution to tackling fleet deployment barriers.
- *Chapter 6* presents two game theoretic models for the interaction of an energy seller with their customers to lay a foundation for the next chapter.
- *Chapter 7* models the routing and scheduling of a transit-owned MES that has the primary goal of serving its internal customer (transportation fleet) and utilizing excess energy capacity to serve external customers and generate revenue streams.
- *Chapter 8* summarizes and concludes this research and presents recommendations for future work.

Chapter 2

Background and Literature Review

2.1 Introduction

As discussed in Chapter 1, the electrification of Public Transportation (PT) has gained increasing traction in recent years due to its positive impact on climate change and greenhouse gas emissions. Some countries already operate large electric bus fleets, while others require electric bus conversions by a specific date in the next twenty years, meaning that the transition to electric buses is inevitable. However, numerous questions remain unanswered with regard to fleet sizing, transitioning, and the potential of various technologies in supporting the transition. This chapter provides an overview of the state of the art in the transition to electrified PT and the utilization of Mobile Energy Storage (MES). Finally, the research gaps are highlighted to solidify the motivations and objectives of this thesis.

2.2 Transportation Electrification

The transition to electric fleets is no longer a question of if, but rather when. Due to the immaturity of the Battery Electric Bus (BEB) technology, multiple parties have to deal with operational challenges: transit agencies, since they have to replace a smoothly running system, electrical distribution companies since BEBs will put a lot of strain on the systems, and numerous stakeholders, including BEB makers and bus drivers, among others. As a result, a more detailed and comprehensive analysis is crucial to assessing the prospects for a world where most public transportation will be electric.

2.2.1 Electric Bus Fleet Transition

It is important to note that the planning process for PT is quite extensive, and it is made more complex by the integration of BEBs. Prior to implementation, the planning process begins with strategic planning, which involves decisions regarding infrastructure, routes, and even service frequency. As part of the tactical planning process, scheduling, crewing, and vehicle scheduling problems are typically solved within one year prior to implementation. Last but not least, operational planning aims to recover from service disruptions in real-time and is intrinsically concerned with operational issues. [14] provides a comprehensive survey on Electric Vehicle (EV) demand management applications for infrastructure planning and transportation system coordination. The authors devote a portion of their study to examining coordinated planning in coupled power and transportation networks. More specifically, a number of planning problems have discussed the development of methods for converting an entire diesel fleet to electric at once, under current system conditions [15–17]. Using a two-stage optimization problem, [15] analyzes the electrification of a single route in Seogwipo, South Korea. This research focuses on reducing fleet procurement costs, infrastructure costs, and energy consumption costs by utilizing two charging methods: buses can only charge at the depot, and an additional charger is provided. Furthermore, in [16], a systematic analytical approach is developed for performing fleet sizing, where Electric Buses (EBs) can charge both in-depot and on-route. Contrary to these, the authors of [17] do not incorporate depot charging, but rather rely on fast charging along the route, as well as the less popular dynamic wireless power transfer (DWPT). Despite the fact that all of the above results discuss purchase decisions, they do not address when decisions should be made.

Given the favorable trends in energy storage performance, costs, and utilization, combined with the unfavorable trends in fuel prices, BEBs offer a significant opportunity for potential savings. Thus, when to purchase which buses becomes a very important question. First of all, funds take time to come in, electrification goals change over time, and not just that, but civil and electrical infrastructure may need to be reinforced. An overview of practical fleet transitioning purchase decisions – how these decisions are made, and the purchasing process – based on feedback from Californian transit agencies can be found in [18, 19]. According to interviews and surveys conducted in [18], a group of over twenty transit agencies that have adopted zero-emission buses (ZEBs) concurred that fleet transitioning should not be undertaken in large leaps, but rather in small, gradual steps to ensure smooth operations. When creating a transition plan, the collaboration between all agencies as well as all stakeholders is key to ensuring a smooth transition. Transit Agencies (TAs) in [19] report that local electrical utilities are willing to aid transit agencies with their conversion. For these reasons, a transition plan that incorporates the electric and transit agencies' perspectives is imperative as it outlines a schedule of replacement decisions for the asset under consideration - buses - in the future.

Traditionally, fleet replacements or fleet transitions have been viewed from a transportation perspective, where numerous assumptions have been made to ignore the electrical implications of the issue. Works like [20] presume a one-to-one replacement of diesel fleets with electrical fleets and hence do not account for battery life and charging infrastructure. Contrary to this, the authors in [21] account for charging infrastructure costs but do not study the location, thus overlooking the impact on the electrical grid, which may result in an infeasible result. To address all of these assumptions, the authors in [22] develop a cost-minimizing strategic transition plan while factoring in fleet size and mix and charging infrastructure capacities as numerical decisions devoid of any analysis of an electrical distribution network. Similar logic is used in [23], where the electrical perspective is seen as ratios, meaning that a charger-to-bus ratio is assumed and used. While all these works advance important decision-making strategies in fleet transitions, it is crucial to include an electrical system in the study of an electrified fleet.

To the authors' knowledge, there exists limited research available that postulates a convergence between both the electric utility's perspective and goals as well as those of the transit agencies in fleet transition problems, hence one of the major objectives of this thesis is the development of a comprehensive fleet transition plan for transit agencies interested in electrifying their existing bus fleets considering multiple modes of charging, while incorporating the perspectives of the transportation and electrical sectors.

2.2.2 Battery Electric Buses

Two main concepts of compensating the BEB's energy needs are studied in the literature: battery charging and battery swapping. With battery swapping arise numerous challenges such as the need for specialized labor, infrastructure, capital costs, and reserve batteries to allow for the swapping mechanism to work. Battery swapping has been studied more thoroughly in EVs, where the challenge of battery ownership and degradation arises. However, since all BEBs in a study are owned by the same fleet operator, this issue becomes obsolete. However, the time and investment requirements for a swapping technology are extensive and so the majority of the literature on BEBs focuses on charging mechanisms rather than battery swapping [24].

BEBs have three main charging technologies: plug-in charging stations, overhead fast charging, and wireless charging. Wireless charging can be categorized into 3 types: stationary wireless charging (SWC), where the bus is charged only at times when it is parked or not in motion, quasi-dynamic wireless charging (QWC), where the power is transferred when the bus moves slowly, and finally, dynamic wireless charging (DWC), where the bus is charged while in motion and is also referred to as move and charge, road-way powered system, or dynamic inductive charging [25]. There are three main charging mechanisms for BEBs: Overnight Charging (OVNC) where a BEB charges once overnight and does not recharge along its routes during the day, flash charging, and finally, Opportunity Charging (OPPC) in which a BEB charges along its route. Due to the nature of the former methodology, OVNC requires large battery capacities as it does not recharge along the route, a long duration for charging but low charging power. The reverse is seen in flash charging and OPPC which are basically the same concept with flash charging having higher charge rates. Finally, in-motion charging corresponds to the DWC discussed above. All methodologies are acceptable and deployed in projects around the world, with overnight being the least concerning for transit agencies and hence the most deployed. Numerous works have tackled the operation and planning of BEBs in the Power Distribution System (PDS) focusing on multiple aspects as seen in [24, 26–28]. Additionally, it is significant to note that the length of the bus route - long-distance (intercity) versus short-distance (intracity) - has a significant impact on electrification studies, however, this is not commonly discussed [29].

BEB Energy Consumption Modeling

Electric Bus Energy Consumption (EBEC) profile modeling is dependent on the purpose for which the model was built and is the first step to modeling and utilizing BEBs within a larger system such as a power system, where BEBs act as loads when charging and when equipped with Vehicle-to-Grid (V2G) capabilities can discharge to provide services to the grid for a cost. In order to study the electrification of the public transportation network, EBEC must be studied in detail. A sole average or median value, averaging at 1.24 kWh/km is used to represent energy consumed by battery electric buses in a range of works [30–32]. The works that model EBEC as average numbers select appropriate average numbers based on several criteria: bus length, single vs. double-decker, bus route (intercity or not), and finally the bus technology (BEBs, plug-in hybrid buses, series hybrid buses, parallel hybrid with and without super-caps). In spite of the fact that this model is appropriate for the purpose for which it was built, it is insufficient for the application desired in this research, so the state-of-the-art in EBEC modeling is studied and presented in order of increasing complexity. Rather than a single average number, the work in [31] utilizes an operating mode binning method, where each BEB is represented by multiple average values depending on the time of operation. A more detailed and complex approach, that better represents reality is based on the vehicle longitudinal dynamics equations, which consist of multiple unknowns such as bus velocity and mass. The authors in [33] and [32] represent EBEC using the above-mentioned equations; however, the unknowns are represented by approximated average values. It is clear from the previously discussed models that they are not representative of real life as they lack the integration of numerous parameters into the model. These include traffic, changes in mass along the route, considering whether the bus stops at each stop or traffic light, and finally, heating, ventilation, and air conditioning (HVAC) modeling. Hence, average numbers whether in a simple form, binning mode or embedded in vehicle longitudinal equations are insufficient to provide EBEC profiles representative of real life.

A further enhancement is using stochastic methods to model speed profiles, the stops at which a bus stops, and the traffic lights at which a bus stops. Finally, due to the availability of historical data, some works were able to forecast EBEC profiles based on large high-resolution historical data, while the authors in [26] perform short term forecasting in a multi-phase problem where historical data is pre-processed in stage one and entered into a learning stage (wavelet neural network). Finally, the authors in [34] develop two probabilistic optimization problems that build onto each other, of reasonable complexity, based on vehicle longitudinal equations, without the need for historical data. EBEC has been studied in numerous works over the past years, the general categories present in the state-of-the-art have been discussed in this section. All models discussed work effectively in the applications for which they were developed. However, for the specific application of this research, a detailed model that does not require historical data – as it is not publicly available – is necessary. For this reason, a modified version of the final model presented in [34] is utilized.

2.2.3 Barriers to BEB Deployment

In spite of the fact that buses are a good electrification candidate, BEBs have not been heavily deployed. The reason for this is: there are several major barriers to the deployment of BEBs that must be overcome in order to enable a smooth transition to electrified PT and meet the climate change objectives. BEB deployment is hindered by three major barriers; technological barriers, financial barriers, and electrical network barriers [5,6]. There are two major technological barriers: driving range anxiety and battery performance anxiety where major stakeholders are reluctant to transition to BEBs because of their limited driving ranges as well as a lack of knowledge and understanding of BEBs, their manufacturing, operation, and maintenance. Further, Public Transportation Electrification (PTE) poses multiple financial challenges due to the high capital costs associated with the purchase of BEBs and the necessary charging infrastructure. Additionally, the installation of the required infrastructure may require a large amount of space, resulting in the need for land purchase. Lastly, electrical network barriers are primarily caused by a lack of knowledge, standards, and regulations regarding charging infrastructure. Further, grid instability poses another serious issue, particularly as electrification expands.

The barriers presented above have slowed down the adoption of BEBs despite their numerous advantages, therefore, multiple research works as well as industry innovations present solutions to encourage BEB adoption. As a means of overcoming the aforementioned technological challenges, several transit agencies have opted to utilize hybrid electric buses as a first step, in an effort to gain a better understanding of the concept of electrification to ease into the transit to BEBs [7]. Further, the placement of Fast Charging Stations (FCSs) along bus routes is an important research area, aimed at reducing drivers' range anxiety by allowing buses to recharge along the route [8]. Additionally, researchers have studied optimal purchase decisions as well as optimal charging schedules to minimize capital and operating costs. Finally, to tackle some of the barriers related to the electrical network a commonly presented solution entails placing Stationary Energy Storage (SES) at FCSs to offset power peaks caused by buses' fast charging along the routes [9–11]. Moreover, BEB energy consumption and the impact of charging stations on the grid are studied to enhance the understanding of BEB deployment and lay a foundation of knowledge for the widespread deployment of BEBs.

As previously discussed, the barriers to BEB deployment are addressed individually rather than holistically. In contrast, the MES system proposed in this study offers an innovative approach for overcoming technological, financial, and electrical barriers simultaneously. With MES, driving anxiety is reduced as BEBs are met and recharged along their routes at the exact time they specify, and in case of an emergency, they can be sent elsewhere and their schedule adjusted. Additionally, MES reduces capital costs since one MES can replace several FCSs, as it acts as an appearing and disappearing FCS. Further, the BEBs will no longer have to charge directly from the grid during peak hours at peak prices, thereby reducing operational costs. Last but not least, MES reduces grid peaks caused by FCSs and defers the need for costly upgrades to electrical infrastructure by reducing or eliminating the need for FCSs. For these reasons, one of the objectives of this work is the optimal sizing, routing and scheduling of transit owned MES to realize the multi-faceted techno-economic benefits of utilizing MES in the transition to electrified transportation. The coming sections focus on the state of the art in MES, as it is introduced in this research as a means of tackling the barriers to BEB deployment.

2.3 Mobile Energy Storage Systems

MES is in simple terms, energy storage mounted on a truck, hence any services that SES systems are capable of providing, can also be provided by MES but in a more targeted manner. This is due to the fact that an MES unit has the added advantage of mobility which elevates the already beneficial energy storage technology to an even higher level as will be discussed in the coming section.

2.3.1 State of the art in MES

MES has been studied in several works in the literature, where the authors are mainly concerned with economic objectives such as minimizing costs or improving profits; however, the technical objectives, problem formulation, and solution approaches have varied depending on the problem. To begin with, the authors in [35] operate MES as partially stationary energy storage where under normal conditions, their positions are fixed, however during times of emergency or natural disasters, they can move to real-time determined optimal locations to enhance grid resiliency. Here, a second-order conic ac relaxation of power flows is used to model the power flow in a 15-bus radial distribution system. They later develop their work in [36] by allowing the MES to travel and form microgrids. Both problems are modeled as two-stage stochastic (MISOCP) and are solved using a progressive hedging (PH) approach. A similar idea is presented in [37], where the authors utilize mobile emergency generators to enhance distribution system resiliency post disasters or extreme weather conditions that threaten power supply continuity, hence highlighting the possibility of MES systems performing such a service. However, in these works, the MES served a single customer and were only partially mobile. On the contrary, the authors in [38], modeled an MES system that is composed of a lithium-ion battery array mounted atop an electric truck, with additional rooftop Photovoltaic (PV) panels that charge the MES on board. This problem was formulated as an Mixed Integer Non-Linear Programming (MINLP) with the goal of serving multiple customers in a day-ahead approach. Additionally, Abdeltawab and Mohamed also developed a day-ahead Energy Management System (EMS), operated from the perspective of a Distribution Network Operator (DNO) where the DNO's profits are maximized through minimizing the cost of power purchased from the grid. To begin with, a large assumption was made that the transit times for the MES system are 0 and they can move instantaneously from one location to the next. This problem was formulated as a non-convex mixed-integer problem in [39–41], and was then converted into a MISOCP to facilitate feasibility. The authors then developed a transit delay model based on the distances between stations and the time it takes to travel between them, and the problem was modified using a particle swarm optimizer to find the optimum delay set that maximized the DNO's profits which they tested on a 41-bus radial distribution system. In [41] the authors included an additional planning phase that incorporated the sizing and allocation of the MES in the study, while the MES participated in providing multiple services to the PDS by participating in power loss minimization, voltage regulation and energy arbitrage. The work in [42], exploits the benefits of MES in mitigating the seasonal spike in demand on a rural distribution transformer in China as a result of the annual Spring Festival.

The research done on MES is primarily focused on resiliency, particularly the authors focus on utilizing MES to form microgrids. Several recent works study the ability of MES to enhance service restoration and hence resiliency in an MG environment – microgrid-based restoration techniques. These include [43] and [44], where Yao et al. model MES as a battery that travels through the shortest paths and is scheduled with the goal of maximizing service restoration through a Markov decision process solved using a deep reinforcement learning approach (twin delayed deep deterministic policy gradient). Moreover, an MES and power transaction-based strategy is used to boost system flexibility and allow for additional renewable penetration in a multi-microgrid environment. This problem is formulated as a single objective optimization problem where the multi-microgrid's economic costs are minimized using an evolutionary predator and prey strategy algorithm as shown in [45]. A similar idea regarding the utilization of MES to reduce renewable power curtailment from wind farms and harness the excess energy by storing it in transportable lithium-ion batteries is studied in [46]. Additionally, a single privately owned MES is used in combination with multiple renewable energy resources to reduce an airport's (MES owner) fuel dependency, maximize profit, and minimize environmental impact in a hybrid microgrid environment [47]. Here MES demonstrated an ability to respond appropriately to price signals and participate in energy arbitrage. Finally, the work in [48] studies multiple benefits of MES in cooperation with shiftable loads such as water desalination equipment, in an isolated microgrid environment, for a secluded military location. Mobile energy storage systems are considered of known number and capacity and are simply used as a last resort in a system that is heavily dependent on renewable energy resources, stationary storage, and diesel generators.

The most prominent works on MES that are within the scope of this research are discussed in this section. Other works regarding MES include studying the battery electronics, battery construction, etc. that are not mentioned in this survey as they are beyond the scope of this research. As per the above discussions and as reviewed in [39], comprehensive energy management, as well as optimal scheduling of MES, that are representational of real-world dynamics, are not studied in the literature. To further clarify, none of the presented models provide a complete detailed picture of what it would entail to own and operate MES, usually limiting the MES to providing only one service or comprising of only one technology or disregarding the matter of ownership, while including numerous approximations. This creates a gap in the literature as the significance of mobile energy storage systems as their potential technical and economic benefits are abundant. Moreover, as seen from the above discussion, a majority of the work done on MES has been focused on using MES to supply critical loads during times of emergency, in other words enhancing grid resiliency. Not just that, but a majority of the work is of an operational nature, while the planning and resource allocation of the MES technology used is not discussed or studied. A unique concept is presented in [49], where the authors minimize total operating costs through the day-ahead optimal operation of a single MES unit serving several EV parking lot charging stations, which they formulate as an MINLP.

To conclude, MES is no foreign concept in providing numerous services, but as per the authors' knowledge very limited research has been done on utilizing it within the private transportation framework, and no research has been done on integrating it into public transportation electrification. Hence, the limited scope of the work done on MES in PTE research is noteworthy.

2.3.2 Mobile Energy Storage Projects

Several large MES projects worth mentioning are a Hawaiian company Mana Security and Power which is working to support Hawaii's clean energy initiative of obtaining 100% of its electricity needs from sustainable RES. Moreover, Aggreko also provides MES solutions and operates across London, UK, Berlin, Germany, and Texas while Alfen has also developed multiple mobile energy storage projects over the last few years. A summary of several prominent global MES projects has been provided in Table. 2.1. The solutions in practice are many but are restricted to the region or consumer that they were optimized and designed for.

Customer Categories

A majority of the aforementioned companies such as Mana Security and Power, Aggreko, Alfen, and Greener work with their customers to come up with the ideal plan for their business or residence in order to supply their energy needs while providing some of the benefits that the company is capable of providing as can be seen from the table. For example, Mana Security and Power aim to harness the curtailed energy from renewables,

Table 2.1: Summary of MES projects.

Company	**Ref.**	**MES Project title**	**Services Provided**	**Energy Capacity**
Mana Security and Power	[50]	Mobile Energy Storage on Demand	Support during power outages, and natural disasters. Provide energy savings, demand peak shaving and grid management.	750 kWh
Aggreko	[51]	Y. Cube	Spinning reserve displacement, ramp rate control, load/peak shifting, frequency regulation, energy arbitrage, black-start, UPS, and power factor correction.	610-1187 kWh
Alfen	[52]	The Battery Mobile	Peak shaving, frequency response, SoC control, MG, and backup functionality. Can be utilized for EV charging.	169-422 kWh
Greener	[53]	Mobile Batteries	Peak shaving, and energy profile forecasting.	336 kWh
Axion Power International Inc.	[54]	PowerCube for PJM	Power resource for the PJM regulation market.	250 kWh
Fujian Electric Power Research Institute	[54]	Fujian Electric Power Research Institute MES Station	Provides peak electricity to commercial electricity customers in the tea production industry across multiple locations.	250-375 kWh
Toshiba	[55]	N/A	Voltage regulation and peak shaving in a distribution system.	776 kWh
Mobile Edison	[56], personal communication	Mobile Edison	Serving utilities, commercial/industrial customers, EV parking lots and power producers.	0.5 - 1.3 MWh

while building their own solar farm to generate clean electricity and store it; they capture and store clean energy, then deliver and utilize it. Other companies such as Axion power international inc. provide services to the electric grid itself or regional transmission organizations, where Axion developed a project called PowerCube for PJM (an Regional Transmission Organizations (RTO) in the eastern interconnection grid in the United States). Finally, Power Edison is currently developing the largest mobile energy storage solution to aid electric grids. The MES project consumers can be categorized into 5 major groups:

- Small businesses: as they struggle with expensive energy costs and peak demand charges.
- Schools or hotels or large energy consumers with clear patterns: can provide timely services depending on their most challenging time of day.
- Renewable energy resource owners: aid in avoiding curtailment.
- Residential areas.
- Utilities and electric grids.

MES Ownership

Due to the risk of their high capital costs and on the other hand, the potential benefits they can provide to numerous parties, MES ownership is a matter of debate. Several works that study the functionality and the scheduling of MES systems treat them as isolated entities and do not tackle the ownership query, such as the authors in [38]. As stated in [35] and [36], the authors ascribe MES ownership to the respective distribution systems that employ them. Furthermore, the authors of [39] also attribute ownership to the operators of the distribution networks. By contrast, the work in [47] was conducted with a specific target audience - airports, thus the MES studied was owned by the airport. MES ownership is not a deeply studied matter, and depending on the requirements of the work, ownership is commonly assigned to the distribution system or the DNO, or privately owned by the entity that operates it. Both of these cases, as well as the majority of the available research, attribute MES ownership to the entity that benefits from its services. However, an additional objective of this research presents a novel concept in which MES units are owned by transit authorities and serve both their own internal system and external customers. Depending on the type of ownership, the problem might take on a completely different form; for this reason, it must not be overlooked.

2.4 Game theory in Energy Storage

Several works have tackled the energy storage problem from an optimization perspective [57–59]. In [57], the authors solve the optimization problem using a similar decoupled form approach while in [58] and [59], the hub's structural and operational linear optimization is tackled to understand the energy hubs. Various other techniques have also been used to tackle the energy storage problem, where game-theoretic approaches have been significant in modeling real-life decision-making as shown in [60–62]. In [62], the authors study a scenario where two business owners who own the same energy storage technology want to enter the market together and attempt to develop a decision mechanism concerning who will participate in the energy market and who will participate in the ancillary service market. This can be plainly modeled as a simple competition game and the results were found. Moreover, the authors in [61], study coalitions of homes as well as the grid, and how they interact with each other; how the grid prices energy while the homes purchase it. This is modeled as a Stackelberg game. Finally, in [60], the authors discuss that the energy market could hypothetically be modeled using a Vickrey-Clarke-Groves (VCG) auction model however no methodology is presented. Hence, it is apparent that the energy storage problem is of interest to researchers for multiple reasons and is being resolved using multiple methodologies. Moreover, there is a lot of potential for energy storage problems to be modeled using several game-theoretic approaches however, it is unclear which one is best. Hence, in this research, two approaches will be used, a cooperative one that strives to achieve a correlated equilibrium with the help of a regret matching algorithm, and the second approach is the clinching auction approach. The former cooperative approach has been used in several works such as [63], in the demand side management context in the power industry, however, has not been used in the energy storage discussion as per the authors' knowledge.

2.5 Conclusions and Discussions

In conclusion, public transportation electrification is of significant interest due to its potential positive impact on the environment. Fleet and charger sizing is a topic frequently discussed in the literature and is often approached using optimization and analytical techniques with the objective of minimizing costs while the incorporation of manufacturer's procurement bids is not considered. It should be noted, however, that technology manufacturer agreements and the bidding process are significant factors influencing the decision of transit agencies. To address the above gap, the first objective in this thesis is the development of a methodology for sizing fleets and chargers that is iterative and representative of real-life asset selection and manufacturer cooperation. As soon as asset sizing is determined, another important question arises: when to make purchase decisions in order to meet electrification goals? This necessitates the development of a fleet transition plan. It is common practice to view fleet replacement or transitions from a transportation perspective, ignoring the electrical implications of the issue, creating a gap that is addressed in the second objective of this thesis where a comprehensive transition plan that incorporates the electrical and transportation systems' perspectives is presented. As soon as the transition plan is determined and transit agencies establish a clearer vision of their future, several barriers (financial, technical and electrical) begin to arise that impede the actual deployment of battery electric buses. There are several works in the literature that attempt to address these barriers one by one, such as operating fast charging to reduce driving range anxiety or deploying energy storage to lessen the impact of fast chargers on the grid. However, no comprehensive study has addressed these issues holistically. MES is proposed in this thesis as a comprehensive, fast, and flexible solution to overcome the electrification barriers while providing numerous benefits to both the transportation and electrical systems. As a means of maximizing this acquired asset's potential, MES is not solely operated to serve the transit system, rather its unused capacity is utilized to provide services to external customers, thus providing the transit agency with additional revenue streams. In order to study the interaction between the transit-owned MES and its customers, as a first stage, a transit-owned stationary energy storage hub is modeled using two contrasting game-theoretic approaches, and as a next stage, mobility is added on. Finally, this research presents a practical walk-through of the questions posed by transit agencies as they aim to electrify their systems, addressing numerous questions sequentially creating a novel comprehensive roadmap to public transportation electrification while incorporating MES for additional financial and technical benefits.

Chapter 3

Comprehensive Fleet and Charger Sizing for Public Transportation Electrification Considering Route Assignment

3.1 Introduction

In one of Ontario's most popular transitions to electrified Public Transportation (PT), fleets and chargers were purchased through "combining funding from the Government of Canada, the Province of British Columbia, the City of Brampton and York Region, the Town of Newmarket and additional utility and ***manufacturer in-kind investments in the form of extended operational and maintenance support during the initial launch and post-commissioning phases of the project.****"* [64]

As the PT sector strives for complete fleet electrification, it is imperative to study the sizing of the electric fleet and the chargers used. It is not a transit agency's primary goal to implement the fleet or charger sizing for its routes that minimize expenditure or operating costs, rather, ensuring continuity of service, meeting governmental or industrial funding criteria, etc. are the factors that often drive their purchase decisions. Numerous studies have been conducted to develop algorithms to determine the optimal fleet size based on cost minimization. However, two factors that significantly impact transit agencies' decisions are oftentimes overlooked. The first factor is the detailed route assignment of each Battery

Electric Bus (BEB) to trips, which influences the charging operation. The second factor is that transit agencies, as quoted above by Canadian Urban Transit Research and Innovation Consortium (CUTRIC), take into consideration not only the costs but also funding factors and cooperation prospects with fleet manufacturers when making purchase decisions. Indirectly, BEB manufacturers often provide funding to transit agencies through long-term maintenance agreements, operational support such as crew training, discounts or reduced costs, and other means. For this reason, it is critical to incorporate the manufacturer's procurement bids into fleet and charger sizing. Accordingly, the goals and contributions of this chapter can be summarized as follows:

- Developing an operational-planning fleet and charger sizing methodology while incorporating detailed Electric Bus Energy Consumption (EBEC) and optimal route assignment while ensuring smooth and reliable transit service.
- Developing an iterative process representative of real life for selecting assets based on cooperating manufacturers.

In Section 3.2, a detailed description of the problem is presented, followed by two sections, 3.3 and 3.4, which describe the problem formulation for Day-time (DT) operation of fleets using adopting overnight and opportunity charging modes respectively. The planning or selection process is presented in Section 3.5. Following is the presentation of results in Section 3.6, and the work is concluded in Section 3.7.

3.2 Problem Description

Once the transit agency makes the decision to electrify its routes, one of the first steps in the process is to reach out to BEB manufacturers to better understand the bus and charging technology, and to receive procurement bids. They are then contacted by multiple fleet manufacturers with their offers. The following BEB specifications are gathered from every manufacturer: BEB design, passenger capacity, power and energy rating, capital cost, maintenance and warranty information, lifetime and much more. Once this information is collected, the TA considers three modes of charging: overnight, opportunity and flash charging. While flash charging will occasionally be discussed for completeness, it is beyond the scope of this work.

It is current practice for transit agencies to electrify their fleets route by route so as to not overwhelm both their transit system or their local power distribution network.

Hence, the fleet sizing of every route is studied on its own to ensure that it is able to meet its requirements. However, in order to study the charger sizing there are two aspects to this: chargers placed on the route and chargers placed in the depot. When studying the chargers placed along the route, each route is once again studied individually as routes usually intersect either in large park-and-ride parking lots, large depots, city center parking lots or a city's central station. Due to the large traffic on these locations, each route must ensure that its own charging needs are met, hence it must have its own designated chargers to ensure that emergencies or delays in one route do not impact the continuity of service of another. Additionally, large central stations as discussed above are typically shared by numerous transit agencies, so each TA would rather ensure their own continuity of service. However, when studying charger sizing in the depot where the buses park overnight, it would yield inefficient results to study each route on its own. This is due to the number of hours that buses spend in the depot, allowing for multiple buses to be charged using the same charger. Additionally, each route's fleets do not all leave the depot at the same time and these changes in departure time from the depot can be utilized for charging management. For this reason fleet sizing and on-route opportunity charger sizing are done in a per route manner while depot charger sizing is done for multiple routes owned and operated by the same agency that retreat to the same overnight depot following the end of their service hours. This operational-planning problem formulation is displayed in detail in the following section.

3.3 Operational Problem Formulation

Studying the operation of BEB fleets requires identification of the charging mode, as this determines the operational requirements of the fleet. Furthermore, daytime operations are studied separately from nighttime operations. During daytime operations, each route is analyzed separately to ensure that the fleet's needs are met. At night, however, fleets that serve different routes are all parked at the same depot for recharging to prepare for the following day. For this reason this section is split into the following subsections: Overnight Charging (OVNC) DT operation, Opportunity Charging (OPPC) DT operation, followed by Night-time (NT) depot operation.

In the DT operation, BEB operation is done to ensure the following:

- Routes are assigned to buses, where all routes are served to ensure continuity of service.

- The power consumed by every bus along a route is accurately modeled considering high traffic conditions to account for the worst case scenario.
- In the OVNC mode, BEB State of Charge (SOC) is modeled to ensure that a bus is only assigned trips until its battery has depleted without the possibility of recharging and in the OPPC mode, BEBs are allowed to charge during the day.

In the NT operation, BEB operation and charger sizing is done to ensure the following:

- Each bus is assigned to only one charger overnight.
- Each BEB's arrival time, departure time, arrival and departure SOC is accounted for separately.
- A selection of the charger combination that minimizes expenditure and operating costs.

The BEB sizing is taken care of in the planning formulation.

3.3.1 OVNC Day Time Operation

Overnight charging is one of several fleet charging technologies. This charging practice is characterized by a fleet charging only at night - outside of its operating hours. BEBs operated using this mode of charging typically have larger battery capacities to hold charge for longer periods of time, as well as Slow Chargers (SCs) as they have all night to charge. OVNC is oftentimes selected for real world fleet deployment. The reason for this being that this mode of charging has far fewer technical, practical, and economic limitations. With regards to OVNC, this DT problem is formulated as an optimization problem that minimizes the total cost of the assignment, where the cost of each assignment is the same, as the general characteristics of the buses and trips are the same, so the objective of the problem is to determine the assignment regardless of the cost. Hence, in more accurate terms, this problem is actually a constraint satisfaction problem, formulated as a Mixed Integer Programming (MIP) problem.

The inputs to the DT operation problem are the set of buses, b,and trips, r, as well as an input binary parameter, $aT_{t,r}$, that indicated whether or not a trip is active (being run). $aT_{t,r}$ is 1 if trip, r, is being run at time instant, t. It is noteworthy that even if a trip is being run but a BEB is stopped at a station on its route this $aT_{t,r}$ is 0. Additional inputs from the manufacturers include: the battery energy capacity $E_b^{bat,cap}$ and the battery's discharging efficiency η_b^{dch} for a particular BEB model.

Route assignment constraints

When a known number of buses, b, make a known number of trips, r, the goal is to determine which bus will make which trip. The assignment is represented as a binary variable, $a_{b,r}$, where $a_{1,13}$ indicates that bus 1 was assigned to run trip 13. It is noteworthy to distinguish between routes and trips in this research, where a route is a bus line that travels from a starting location to an end location and back. Each route is run at a frequency predetermined by the transit agency depending on their ridership. If a route is operated from 6:00 am to 8:00 pm every day, with a frequency of every half an hour, this means that this route is run 28 times a day. Hence, this route has 28 round trips.

The major route assignment constraints are displayed in equations (3.1)-(3.3). In order to prevent service interruptions, constraint (3.1) ensures that every trip is served by one bus. In (3.2), a binary variable, $inR_{b,t,r}$, is calculated to indicate whether bus b is on trip r at time t. The next constraint in (3.3) ensures that each bus serves no more than one route at any given time.

$$\sum_{b} a_{b,r} = 1 \tag{3.1}$$

$$inR_{b,t,r} = a_{b,r} aT_{t,r} \tag{3.2}$$

$$\sum_{r} inR_{b,t,r} \leq 1 \tag{3.3}$$

SOC constraints

The next set of constraints governs the BEB SOC. It is important to note that the EBEC for every trip along a trip is modelled as power consumption at every time instant $P_{t,r}^{rdch,profile}$. This is known in advance because which trip runs at which time is known. Additionally the binary variable $a_{b,r}$ assigns trips to BEBs, hence the power consumed by a BEB at any time is governed by whether it is running a trip r and the power consumed along that trip. This is formulated in (3.4) and (3.5),

$$bP_{b,t,r}^{dch,profile} = P_{t,r}^{rdch,profile} a_{b,r} \tag{3.4}$$

$$P_{b,t}^{dch} = \sum_{r} bP_{b,t,r}^{dch,profile} \tag{3.5}$$

where $bP_{b,t,r}^{dch,profile}$ is the power consumed by bus b at time t running trip r, and when summed over the set of trips r, can be used to determine the power consumed by the BEB and discharged from its battery at every time instant, $P_{b,t}^{dch}$. The battery action is presented in equations (3.6) and (3.7), where the battery discharging governs its SOC. It is noteworthy that charging power is not modeled into this equation since the BEB is not allowed to charge during the day and the time step is in minutes.

$$SOC_{b,t}^{day} = SOC_{b,t-1}^{day} - 100\frac{P_{b,t}^{dch}\Delta t^{day}}{\eta_b^{dch}E_b^{bat,cap}}, \forall t \geq 2 \tag{3.6}$$

$$SOC_{b,1}^{day} = SOC0_b - 100\frac{P_{b,1}^{dch}\Delta t^{day}}{\eta_b^{dch}E_b^{bat,cap}} \tag{3.7}$$

$$SOC_{b,t}^{min} \leq SOC_{b,t} \leq SOC_{b,t}^{max} \tag{3.8}$$

$SOC_{b,t}^{day}$ is the BEB's SOC at every time instant, while $SOC0_b$ is the SOC at the beginning of the day, in other words, it is the SOC that it leaves the depot with and is an input to the problem. Finally constraints (3.8) presents the upper and lower SOC limits. In a webinar held by CUTRIC, the Toronto Transit Commission (TTC) discussed that in practice, its fleets alarm the drivers twice: when the SOC reaches 12% and 7% alerting them to retreat to their depot, however, a minimum SOC of 15% is set in this problem to allow for leeway in operation and to maintain battery life.

3.3.2 OPPC Day Time Operation

In the opportunity charging mode, the BEBs are charged during the day, whenever the opportunity arises. Rather than pre-determining the number or location of the opportunity chargers placed along the route, in this formulation the BEBs are operated as discussed previously, where they are assigned routes, with the only difference being: they are now allowed to charge at any time instant in which they are not in operation. Then, based on the results, the time instances in which a BEB charges can then be mapped to a location and this location is then selected for charger placement.

The goal of this problem is to determine the optimal assignment of buses while allowing them to charge, as well as respecting the state of charge constraints. Equation (3.6) that was utilized to determine the BEB's SOC when it was not allowed to charge, is modified as shown in (3.9) to reflect that the BEBs are now allowed to charge during the day.

SOC constraints

$$SOC_{b,t} = SOC_{b,t-1} + 100\Big(P^{ch}x_{b,t}^{ch}\eta_b^{ch} - \frac{P_{b,t}^{dch}}{\eta_b^{dch}}\Big)\frac{\Delta t^{day}}{E_b^{bat,cap}} \tag{3.9}$$

P^{ch} is a parameter indicating the power rating of the charger selected along this route, hence also dictating the power used to charger the BEB on its route. $x_{b,t}^{ch}$ is a binary variable that is 1 when bus b is charging at time t. η_b^{ch} is the charging efficiency of bus b. In order to ensure that a BEB is only charging or discharging (in its route) at everytime instant an equation can be added as follows: $x_{b,t}^{ch}P_{b,t}^{dch} = 0$, however this would add non-linearity to the problem, making it a Mixed Integer Non-Linear Programming (MINLP). To avoid that, equations (3.10) and (3.11) were introduced, where (3.10) states that binary variable $x_{b,t}^{dch}$ is 1 whenever the bus is running a route and the equation (3.11) ensures the exclusivity of the charging and discharging events.

$$\sum_r inR_{b,t,r} = x_{b,t}^{dch} \tag{3.10}$$

$$x_{b,t}^{ch} + x_{b,t}^{dch} \leq 1 \tag{3.11}$$

$$sw_{b,t}^{on} - sw_{b,t}^{off} = \begin{cases} x_{b,t}^{ch} - x_{b,t-1}^{ch}, \forall t \geq 2 \\ x_{b,t}^{ch}, t = 1 \end{cases} \tag{3.12}$$

Finally, equation (3.12) assigns values to the binary variables $sw_{b,t}^{on}$ and $sw_{b,t}^{off}$ where $sw_{b,t}^{on}$ is 1 when at the first time instant when a BEB begins charging and 0 otherwise, and $sw_{b,t}^{off}$ is 1 at the first time instant the BEB stops charging. These are utilized to evaluate the number of charging events by each bus and play a role in allowing this formulation to be adaptable to opportunity and flash charging modeling.

Objective function

Where for the overnight charging, the problem was formulated as a constraint satisfaction problem, with the only objective being to satisfy the assignment and no explicit objective function involved, this is not the same for opportunity charging. For opportunity charging the objective of this problem is as follows:

$$\min C^{ch,op} = \sum_{b,t} \Big(\underbrace{C^{conn}_{b,t} sw^{on}_{b,t} + C^{dconn}_{b,t} sw^{off}_{b,t}}_{\text{Daily charging events}} + \underbrace{C^{grid}_{t} P^{ch}_{b,t} x^{ch}_{b,t} \Delta t^{day}}_{\text{Daily cost of charging}} \Big) \tag{3.13}$$

$$\text{s.t. } (3.1) - (3.12)$$

Since this problem studies OPPC, the objective function is designed to minimize the cost of charging during the day as seen by the "cost of charging" term in the objective, where C^{grid}_t is the cost of purchasing energy from the grid in \$/kWh as well as to minimize the number of charging events to encourage the BEBs to charge for longer periods but less instances. Here $C^{conn}_{b,t}$ and $C^{dconn}_{b,t}$ are the cost of connecting and disconnecting to a charger. There are many ways that the objective function of this problem can be selected to meet the needs of the transit agency. For instance only the "cost of charging" could have been included, and this would be beneficial for systems that utilize flash charging, as the BEBs are encouraged to charge frequently and for short periods of time. Flash charging in this case can be viewed as a special case of opportunity charging, where BEBs are allowed to charge at any time instant as long as it respects equation (3.11). However, in this scenario, opportunity charging is utilized, where the BEBs are encouraged to charge only during their dwelling and recovery times and the formulation of the objective in this way allows for a smooth way to do so.

3.3.3 Night Time Operation

NT operations and charger sizing can be done in 2 ways: assume that the number of chargers installed at the depot are equal to the number of parking spots and consider performing smart charging a a future step, or to install sufficient chargers that implicitly utilize smart charging when they are sized where one charger can charge multiple buses, [13]. The formulation presented below sizes the chargers based on the assumption that the Transit Agency (TA) has sufficient overnight crew to move the BEBs between chargers, and hence the chargers are sized to ensure that BEBs are sufficiently charged while minimizing the cost of purchasing chargers. The NT operation takes in the following inputs from the DT operation: the number of BEBs operating each route, every BEB's arrival and departure time from the depot, every BEB's SOC at the time of its arrival at the depot and the requires SOC upon departure. It then proceeds to determine the optimal charger sizing to charge these BEBs overnight.

SOC constraints

The BEB SOC is modeled as shown below where discharging power is not included as at the overnight depot, the bus is parked and switched off hence no discharging is taking place:

$$SOC_{b,t}^{night} = \begin{cases} SOC_{b,t-1}^{night} + 100\frac{P_{b,t}^{ch,depot}\Delta t^{night}\eta_b^{ch}}{E_b^{bat,cap}}, \forall t \geq 2 \\ SOC_b^{eod} + 100\frac{P_{b,t}^{ch,depot}\Delta t^{night}\eta_b^{ch}}{E_b^{bat,cap}}, t = 1 \end{cases} \tag{3.14}$$

Given that not every bus begins its daily routes at the same time, constraint (3.15) is formulated to ensure that every bus b is charged to a minimum required SOC to depart SOC^{depart}, by the time it needs to go. In order to do this, a binary parameter is input to the problem, $T_{b,t}^{leaving}$ that signals when a bus will be leaving the depot the next morning for the start of its daily trips. For example, $T_{1,10}^{leaving} = 1$ indicates that bus 1 will be leaving the depot at time 10. The rest of the entries for bus 1, $T_{1,1}^{leaving}, T_{1,2}^{leaving}, T_{1,3}^{leaving}$... are 0.

$$SOC_{b,t}^{night} \geq SOC^{depart} T_{b,t}^{leaving} \tag{3.15}$$

Charger assignment constraints

The following set of constraints govern the BEB assignment to chargers. Here $a_{b,cn}^{charger}$ is a binary assignment variable that is 1 when bus b is assigned to charger cn. cn is the set of charger selections where each charger cn has its own capital cost $C_{cn}^{ch,cap}$ and power rating $P_{cn}^{ch,rat}$. Equation (3.16) ensures that each BEB must be assigned to only 1 charger and equation (3.17) ensures that the charging power of each BEB at every time instant, $P_{b,t}^{ch,depot}$ is less than the rated power of the charger it has been assigned to.

$$\sum_{cn} a_{b,cn}^{charger} = 1 \tag{3.16}$$

$$P_{b,t}^{ch,depot} \leq \sum_{cn} (a_{b,cn}^{charger} P_{cn}^{ch,rat}) \tag{3.17}$$

Constraint (3.18) assigns a value of 1 to the binary identifier $x_{b,t}^{ch,depot}$ when a BEB is charging at that time instant, where M is an arbitrarily large number.

$$P_{b,t}^{ch,depot} \leq M x_{b,t}^{ch,depot} \tag{3.18}$$

Constraint (3.19) assigns values to the binary variable $iU_{b,cn,t}$ which determines whether a charger is in use or not; this is 1 when bus b is charged by charger cn at time t. Equation (3.20) ensures that at every time instant, every charger is charging one bus or less.

$$a_{b,cn}^{charger} x_{b,t}^{ch,depot} = iU_{b,cn,t} \tag{3.19}$$

$$\sum_{b} iU_{b,cn,t} \leq 1 \tag{3.20}$$

The following constraint in (3.21) ensures that a BEB only begins charging after its arrival time at the depot, $t_b^{dep,arr}$. Equation (3.22) follows the same logic as (3.18), where b_{cn}^{ch} is a binary variable indicating if charger cn is utilized over the course of the night. This constraint is added to determine which of the chargers in set cn is utilized and is used in the objective function to minimize the chargers used. Finally, equation (3.23) determines the total load profile of all the chargers at the depot.

$$x_{b,t}^{ch,depot} = 0, \forall t \leq t_b^{dep,arr} \tag{3.21}$$

$$\sum_{b} a_{b,cn}^{charger} \leq M b_{cn}^{ch} \tag{3.22}$$

$$P_t^{L,depotch} = \sum_{b} P_{b,t}^{ch,depot} \tag{3.23}$$

Power system constraints

The final set of constraints are the real and reactive power flow constraints, and voltage and power limits as seen in (3.24) to (3.27).

$$P_{o,t}^{G} - P_{o,t}^{L} - z_o^{depotch} P_t^{L,depotch} = V_{t,o} \sum_{p}^{N_{bus}} V_{t,p}(G_{o,p} cos(\delta_{t,o} - \delta_{t,p}) + B_{o,p} sin(\delta_{t,o} - \delta_{t,p})) \tag{3.24}$$

$$Q_{o,t}^{G} - Q_{o,t}^{L} = V_{t,o} \sum_{p}^{N_{bus}} V_{t,p}(G_{o,p} sin(\delta_{t,o} - \delta_{t,p}) - B_{o,p} cos(\delta_{t,o} - \delta_{t,p})) \tag{3.25}$$

$$V_o^{min} \leq V_{o,t} \leq V_o^{max} \tag{3.26}$$

$$P_o^{G,min} \leq P_{o,t}^{G} \leq P_o^{G,max} \tag{3.27}$$

Objective function

Once the fleet size is determined, the night time operation describes how the optimal depot chargers are selected. This is formulated as a MINLP problem, with the objective function as shown below:

$$\min \sum_{b,t} (\underbrace{N^{year} C_t^{grid} P_{b,t}^{ch,depot} \Delta t^{night}}_{\text{Annual cost of charging}}) + \underbrace{\sum_{cn} (AW^{ch} C_{cn}^{ch,cap} P_{cn}^{dch,rat} b_{cn}^{ch})}_{\text{Annualized capital cost of chargers}} \quad (3.28)$$

$$\text{s.t. } (3.14) - (3.27)$$

N^{year} is the number of nights in a year, C_t^{grid} is the cost of purchasing energy from the grid, and AW^{ch} is the capital recovery factor used to annualize the capital cost of purchasing chargers. With regards to night time charging at the depot, the same formulation is utilized for both overnight and opportunity charging. The only difference between both formulations is that during the day, BEBs may choose to charge during their recovery or dwelling time at the depot. For this reason, if any DT chargers were selected for placement at the depots, this allows for an additional constraint to be included in the formulation to ensure the inclusion of this charger when performing depot charger sizing as follows. If charger 3 (as per its specifications) was selected for DT OPPC, constraint $b_3^{ch} = 1$ would be added to clarify that this charger must be purchased at the depot.

3.4 Planning Problem Formulation

When planning for their transit system electrification, TAs send out requests for proposals with their minimum required criteria and the BEB manufacturers then return bids or tenders and finally, the TA determines their final contracts [65, 66]. The planning procedure is done in 2 phases, the first phase determines the most economical option of the following:

- Which manufacturer will be awarded the contract.
- The number of BEBs purchased per route.
- The number of on-route and depot chargers required for DT charging when utilizing the OPPC mode.

The outputs of this phase are then input into the next phase: the NT operation formulation which determines the charging schedules of the fleet through the night and the sizing of depot chargers.

In order to determine the aforementioned outcomes of the DT operational-planning formulation, the procedure utilizing in Fig. 3.1 is followed where N_{pb} is the number of procurement bids or tenders submitted to the TA by the technology manufacturers, N_{ro} is the number of routes to be electrified, N_{eb} are the number of different Fast Charger (FC) rated capacities considered for OPPC. Finally, N_b is the number of BEBs input to the problem.

In the OVNC formulation the outcome is a three dimensional parameter $C^{ann}_{pb,ro,b}$ that encapsulates the annualized cost of purchasing and operating BEBs during the day when using OVNC. For clarification, $C^{ann}_{1,2,5}$ carries the annual cost of awarding manufacturer 1 the contract to electrify route 5 by purchasing 5 BEBs. This is calculated as follows:

$$C^{ann}_{pb,ro,b} = AW^{BEB} N_b C^{BEB,cap}_{pb} + N_b C^{BEB,op}_{pb,ro} \tag{3.29}$$

$C^{BEB,cap}_{pb}$ is the capital cost of purchasing BEB from manufacturer pb and $C^{BEB,op}_{pb,ro}$ is its operating cost when running route ro. $C^{BEB,op}_{pb,ro}$ is calculated as $C^{BEB,cap}_{pb} K_{ro} PC^{cap}$, where K_{ro} is a factor for every route that accounts for topology impact however, is assumed as unity in this work [24, 67]. Finally, AW^{BEB} is the annualization factor or capital recovery factor converting the capital costs to annual amounts.

For the OPPC formulation, the DT operation has an additional component, the chargers utilized during the day. Hence, the outcome is a four dimensional parameter $C^{ann}_{pb,ro,eb,b}$ that accounts for the charger selection as seen in (3.30), where $C^{ch,op}$ is as determined in equation (3.13) and N^{days} is the number of days per year.

$$C^{ann}_{pb,ro,eb,b} = AW^{BEB} N_b C^{BEB,cap}_{pb} + N_b C^{BEB,op}_{pb,ro} + AW^{ch} NE_{eb} EC_{eb} C^{ch,cap}_{eb} + N^{days} C^{ch,op} \tag{3.30}$$

The selection process

Once all the costs are determined, it is now time for the selection process to determine the manufacturers to be awarded the contracts. For the OVNC methodology, the selection process can be visualized as seen in Fig. 3.2. There are 2 different ways of making the selection process. As seen on the left side, each route can be viewed separately: for example, when viewing the results for route 1 it can be seen that for manufacturer 1 with procurement bid (PB) ID 1, route 1 requires at least 6 BEBs at a high cost, while with PB

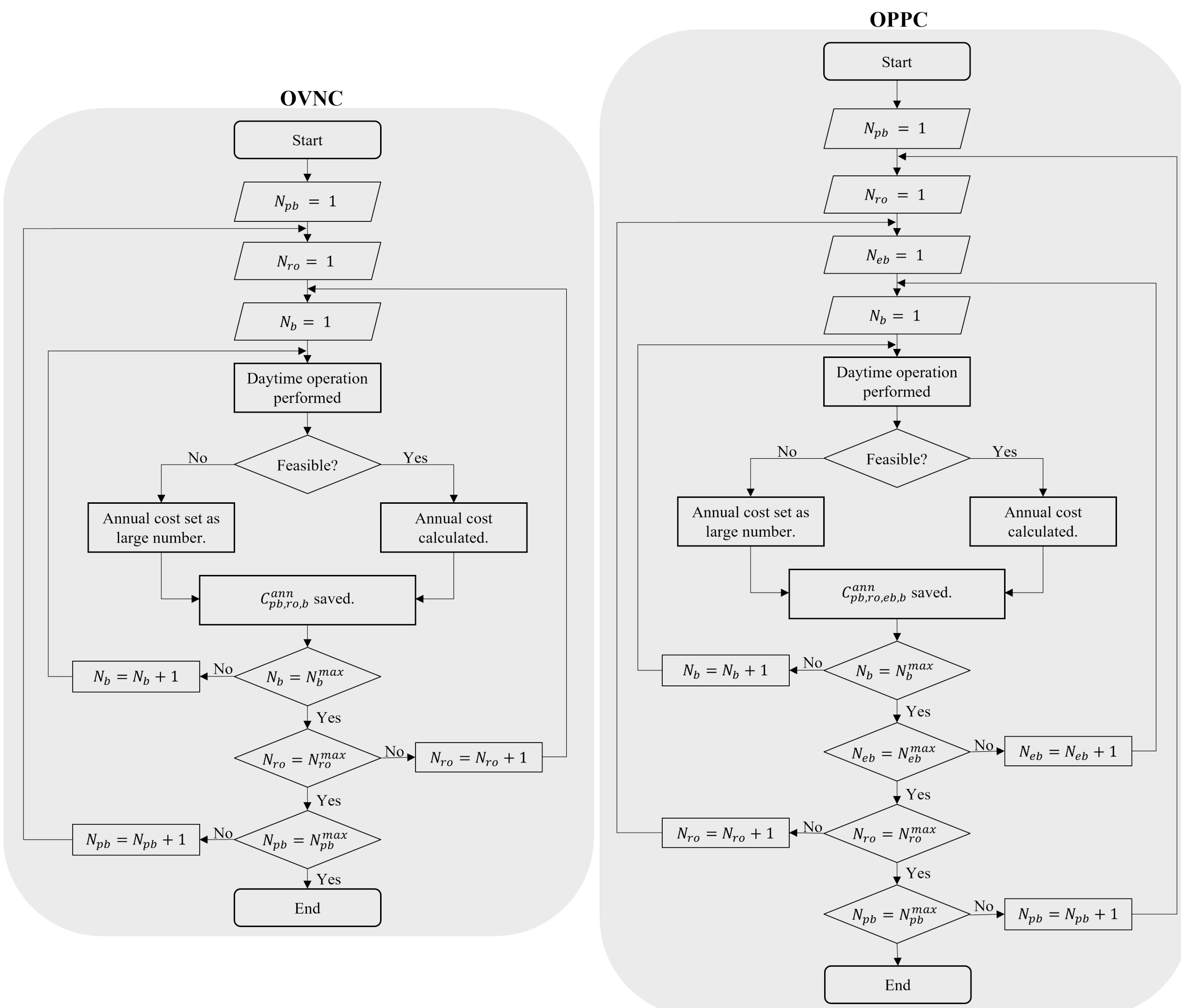


Figure 3.1: DT operational-planning formulation.

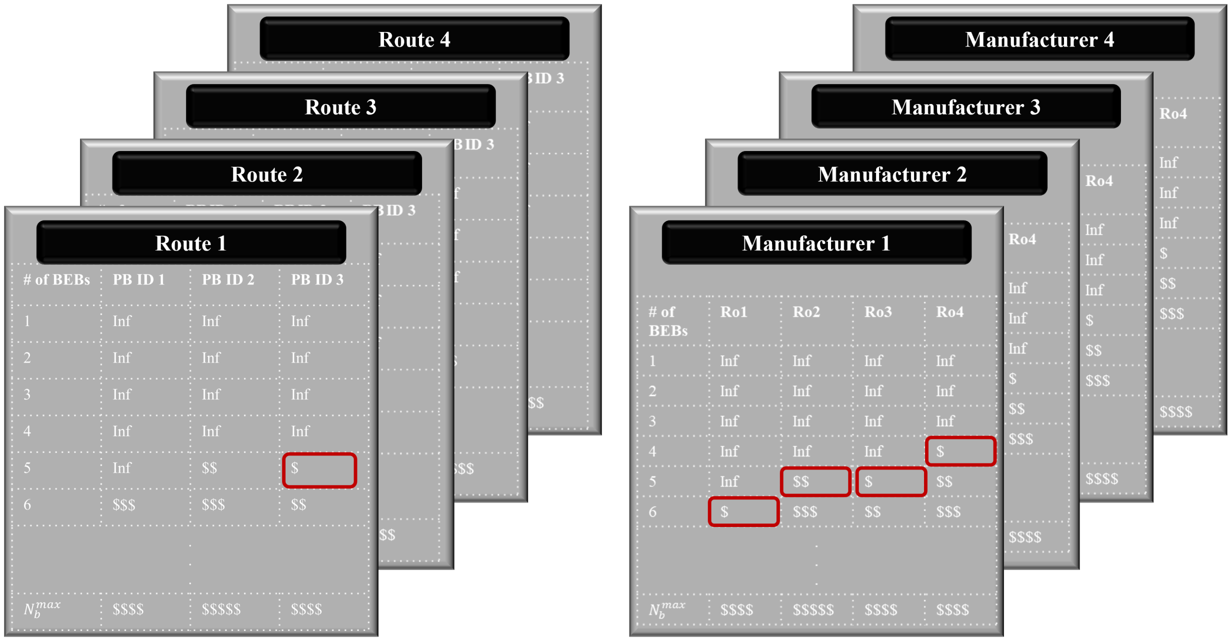


Figure 3.2: Outcome of the planning methodology for OVNC.

ID 2 at least 5 BEB are needed at a moderate cost, and finally for PB ID 3, 5 BEBs are needed at a low cost. Hence, the contract for route 1 is awarded to manufacturer 3 with PB ID 3 and the same procedure is done for every route and the total cost of electrifying the routes becomes the sum of those selections. The alternate selection process involves looking at each manufacturer separately as seen on the right side of Fig. 3.2. Here it can be seen that each manufacturer is studied separately, hence it can be seen that to operate route 1 using manufacturer 1's BEBs at least 6 BEBs are needed, 5 are needed for route 2 and 3 each and 4 are needed for route 4. Hence the total cost of electrifying these 4 routes with manufacturer 1 is the summation of these costs. Once that is determined for each PB ID, the manufacturer with the lowest total cost is selected. For the OPPC, the same is done for the opportunity FC selected as well. The final step after the selection process is to input the results to the NT operation formulation to determine the depot sizing. The outcome is now the fleet and charger sizing to ensure DT operation and finally, the optimal depot sizing to ensure NT operation.

3.5 Case Study and Results

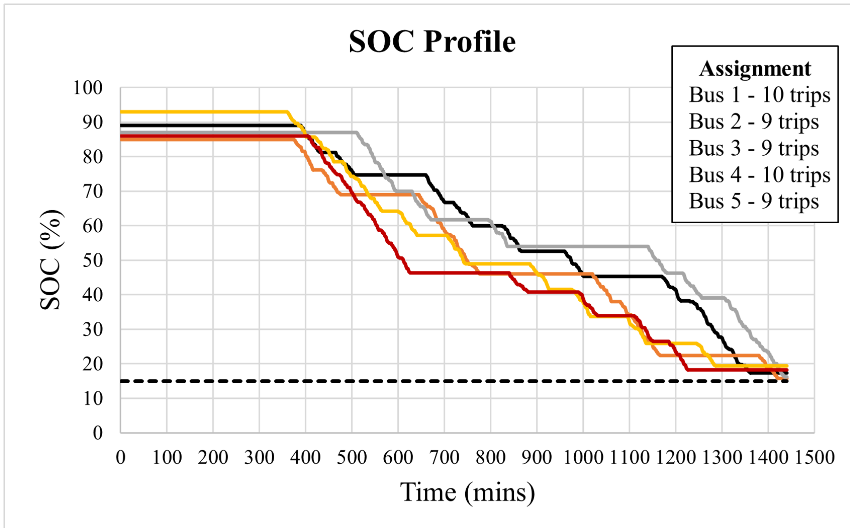
This fleet and charger sizing problem utilizing both OVNC and OPPC was tested on four short distance routes representative of real-world Canadian transit routes from the city of Brampton. The details of the route can be seen in Table. 3.1. The current fleet is operated by 20 conventional diesel buses, all assumed to be parked at the same depot at the end of the day. The formulated, MIP, MINLP problems are formulated and solved using GAMS [68], while the planning formulation and selection process have been modeled in Matlab. The minimum allowable SOC permitted in this research is 15% as previously mentioned to account for weather, route topology, driver behavior and to minimize severe battery depth of discharge which would reduce lifetime.

Table 3.1: Route Parameters

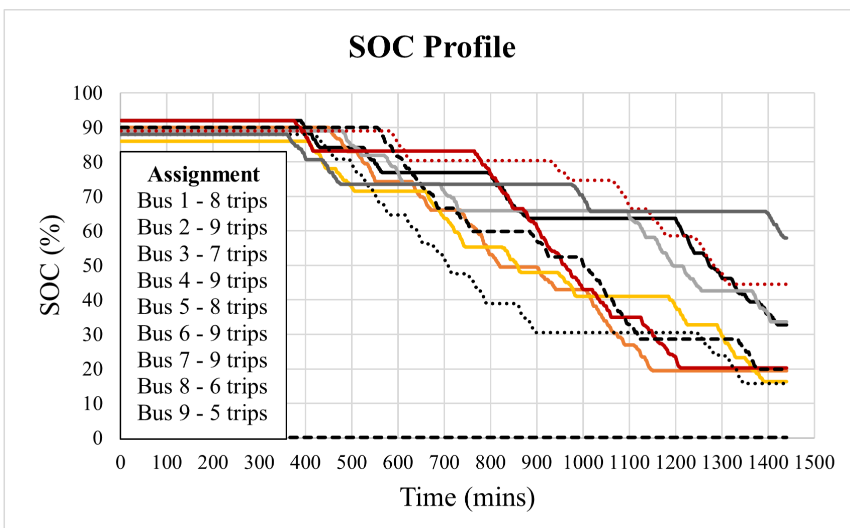
Parameter	**Value**
Number of routes	4
Daily trips per route	70
One way trip length	5.5 km
Number of stops per trip	18
Present diesel fleet per route	5 buses

Daytime Operation with OVNC

When utilizing OVNC is it clear from the results that the BEBs are not allowed to charge during the day. This is visible in Fig.3.3a and Fig.3.3b where the BEB's SOC is strictly decreasing hence indicating that its energy is only being consumed and it is not being recharged. When constraint (3.1) is relaxed to an inequality, and the same number of conventional buses are deployed: 5 BEBs are deployed to run a route without being allowed to charge during the day, the results are as seen in Fig. 3.3a. The buses are depleted to the minimum of 15% SOC and are assigned to a total of 47 trips, leaving 33% of the trips unassigned and hence service continuity is heavily impacted. However, when run with 9 BEBs, all routes are served.



(a)



(b)

Figure 3.3: SOC profiles of OVNC with a) 5 BEBs. b) 9 BEBs

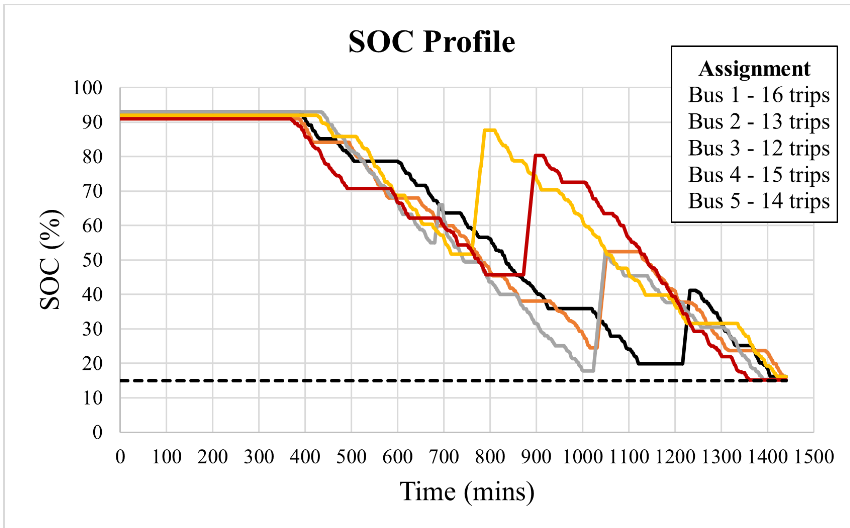


Figure 3.4: SOC profile for opportunity charging for Route 1.

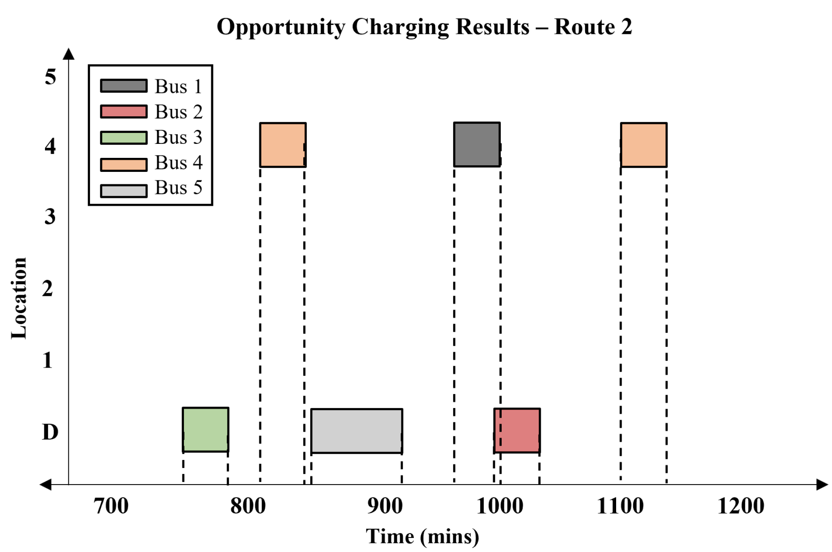


Figure 3.5: Opportunity charging results for Route 2.

Table 3.2: Summary of opportunity charging instances - Route 2.

Variable	**Bus 1**	**Bus 2**	**Bus3**	**Bus 4**	**Bus 5**
Number of charging instances	1	1	1	2	1
Charging location	EOR	D	D	D/EOR	D
Start time (mins)	994	981	763	829/1110	845
End time (mins)	1014	1002	786	837/1122	887
Total charging time	20 mins	21 mins	23 mins	20/12 mins	42 mins
SOC before chg.	26.22%	32.04%	58.02%	41.30% / 15.73%	35.02%
SOC after chg.	51.51%	60.99%	87.30%	47.83% / 29.045%	89.95%
Trips served	14	13	13	13	17
End of day SOC	15.01%	16.58%	18.12%	15.44%	15.02%

Daytime Operation with OPPC

Contrary to OVNC, when utilizing OPPC, the BEBs are allowed to charge during the day. The way in which this formulation was set up encourages opportunity charging for fewer instances but for longer durations. Hence, it is clear from the SOC profiles presented in Fig. 3.4 that the BEBs are charged during the day and their SOC profiles are no longer strictly decreasing, rather they increase indicating charging events. It is also clear that due to the formulation which aims to minimize cost of charging during the day that these BEBs do not charge unnecessarily, rather they only charge for a sufficient duration to allow them to operate their remaining assigned trips.

Along each four route, 6 potential charging locations are identified: these are the 6 stops at which a bus must stop along the route. For Route 2 presented, the depot is the starting location of the route - meaning this route does not have a headway drive, it passes by its depot at the end of each trip. Hence, the 6 locations identified as potential charging locations for Route 2 are as follows: D referring to the depot, locations 1, 2 and 3 depict stops along its route where only the buses running this route stop. Location 4 is the final stop along the route before it starts its journey back. Finally, location 5 is a stop along the route that is served by multiple bus lines/ routes. A depiction of the charging events by time and location for Route 2's 5 BEBs is shown in Fig. 3.5 and Table. 3.2. It can be seen here that 3 out of the 5 buses running this route opted to charge exclusively at the depot, because this is the location they are stopped at for the longest period of time

Table 3.3: Fleet and charger sizing for all 4 routes.

Variable	**OVNC Result**	**OPPC Result**
BEB rated capacity (kWh)	313	313
Number of BEBs	36	20
On-route FCs rated capacity (kW)	N/A	250
Number of on-route FCs	N/A	4
Depot SCs rated capacity (kW)	75	75
Number of depot SCs	28	0
Depot FCs rated capacity (kW)	250	250
Number of depot FCs	0	5

and so the average of 20 minutes of charging would allow them a significant enough boost to keep operating the line. BEBs 1 and 4 chose different charging locations, with bus 1 charging at its End of Route (EOR) and bus 4 charging once at the depot and once at the EOR. For bus 4, it can be seen that due to this location being at the end of its journey, it does not have the luxury to stay and charge for extended periods of time, hence it is only capable of at most a 12 minute charging window before it has to make its way back.

Additionally as seen from Fig. 3.5, there is one occurrence of two BEBs choosing to charge at the same time however, each one is at a different location. Hence, using the aforementioned analysis methods, it is confirmed that 2 FCs were needed to operate this route seamlessly; one at the depot and one at the final stop on this route. Finally, the final results for fleet and charger sizing are as seen in Table. 3.3.

3.6 Conclusion

In this chapter an operational-planning model has been formulated to determine the optimal fleet and charger sizing depending on a TA's preferred mode of charging. The proposed model takes into account the real-world methodologies for fleet selection, where TAs send out requests for proposals which are then met by procurement bids or tenders by multiple BEB manufacturers. A selection process that accounts for these practical interactions is modeled, without being computationally heavy. Accurate operational formulation is embedded into the planning modeling, where realistic day time operations that account for detailed EBEC profiles, route assignment are also modeled.

This chapter builds the foundation for the rest of the discussions presented in this thesis. Once the optimal fleet and charger sizing is determined, it becomes very clear that all these changes cannot happen at once, rather they must be phased. The most resilient way in which this transition or phasing can be performed is to perform the study in blocks. The routes that originate or are run from the same depot are transitioned in phases to ensure that the diesel buses that are still early in their lifetime are not simply discarded and to allow for a route to be operated using a diversified fleet to ensure consistent smooth service till a route is completely transitioned. This operational-planning problem is utilized in multiple stages of this thesis and acts as part of the input to the problems discussed in Chapters 4 and 5.

Chapter 4

Integrated Utility-Transit Model for a Comprehensive Transition Plan for Battery-Electric Bus Fleets

4.1 Introduction

As stated by Toronto Transit Commission's head of vehicle programs:

"There's no bus, by any manufacturer, that's been in service for the entire life of a bus, which is 12 years... And so really, until then, we don't have enough experience, nor does anyone else in the industry, have enough experience to commit to an all-electric fleet ***immediately****."* [69]

Electrification of public transportation is a global trend, but one major question remains: when? By delaying electrification a few years, transit agencies will be able to purchase at reduced prices, but during this time fuel prices will continue to rise, carbon taxes will increase, and the government will place more pressure on cities to go electric. Due to the electric nature of the new fleets, the immaturity of the Battery Electric Bus (BEB) technology, and lack of real-world data from implemented case studies, multiple parties have to deal with operational challenges and are unable to take the step forward to commit as seen above. These include transit agencies, as they are tasked with replacing a smoothly running system, electrical distribution companies, as BEBs exacerbate the electrical distribution system's problems, as well as a wide variety of stakeholders, including

BEB manufacturers and bus drivers. Accordingly, a detailed and comprehensive analysis is crucial to assessing the prospects for a world where most public transportation will be electric.

It is therefore necessary to develop a transition plan that determines when it is most appropriate to make the purchase decision and to allow for stakeholders to take the time to study pilot projects that are currently in place. It is imperative that the transition plan be comprehensive and realistic, accounting for budgeting constraints, purchase costs and salvage costs, in order to ensure that public transit agencies are able to electrify their fleets in collaboration with their local grids in a manner that integrates the perspectives of the transit and electric systems. There exists limited research that postulates a convergence between both systems' perspectives and goals. Hence, motivated by this research gap the goals of this chapter can be summarized as follows:

- Developing a BEB operational-planning approach that performs fleet sizing, charger sizing and route assignment to ensure that the BEBs electrified system meets the demands previously met by the traditional system.
- Developing a novel, comprehensive, transition plan for Transit Agencies (TAs) interested in electrifying their existing bus fleets considering multiple modes of charging, while incorporating the perspectives of the transportation and electrical sectors.

The following sections entail the system architecture in section 4.2, the modeling of the electric bus energy consumption profiles in section 4.3, which is fundamental to generating accurate results and facilitates the detailed modeling of the rest of this thesis. The overall transition approach is performed in two stages: the input stage and transition stage, discussed in sections 4.4 and 4.5. It is noteworthy that the purpose of Chapter 3 was the development of an operational-planning fleet and charger sizing methodology. The aforementioned methodology constitutes a part of the input stage of the transition approach presented in Chapter 4. Finally, the results of the study, and conclusions are presented in section 4.6.

4.2 System Architecture

This transition framework is designed to provide transit agencies with a comprehensive plan for replacing their existing fleets with BEB fleets in order to meet a target deadline

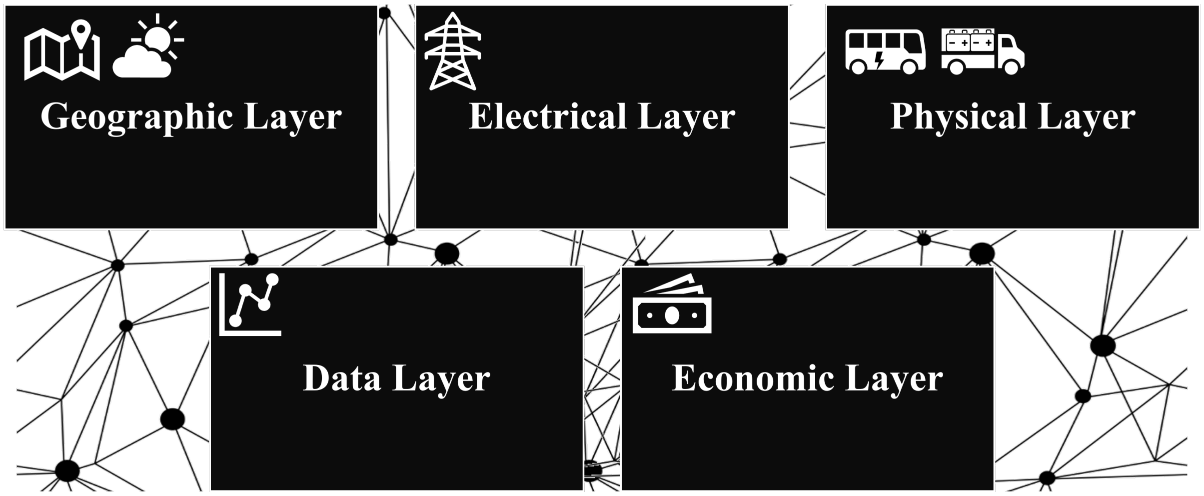


Figure 4.1: Inter-operable system layers.

with multiple smaller milestones along the way. For the generation of this plan, it is therefore important to establish a good system architecture. There are five inter-operable layers in the system described in this work as seen in Fig. 4.1: geographical, electrical, physical, data, and economic. All system maps, descriptions of transportation systems, weather conditions, and traffic data are contained in the geographical layer. Fig. 4.2 illustrates the utility-transit system model, which combines the electrical layer with the geographical layer. To do this, the power distribution network is overlaid onto the geographical network. The physical layer contains information regarding all physical components of the system, as well as market models of diesel buses, BEBs, and charger technology. All components of the physical layer are modeled in the data layer, with the electric bus energy consumption being the most significant aspect, which will be discussed in the following section. Finally, the economic layer encapsulates the system's costs, such as capital expenditures, retirement costs, and operating and maintenance expenses. These inter-operable layers allow a detailed analysis of the problem to be conducted.

4.3 Electric Bus Energy Consumption Modeling

To effectively plan, deploy, and coordinate electric bus fleets and the charging infrastructure they require, an accurate calculation of their energy consumption is essential. In addition to providing motive power, electric buses require energy to support their heating, ventilation, and air conditioning (HVAC) systems and to power auxiliary loads such as lighting. This section discusses the fundamental framework upon which all research on

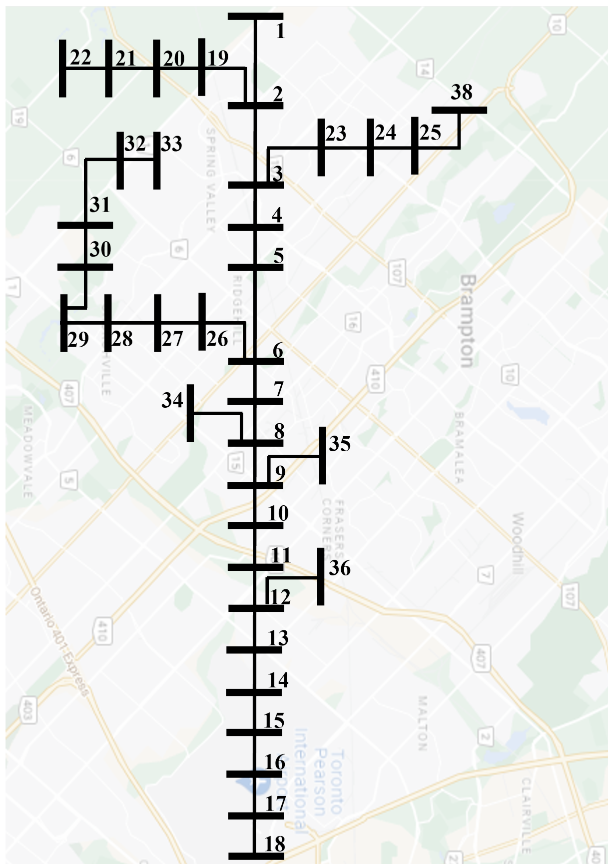


Figure 4.2: Utility-transit system model.

Electric Bus Energy Consumption (EBEC) is based.

EBEC profiles are based on two fundamental physical principles: Newton's second law of motion, which is used to model the traction energy of a bus and the first law of thermodynamics, which accounts for the BEB's HVAC system. To make sure electric bus energy consumption is accurately modeled, several factors are taken into account and so the energy consumed by a bus, E_{BEB}, is broken down into three major components as modeled in equation (4.1), [70]. The amount of energy consumed by the traction of the bus can be calculated as $E_{Traction}$ which is shown in equation (4.2) where $F_{Traction}$, is the traction force necessary to propel the bus over the distance it travels, $D_{Traction}$. Lastly, all energy consumed by the air conditioning and heating of the bus is accounted for in E_{HVAC} [34]. Lighting, radio, and other energy-consuming loads are all integrated in E_{Aux} [70].

$$E_{BEB} = E_{Traction} + E_{HVAC} + E_{Aux} \tag{4.1}$$

$$E_{Traction} = F_{Traction} D_{Traction} \tag{4.2}$$

$$F_{Traction} = F_{acc} + F_a + F_r + F_s \tag{4.3}$$

In order for the bus to move at a speed, v, the traction force required to do so must overcome four opposing forces as described in (4.3): F_{acc}, the force required for the BEB to change its speed or accelerate which is calculated as mv', F_a as shown in (4.4) which is the braking power or the drag force caused by air resistance, F_r in (4.5) which is the rolling friction force and F_s in (4.6), the force required for the bus to travel uphill on a road of inclination ϕ [70,71].

$$F_a = 0.5\rho v^2 C_d A_f \tag{4.4}$$

$$F_r = mgC_r(cos\phi) \tag{4.5}$$

$$F_s = mg(sin\phi) \tag{4.6}$$

where ρ is the air density (1.3 kg/m^3), C_d, A_f and C_r are the aerodynamic coefficient, the bus's frontal area, and the rolling resistance coefficient respectively. Across a known route, the number of stops, distances between stops, total trip distance, slope, speed, average time to get from one stop to the next, average length of the whole trip, as well as dwelling times - how long a bus stops at each stop location - are known. Nevertheless, numerous variables are unknown for every journey along a particular route.

The above equations demonstrate that the tractive force calculation has six unknowns: traffic lights, stops, acceleration profiles, mass profiles, HVAC profiles and velocity profiles. The probability of a bus stopping at each traffic light along a route is expressed as a binomial distribution function. Additionally, the passenger arrival process at the bus stations, which determines whether or not a bus will stop at a designated stop, is modeled as a homogeneous Poisson process with an average arrival rate λ_m. Here λ_m depends on time of day, location of the bus stop, and nature of the route (connecting universities, connecting downtown with major commercial centers, etc.). This concept is thoroughly researched in the transportation industry and is incorporated into this model. Mass is calculated as the combined weight of the bus, as well as the passengers when the bus is full, thereby assuming worst case scenario. In order to account for variations in driver behavior, a factor has been added to account for a driver's efficiency depending on the time of day, the weather conditions, and finally their individual differences; driving style and psychological state. A driver's behavior can account for large variations in energy consumption, therefore has gained recent attention in the fleet tracking industry [72]. Finally, the probabilistic velocity and HVAC profiles are modeled using 2 sequential optimization problems as in [34].

To generate the probabilistic velocity profiles, all input data required for the modeling is collected: maximum and minimum dwelling time, maximum acceleration and deceleration, maximum and minimum velocity of route, trip distance, nominal trip time, stop locations, distance between stops, and a traffic condition parameter ($\frac{v}{c}$) which is the ratio of road traffic volume to capacity and is used to model congestion [73]. The way that traffic congestion is incorporated as is follows:

$$V^{Avg}(\frac{v}{c}) = \frac{D^{Trp}}{T^{Trp,nom}}(\alpha^{Trp,1}(\frac{v}{c})^2 + \alpha^{Trp,2}(\frac{v}{c}) + \alpha^{Trp,3}) \tag{4.7}$$

$$T^{Trp} = \frac{D^{Trp}}{V^{Avg}(\frac{v}{c})} \tag{4.8}$$

$V^{Avg}(\frac{v}{c})$, is the average velocity along the route and is a factor of the traffic condition parameter as developed by the Transportation Research Board of the National Academies of Science in the United States, as shown in equation (4.7). Since the distance of the trip D^{Trp} does not change, the congestion based velocity impacts the time it takes to complete the trip T^{Trp} as seen in (4.8). $T^{Trp,nom}$ is the nominal time is takes to complete the trip and $\alpha^{Trp,1}$, $\alpha^{Trp,2}$ and $\alpha^{Trp,3}$ are dependant on the free-flow speed of the modeled route. Equations (4.7) and (4.8) are some of the constraints incorporated into the velocity profile generating algorithm described in [34]. After the speed profiles are generated, they are

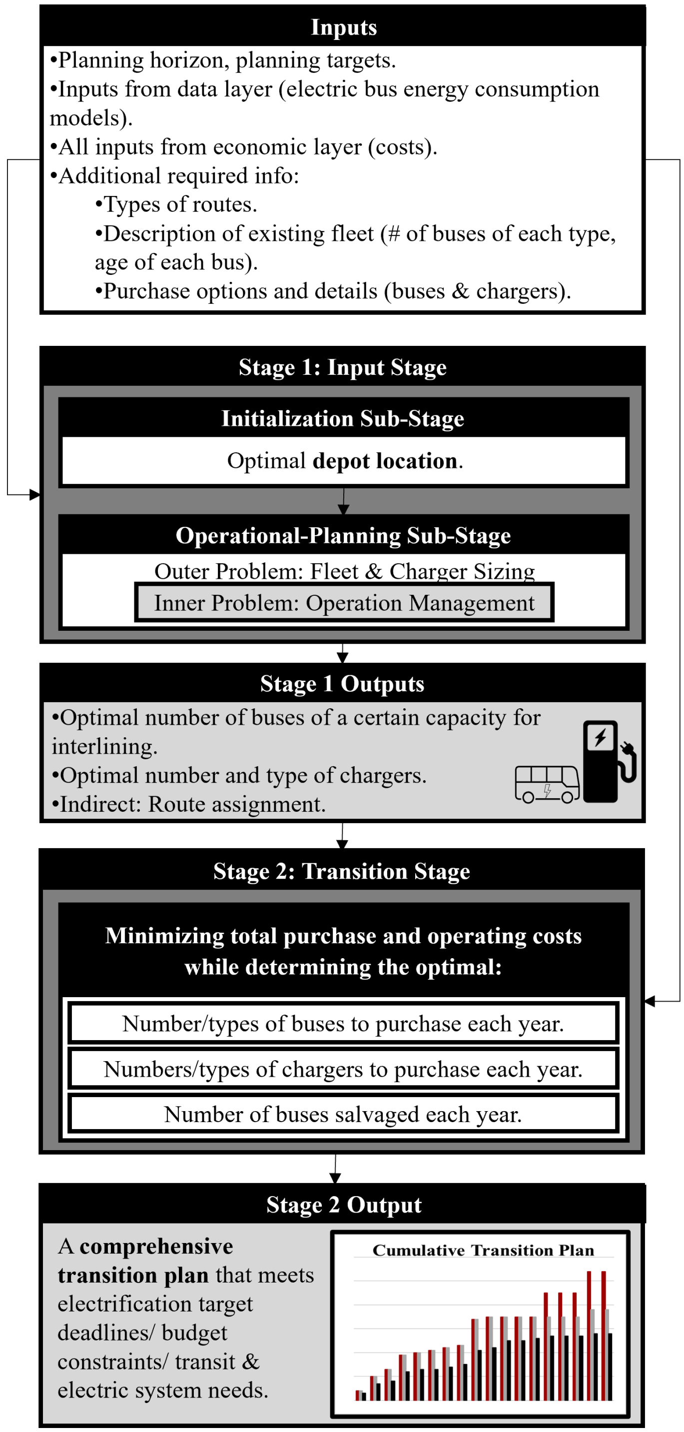


Figure 4.3: Methodology overview.

input into equations (4.1) - (4.6) to calculate the electric bus energy consumption profiles, which form the basis of the coming stages of this approach.

The overall transition plan model presented in this chapter can be conceptualized as a series of sequential stages that lead to the final solution: a transit agency's comprehensive transition plan. The first stage is the input stage which consists of two sub-stages; the initialization and operational-planning sub-stages. The outputs of this first stage are then fed into the following transition stage. Fig. 4.3 provides an overview of the proposed methodology, while the following sections describe the two stages in detail.

4.4 Stage 1: Input Stage

The input stage detailed in this section addresses one question in the first sub-stage (the initialization sub-stage) and the results are then input into the following sub-stage. The initialization sub-stage determines the optimal depot location, following that the operational-planning sub-stage is formulated as discussed in Chapter 3. The operational-planning problem aims to determine the optimal fleet sizing as well as the on-route and depot charger sizing and rating while incorporating fleet route assignment, and Day-time (DT) and Night-time (NT) charging management. This is summarized in Fig. 4.3.

4.4.1 Initialization Sub-Stage

Bus depot locations are frequently determined by choices made in the past that are no longer optimal in light of current technological and market conditions. Additionally, with the additional power requirements that come into effect when electrifying fleets, it is important to determine a depot location that is optimal and effective with respect to both the power distribution network as well as the transit agency [74]. In selecting a depot for overnight charging, consideration is given to the ability of the power system to handle an additional bulk load. Furthermore, the location of the depot in relation to the proposed route is important. In this problem, the goal is to determine the optimal depot location based on a study of the maximum depot hosting capacity as well as the proximity of the depot to the starting station of the routes it serves. Hence, the objective is to determine the optimal power system bus that can simultaneously accommodate the most number of chargers of a given rating, P_o^{depch}, while being reasonably close to the route starting stations.

This problem is formulated as a mixed integer non-linear problem (MINLP) with an objective function of maximizing the accommodated charger capacity less the energy consumed by the buses as they travel back from their trips to the depot at the end of a workday as shown in equation (4.9) below. This difference is denoted as $E^{depotch}$ and the decision variables are as follows: $z_o^{depotch}$ which is a binary decision variable used to indicate whether the depot should be connected to power system bus o, $n_{ch,o}^{depotch}$ which is an integer variable dictating the number of chargers of type ch installed at bus o, $m_{ch,o}^{depotch}$ which is a binary variable indicating whether charger type ch is selected to be installed at bus o. $P_{ch}^{depotch,rat}$ is the power rating of charger type ch and T^{depot} is the average number of hours spent by the buses at the depot overnight. $D_{l,o}$ is the distance between the starting location l and power system bus o, E_l^B and N_l^B are the energy consumption rate (kWh/km) of the buses and the number of buses that depart from location l respectively. The incorporation of the binary variable $z_o^{depotch}$ ensures that the Power Distribution System (PDS) bus selected is the one that can accommodate the largest number of chargers while being within reasonable distance from the starting locations of the transit routes.

$$\max E^{depotch} = \sum_o z_o^{depotch} \Big[\sum_{ch} \Big(n_{ch,o}^{depotch} m_{ch,o}^{depotch} P_{ch}^{depotch,rat} \Big) T^{depot} - \sum_l \Big(D_{l,o} E_l^B N_l^B \Big) \Big] \tag{4.9}$$

s.t. (4.10) - (4.16)

$$P_o^G - P_o^L - \Delta P_o^{depotch} = V_{t,o} \sum_p^{N_{bus}} V_{t,p} (G_{o,p} cos(\delta_{t,o} - \delta_{t,p}) + B_{o,p} sin(\delta_{t,o} - \delta_{t,p})) \tag{4.10}$$

$$\Delta P_o^{depotch} = z_o^{depotch} \sum_{ch} \Big(n_{ch,o}^{depotch} m_{ch,o}^{depotch} P_{ch}^{depotch,rat} \Big) \tag{4.11}$$

$$P^{depot,max} = \sum_o \Delta P_o^{depotch} \tag{4.12}$$

$$Q_o^G - Q_o^L = V_{t,o} \sum_p^{N_{bus}} V_{t,p} (G_{o,p} sin(\delta_{t,o} - \delta_{t,p}) - B_{o,p} cos(\delta_{t,o} - \delta_{t,p})) \tag{4.13}$$

$$V_o^{min} \leq V_o \leq V_o^{max} \tag{4.14}$$

$$P_o^{G,min} \leq P_o^G \leq P_o^{G,max} \tag{4.15}$$

$$\sum_o z_o^{depotch} = 1 \tag{4.16}$$

The problem is constructed as a modified optimal power flow problem with real and reactive power flow equations as the primary constraints, as shown in (4.10) and (4.13). The additional load imposed onto the system by the depot chargers, $\Delta P_o^{depotch}$, is shown in (4.11). o and p are the indices of power system buses. P_o^G and Q_o^G refer to the injected active and reactive powers, and P_o^L and Q_o^L refer to the real and reactive loads, respectively. V_o and δ_o are the voltage magnitude and angle at bus o. Finally, $G_{o,p}$ and $B_{o,p}$ are the conductance and susceptance of line o to p respectively. This objective function is also constrained by upper and lower voltage limits (4.14), power generation limits (4.15), as well as line thermal limits. The last constraint included limits how many depot locations can be chosen depending on the transit agency's needs, as shown in (4.16). Once this is complete, the selected location of the depot is known, additionally, the maximum number of chargers of a certain rating it can accommodate is also known. The maximum load that can be installed in the depot parking lot as determined by this problem is denoted as, $P^{depot,max}$ and calculated in (4.12).

4.4.2 Operational-Planning Sub-Stage

In this section of the study, the goal is to determine the optimal number and type of BEBs, as well as depot chargers, while minimizing average annualized costs. This problem is formulated as shown in Chapter 3. It should be noted that the summation of all charging power consumed by the buses acts as one load on one bus of the power system; the bus where the depot location is located as determined earlier. The outputs of the operational-planning sub-stage can be summarized as seen previously in Fig. 4.3. Finally, these input stage results constitute the inputs to the final and most critical stage - the transition stage. This transition stage as detailed in the following section determines when the procurement of predetermined optimal assets should be undertaken while ensuring budgets and electrification deadlines are met.

4.5 Stage 2: Transition Stage

As the final step of this approach, the transition stage presents a novel fleet transition plan that incorporates all the outputs of the previous stages and establishes a timeline for when purchase decisions should be made. The optimization problem presented in equations (4.17) - (4.37) results in an optimal transition plan for transit agencies to successfully achieve their electrification targets in a timely manner. This is formulated as a Mixed Integer Programming problem with eight decision variables. The first four decision variables govern the BEB purchase and salvage decisions: $\zeta_{k,t}$, the number of buses of type k purchased in period t, $\alpha^{B}_{k,h,t}$, the number of buses of type k, age h, available in the transit system's inventory at time t, $\psi_{k,h,t}$, the number of buses of type k, age h, salvaged during period t, $\beta_{k,t,r}$, the number of buses of type k assigned to run trips of type r, during period t. The remaining decision variables govern the fast and slow charger purchase decisions: $\omega^{Sch}_{sc,t}$ and $\omega^{Fch}_{fc,t}$, which are the number of slow chargers of type sc and fast chargers of type fc purchased during period t respectively, and $\alpha^{Sch}_{sc,t}$ and $\alpha^{Fch}_{fc,t}$, are the number of available slow and fast chargers of type sc and fc, in period t. Here, a period, t is one year.

As seen in equations (4.17) - (4.19), the objective is to minimize the net present value of the total capital cost of purchasing and operating buses, while minimizing the cost of the infrastructure investment and demand charges, which is encapsulated in $Cost^{Trans}$. Additionally, the revenue generated by salvaging buses is also included in this calculation. In order to ensure accurate financial modeling, all costs incurred over the years, $C^{Trans,ann}_{t}$, are converted to the present value using PgF_t as shown in (4.19), which is a function of the nominal and effective interest rates i and $i^{'}$ respectively, as well as the inflation rate in.

$$\min Cost^{Trans} = \sum_{t}(PgF_t C^{Trans,ann}_{t}) \tag{4.17}$$

s.t. (4.18) - (4.37)

$$\begin{aligned} C^{Trans,ann}_{t} = & \underbrace{\sum_{k} C^{B,cap}_{k,t}\zeta_{k,t}}_{\text{Bus capital costs}} - \underbrace{\sum_{k,h} C^{B,salv}_{k,h,t}\psi_{k,h,t}}_{\text{Bus salvage revenue}} + \underbrace{\sum_{k} C^{B,midlife}_{k,t}\alpha^{B}_{k,Hm^k,t}}_{\text{Bus midlife costs}} \\ & + \underbrace{\sum_{r}\sum_{k\in K^c} C^{cB,op}_{r,t}\beta_{k,t,r}}_{\text{Diesel bus operating costs}} + \underbrace{\sum_{r}\sum_{k\in K^e} C^{eB,op}_{r,t}\beta_{k,t,r}}_{\text{BEB operating costs}} \\ & + \underbrace{\sum_{sc} C^{Sch,cap}_{sc,t}\omega_{sc,t}}_{\text{SC capital cost}} + \underbrace{\sum_{fc} C^{Fch,cap}_{fc,t}\omega_{fc,t}}_{\text{FC capital cost}} + \underbrace{DC_t N^{mos}\Big[\sum_{sc} P_{sc}\alpha^{Sch}_{sc,t} + \sum_{fc} P_{fc}\alpha^{Fch}_{fc,t}\Big]}_{\text{Demand charges from charger operation}} \end{aligned} \tag{4.18}$$

$$PgF_t = \frac{1}{(1+i)^t}, i^{'} = \frac{i - in}{1 + in} \tag{4.19}$$

$C_{k,t}^{B,cap}$, $C_{sc,t}^{Sch,cap}$ and $C_{fc,t}^{Fch,cap}$ are the purchase costs of bus type k, slow charger type sc and fast charger type fc in time period t, respectively. Furthermore, $C_{k,h,t}^{B,salv}$ is the salvage cost of bus type k, of age h and $C_{k,t}^{B,midlife}$ is the midlife cost incurred. Hm^k is a subset of H that entails the midlife age a bus of type k. For instance, if a bus has a lifetime of 12 years, Hm^k would be 6. Finally, $C_{r,t}^{cB,op}$ and $C_{r,t}^{eB,op}$ are the annual operating costs incurred when route type r is run using conventional and electric buses respectively. DC_t is the monthly demand charge rate in (\$/kW), N^mos is twelve months, and P_{sc} and P_{fc} are the power consumption ratings of the slow and fast chargers in kW. This problem is subject to several constraints in order to ensure timely purchase decisions and smooth operation of the transit system. Equation (4.20) ensures that the electrification target is achieved, where a percentage (γ_r) of the total number of trips of a certain run type r, $N_{t,r}^{Trips}$, must be run by BEBs by target year, T_{ga}.

$$\sum_{k \in K^e} \beta_{k,t,r} n_{k,t,r}^{trips} \geq \gamma_r N_{t,r}^{Trips}, \forall t \geq T_{ga}, r \in R \tag{4.20}$$

where $n_{k,t,r}^{trips}$ is the number of trips that can be run by a bus of type k, running run type r, in year t. It is common for transit systems to have multiple electrification targets, for example, a temporary target of 50% of trips being operated by BEBs within the next 10 years, followed by a final target of 100% electrification within 20 years. The equation presented above can be replicated with a modified γ_r, for a different target year T_{gb} in place of T_{ga}.

The next set of constraints is concerned with the variable continuity and flow. In accordance with equation (4.21), the number of buses of type k purchased during any period t, $\zeta_{k,t}$, is equal to the number of buses of type k of age 1 available in the fleet during that period, $\alpha_{k,1,t}^B$. For the first period in the study, the number of buses purchased is the same as above with the addition of any new buses (of age 1) that were previously procured, $z_{k,1}$. Next, the number of buses available during any period should be the number of buses available the previous time period less the number of buses salvaged, as seen in (4.22).

$$\zeta_{k,t} = \begin{cases} \alpha_{k,1,t}^B, & \forall t \geq 2 \\ \alpha_{k,1,1}^B + z_{k,1}, & \text{otherwise.} \end{cases} \tag{4.21}$$

$$\alpha_{k,h,t}^B = \alpha_{k,h-1,t-1}^B - \psi_{k,h,t}, \forall t \geq 2, h \in Hf^k \setminus 1 \tag{4.22}$$

where Hf^k is a subset of H that entails all the possible ages a bus of type k can take before being salvaged. For instance, if a bus has a lifetime of 12 years, Hf^k would include $1, 2, 3...11$. Also, Hs^k is another subset of H, entailing the salvage age of bus type k, which for the previous example would be 12. Equations (4.23) - (4.24) also ensure continuity of variables and the relationship between the available number of buses, the salvaged buses and the number of buses already in the fleet at the start of the planning horizon.

$$\psi_{k,h,t} = \begin{cases} \alpha^B_{k,h-1,t-1}, & \forall t \geq 2 \\ z_{k,1}, & \text{otherwise.} \end{cases}, \forall h \in Hs^k \tag{4.23}$$

$$\alpha^B_{k,h,1} = z_{k,h} - \psi_{k,h,1}, \forall h \in Hf^k \setminus 1 \tag{4.24}$$

Constraints (4.25) - (4.26) take care of the assignment of both conventional and electric buses to the different types of runs. Equation (4.25) ensures that all the conventional buses available during a period t, during their working lifetime are assigned to the different runs. Here K^c is a subset of K entailing the conventional bus types, while K^e is another subset of K entailing the electric bus types: $K^c \cup K^e \in K$. Finally, equation (4.27) ensures that the trips for all run types, during all time periods are met by a combination of conventional and electric buses, depending on their assignment.

$$\sum_{h \in Hf^k} \alpha^B_{k,h,t} = \sum_r \beta_{k,t,r}, \forall k \in K^c \tag{4.25}$$

$$\sum_{h \in Hf^k} \alpha^B_{k,h,t} = \sum_r \beta_{k,t,r}, \forall k \in K^e \tag{4.26}$$

$$\sum_k (\beta_{k,t,r} n^{trips}_{k,t,r}) \geq N^{Trips}_{t,r}, \forall t \in T, r \in R \tag{4.27}$$

In light of the fact that electric buses are included in this problem, the decision to purchase chargers is crucial. Following are the equations that take into account charger constraints. Equations (4.28) and (4.29) ensure the continuity of the variables that govern the charger purchase decisions, $\omega_{sc,t}$, and the number of chargers available, $\alpha^{Sch}_{sc,t}$ at time t. Additionally e_{sc} is the number of chargers of type sc previously owned by the transit agency, if any. Equations (4.30) and (4.31) follow the same logic but for fast chargers.

$$\alpha_{sc,1}^{Sch} = e_{sc} + \omega_{sc,1}, \forall sc \in SC \tag{4.28}$$

$$\alpha_{sc,t}^{Sch} = \alpha_{sc,t-1}^{Sch} + \omega_{sc,t}, \forall t \geq 2 \tag{4.29}$$

$$\alpha_{fc,1}^{Fch} = e_{fc} + \omega_{fc,1}, \forall fc \in FC \tag{4.30}$$

$$\alpha_{fc,t}^{Fch} = \alpha_{fc,t-1}^{Fch} + \omega_{fc,t}, \forall t \geq 2 \tag{4.31}$$

While electrification targets are concerned with the percentage of fleets or trips that are now electric, it is imperative to ensure that there are enough chargers available to meet the charging demands of the newly electrified fleet. This is done through equation (4.32), where the energy consumed by the BEBs to complete their trips must be less than the energy supplied by the combination of fast and slow chargers at the depot.

$$\begin{gathered} dT_r^{depot}\Big[\sum_{sc}(\alpha_{sc,t}^{Sch}P_{sc}\mu_{sc}) + \sum_{fc}(\alpha_{fc,t}^{Fch}P_{fc}\mu_{fc})\Big] \geq \\ \sum_{k\in K^e}(\beta_{k,t,r}n_{k,t,r}^{trips}ec_{k,t}D_r^{trip}), \forall t \in T, r \in R \end{gathered} \tag{4.32}$$

$ec_{k,t}$ is the average energy consumption per kilometer of BEB type k, in kWh/km, while D_r^{trip} is the distance traveled in kilometers for run type r. Additionally, dT_r^{depot} is the time spent by the BEBs at the depot to be charged overnight when assigned to run type r, and μ_{sc} and μ_{fc} are the efficiency of charger type sc and fc respectively. The charging needs of the routes can be satisfied by multiple combinations of fast and slow chargers. For this reason, in order to ensure that the optimal charger mix is procured the following constraints are added: $\sum_{fc}\alpha_{fc,t}^{Fch} = N^{Fch}$ and $\sum_{sc}\alpha_{sc,t}^{Sch} = N^{Sch}$ for $t = T_{ga}$.

Finally, equation (4.33), ensures that the power consumed by all chargers if operated simultaneously is less that the acceptable capacity dictated by the power grid, $P^{depot,max}$ in (kW), to account for the worst case scenario. This was determined in Stage 1 equation (4.11). Additionally, the area restrictions are accounted for in (4.34), where $PS^{depot,max}$ is the maximum number of bus parking spots and hence number of chargers allowed.

$$\sum_{ch}(\alpha_{ch,t}^{Ch}P_{ch}) \leq P^{depot,max}, \forall t \in T \tag{4.33}$$

$$\sum_{ch}\alpha_{ch,t}^{Ch} \leq PS^{depot,max}, \forall t \in T \tag{4.34}$$

Additionally, the last set of constraints are intended to ensure that the transit agency does not exceed its annual budget while at the same time, if there is unused budget from the previous year, it can be used in future years. This is addressed in equations (4.35) - (4.37), where Bd_t is the annual budget, UBd_t is the unused budget during period t, and BG_t are any additional bonuses or grants acquired in that period.

$$UBd_t = Bd_t + BG_t - C_t^{Trans,Ann}, \forall t \in T \tag{4.35}$$

$$Bd_1 + BG_1 \geq C_1^{Trans,Ann} \tag{4.36}$$

$$Bd_t + Ubd_{t-1} + BG_t \geq C_t^{Trans,Ann}, \forall t \in T \tag{4.37}$$

To conclude, the outputs of this stage are the optimal decision variable results as listed in the beginning of this section. Upon completing this last phase of the proposed transition approach, a comprehensive transition plan incorporating both electric utility as well as transit agency perspectives is developed.

4.6 Results and Discussions

The proposed methodology is applied on four short distance routes based on a real-life 18-stop, 11.5 km round-trip route, with a frequency of 70 trips per day in the city of Brampton, Canada. Modeling and simulation of four variations of this route are used in order to mimic a transit agency's transit system. These routes are classified as short distance or intra-city routes, where each is currently operated by five diesel buses. Due to the unavailability of the power distribution network details, an IEEE-38 bus system is overlaid on top of each of the routes, to create a realistic geographical-electrical layer for the study as seen in Fig. 4.2.

After collecting all input data, the EBEC profiles are generated for the buses under heavy and light traffic conditions. The methodology and results of this study are consistent with those discussed in the literature, with two modifications: the passenger loading process and the driver behavior parameter. It is important to note that the addition of these features does not increase the complexity of the problem, but they simulate realistic speed profiles that closely resemble those observed in reality. Histograms of total consumption are shown in Fig. 4.4, with results comparable to real-life calculations. as per the histograms, under light traffic conditions, the EBEC lies within the range of 1.4 to 1.6 kWh/km,

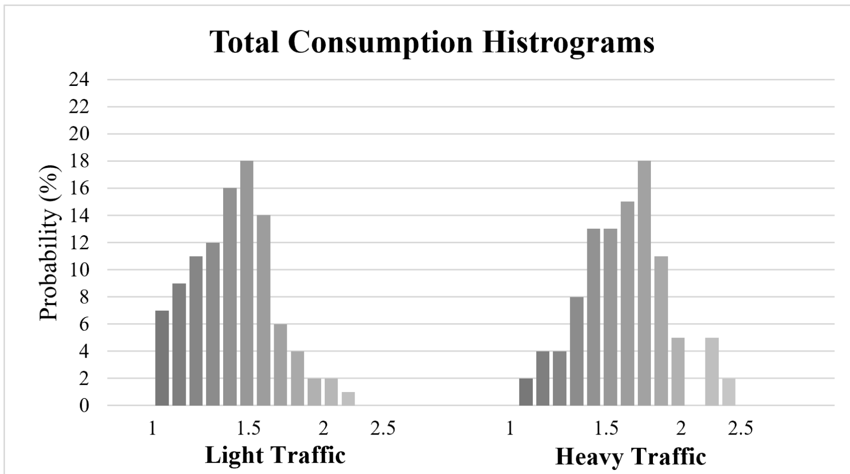


Figure 4.4: Total consumption histograms (kWh/km) under different traffic conditions.

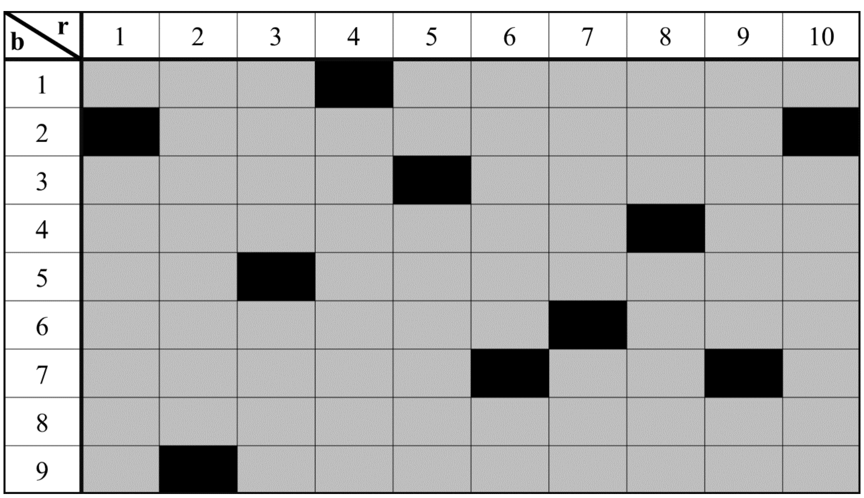


Figure 4.5: Assignment of trips r to buses b.

whereas under heavy traffic conditions, this range moves to 1.5 to 1.8 kWh/km, illustrating the impact of traffic on energy consumption.

Depending on the traffic conditions, each route has a known energy requirement. Based on the optimal depot location initialization problem, the depot connection location is determined as bus 19 of the IEEE 38-bus power system, with a maximum additional load of 3.75 MW. Next, Fig. 4.5 illustrates a sample of the route assignment results. Each bus, b, is assigned to run a trip, r, with black boxes indicating which bus is assigned to which trip. Once the initialization sub-stage is complete, the operational-planning sub-stage is run to determine the optimal fleet and charger sizes. The results of this analysis will be discussed in more detail in the following subsections. Several case studies were conducted in order to fully assess the scalability and adaptability of the generated model: modeling the four short distance routes when operated with overnight charging versus opportunity charging. Overnight charging allows the BEBs to recharge only while parked at their depots, whereas opportunity charging allows the BEBs to recharge while traveling, by utilizing fast chargers along the route.

4.6.1 Case A: Overnight Charging

When the initialization sub-stage has been resolved, operational-planning takes place where, for operation of four short distance routes requiring overnight charging, a selection of 36 313 kWh buses and 28 75 kW chargers is determined as the optimal fleet size, charger size and selection. The optimal decision variables minimize annualized costs and ensure two things: the BEBs depart the depot fully charged at the beginning of their operation (this ranges from 6 am - 8 am depending on the trip assignment) and during the day the battery state of charge (SOC) never drops below the minimum 15%. In Fig. 4.6, the black curve illustrates the battery's operation during the day for one of 36 BEBs operating these routes, with all BEBs exhibiting similar behavior. This figure displays the change in the battery's SOC over time, the SOC decreases when the bus is running a route as it utilizes energy to travel. It is important to note, however, that when the bus is at rest or has completed its trip for the day, the SOC, which represents how much energy remains in the battery, does not change. As the BEB travels, it consumes energy depending on the traffic conditions and its speed, which govern its consumption profile as discussed earlier. In turn, this determines the SOC, as the more energy the bus consumes, the lower its SOC. Consequently, every trip results in a decrease in SOC, resulting in a declining SOC profile for each bus as seen in the figure.

The inputs to the last stage of the approach - the transition stage - are all known once this is done. In this research, the planning horizon is a period of 18 years, from

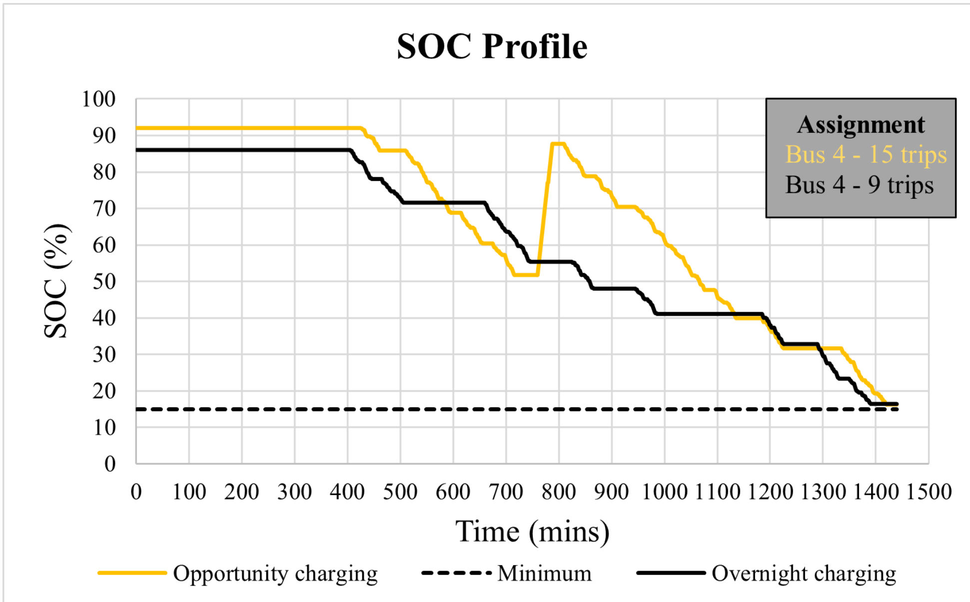
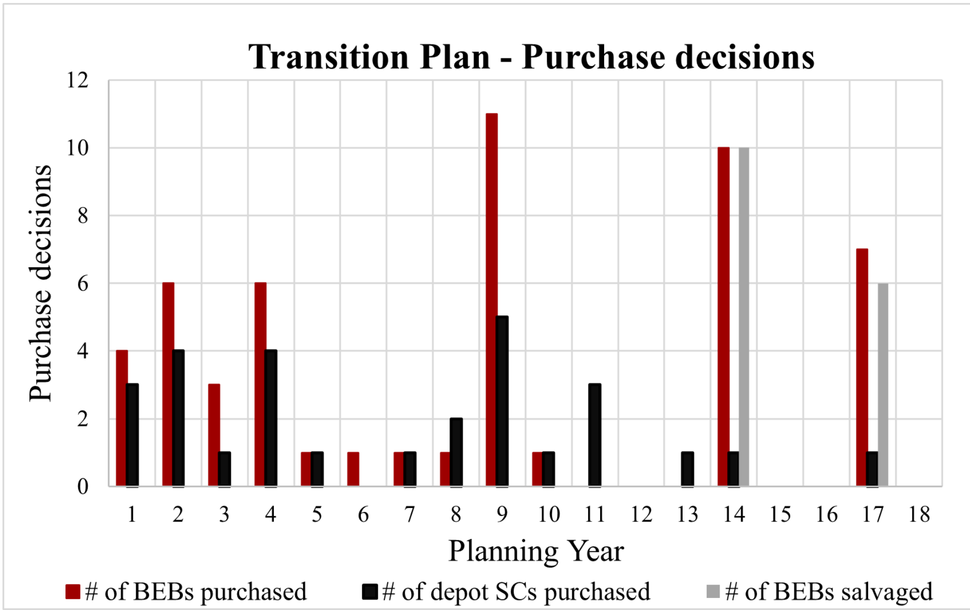


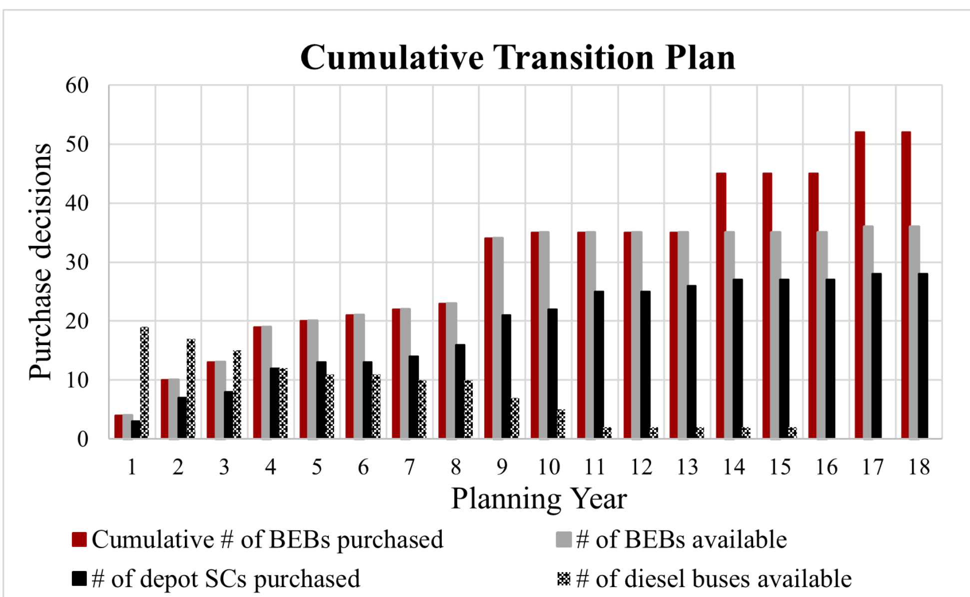
Figure 4.6: State of Charge (SOC) profiles of optimal fleet.

2023 to 2040, with a goal of electrifying 50% of the route by 2030 and the remaining 50% by 2040. Our previous work in [75] involved transitioning only one short-distance route, while utilizing overnight charging. It was demonstrated that by year 8, 2030, 5 BEBs were purchased, and by year 18, 2040, all 9 BEBs were purchased. Moreover, by year 9, 5 chargers were purchased while, by the year 2040, all 7 chargers required were purchased. The small-scale study presented in our previous work acted as a proof of concept, whereas the larger system demonstrated in this work is representative of a real-life transit system. Further, with the large number of BEBs and chargers, the budgetary constraints become the most critical constraints, as transit agencies must plan carefully and in advance, as well as apply for potential funds and bonuses to be able to undertake such large scale transitions.

The large scale comprehensive transition plan can be summarized as seen in Fig. 4.7, where the purchase decisions are displayed in Fig. 4.7a and a cumulative transition plan is displayed in part Fig. 4.7b. It can be see that by the year 2030, 22 of the 36 buses were transitioned to BEBs, while 15 75 kW chargers were purchased to ensure sufficient charging requirement. This decision is based on multiple governing constraints: making sure that at least 50% of the fleet trips are run by BEBs, the ages of the previously owned diesel fleet and whether or not they have reached their salvage age, amongst budgetary and operational constraints. Finally, by the year 2039 and hence by the year 2040 all routes



(a)



(b)

Figure 4.7: a) Annual, b) Cumulative purchase decisions for 4 SD routes using OVNC.

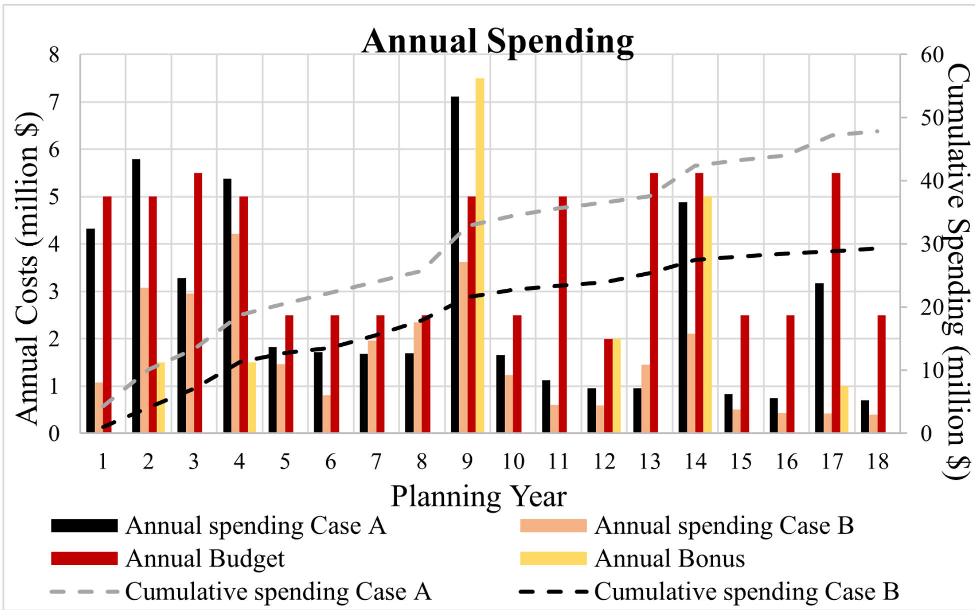


Figure 4.8: Summary of annual budget and spending.

are run by BEBs, with the fleet consisting of 36 313 kWh BEBs and 28 slow chargers with a 75 kW rating. It can be seen that several BEBs are salvaged at the end of year 14, this is due to the fact that they were purchased in the first two years of operation and hence have reached their salvage age of 13 years. Salvaging BEBs provides additional income that can be utilized in future purchases. Additionally, the budgets, grants, bonuses, annual expenditures, as well as cumulative expenditures are presented in Fig. 4.8. Using declining energy storage costs, increasing electricity costs, and other costs over the years, the net present value of purchasing and operating the transitioned fleet is determined to be $47.90 million. Based on inputs derived from the underlying electrical network, this transition is comprehensive as no assumptions are made that would compromise grid stability or transit continuity. As a final note, the framework presented here is scalable to account for any system size accurately.

4.6.2 Case B: Opportunity Charging

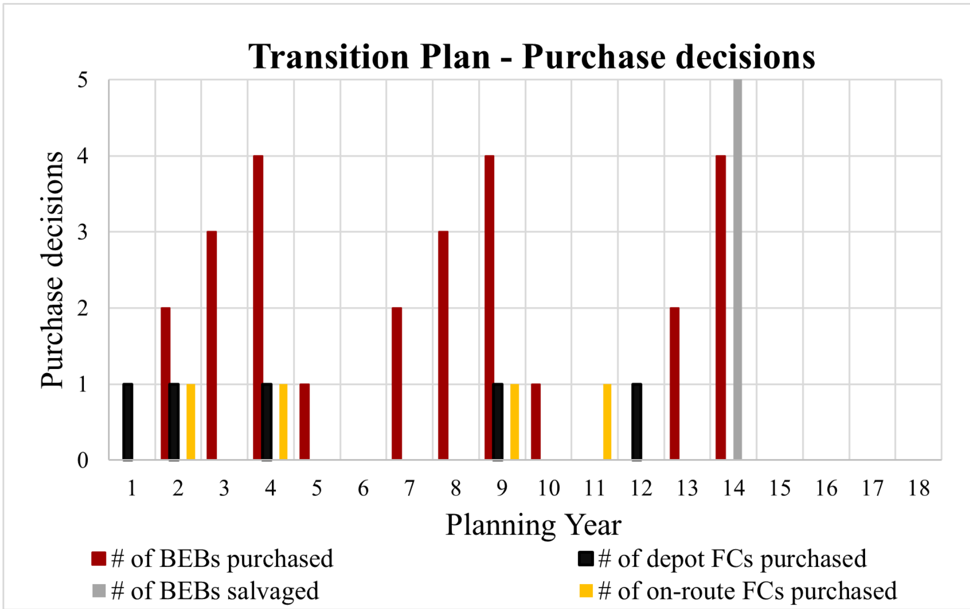
As per the operational-planning stage, to electrify the same four short-distance routes with the utilization of opportunity charging, the optimal fleet size is determined as 20 313 kWh BEBs, 4 250 kW chargers on the route and 5 250 kW chargers at the depot. The locations of these FCs are determined in the operational-planning sub-stage. The SOC profile of one of the 20 BEBs is displayed by the yellow curve in Fig. 4.6, where the distinction between the operation of overnight versus opportunity charging is quite visible as opportunity charging allows for on-route charging during the day. This is reflected by the increasing SOC occurring at minutes 760 , corresponding to 12:40 PM. Once these optimal decisions are determined, the transition stage is begun, with the same electrification targets as above.

The transition decisions for the opportunity charging scenario can be seen in Fig. 4.9, where the individual purchase decisions can be seen in Fig. 4.9a, and once again, the cumulative transition plan is displayed in Fig. 4.9b. As of 2030, 15 of the 20 BEBs (75%) had been converted, while three depot chargers and two on-route chargers were purchased to ensure the on-route and depot charging needs are met. In addition, by the year 2040 all routes will be operated by BEBs, with the fleet consisting of 20 313 kWh BEBs, equipped with 4 fast chargers at the depot and 4 more on-route chargers. Also included in Fig. 4.8 are budgets, grants, annual expenditures, and cumulative expenditures. A net present value of $29.28 million is determined as the cost of purchasing and operating the transitioned fleet. Once more, the framework presented here is flexible enough to accommodate multiple charging methodologies and system sizes, making it universally applicable, adaptable and scalable.

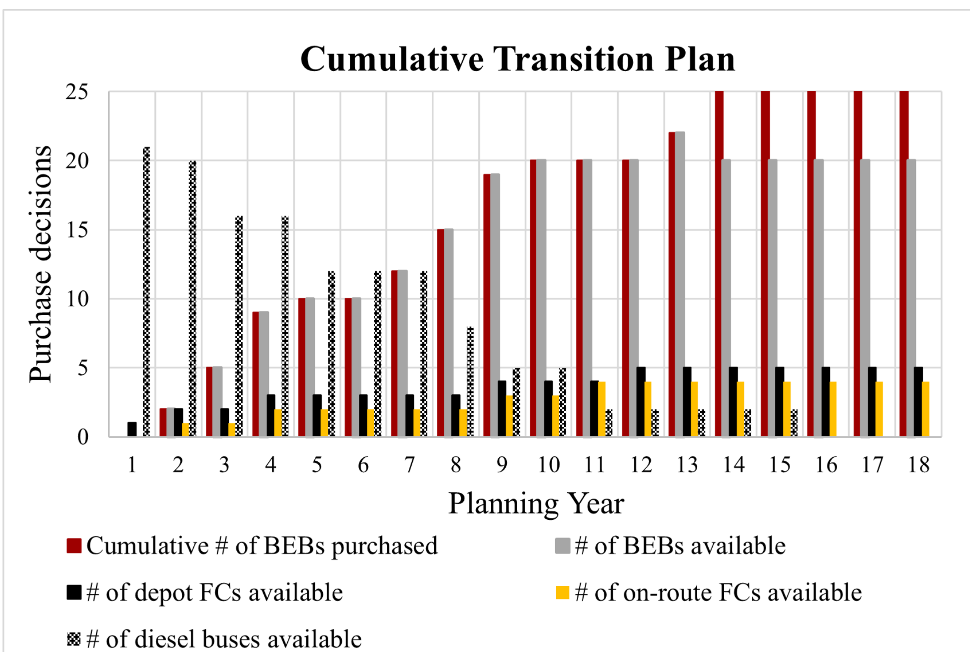
4.6.3 Charger to Bus Ratio (CBR)

While most works disregard the need to maintain a relationship between the number of chargers required to the number of BEBs purchased (charger to bus ratio), those that consider the CBR, regard it as a simple one-to-one ratio or a percentage as discussed earlier [23]. Nevertheless, this is not realistically feasible due to two reasons: first, battery size, charging rating, number of charging hours, and many other factors play a substantial role in developing this ratio, second, mode of charging has a significant impact on the number of chargers required and therefore the ratio. Therefore, a CBR was not utilized in this research. Instead, a direct formulation of the energy required by the BEBs based on the number of routes they run is used to determine the number of chargers required by incorporating charger ratings, number of hours spent at the depot, and many other factors. Following the completion of the proposed transition approach, the CBR generated by the study over the years was evaluated.

As seen in Fig. 4.10, when utilizing overnight charging, the average CBR when analyzed over the planning horizon is 0.695, where all the chargers deployed are of the same charger rating - 75 kW. Additionally, when opportunity charging is used. Based on these figures,



(a)



(b)

Figure 4.9: a) Annual, b) Cumulative purchase decisions for 4 SD routes using OPPC.

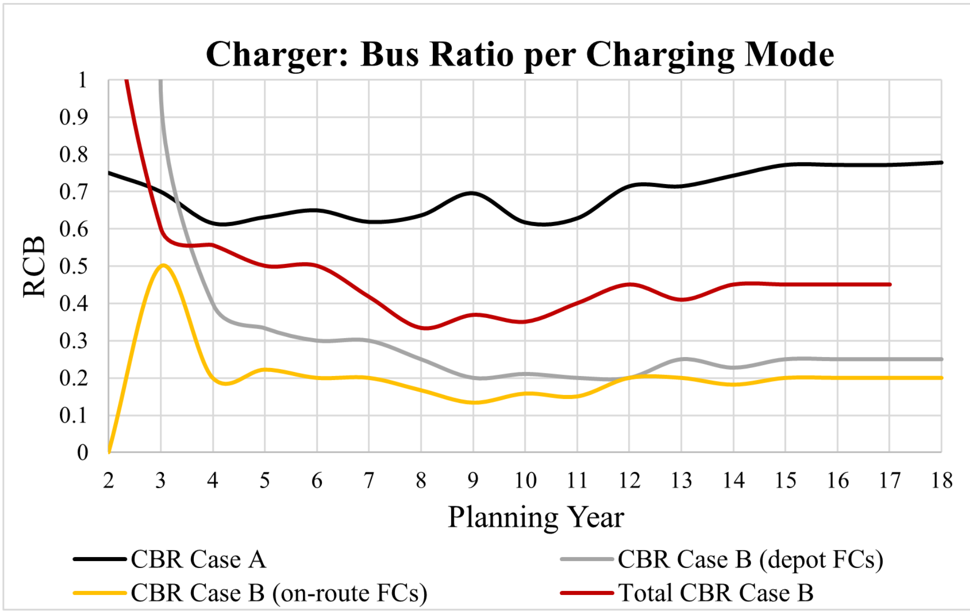


Figure 4.10: Ratio of chargers to buses per planning year per charging mode.

it can be seen that the average CBR for the cumulative number of chargers needed for opportunity charging is 0.54, while the average CBR for depot chargers is 0.35, and the average CBR for the on-route chargers is 0.20. It can be therefore concluded that using a CBR as a one-size-fits-all solution is not feasible or realistic. These numbers are specific to the route studied, and they have a strong basis in the electric needs of the system. Consequently, according to the results of this work, the use of a CBR may result in a shortage of available chargers, which would result in unfulfilled charging needs, resulting in incomplete routes, a loss of service and hence transit agency dissatisfaction.

4.7 Conclusion

To conclude, the transition to electric fleets is imminent, and BEBs are still an emerging technology in comparison to diesel buses. Additionally, there is no simple transition from a diesel fleet to an electric fleet; it necessitates a complete overhaul of the infrastructure. As such, conducting a transition study is essential to ensure that buses are acquired in a systematic way, with the necessary preparations in place, such as infrastructure updates, on-route updates, adequate staff training, and an energy management strategy that allows the technology to be utilized to its fullest capacity. This chapter presents a realistic and comprehensive fleet transition model to be applied by transit agencies and procurement decision-makers. The proposed approach is designed as a series of sequential stages that, when completed, produce realistic results which satisfy the needs of both the electric grid and the transit agency. To begin with, a solid basis for the analysis is guaranteed by accurate EBEC profile modeling. Next, in order to ensure the continuity of service, the input stage is designed to ensure the optimal selection of depot locations, the optimal sizing of the fleet and chargers, and the optimal operation of all assets. Results obtained guarantee that the depot location selected will be optimal and feasible, and additionally, fleet sizing, charger sizing, and selection, as well as system operation management will produce minimum capital and operating costs. The final and most important stage involves the development of a novel, comprehensive fleet transition plan that utilizes all the aforementioned results in order to generate timely decisions while adhering to budgetary, spatial, and operational constraints amongst others. Additionally, the work developed demonstrates the volatile nature of the CBR, demonstrating its dependence on the specific problem characteristics and charger methodology, thus demonstrating that it cannot be overlooked in the transition formulation process. Considering the general nature, adaptability, and scalability of the proposed formulation, any transit agency may apply it regardless of how they elect to charge their fleets. By utilizing the proposed formulation, transit agencies could efficiently transition their fleets at minimum costs while cooperating with the technology manufacturers and their local electric grid to meet target deadlines, and ensure service reliability. Although a smooth transition is possible, barriers to the deployment of electric buses will still exist, and so a comprehensive solution needs to be devised to address these barriers and facilitate a rapid and smooth transition to electrified Public Transportation (PT) as discussed in the following chapter. [1]

[1] Initial stages of this work were presented in the IEEE SeFeT 2022 conference and awarded the Best Paper Award (http://www.sefet.griet.ac.in/best-paper-awards.html) [75]. The full form of this chapter is under review in IEEE Transactions on Industry Applications.

Chapter 5

Optimal Mobile Energy Storage Sizing, Routing, and Scheduling to Support the Electrification of Public Transportation

5.1 Introduction

"The IESO forecasts that electrification of Ontario's transportation sector is expected to grow an average of 20 per cent a year for the foreseeable future. For local utilities and the IESO, this presents a challenge of meeting increased electricity demand – as well as ***the opportunity to use new technologies to create dynamic solutions to meet long-term energy needs.****"* [76]

Despite the importance of developing and implementing a comprehensive fleet transition plan, as discussed in the previous chapter, there are numerous barriers that get in the way of the implementation of these plans and hinder the adoption of electrified public transportation. These barriers can be classified into three main categories: financial, technical and electrical. There are two major technological barriers: driving range anxiety and battery performance anxiety where major stakeholders are reluctant to transition to BEBs because of their limited driving ranges as well as a lack of knowledge and understanding of BEBs, their manufacturing, operation, and maintenance. Further, the electrification of PT poses multiple financial challenges due to the high capital costs associated with the purchase of BEBs and the necessary charging infrastructure. Additionally, the installation of the required infrastructure may require a large amount of space, resulting in the need for land purchase. Lastly, electrical network barriers are primarily caused by a lack of knowledge, standards, and regulations regarding charging infrastructure. Further, grid instability poses another serious issue, particularly as electrification expands. Transit agencies have the ability to quickly purchase BEBs, but charging infrastructure is not as straightforward. From a practical industrial perspective, installation and construction of "four to eight charging stalls can take anywhere from 12 to 18 months" [77]. This is a consequence of the numerous entities involved in bringing the charging stations to life; it takes a considerable amount of time to arrange accommodations, request permits and more. Hence, as seen from above, the key to fast and efficient fleet electrification is the adoption of a fast, flexible and efficient holistic solution that can tackle all the aforementioned barriers.

A fast solution is necessary for the following reasons:

- In many cases, collaboration between multiple entities - such as the electric grid, transit agencies, etc. - consumes long periods of time.
- Several electrical utilities will "only invest in electrical grid upgrades to serve load they are confident will be used" [13]. Fully electrified transportation networks will require upgrades to the electrical infrastructure, which will be both time and cost-intensive.

Additionally, a flexible solution is also necessary for the following reasons:

- Accidents, blackouts or emergencies are bound to happen, such as the charger fire in 2020 [12] which had a huge impact on service continuity and forced the Transit Agency (TA) to revert to its non electric fleet.
- Transit systems are not set in stone - routes are constantly evolving as cities grow and develop, and in time, routes with low traffic are usually eliminated or converted into on-demand services while routes with higher traffic are run more frequently.
- It is not uncommon for roads to be closed for months on end as a result of construction, resulting in transit systems temporarily rerouting their routes.

For these reasons Mobile Energy Storage (MES) is proposed in this chapter as a plug-and-play solution that is both fast and flexible. As previously discussed MES is sold in a "build-your-own" manner, where all the system components are put together by the manufacturer as per the purchaser's request. Consequently, TAs can customize their MES according to their specific requirements, acquire it in a timely manner, and deploy it immediately. Furthermore, its mobility provides it with a degree of flexibility that is not possible with Stationary Energy Storage (SES). Moreover, it reduces the heavy burden placed on the electric grid by transportation electrification. MES offers an innovative approach for overcoming technological, financial, and electrical barriers simultaneously. With MES, driving anxiety is reduced as Battery Electric Buses (BEBs) are met and recharged along their routes at the exact time they specify, and in case of an emergency, they can be sent elsewhere and their schedule adjusted. Additionally, MES reduces capital costs since one MES can replace several Fast Charging Stations (FCSs), as the MES acts as an appearing and disappearing FCS. Further, the BEBs will no longer have to charge directly from the grid during peak hours at peak prices, thereby reducing operational costs. Last but not least, MES reduces grid peaks caused by FCSs and defers the need for costly upgrades to electrical infrastructure by reducing or eliminating the need for FCSs. For these reasons, the goal of this work is the optimal sizing, routing and scheduling of transit owned MES to realize the multi-faceted techno-economic benefits of utilizing MES in the transition to electrified transportation.

MES is no foreign concept in providing numerous services, and while it has been researched and deployed to support private Electric Vehicle (EV) charging, very limited research exists on utilizing MES within the public transportation framework. Therefore, the contributions of this work can be summarized as follows:

- To our knowledge, this is the first work that introduces MES as a fast and flexible solution to tackle BEB deployment barriers, providing a holistic solution to address technological, financial as well as electrical barriers.
- The development of a novel MES sizing, routing and scheduling approach, that accounts for battery depletion as well as charging.

The rest of this chapter is organized as follows: Section 5.2 presents an overview of the problem. Following that Sections 5.3 and 5.4 provide detailed modeling and formulation of the problem. Finally, the proposed solution methodology is presented in Section 5.5 and the case studies, results, and conclusions are discussed in Sections 5.6 and 5.7.

5.2 Problem Description

The objective of this work is the optimal sizing, routing, and scheduling of transit-owned MES to realize the multi-faceted techno-economic benefits of utilizing MES in the transition to electrified transportation. Several questions are addressed in this work, including the following: given a transit network, how many and what capacity of MES are needed to reduce transit costs and enhance transit operations. In addition, given the optimal MES sizing, what would be the optimal schedule and route to meet transit demands while minimizing travel time. Lastly, even though the MES is owned and operated by the TA, this does not limit the benefits of its deployment to the TA alone. MES provides economic benefits to the TA through capital and operating cost reduction, and technical benefits through ensuring smooth operation at times of emergency or unanticipated circumstances. Additionally, MES indirectly provides technical benefits to the grid by reducing peaks that occur during the day due to the FCSs, while delaying the need for system upgrades as the load imposed on the system is reduced. In order to meet the aforementioned objectives, the proposed problem aims to solve for the following decision variables:

- The number of MES required to meet the demands of the routes under study,
- The energy capacity of each MES,
- The optimal schedule for each MES,
- The optimal number of Slow Chargers (SCs) and Fast Chargers (FCs) to be placed at the depot for MES and BEB overnight charging.

5.3 Energy Consumption Modeling

This section is dedicated to modeling all inputs to the proposed optimization problem described above. As the purpose of this chapter is to identify the impact of MES on the electrification of Public Transportation (PT), the two main components that require detailed modeling are the BEBs and the MES. To begin with, there is a need to model BEB and MES energy consumption in order to fully comprehend the impact of MES (Electric Bus Energy Consumption (EBEC) modeling is discussed in Chapter 4). Moreover, an MES is also an electric vehicle that is powered by the same storage system that is used to serve its customers. Therefore, the energy consumption of a MES along its traveled routes must also be accurately modeled. Finally, to understand the impact of MES on BEB charging, traditional BEB charging must also be modeled. In this study, two methods of charging BEBs are discussed: Overnight Charging (OVNC) and Opportunity Charging (OPPC). This section examines all of the inputs mentioned above in detail.

5.3.1 MES energy consumption modeling

This subsection is focused on modeling the MES energy consumption. In this research, every MES has a set of candidate locations at which they provide their services, and as previously discussed, the MES consumes energy in traveling between locations. As discussed in Chapter 4, the same fundamental principles and equations are used to model the energy required to propel the MES forward, referred to as traction energy. For this reason the energy consumed by a MES is modeled as shown in (5.1), where $E_{Traction}$ can be found in equations (4.2) - (4.6).

$$E_{MES} = E_{Traction} + E_{HVAC} + E_{aux} \tag{5.1}$$

As previously discussed, velocity and acceleration are unknowns. It is therefore necessary to develop velocity and concomitantly acceleration profiles for the MES and finally, utilize them to generate energy consumption profiles. Creating velocity profiles requires the generation of both time and speed axes. In order to construct the speed profiles, two sequential optimization problems are solved in accordance with the methodology described in [34], to determine the energy consumption of the MES. The first optimization problem solves for one variable; travel time from one candidate location to the next, while each section has a constant average velocity. The average velocity along the route is a quadratic function of the traffic condition parameter which indicates the level of service along a roadway as shown in Chapter 4 [73]. Following this, the second optimization problem solves for actual velocity at each time instant of travel between one location to another, developing accurate real-life speed profiles that depend on traffic conditions.

The outcome of the first stage is a velocity profile where the time profile is accurately generated but the velocity is an average number for each section along the trip. The output of the second stage however, is a comprehensive velocity profile with the velocity accurately modeled. Finally, using the generated velocity profiles, the energy consumed in traveling from one location to the next can be calculated. EBEC and MES energy consumption are modeled in similar manners. The main difference between MES energy consumption and EBEC modeling is that for the former, the MES travels from one location to the next and the waiting time at each location depends on the service needs of the customer it stops at, or it is not in use. However, regarding the BEBs, the stopping time between sections of the trip varies depending on the loading and off-loading of the bus and the route schedules as defined by the transit agency. Hence, for BEBs, the optimization problem is modified to account for these dwelling times. Where the first optimization problem once solved for one variable, it now solves for two variables; travel time along each section of the trip, as well as dwelling time after each section.

5.3.2 BEB demand modeling

To begin with it is important to understand that the MES has one customer: the BEBs. The MES are acquired with one purpose, to serve the needs of the transit system, i.e. the BEBs. To understand how the acquisition of MES by transit agencies to serve BEBs it is essential to understand their daytime and nighttime energy requirements. Charging requirements vary depending on the charging mode selected by the transit agency. During overnight charging, BEBs do not return to charge during the day; rather, they complete their daytime routes and return to their depot to charge for the next day. BEBs are typically equipped with batteries of a greater energy capacity when using this mode of charging, and chargers are located exclusively at the depot. Alternatively, opportunity charging permits BEBs to charge along their route at any time - therefore fast chargers are situated along the route. The impact of MES is studied on the Day-time (DT) operations of the transit system, as the MES is charged overnight to benefit from the off-peak charging prices. Additionally, they are not needed during the nighttime as the entire transit system is halted during the night hours. A TA utilizing OVNC consists of the BEBs and their overnight mix of chargers. These BEBs and their depot chargers are already sized to ensure that they can perform all their daily tasks without running out of energy. To study the impact of MES, we maintain the same BEB battery energy capacity, and then we study the impact of MES on the number of BEBs required, N_b. Next, with respect to OPPC, the system includes an additional component: the on-route FCs. In order to determine the impact of MES on such a system, the goal is to size MES to reduce or eliminate the need for opportunity charging on the route.

In order to determine the size and number of the MES systems required to serve the transit system, the most important input to the problem is the energy required by BEBs from the MES to complete their routes. This is determined through the formulation presented in (5.2) below which is done for every individual route. Given a number of buses, and trips, this formulation aims to assign the buses to trips to ensure continuity of service while determining the energy required by the BEBs from the MES by minimizing the

MES service time per customer. Here the MES's customers are the BEBs and in calculating the service time for each customer, two components are taken into account: the connection/disconnection time of the BEB to the MES and the amount of time the MES is connected to the BEB to provide energy.

$$\min Service^{MES} = \sum_{b,t} \Big(\underbrace{T^{conn}_{b,t} swM^{conn}_{b,t} + T^{dconn}_{b,t} swM^{dconn}_{b,t}}_{\text{MES connection/ disconnection time}} + \underbrace{x^{ch}_{b,t}}_{\text{MES service time}} \Big) \tag{5.2a}$$

$$\text{s.t.} \tag{5.2b}$$

$$\sum_{b} a_{b,r} = 1 \tag{5.2c}$$

$$inR_{b,t,r} = a_{b,r} aT_{t,r} \tag{5.2d}$$

$$\sum_{r} inR_{b,t,r} \leq 1 \tag{5.2e}$$

$$bP^{dch,profile}_{b,t,r} = P^{rdch,profile}_{t,r} a_{b,r} \tag{5.2f}$$

$$P^{dch}_{b,t} = \sum_{r} bP^{dch,profile}_{b,t,r} \tag{5.2g}$$

$$SOC_{b,t} = \begin{cases} SOC_{b,t-1} + 100\Big(P^{ch} x^{ch}_{b,t} \eta^{ch}_{b} - \frac{P^{dch}_{b,t}}{\eta^{dch}_{b}}\Big) \frac{\Delta t^{day}}{E^{bat,cap}_{b}}, \forall t \geq 2 \\ SOC0_{b} + 100\Big(P^{ch} x^{ch}_{b,t} \eta^{ch}_{b} - \frac{P^{dch}_{b,t}}{\eta^{dch}_{b}}\Big) \frac{\Delta t^{day}}{E^{bat,cap}_{b}}, t = 1 \end{cases} \tag{5.2h}$$

$$SOC^{min}_{b,t} \leq SOC_{b,t} \leq SOC^{max}_{b,t} \tag{5.2i}$$

$$\sum_{r} inR_{b,t,r} = x^{dch}_{b,t} \tag{5.2j}$$

$$x^{ch}_{b,t} + x^{dch}_{b,t} \leq 1 \tag{5.2k}$$

$$swM^{conn}_{b,t} - swM^{dconn}_{b,t} = \begin{cases} x^{ch}_{b,t} - x^{ch}_{b,t-1}, \forall t \geq 2 \\ x^{ch}_{b,t}, t = 1 \end{cases} \tag{5.2l}$$

Solving this Mixed Integer Programming (MIP) problem results in the amount of energy required by each BEB and the time it is required. A mapping is then done to determine where each BEB is at the time it requires the energy and this brings an end to the inputs to the problem discussed in the following section.

5.4 Operational Problem Formulation

Once the inputs are determined, the purpose of this section is to provide a detailed mathematical formulation of the problem discussed above. As per the TA's perspective, the objective of utilizing MES within their transit system is to minimize the transit system's Average annual cost of operation (AACO), while tackling numerous BEB deployment barriers.

5.4.1 MES Routing and Scheduling Problem

This subsection describes in detail the mobile energy storage routing and scheduling problem. The inputs to this problem are the number of BEBs, N_b, the energy request of each BEB, with every individual energy request formulated as a unique customer of the MES. For example, if a BEB was to require 2 charging events, 1 at 1 pm and once more at 4 pm, these would be formulated as two separate customers of the MES. Additional inputs to this problem include the number of MES, B_{MES} and the capacity of each MES, eB_m. The MES routing and scheduling problem is then formulated to determine the following: for a system with a set number of BEBs, and a set number and energy rating of MES, how would the MES be operated and which BEBs would it serve. This is formulated as a cost minimization problem where the objective aims to minimize the cost of operating the MES. The constraints ensure that each MES performs its required task: serving BEBs, while ensuring that the State of Charge (SOC) of each MES never drops below a specified lower threshold. The MES flow constraints ensure that the flow of the MES from one location to the next is reasonable as seen in equations (5.4) - (5.8) below.

Trip constraints

The first constraint, (5.3), ensures that each route from i to j is visited by at most 1 MES. The binary variable $x_{i,j,m}$ is 1 when route i to j is completed by MES m, otherwise 0, and $N^{'}$ is the set of all locations: starting depot, charging station locations and customer locations. The customer locations are dictated by the input energy requests, where each request by a BEB is viewed as an individual customer. When serving customers (BEBs), it is important to ensure that a customer is not visited by multiple MES to ensure resources are not wasted. For this reason, constraint (5.4) ensures that each customer is reached from any starting location i, by any MES m at most once, where C is a subset of $N^{'}$, indicating customer locations only. This equation has a big role in terms of the operation, depending on the needs of the TA. For example if the goal of the TA is to reduce opportunity charging, hence meaning some of the BEB's needs are met by the MES, this equation would remain an inequality. However, if the system were to enforce that every customer must be served, hence completely eliminating opportunity charging, this inequality would then be replaced by an equality.

$$\sum_{m} x_{i,j,m} \leq 1, \forall i, j \in N^{'} \tag{5.3}$$

$$\sum_{i,m} x_{i,j,m} \leq 1, \forall j \in C \tag{5.4}$$

Each MES has one starting depot location, SD that is preassigned. Constraint (5.5) dictates that each MES would leave its starting depot at most one time. Finally, the total number of MES that leave the depot must be limited by the total number of MES available, B_{MES}, which is taken care of in constraint (5.6).

$$\sum_{j} x_{i,j,m} \leq 1, \forall i \in SD, \forall m \in M \tag{5.5}$$

$$\sum_{j,m} x_{i,j,m} \leq B_{MES}, \forall i \in SD \tag{5.6}$$

Finally, equations (5.7) and (5.8) impose flow conservation between the nodes; when a MES arrives at a location, it must leave that location as shown in equation (5.7). Additionally, in order to avoid MES going back and forth between two locations and creating a closed loop within their journey, constraint (5.8) is included. An equation is added in this section to determine which customers are not served as seen in (5.9), where xns_j is 1 if location customer location j isnot served.

$$\sum_{j} x_{i,j,m} = \sum_{j} x_{j,i,m}, \forall i \in N^{'}, \forall m \in M \tag{5.7}$$

$$\sum_{m} x_{i,j,m} + \sum_{t} x_{j,i,m} \leq 1, \forall i, j \in N^{'} \tag{5.8}$$

$$xns_j = 1 - \sum_{i,m} x_{i,j,m}, \forall j \in C \tag{5.9}$$

Together these equations ensure the smooth travel of each MES from one location to the next. However, since the MES is battery operated and consumes energy or discharges while traveling from one location to the next as well as while serving customers, it also needs to charge. This is taken care of in the battery operation section.

Battery operation constraints

As each MES, travels an unknown number of trips, it is imperative to ensure that throughout its journey, the MES has enough energy on board to return to its home depot, which can be formulated as

$$ec_{i,m} \geq df_m x_{i,j,m} e_{i,j,m}, \forall i \in N', \forall j \in SD, \forall m \in M \tag{5.10}$$

where $ec_{i,m}$ is the state of charge as an energy amount in kilowatt-hours (kWh) indicating the remaining energy on board MES m, upon departure from node i. For the remainder of this routing and scheduling problem, SOC is indicated as an energy amount, $ec_{i,m}$, in kilowatt-hours which can be converted to a percentage when divided by the total energy capacity of the MES, eB_m. For example if $eB_m = 1MWh$ and $SOC = 70\%$, this would mean that $ec_{i,m} = 0.7MWh$. The six upcoming equations govern the state of charge of the MES, ensuring that it discharges, consumes energy, when traveling from one location to the next and while serving customers, and that it charges when docked at a charging station. These equations have their basis in the fundamental battery SOC operation equations, however, they have been modified for the MES application. Equations (5.11) and (5.12), govern the MES battery SOC when departing from any node, to visit a customer. These constraints ensure that the drop in SOC after traveling to and serving a customer is the sum of two components: the energy required to travel to the customer, $e_{i,j,m}$, while accounting for the driver's behavior, df_m, and the second is the energy dissipated to serve the customer for a duration of st_j in minutes, at a power rating of Pdc_j in kilowatt (kW). The next part of the equation is added to ensure that the variables are not forced to a value of 0 if the MES does not run that route. When the binary variable $x_{i,j,m}$ is 1, both equations combined become an equality constraint. However, when $x_{i,j,m}$ is 0, they become equivalent to the upper and lower limits for the variables. μ_m^{dc} and μ_m^c are the charging and discharging efficiencies of the MES.

$$(x_{i,j,m})(\underbrace{df_m e_{i,j,m}}_{\text{Travel energy}} + \underbrace{\frac{st_j Pdc_j}{\mu_m^{dc} 60}}_{\text{Service energy}}) - (1 - x_{i,j,m})(eB_m^{max}) \leq ec_{i,m} - ec_{j,m}, \tag{5.11}$$

$$\forall i \in N', \forall j \in C, \forall m \in M$$

$$ec_{i,m} - ec_{j,m} \leq (x_{i,j,m})(df_m e_{i,j,m} + \frac{st_j Pdc_j}{\mu_m^{dc} 60}) + (1 - x_{i,j,m})(eB_m^{max}), \quad \forall i \in N', \forall j \in C, \forall m \in M \tag{5.12}$$

Following the same logic as above, equations (5.13) and (5.14) below govern the situation where the MES travels to its charging station. The drop in SOC is due to the energy consumed during travel, however it increases after charging for a duration of ct_j in minutes, at a power rating of Pc_j in kW.

$$(x_{i,j,m})(\underbrace{df_m e_{i,j,m}}_{\text{Travel energy}} - \underbrace{\frac{ct_j \mu_m^c Pc_j}{60}}_{\text{Charging energy}}) - (1 - x_{i,j,m})(eB_m^{max}) \leq ec_{i,m} - ec_{j,m}, \quad \forall i \in N', \forall j \in CS, \forall m \in M \tag{5.13}$$

$$ec_{i,m} - ec_{j,m} \leq (x_{i,j,m})(df_m e_{i,j,m} - \frac{ct_j \mu_m^c Pc_j}{60}) + (1 - x_{i,j,m})(eB_m^{max}), \quad \forall i \in N', \forall j \in CS, \forall m \in M \tag{5.14}$$

Finally, the energy available in each MES is constrained by the minimum and maximum allowable state of charge that the MES's battery is allowed to reach. This is formulated in constraints (5.15) and (5.16) below.

$$ec_{i,m} \geq eB_m \frac{SOC^{min}}{100}, \forall i \in N', \forall m \in M \tag{5.15}$$

$$ec_{i,m} \leq eB_m \frac{SOC^{max}}{100}, \forall i \in N', \forall m \in M \tag{5.16}$$

Time and schedule constraints

The final set of MES constraints displayed in (5.17) to (5.22) are the time and schedule constraints. Equation (5.17) ensures that if MES m, travels from location i to customer j, its arrival time at its latter destination, $t_{j,m}^{arr}$ accounts for its arrival time at its initial destination, $t_{i,m}^{arr}$, the time it takes to travel to its customer, $t_{i,j}^{tr}$, and the time it takes to serve the customer, st_i. In the same way, equation (5.18), ensures the MES schedule is maintained when traveling to its charging stations, where ct_i is the time the MES takes to charge at location i.

$$t_{j,m}^{arr} \geq t_{i,m}^{arr} + x_{i,j,m}(t_{i,j}^{tr} + st_i) - (1 - x_{i,j,m})(lt_m^{sd}), \forall i \in C, \forall j \in N^{'}, \forall m \in M \tag{5.17}$$

$$t_{j,m}^{arr} \geq t_{i,m}^{arr} + x_{i,j,m}(t_{i,j}^{tr} + ct_i) - (1 - x_{i,j,m})(lt_m^{sd}), \forall i \in CS, \forall j \in N^{'}, \forall m \in M \tag{5.18}$$

Additionally, each customer identifies the earliest time st_i^{early} and the latest time st_i^{late} at which they can begin to receive service from a MES. Hence, an MES must arrive at a customer's location between these times as seen in (5.19).

$$st_i^{early} \leq t_{i,m}^{arr} \leq st_i^{late}, \forall i \in C, \forall m \in M \tag{5.19}$$

Finally, it is important to ensure that when departing from its starting depot, and returning to it at the end of the day, the MES's earliest departure time from the depot, et_m^{sd}, as well as its latest return time to its depot, lt_m^{sd}, are respected, as detailed in equations (5.20) - (5.22) below.

$$t_{j,m}^{arr} - t_{i,j}^{tr} \geq et_m^{sd}, \forall i \in SD, \forall j \in N^{'}, \forall m \in M \tag{5.20}$$

$$t_{i,m}^{arr} + t_i^{sv} + t_{i,j}^{tr} \leq lt_m^{sd}, \forall i \in C, \forall j \in SD, \forall m \in M \tag{5.21}$$

$$t_{i,m}^{arr} + t_i^{ch} + t_{i,j}^{tr} \leq lt_m^{sd}, \forall i \in CS, \forall j \in SD, \forall m \in M \tag{5.22}$$

MESRSP objective function

The objective of the MES Routing and Scheduling Problem (MESRSP) as discussed above is to minimize the cost of operating the MES, $C^{op,MES}$. This cost is composed of five components: cost of travel, C^{travel} in \$/km and $d_{i,j}$ is the distance in kilometres between two locations, cost of charging from the grid C^{grid} in \$/kWh, and cost of labor C^{labor} in \$/hour where H_{MES} is the operating hours of the MES. $C^{penalty}$ is a penalty cost associated with not providing an energy need. The formulation of the objective in this way ensures the minimization of cost while maximizing the customers served. Finally, C^{deg} is the degradation cost of the MES in \$/kWh and is obtained as seen in (5.24) where $CC_m^{cap,MES}$ is the MES capital costs, DOD_m is its depth of discharge and LC_m and μ_m^r are its cycle life and round-trip efficiency [49,78].

$$C^{op,MES} = N^{op,days}\Big(\underbrace{\sum_{i,j,m} x_{i,j,m} C_m^{travel} d_{i,j}}_{\text{Cost of travel}} + \underbrace{\sum_{i,j \in CS,m} x_{i,j,m} C^{grid} \frac{Pc_j ct_j}{60}}_{\text{Cost of day-time charging}}$$
$$+ \underbrace{C^{labor} H_{MES} B_{MES}}_{\text{Cost of labor}} + \underbrace{C^{penalty} \sum_{j \in C} xns_j}_{\text{Penalty cost}} \tag{5.23}$$
$$+ \underbrace{\sum_{i,j \in C,m} C_m^{deg} x_{i,j,m} \frac{st_j Pdc_j}{60}}_{\text{MES degradation cost}} \Big)$$

$$C_m^{deg} = \frac{CC_m^{cap,MES}}{eB_m DOD_m LC_m \mu_m^r} \tag{5.24}$$

The constraints for this problem are as seen in equations (5.3) - (5.22). This formulation determines the day-time operation of the MES given numerous inputs as constants. This leaves the question of what happens when an energy request is not met - if a customer is not met, it must be met by a depot charger, this is determined in a post-processing stage where xns_j is evaluated.

5.4.2 MES Operational Feasibility Problem

As can be seen from the MESRSP, the operational feasibility is not incorporated into the constraints. This was done to reduce the computational complexity of the problem to allow for scalability and to allow for efficient analysis of the geographical and electrical networks involved. If the MES chooses to charge during the day, it must charge at the depot, and if any BEB requests are not met by the MES, they must also be charged at the depot. Hence, the outcomes of the MESRSP are evaluated and the location variable $x_{i,j,m}$, the arrival time variable $t_{i,m}^{arr}$, the charging power and time Pc_j and ct_j are utilized to determine the charging profile of the MES $P_{t,m}^{chprofile,MES}$. Additionally, the customers not served xns_j, their request time st_i^{early}, the length of the service required st_i and the power required are also used to generate the charging profiles of the unserved customers, $P_{t,c}^{chprofile,cus}$. These then determine the additional load, $\Delta P_{t,o}^L$, on the power system during the day in order to ensure all BEBs and MES are able to complete their assignments as shown in (5.25).

$$\Delta P_{t,o}^{L} = z_{o}^{depotch}(\sum_{c} P_{t,c}^{chprofile,cus} + \sum_{m} P_{t,m}^{chprofile,MES}) \quad (5.25)$$

$z_o^{depotch}$ is a binary variable indicating the location of the depot on power system bus o. This last set of constraints is concerned with ensuring that the power system on which the charging operation of all MES and BEBs occurs is capable of handling the additional imposed load without violating its limits. Equations (5.26) and (5.27) show the real and reactive power flow constraints of the power system where o and p represent power system buses, while $P_{t,o}^{G}$ and $P_{t,o}^{L}$ are the real power generated and the real load power on bus o respectively. Each bus's voltage is formulated as $V_{t,o}$, $G_{o,p}$ and $B_{o,p}$ are the conductance and susceptance of the line o to p respectively, and $\delta_{t,o}$ is the voltage angle of bus o at time t.

$$P_{t,o}^{G} - (P_{t,o}^{L} + \Delta P_{t,o}^{L}) = V_{t,o} \sum_{p}^{N_{bus}} V_{t,p}(G_{o,p} cos(\delta_{t,o} - \delta_{t,p}) + B_{o,p} sin(\delta_{t,o} - \delta_{t,p})) \quad (5.26)$$

$$Q_{t,o}^{G} - Q_{t,o}^{L} = V_{t,o} \sum_{p}^{N_{bus}} V_{t,p}(G_{o,p} sin(\delta_{t,o} - \delta_{t,p}) - B_{o,p} cos(\delta_{t,o} - \delta_{t,p})) \quad (5.27)$$

To determine the number of depot FCs required to ensure continuous BEB and MES operation, two binary variables $xc_{t,c}^{day,cus}$ and $xc_{t,m}^{day,MES}$ are developed that indicate whether the unserved customer c or the MES m are charging at the depot at time t. Equation (5.28) is then used to determine the required number of FCs at the depot. This equation ensures that at every time instant the total number of BEBs and MES charging at the depot are less than the integer variable $T^{FC,day}$, the number of FCs at the depot. Additionally, the power consumed by every MES and every BEB is limited by the power rating of the charger where u_h^{FC} is a binary variable indicating whether FC of type h with power rating P_h^{FC} is selected for depot installation as seen in (5.30). For the purpose of this work $\sum_h u_h^{FC} = 1$, indicating only one kind of FC is installed at the depot. Lastly, the annual cost of day time charging of BEBs (unserved MES customers) from the grid $C^{op,ch,day}$ is calculated as shown in (5.31). MES charging costs are not included here as they are accounted for in (5.23).

$$\sum_{c} xc_{t,c}^{day,cus} + \sum_{m} xc_{t,m}^{day,MES} \leq T^{FC,day} \quad (5.28)$$

$$0.95 \leq V_{t,o} \leq 1.05 \quad (5.29)$$

$$P_{t,c}^{chprofile,cus} \leq \sum_h u_h^{FC} P_h^{FC} \tag{5.30a}$$

$$P_{t,m}^{chprofile,MES} \leq \sum_h u_h^{FC} P_h^{FC} \tag{5.30b}$$

$$C^{op,ch,day} = N^{op,days} C_t^{grid} (\sum_c P_{t,c}^{chprofile,cus}) \tag{5.31}$$

This operational feasibility problem ensures the following: the MES and BEBs that are not served by the MES are charged, while ensuring the power system limits are not violated. This objective function that minimizes the annualized cost of purchasing and operating depot fast chargers as seen in (5.32).

$$\min DepFC = T^{FC} \tag{5.32}$$

Finally, constraint (5.29) ensures that the voltage of all power system buses is maintained within acceptable limits. Additional constraints are also included such as ensuring thermal limits are met. The above mentioned formulation dictates the day time operation of the MES. Night-time operation is as formulated in Chapter 3, where the MES is modeled in the same manner as one of the BEBs, having an arrival time, departure time and rated battery capacity and its own SOC requirements.

5.5 Proposed MES Sizing Solution

As seen from above due to the scale of the problem and its numerous components, the MES operation is run in two stages: the MESRSP and the MES operational feasibility problem. For both of these stages, the MES sizing was an input not a variable. Additionally, the number of BEBs was also an input. In order to perform appropriate MES sizing, the aforementioned inputs must be optimized, however, introducing sizing variables into these problems would result in a very computationally complex program. For this reason, the problem is continued to be run in stages within a larger sizing framework.

The proposed framework aims to make decisions on the following variables: the number of MES required, the energy capacity of each MES, the optimal schedule for each MES, the number of BEBs, the optimal number of FCs to be placed at the depot for day-time charging and finally, the optimal sizing of chargers to be placed at the depot for MES

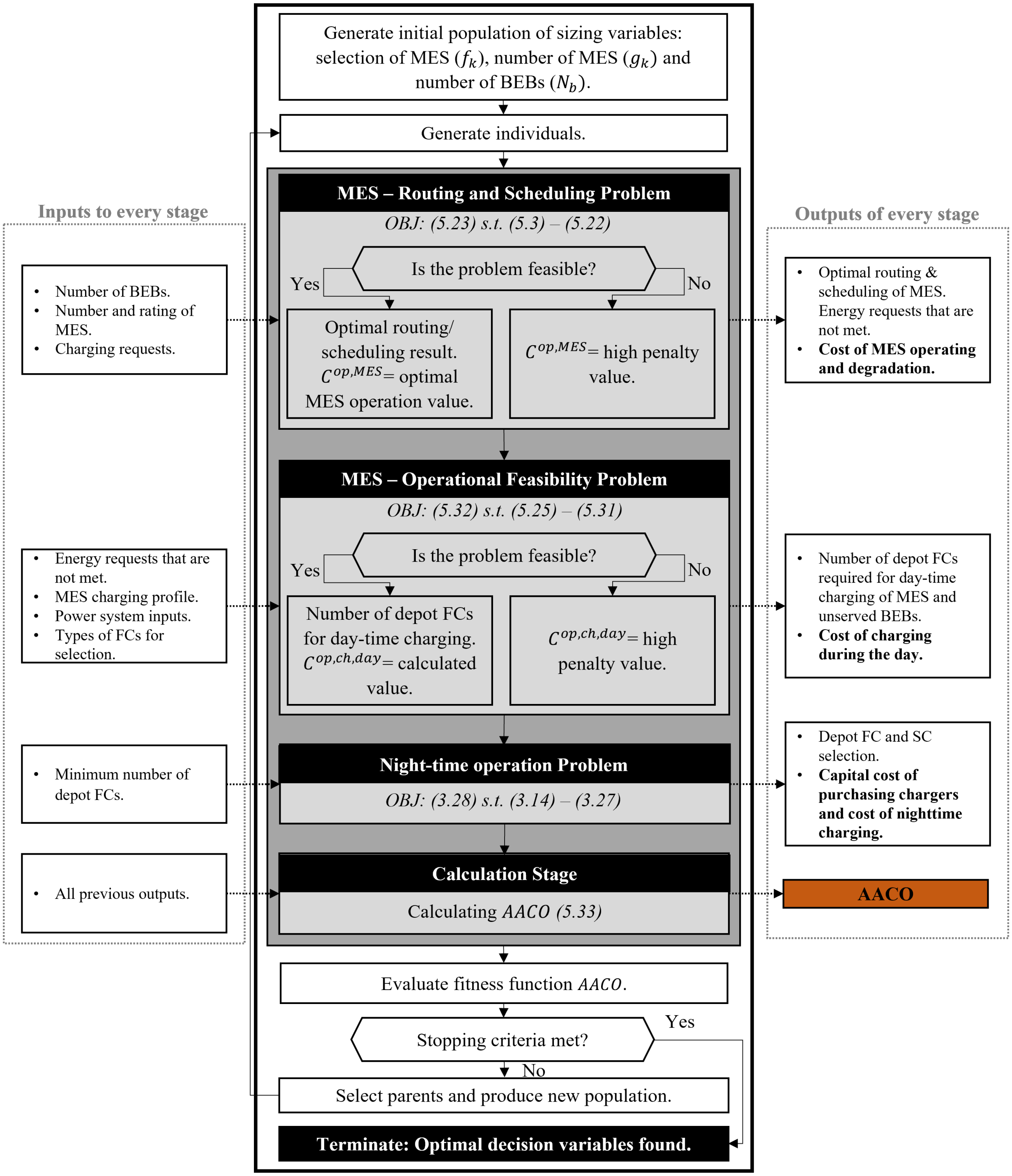


Figure 5.1: Overall solution framework.

overnight charging. The overall problem is run in stages within a large overall framework as seen in Fig. 5.1, in order to determine the optimal decision variables. The first inner problem is the MES routing and scheduling problem (MESRSP), which determines the optimal routing and scheduling of the MES as well as the cost of operating the MES $C^{op,MES}$. This is formulated as a MIP problem, solved using the CPLEX MIP solver in the General Algebraic Modeling System (GAMS) [68]. Once this is complete, the load profile of the MES and the BEB energy requests that are not served are input into the next problem which is the MES operational feasibility problem (MESOFP), modeled as a Mixed Integer Non-Linear Programming (MINLP) and solved with the BARON solver in GAMS, which determines the optimal number of fast chargers to be located at the depot to charge the MES and BEBs during the day. Finally, the required number of day time chargers is input to the night-time operation problem detailed in Chapter 3 which determines the optimal charger mix for overnight charging at the depot as well as ensures that the additional load imposed by the MES on the system does not violate the power system limits. Matlab's Genetic Algorithm (GA) toolbox is used in this study to solve the outer meta-heuristic. The outer problem is solved using the Genetic Algorithm, which aims to minimize the average annual cost of operation and solves for the following decision variables: f_k, g_k, N_b, where $f_k, k = 1, 2, ..., N_{MES}$ is a binary decision variable indicating whether MES of rating k is selected or not, and g_k is an integer variable indicating how many MES of type k are purchased, and N_b is the number of BEBs purchased. Annualized capital costs, C^{cap} as well as operating and maintenance costs, C^{op}, together make up the AACO which is minimized as shown in the objective function below:

$$\min_{f_k, g_k, N_b} AACO = C^{cap} + C^{op} \tag{5.33}$$

$$C^{cap} = C^{cap,MES} + C^{cap,BEB} + C^{cap,ch} \tag{5.34}$$

where C^{cap} is the summation of $C^{cap,MES}$, $C^{cap,BEB}$, and $C^{cap,ch}$ as shown in (5.34). These are the annualized capital costs of purchasing MES, BEBs and chargers respectively and C^{op} is the cost of operating and maintaining the transit system as a whole. The objective function is minimized with respect to the sizing decision variables f_k, g_k, N_b as mentioned above. The annualized capital cost of purchasing MES is presented in (5.35), where $CC_k^{MES,e}$ is the capital cost of purchasing MES type k in dollars per kilowatt-hour (\$/kWh) and $eB_k^{rat,MES}$ is the energy rating in kWh. $CC_k^{MES,p}$ is the power investment cost of purchasing MES in (\$/kVA), and sB_k is the MES's rated apparent power in kVA. Every MES type has a unique power and energy rating.

$$C^{cap,MES} = CRF^{MES} \sum_{k=1}^{N_{MES}} f_k g_k \Big(eB_k CC_k^{MES,e} + sB_k CC_k^{MES,p} \Big) \tag{5.35}$$

Additionally, $u_h, h = 1, 2, ..., N_{FC}$ and $v_l, l = 1, 2, ..., N_{SC}$ are binary variables that indicate whether or not a FC of rating h is selected, and whether or not a SC of rating l is selected respectively. For the purpose of this work $\sum_h u_h = \sum_l v_l = 1$, and T^{FC} and T^{SC} are the total number of fast and slow chargers placed at the depot respctively. The annualized capital cost of purchasing BEBs, $C^{cap,BEB}$, can be found using the number of BEBs, N_b, the capital cost of purchasing the BEB in \$, $CC^{cap,BEB}$, and the capital cost of the BEB battery as shown in (5.36). The energy investment cost of the battery, $CC^{BEB,e}$, in \$/kWh depends on the battery energy rating, eB, while the power investment cost of the battery, $CC^{BEB,p}$, in \$/kVA depends on the battery apparent power rating, sB, where all BEBs have the same rating for interlining. Equation (5.37) presents the annualized capital costs of purchasing chargers: whether SCs as depicted by the first half of the equation or FCs as presented in the second half. P_h^{FC} and P_l^{SC} are their power ratings in kW, and finally $CC_h^{FC,p}$ and $CC_l^{SC,p}$ are their respective capital costs in \$/kW. Finally, CC_h^{FC} and CC_l^{SC} are the installation costs of FCs and SCs in \$ respectively.

$$C^{cap,BEB} = CRF^{BEB} N_b \Big(CC^{cap,BEB} + CC^{BEB,e} eB + CC^{BEB,p} sB \Big) \tag{5.36}$$

$$\begin{aligned} C^{cap,ch} = CRF^{ch} \Big(&\sum_{h=1}^{N_{FC}} u_h T^{FC} (P_h^{FC} CC_h^{FC,p} + CC_h^{FC}) \\ &+ \sum_{l=1}^{N_{SC}} v_l T^{SC} (P_l^{SC} CC_l^{SC,p} + CC_l^{SC}) \Big) \end{aligned} \tag{5.37}$$

In view of the fact that the objective function contains a mixture of costs, some of which are capital costs paid at the time of acquisition and some of which are annual costs, all costs are required to be annualized. Consequently, all capital costs are annualized by using an annualization factor also known as a capital recovery factor, CRF, as calculated in (5.38) and (5.39). This factor is based on four values: nominal and effective interest rates, ir and ir' respectively, as well as the inflation rate, inr, over the lifetime of the asset lf. It is for this reason that the CRF of each asset is calculated separately, to account for their different lifetimes. The above objective function in (5.33) is subject to the constraints described in the consequent subsections.

$$CRF = \frac{ir'(1+ir')^{lf}}{(1+ir')^{lf}-1} \tag{5.38}$$

$$ir' = \frac{ir - inr}{1+inr} \tag{5.39}$$

Finally, the operation and maintenance costs C^{op} are found as shown in (5.40), where $C^{op,MES}$ and $C^{op,BEB}$ are the operation and maintenance costs of MES and BEBs respectively. While $C^{op,MES}$ is the cost of operating the chargers which comes from the cost of charging BEBs and MES. $C^{op,MES}$ is found as in equation (5.23). $C^{op,BEB}$ is found as the product of the kilometres traveled by the fleet and a cost in \$/km. Finally, $C^{op,ch}$ is the summation of two components: $C^{op,ch,day}$ as determined in (5.31) and $C^{op,ch,night}$ as determined through the night-time formulation.

$$C^{op} = C^{op,MES} + C^{op,ch} + C^{op,BEB} \tag{5.40}$$

5.6 Case Studies, Results and Discussions

The presented cases demonstrate the effectiveness of MES in facilitating and supporting the transition from conventional to electrified public transportation. Table 5.1 summarizes the case studies discussed in this work, which are intended to provide a comprehensive and realistic overview of the impact of MES on both short and long distance bus routes the parameters of which are shown in Table. 5.2. Furthermore, two charging strategies are examined for each route type: overnight charging and opportunity charging.

Table 5.1: Case Study Description.

	S-1	***S-2***	***S-3***	***S-4***	***L-1***	***L-2***	***L-3***	***L-4***
Route type	4 short distance (SD)				4 long distance (LD)			
Charging Strategy	OVN	OPP	OVN	OPP	OVN	OPP	OVN	OPP
MES utilized	✗	✗	✓	✓	✗	✗	✓	✓

Table 5.2: Route Parameters.

Parameter	SD Value	LD Value
Number of routes	4	4
Daily trips per route	70	40
One way trip length	5.5 km	53 km
Number of stops per trip	18	14
Present diesel fleet per route	5 buses	10 buses

5.6.1 System Inputs

As shown in the case summary table, the developed algorithm is applied on two types of routes; short distance and long distance routes. The basis input parameters of both route types are obtained from real-life Canadian transportation routes with input data as shown in Table 5.2. In practice, in order to meet the assignment requirements, each SD route is currently operated by 5 conventional diesel buses, while the LD route is operated by 10 buses, where each transit agency includes additional buses as reserve assets to cover during maintenance periods and in cases of emergencies. The four routes of the same kilometer range have essentially the same parameters as shown in the system inputs section, with the only difference being the locations that each route covers - with the only overlap being the base depot, a characteristic of real-world PT systems. To develop a comprehensive study, each route type is studied using overnight charging, without the utilization of MES (S-1, L-1) and while including MES (S-3, L-3) and again using opportunity charging without MES (S-2,L-2) and with MES (S-4, L-4) to obtain a thorough comparison of results. In the overnight charging cases, BEBs are not permitted to charge throughout their daily assignments, but rather only during the night time upon arrival at their depot. On the other hand, the opportunity charging cases entail placing fast chargers along the BEBs' routes to allow them to recharge along their trips, which allow for increased driving range.

In order to realize the impact of MES incorporation, some inputs to the problem are maintained as constants; only 313 kWh BEBs are utilized as they were the optimally selected BEB sizes in the previous chapters. Transit agencies generally purchase buses with similar battery capacity to facilitate route interlining, hence making this a reasonable assumption for the study [79]. Four slow charger and fast charger options were selected as the input choices for this work, therefore $l = 4$ and $h = 4$ respectively, with the slow charger selections rated at 60 kW, 75 kW, 80 kW and 90 kW, and the fast charger selections rated at 250 kW, 300 kW, 350 kW and 400 kW. Additionally, four MES rating selections were also selected for this work, 660 kWh, 750 kWh, 1 MWh and 1.2 MWh, hence $k = 4$.

The maximum power output for each MES is 150 kW, 250 kW, 250 kW and 500 kW respectively [80]. For the purpose of this study the BEB and MES lifetimes are 12 and 10 years respectively, while the MES charging efficiency is considered as 95% and the fast and slow charger efficiencies are 90% [81,82]. Finally, the inflation rate is 1 % and the interest rate is 5 % [81]. A detailed list of BEB, charger and MES costs is presented in Table 5.3.

Table 5.3: Cost Parameters.

Item	**Cost**	**Reference**
BEB fixed capital cost	\$ 525,000	[16,82]
BEB variable cost	750 \$/kWh	[16,82]
BEB maintenance cost	0.4 \$/km	[16,82,83]
MES capital cost	850 \$/kWh	Personal communication with [56,84]
MES capital power cost	175 \$/kW	[81,85]
MES maintenance cost premium	10%	[86,87]
Depot slow charger cost	715 \$/kW	[82]
Depot installation cost	18,000 \$/charger	[82]
FCS charger cost	1,540 \$/kW	[82]
FCS installation cost	200,000 \$/charger	[82]

The research in this chapter overlays three systems, the geographical map, the power distribution system and the public transportation route map as shown in Fig. 5.2. To create a realistic geographical-electrical system, an IEEE-38 bus distribution system with base values 10 MVA and 12.66 kV as detailed in [88] is overlaid onto the routes due to the fact that the exact specifications of the power distribution network are not available at these route locations. The short distance route system as modeled in cases S-1 to S-4 is displayed in Fig. 5.2. Four SD trips marked in green are overlaid on the distribution system with the starting location of each trip being the depot, and the end trip marked by the black square as shown in the figure. Some routes start their trips from the depot - meaning loading passengers from the depot station (routes A and B), where others must travel to begin their trips and at the end of the day must travel back once more to park at the depot, known as pull-in and pull-out routes (routes C and D). As soon as all input data has been collected regarding the routes under study, the energy consumption profiles of the BEBs as well as MES as they travel along a route are generated by modeling probabilistic synthetic speed profiles as per the methodology described in [34]. This is done considering heavy traffic and winter conditions to allow for MES sizing that accounts for the worst-case scenario. Additionally, the setting of minimum SOC for all BEBs and MES ensures sufficient remaining charge to allow for impacts of weather or driving conditions. Total electric bus energy consumption during heavily loaded traffic is found to have an average of 1.6 kWh/km, ascertaining realistic results as in [30]. This increases to 1.8 kWh/km when factoring in harsh weather conditions, resulting in additional HVAC use and slower average speeds.

PT fleet electrification does not occur overnight, rather transition plans are implemented to gradually replace existing fleets with electrified fleets as discussed in Chapter 4. Numerous electrification initiatives are governed by deadlines, with several global organizations setting targets of 50% electrification by 2030 and 100% by 2040. An optimally sized and operated MES can result in significant cost savings and many subsequent benefits through all phases of the transition. All cases will be studied twice for two different electrification percentages; with 100% of the trips electrified and with only 50% electrified. The following subsections detail the results.

5.6.2 Overnight Charging Results

The charging methodology analyzed in this subsection is overnight charging. The addition of MES allows for the BEBs to charge during the day. Due to the nature of short-distance routes, most buses do not stop for more than 2 minutes along their trips other than at their home depot or at the final stop along a route. For this reason, regarding short-distance routes, the MES service locations as determined by the input problem are as follows: the shared home depot, the four final locations served by each of the four routes. On the other hand, for long-distance routes, any location where the BEB stops for longer than 8 minutes as well as the start, and end locations of each trip are considered as candidate MES locations. In the overnight charging case, the MES is sized to ensure that it meets all the BEBs' charging needs. The BEBs are able to complete their trip assignments with their overnight charge and the MES's mid-day boost.

S-1 vs. S-3: Overnight Charging of SD Routes

When four Short Distance (SD) routes are operated by BEBs, in order to optimally complete their assignments without running out of charge, a total of 36 BEBs with battery capacities of 313 kWh, as well as 28 75kW depot chargers. Of the 70 daily trips per route (a total of 280 trips for all four routes), each bus runs 7-10 round trips, where the

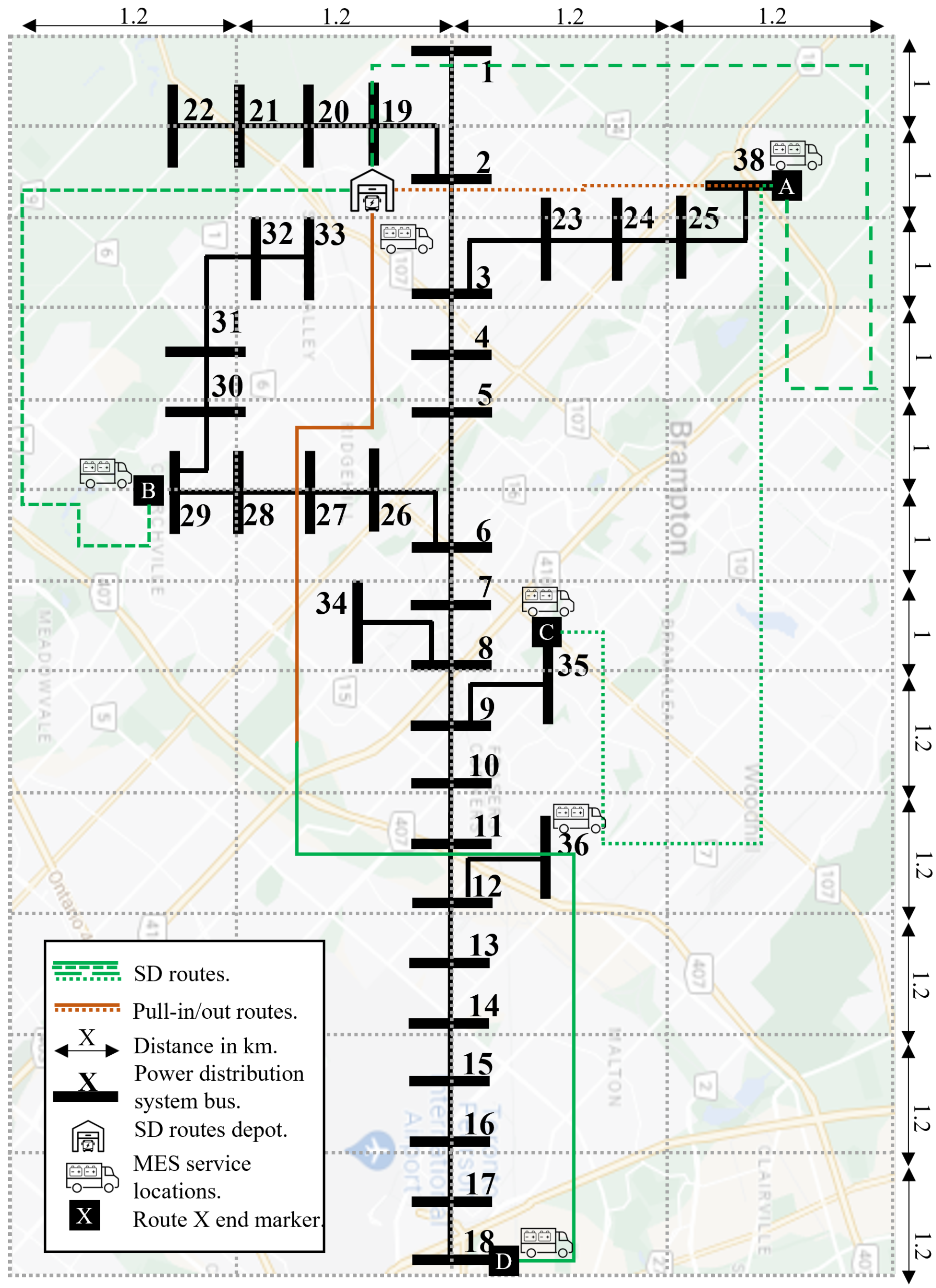


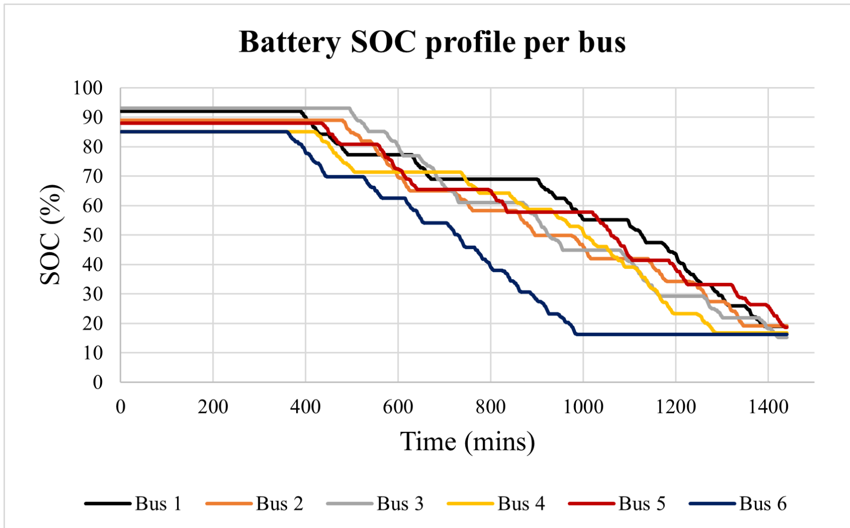
Figure 5.2: Test system with short distance routes.

bus scheduling is performed to ensure that each bus runs one trip at a time, while its battery SOC never falls below 15%, where the SOC profiles of 5 buses of the same route are displayed in Fig. 5.3a. The SOC of each BEB is a measure of the remaining energy as a fraction of the battery's total capacity. According to the overnight charging schedule, each BEB begins the day with an SOC of between 80% and 93%. With each trip assigned to the BEB throughout the day, more energy is consumed in completing those trips, resulting in a decrease in SOC. Finally, due to the charging methodology utilized here, there is no increase in SOC over the course of the day.

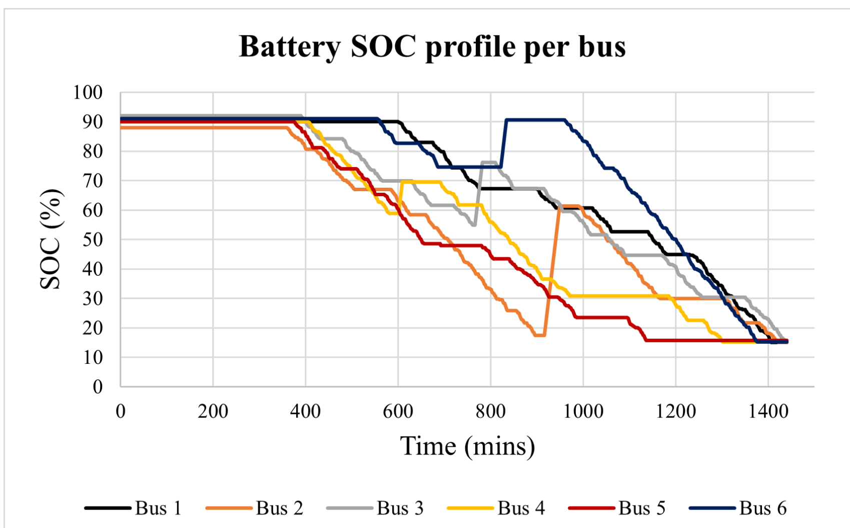
The benefits of MES can be observed within this transit system. Instead of 36 BEBs, 24 BEBs with the same battery capacity can run the same 280 trips, where each bus serves 10-15 trips a day. The additional trips per bus means that each BEB consumes more energy, requiring the MES to charge it during the day, resulting in an increase in BEB SOC during operating hours as seen in Fig. 5.3b. According to Fig. 5.4a, bus 2 was once capable of running 10 trips, with red markings indicating each trip's consumption profile, and following MES integration can run 15, as shown in Fig. 5.4b. MES increases the driving range of each of the BEBs by at least 50%, allowing each bus to serve at least four additional trips per day. Additionally, 2 MES with a capacity of 1 MWh are sufficient to replace 12 BEBs due to the proximity of the depot and all four routes. All the above result in cost savings of 19.8% where the system's total annualized cost without MES is $5.95 million per year (S-1), while the incorporation of MES reduces this amount to $4.78 million (S-3). In essence, instead of charging only at the depot overnight, the MES can now serve all bus routes at their end locations or the depot, as the BEBs stop for reasonable amounts of time only at these locations for short routes. Finally, slow charging was more economical than fast charging when buses were only charging overnight. Now that the presence of a fast charger is required for charging the MES, a large number of slow chargers are no longer needed.

L-1 vs. L-3: Overnight Charging of LD Routes

Without the incorporation of MES, when studying LD routes using overnight charging (L-1), parking space limitations would render this problem unsolvable since a significantly large number of BEBs (over five times the number of current conventional fleet) would be required to operate long-distance routes without recharging on route or between trips. Alternatively, BEBs with very large onboard batteries can serve long-distance routes, but the larger batteries require more space and weigh more, increasing the BEB's energy consumption while reducing its passenger capacity. Due to this limitation, overnight charging is not a practical option for long-distance electrification. By implementing MES, this prob-

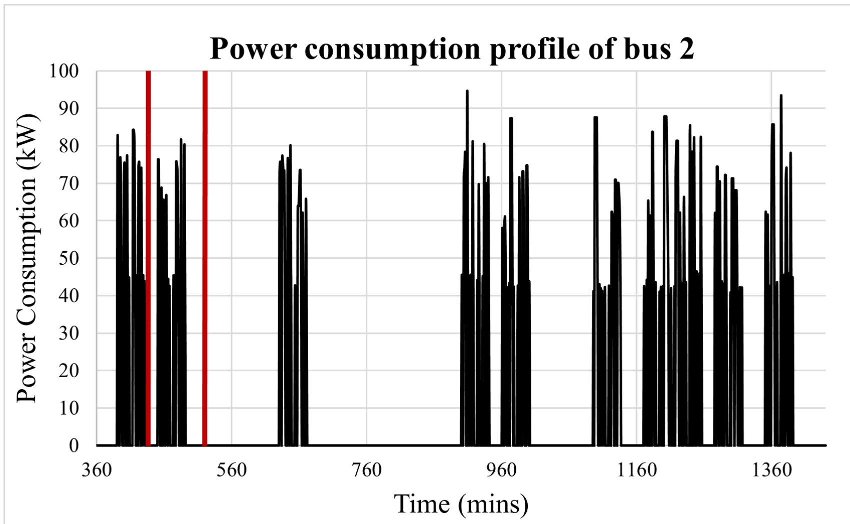


(a)

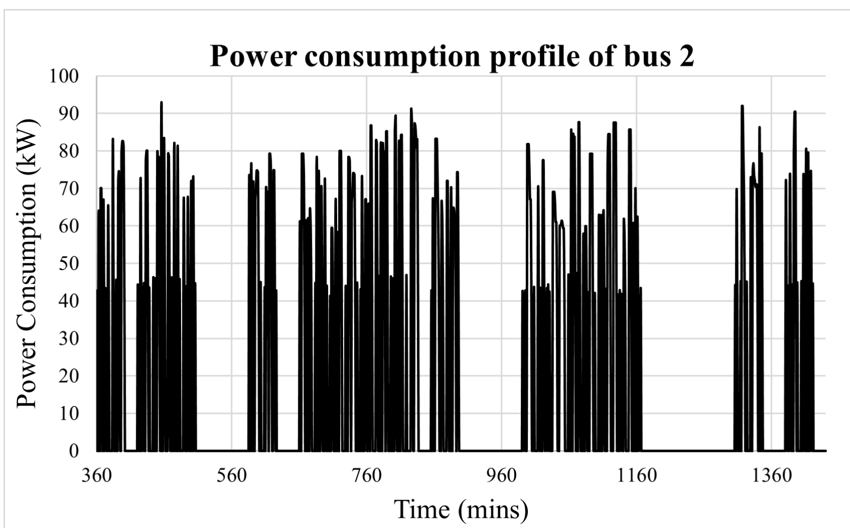


(b)

Figure 5.3: (a) SOC profiles of 5 BEBs utilizing overnight charging without MES. (b) SOC profiles of 5 BEBs utilizing overnight charging with MES.



(a)



(b)

Figure 5.4: Consumption profile of bus number 2: (a) without MES integration, (b) with MES integration.

lem can be solved for an annualized cost of $14.63 million, where 4 MES are required to travel between the large driving ranges of the BEBs. Where it might seem infeasible to have MES serve LD routes as this implies MES would also travel long distance, this is not the case. The MES do not travel the same routes as the BEBs, as the BEBs do not take the shortest distance between two locations due to their route restrictions. Located at the depot, fourteen 75 kW chargers and eight 250 kW chargers ensure that the BEBs and MES are adequately charged to perform their daily functions. Finally, it is quite realistic to consider overnight as a charging strategy to electrify LD routes, as it is considered by agencies such as the TTC, where for some projects, they plan for PT Electrification projects with the consideration of only overnight charging [89]. A summary of the results can be found in Table. 5.4.

5.6.3 Results for Opportunity Charging

The impact of MES on the electrification of PT when opportunity charging is used is also studied using the same four short-distance routes and four long-distance routes. This charging strategy relies on FCSs which in addition to being expensive to install, place a heavy demand on the electricity system. Therefore, transportation electrification necessitates upgrading electric infrastructure. Thus, MES integration is advantageous to replace on-route FCSs, allowing BEBs to recharge on their way without imposing a large load on the grid. Regarding SD routes, FCSs are only placed at depots and final stops (end-stops), or at the stops where multiple routes intersect. In this work, these stops are considered the MES service locations as marked in Fig. 5.2. However, concerning LD routes, MES service locations are the same locations as the installed FCSs.

S-2 vs. S-4: Opportunity Charging of SD Routes

Twenty 313 kWh BEBs are required to ensure uninterrupted service on four short-distance routes while utilizing opportunity charging. Four 250 kW chargers are installed along the route for daytime charging, while four others are placed in the depot for opportunity charging during the day and for nighttime charging in preparation for the next day. MES can completely replace the four on-route FCSs when they are integrated into the system, allowing the BEBs to run mainly on the energy charged overnight and the boost from the MES, with only four of the 20 BEBs requiring a mid-day fast charge at the depot. As a result of the MES's purchase costs, the annualized capital costs for the system with MES are quite comparable, however the operating and maintenance costs are much lower. Consequently, the annualized cost is reduced by 19.36%, from $7.18 million to

Table 5.4: Optimal Sizing Decisions.

Variable	**Optimal Sizing Decisions Per Case**							
	S-1	**S-2**	**S-3**	**S-4**	**L-1**	**L-2**	**L-3**	**L-4**
Number of BEBs	36	20	24	20		44	52	44
Selection of slow chargers (kW)	75	0	75	0		0	75	0
Number of slow chargers	28	0	16	0		0	14	0
Selection of fast chargers (kW)	0	250	250	250		250	250	250
Number of on-route fast chargers	0	4	0	0		8	0	0
Number of depot fast chargers	0	4	1	5		12	8	14
Selection of MES (kWh/kW)	N/A	N/A	1000 /250	1000 /250		N/A	1000 /250	1000 /250
Number of MES	N/A	N/A	2	2		N/A	4	4
Annualized Capital Costs (M$)	3.15	2.36	2.42	2.31	N/A	5.13	5.55	5.24
Annualized Operation and Maintenance Costs (M$)	2.81	4.92	2.36	3.48	N/A	12.06	9.08	8.17
Total Annualized Cost (M$)	**5.95**	**7.28**	**4.78**	**5.79**	**N/A**	**17.19**	**14.63**	**13.41**

$5.79 million yearly. The 2 MES replace the on-route FCSs by providing the same energy needs that the FCS would have met. In this context, it is important to note that the SOC profiles of the BEBs as seen in Fig. 5.5 are quite similar regardless of whether they are charged through the FCSs or the MES, with only slight variations in timings in order to adhere to the MES service schedules and travel times. Fig. 5.5 shows the 5 BEBs that operate route 1.

The optimal schedule and operation of MES 1 sized in case S-4 is displayed in Table. 5.5, while the SOC profiles of both 250 kW / 1 MWh MES are shown in Fig. 5.6. If charged through an on-route FCS as in case S-2, the cost of purchasing energy from the grid would have been very high, however, utilizing MES allows the BEB to receive the

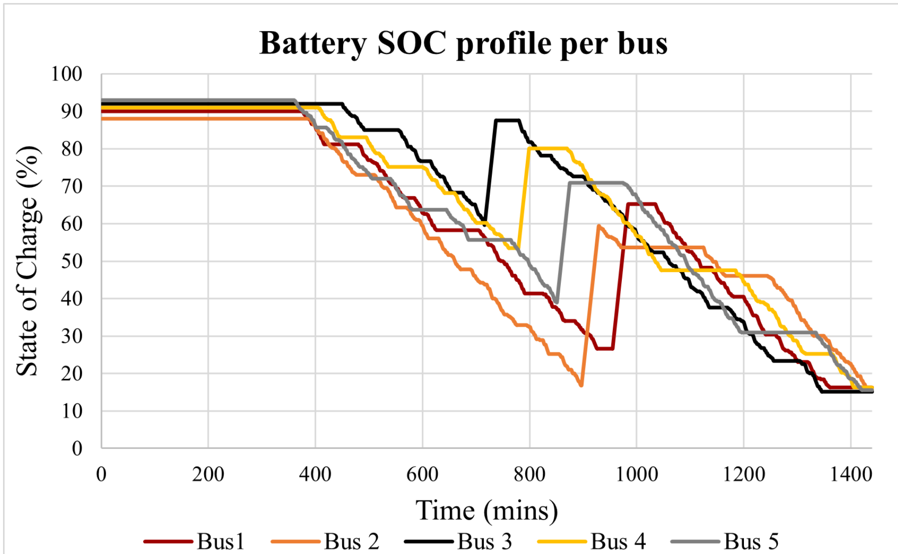


Figure 5.5: SOC profiles of 5 BEBs operating Route 1 utilizing opportunity charging with MES.

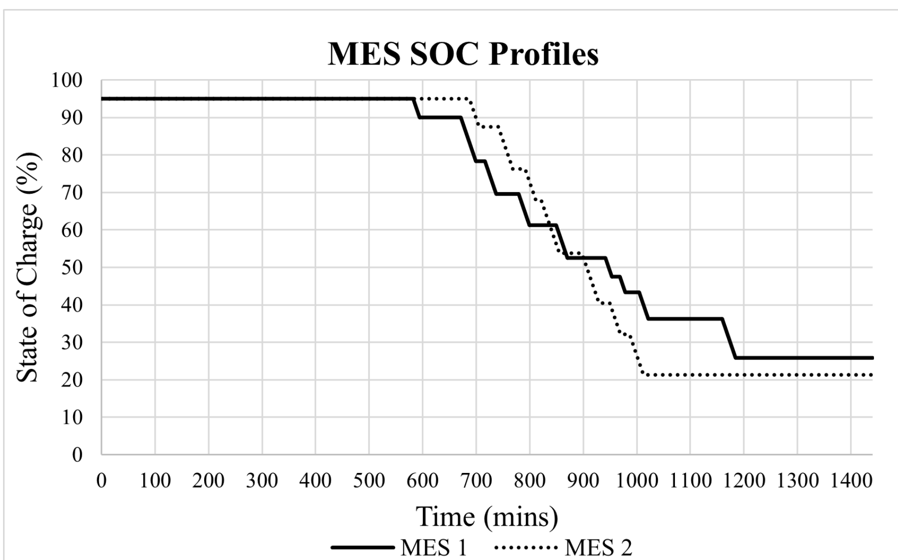


Figure 5.6: SOC profiles of 5 BEBs utilizing opportunity charging with MES.

Table 5.5: MES 1 schedule and operation for Case S-4.

Route No.	**BEB No.**	**Arrival time**	**Service duration (mins)**	**Arrival SOC**	**Departure SOC**
4	3	09:43	12	94.58%	90.58%
4	5	11:12	28	89.57%	78.5%
1	3	11:57	21	77.92%	69.58%
1	4	13:00	20	69.2%	61.25%
3	5	14:10	21	60.83%	52.5%
3	4	15:42	12	52.08%	47.5%
4	4	16:09	10	47.83%	43.33%
2	3	16:45	17	42.92%	36.25%
3	3	19:20	25	35.83%	25.83%

same energy required but not directly from the grid, while the MES is charged at off-peak hours (if needed), hence resulting in significant cost savings while simultaneously reducing the stress on the grid. It is therefore clear that the MES is able to provide the same energy needs at a significant cost reduction, proving the efficacy of the proposed solution.

L-2 vs. L-4: Opportunity Charging of LD Routes

In the absence of MES, opportunity charging is the only way to power LD routes. This is due to the fact that buses can charge during long trips, thus enabling the trips to be completed with a reasonable number of BEBs. In this case 44 BEBs, 8 on-route chargers and 12 depot fast chargers, rated at 250 kW are needed. The incorporation of MES allows LD routes to be served with the same 44 BEBs while eliminating the on-route fast chargers and reducing the cost of operating the system. As with SD routes, MES completely eliminates the need for on-route charging on these routes as well. This reduces the total annualized cost from $17.19 million to $13.41 million, delivering a cost saving of 21.99%. A summary of these results are also presented in Table. 5.4.

5.6.4 MES to Support PT Electrification

As discussed previously, fleet electrification is a long process, with purchase decisions made over a large number of years. The transition of the SD routes using the two charging

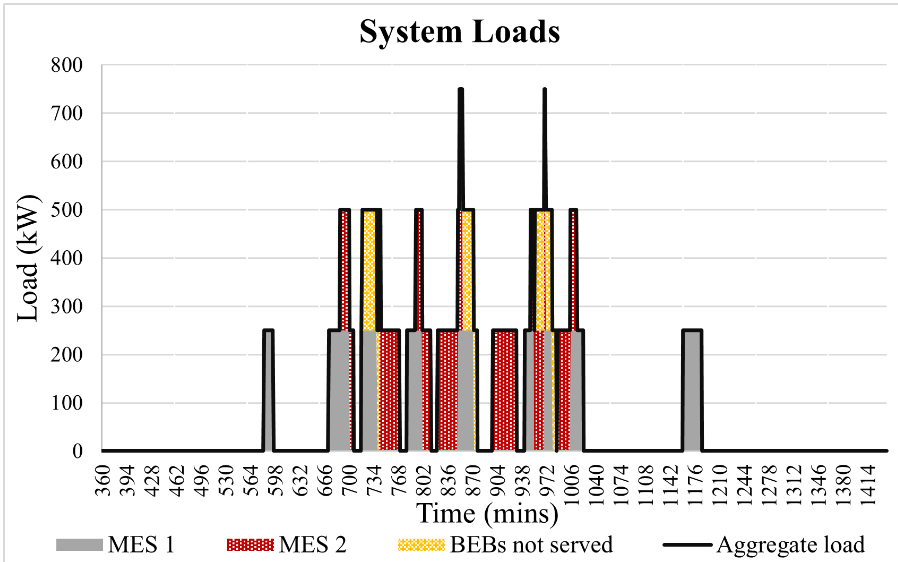


Figure 5.7: System loads.

strategies presented in this work is modeled and presented in Chapter 4. As seen from the results of this chapter, MES yields significant benefits across many aspects. When running a fully electrified transit system with short-distance routes, without the incorporation of MES, heavy loads are imposed on the power system through the opportunity charging of BEBs. This can be seen by the solid black line in Fig. 5.7 where this is the load imposed on the power system. The incorporation of MES allows for the two-sized MES to serve 81.48 % of the system's loads, with the only loads remaining being those marked in yellow. Hence, the incorporation of MES allows for the peak load to be reduced from 750 kW to 250 kW resulting in significant operational cost savings for the transit system as well as reduced stress on the electric grid. Since MES is able to result in such significant savings for a completely electrified system, MES would also be very beneficial throughout the transition where it would be utilized for shorter time periods and be on standby for the remaining time periods to support in case of emergencies. MES yields cost savings and allows for a faster transition to electrified fleets in the case where charging infrastructure will not be readily available. Incorporating MES within the fleet electrification would allow for benefits in terms of the following:

- Financial benefits resulting from operational cost savings as operating fast charging stations is very expensive. Additionally incorporating MES reduces the number of BEBs needed to operate a route, hence resulting in savings of these amounts.

- Technical benefits to the transit system by increased resilience to charger failures and emergency situations such as getting stranded away from the depot.
- Technical benefits as driving range is improved through a flexible solution that is able to meet the driver rather than having the driver reach it, hence reducing driving range anxiety.
- Electrical benefits through reduced peaks on the grid, hence delaying the need for grid reinforcement. Additionally, reduced the time in waiting for permits to install on-route chargers.

If purchased at the beginning of the electrification process, the MES has the potential to ensure the smooth operation of the transit system, while allowing TAs the flexibility to change and modify their newly electrified routes as needed without the commitment to specific on-route charging locations resulting in a wastage of resources.

5.7 Conclusion

This chapter presents MES as an integral solution to all categories of barriers that inhibit the widespread deployment of BEBs. Incorporating MES into Public Transportation Electrification (PTE) helps reduce the driving range anxiety of BEB drivers and transit agencies since MES provides on-the-go charging and, in an emergency, meets BEBs at their location. MES integration also eliminates some financial barriers, as demonstrated by the results where MES has led to significant cost reductions. Moreover, even if the annualized capital costs are comparable pre and post-MES integration, the annual operating costs are much lower. Last but not least, MES reduces the peak load imposed on the power grid during the day, thus reducing some of the obstacles associated with it. The objective of the proposed problem is to perform the optimal sizing, routing, and scheduling of transit-owned MES to realize the multi-faceted techno-economic benefits of utilizing MES in the transition to electrified transportation. To ensure that the MES meets the needs of the transit system and is recharged during the day, a novel routing and scheduling strategy is proposed. Two different charging technologies are tested: opportunity and overnight, as well as two different transportation systems: long-distance and short-distance. With the use of MES, transit agencies using overnight charging can save 32.89% on short-distance routes, and in the case of long-distance routes, the problem, which was once infeasible, becomes feasible with the use of MES. Furthermore, when combined with opportunity charging, MES can save 28.17% on short-distance routes and 24.89% on long-distance

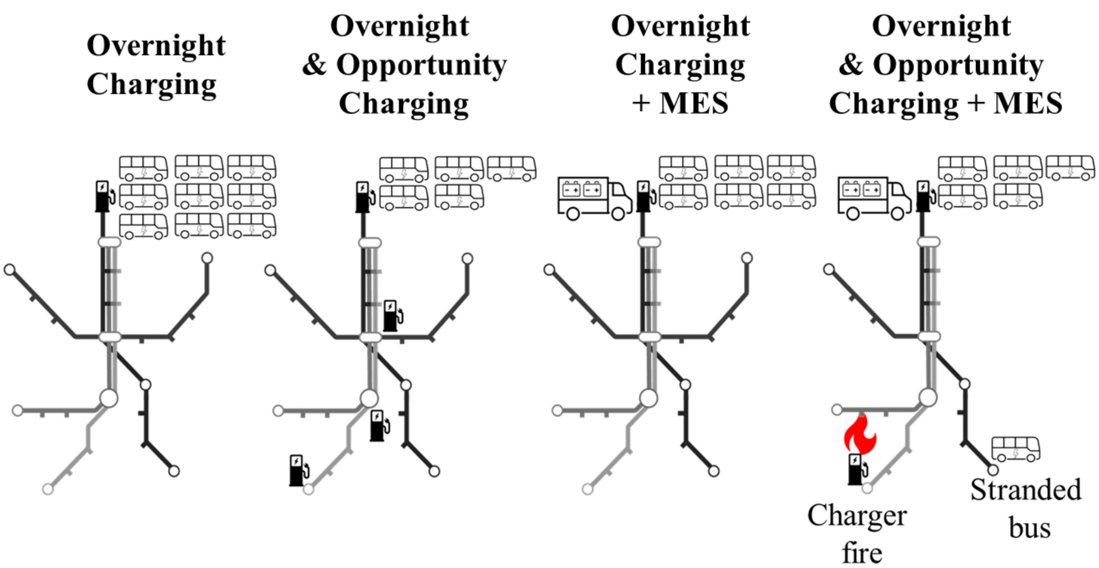


Figure 5.8: Possible modes of operation.

routes. Overall, from both a technical and economic standpoint from both the transit and the electrical systems' perspectives, MES is an advantageous solution.

In summary, the key difference between electric and conventional fleets is the method of refueling. For the conventional fleet, the locations where a bus could refuel during the day do not matter. Transit agencies can simply decide where to set up designated gas stations for their buses to refuel and they will transport the gas to that location because gas is mobile. The MES proposed in this work is aimed at accomplishing the following – electricity is not exactly mobile, so a transit agency cannot simply decide to charge at any location (agreements must be made, charging ports must be made available, etc.). Therefore, MES makes the electric transit system comparable to the conventional transit system in terms of flexibility.

It should be noted that this does not imply that a transit agency must operate all of its routes using MES. This thesis presents the operation methodologies for four different possibilities (overnight and opportunity charging, which are well studied), as well as two novel concepts that incorporate MES into the prior formulation all of which can be seen in Fig. 5.8 and the costs of which can be seen in Table. 5.4. It is then the transit agency's discretion to make their own selections. However, if they choose MES, there are several advantages that can simplify the complicated transition process, while also improving the transit system's resiliency to emergencies and allowing it to make changes to routes as necessary. In essence, MES provides transit agencies with a dynamic solution for a dynamic system. The transit agency at this point owns an asset that has the potential to serve even more customers when the MES is not being used by the transit system, but the key is to understand the best way to utilize the asset or to sell any unused energy capacity to external customers. The ensuing chapters detail the possibility of further utilizing the MES units to serve external customers with any unused capacity, ensuring that the acquired asset is used to its full potential.

Chapter 6

A Cooperative vs. Non-Cooperative Game-Theoretic Approach for Customer-owned Energy Storage

6.1 Introduction

As seen in the previous chapters, in the process of electrifying its fleets, the transit system has now acquired a very powerful technology - Mobile Energy Storage (MES) to tackle numerous barriers to Battery Electric Bus (BEB) deployment. While the MES was sized to satisfy the transit system's needs, this was done based on the worst-case scenario and with added contingency criteria. Consequently, the transit agency now owns an asset that has additional capacity, but the key is to understand how to utilize this asset. As MES is an advanced version of Stationary Energy Storage (SES), a SES hub consisting of multiple energy sources is studied in order to determine the most appropriate methodology for modeling interactions with customers. This energy storage hub was modeled to contain multiple energy sources to allow it to be adaptable to any application with single or multiple energy sources. There exists a lot of potential for energy storage problems to be modeled using several game-theoretic approaches; however, it is unclear which one is best. Hence, in this work, two approaches were used: the first approach is a cooperative one that strives to achieve a correlated equilibrium and maximize the social welfare of all the players with the help of a regret matching algorithm, and the second is the clinching-auction approach which is a non-cooperative game, thus modeling players to have greedier tendencies of improving their personal benefit.

The research presented in this chapter does not aim to prove the superiority of one of the approaches over the other, but rather to observe how the players behaved in each approach and to determine which of the game models could be further developed depending on the application. For the scope of this thesis, it is assumed that the Energy Storage Hub (ESH) owner (the Transit Agency (TA)) owns a SES hub, with a predetermined energy mix and a predetermined capacity. The hub serves three categories of consumers: the electric grid, residential consumers, and industrial consumers, each with its unique needs and behaviors. The regret matching algorithm, which is a cooperative approach, was first applied followed by a non-cooperative interaction approach modeled as an ascending price-clinching auction. While energy storage hubs are a unique concept, the main focus is usually energy allocation modeled as optimization problems. To the authors' knowledge, the modeling of the interactions between an energy storage hub's owner and its customers has never been studied. Hence, the contributions of this work can be summarized as follows:

- The development of two contrasting expandable games that model the interactions between the energy storage hub owner and customers, where the ESH incorporates multiple energy storage technologies.
- The development of the players' utility functions to model their satisfaction levels with different game outcomes, while ensuring that the risk-averse human nature is reflected.

The rest of this chapter is organized as follows: Section 6.2 discusses the modeling of the problem. Sections 6.3 and 6.4 entail an in-depth explanation of the cooperative and the non-cooperative approaches respectively. These are followed by the case study results and discussion in section 6.5 and the work is concluded in section 6.6.

6.2 Game Model

As mentioned earlier, this chapter aims to study the behavior and interaction of an ESH owner - which in this research is the TA - and its customers as realistically as possible using game-theoretic approaches. The game's setup is described in this section.

6.2.1 System Overview

The ESH modeled here is a collection of three different types of energy storage technologies: batteries, supercapacitors, and flywheels, each with unique electrical characteristics

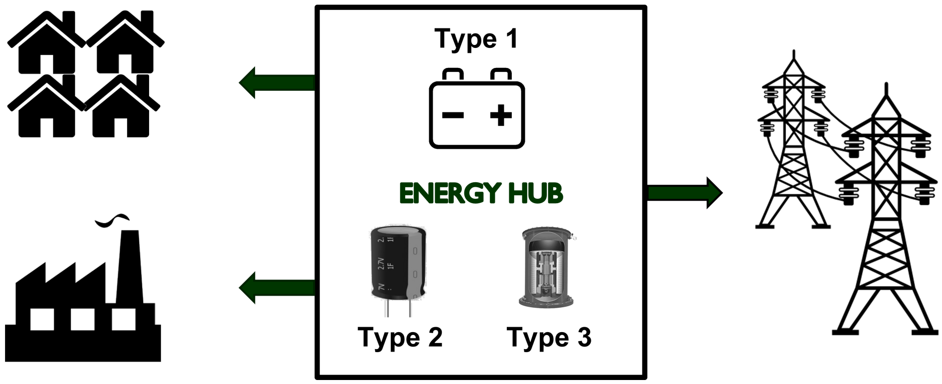


Figure 6.1: System overview

such as charge and discharge time, capacity, and ramp rate. Batteries, for example, are characterized by low power density but a high energy density, while supercapacitors are the inverse. Thus, batteries, supercapacitors, and flywheels each respond to a specific consumer need because of their complementary qualities. An overall view of the system can be seen in Fig. 6.1.

In this model, each customer has one of three energy needs: reducing peak demand, power quality improvement, and finally, voltage regulation. Consumers may have additional requirements, while the hub may host far more technologies, but this model is easily scalable to meet any formulation. An Energy Storage Management Platform (ESMP) is assumed to enable communications between all end-users and the grid, as well as between all end-users and the ESH. All the ESH customers in this model are energy consumers. In order for the game to begin, customers must submit their forecasted energy needs for the next 24 hours to the ESMP (day-ahead) for an internal optimization problem to determine the optimal charging schedule of the energy storage technologies to incur minimal costs while meeting the predicted demand for the following day. Once that is done, the consumers' needs during the day may differ from their forecasted needs. Consumers would be penalized if their consumption changed drastically, however, if they changed within acceptable limits, they must inform the hub every time the system's power flow is calculated and optimized. This system is run in hourly time slots, hence every hour, a game is played to determine how the energy hub and its users will behave. Two very different approaches are considered in the coming sections, both yielding remarkable results.

6.2.2 Players and Actions

As discussed above, in this game two types of players are defined: the ESH's owner and the hub's customers. The hub's customers can then be classified into three major groups: the electric grid, aggregated residential customers, and industrial customers, where each group behaves differently and has unique energy storage requirements. Accordingly, energy need i is modeled by energy type i, with $i = 1, 2, 3$. As a further clarification, this means that there are three possible energy demands and three possible energy sources to meet those demands. Due to the scope of this work, no matching algorithm is provided to match each need with the appropriate technology, hence the aforementioned assumption. Lastly, j refers to the player number in this work, where player 1 is the hub owner, 2 is the grid, 3 is the residential customer and 4 is the industrial customer. In summary, the energy hub has a single owner and three major consumer categories which will be discussed in further depth in the remainder of this section (the electric grid, residential customers, industrial customers).

Energy Hub Owner

The owner of the hub, as the energy seller, has one major responsibility: to determine the \$ per kilowatt-hour (\$/kWh) price for every type of energy sold. Therefore, they make a decision: p_i, which is the price in dollars of 1 kilowatt-hour of energy resource type i. The goal of this player is to maximize profit.

Energy Hub Customers: The electric grid

In this work, the electric grid operates in two modes. Firstly, there is the normal mode of operation, in which the grid operator requests energy from the ESH to improve voltage profiles, reduce renewable curtailment, or serve any other standard purpose that enhances the current system. A failure to obtain the full amount of energy requested would not lead to system collapse, it would simply result in higher operational costs.

The second possible mode of operation is the emergency mode. This mode is crucial for distribution networks since it involves service restoration. After an interruption, a self-healing distribution network would need to identify the fault and then restore service. The fault identification process and restoration details are beyond the scope of this thesis, as our objective is to model the interactions of the MES. Promptly restoring service is a crucial part of enhancing the resilience of distribution networks, so the operator's energy requests under emergency mode (during restoration) must be met in a timely manner [90]. Hence, the game must be designed so that the electric grid is the hub's most important customer, thereby guaranteeing that the network operator's needs are always met. Under normal and emergency conditions the grid must perform internal power flow analysis, and report hourly on the maximum possible demand for energy as well as the actual energy demanded from each energy resource, $e_{j,i}^{max}$ and $e_{j,i}$ respectively. The sections following include a discussion on how to find the latter by evaluating utility functions in different ways. Lastly, they should identify whether they are operating in emergency conditions or under normal circumstances.

Energy Hub Customers: Residential

Residential customers can only operate under one mode. By purchasing energy under normal mode, they can improve their operational conditions and generate profits. The residential customer can benefit, for instance, if energy is used for peak shaving, as this will decrease their electric utility bills since they are dependent on the peak energy consumed. Moreover, they could request energy to enhance the power quality of their system.

Additionally, residential consumers are also required to report the maximum possible energy demanded as well as the actual energy demanded from each energy resource, $e_{j,i}^{max}$ and $e_{j,i}$.

Energy Hub Customers: Industrial

For industrial customers, the same values must be reported as for residential customers. In addition, another value must be reported: the cost of service failure, which is specific to every industry and is a function of the duration of service interruption, $cf_{j,i}$, [91]. Accordingly, industrial customers have two utility functions, one for each mode of operation depending on the type of industry and the type of costs incurred due to failures in the system.

6.2.3 Utility Functions

Following discussion of the actions and goals of all the players, it is necessary to model their utility or payoff functions. In this subsection, all utility functions are listed in accordance with the user's behavior as described earlier.

Energy Hub Owner

A utility or a payoff function describes the mapping of real-life outcomes of the game to numbers. According to the seller, the goal is to maximize profit hence, increasing profit would increase their satisfaction. For this reason, the ESH's owner's utility function can be defined as the revenue made from selling the different energy resources, $e_{j,i}$, to the different consumers, at a price of p_i, minus the cost of operating the facility, $OPEX$, as shown in (6.1).

$$u_1 = \sum_{j \neq 1} \sum_{i} (p_i e_{j,i}) - OPEX \tag{6.1}$$

Energy Hub Customers: The electric grid

A consumer's utility is represented by the monetary gain generated from satisfying an energy need through the ESH. If, for instance, a consumer was to contract the hub to supply energy for peak shaving purposes, the utility function would describe the benefit to the consumer from reducing their peak energy charges while deducting the price of the purchased energy. Equation (6.2) describes the electric grid's utility function, where $\beta_{j,i}$, is consumer's price sensitivity coefficient per consumer j and energy type i [92]. This coefficient varies with time depending on the user's need for energy type i. The first term refers to the benefit the player receives from acquiring a specific amount of energy. Furthermore, the second term illustrates the concave nature of the user's behavior, which represents a rational game player, while the last term describes the loss the consumer would incur as a result of the price of the energy resources they purchase.

$$u_2 = \max(0, \sum_{i} (\beta_{2,i} e_{2,i} - \frac{\beta_{2,i} e_{2,i}^2}{2 e_{2,i}^{max}} - p_i e_{2,i})) \tag{6.2}$$

Energy Hub Customers: Residential

The residential customers have the same behavior as the electric grid. Constraints are added in order to ensure that any player's utility function is always non-negative.

Energy Hub Customers: Industrial

Under normal conditions, industrial customers behave in the same manner as the residential customers as well as the grid, however, under emergency conditions, the utility function is modified as shown in equation (6.3). Adding the coefficient $cf_{j,i}$ to the equation indicates that if there is some kind of disconnection from the grid, which leads to a failure in the industrial customer's plant, the customer now values the energy resource even more than they did before. As an example, loss of service in the telecommunications industry is critical, therefore, their factor would be a high value indicating the significance of the energy received to the continuity of service.

$$u_4 = \max(0, \sum_i (cf_{4,i}\beta_{4,i}e_{4,i} - \frac{\beta_{4,i}e_{4,i}^2}{2e_{4,i}^{max}} - p_i e_{4,i})) \tag{6.3}$$

The above equations all describe how the users behave. Upon analysis, it is evident that all of the utility functions except for that of the ESH's owner's, (6.1), behave in a quasi-linear manner.

Table 6.1: Game sets, parameters and descriptions.

Parameter	**Parameter Description**
i	Energy resource type. $I = 1, \ldots, i, \ldots N_i, \|I\| = N_i = 3$
j	Game player, where player 1 is the ESH owner and the remaining players are energy consumers. $J = 1, \ldots, j, \ldots, N_j, \|J\| = N_j = 4$
p_i	Price of one unit of energy type i, in cents per kilo-Watt hour.
$e_{j,i}^{max}$	Maximum possible demand for energy based on historical data.
$\beta_{j,i}$	Price sensitivity coefficient of player j, in cents per kilo-Watt hour to energy type i.
$cf_{j,i}$	Continuity of service coefficient for player, j, and energy resource, i.

In summary, this is the following game amongst users:

- Players: The ESH's owner and the hub's customers. The hub's customers are the electric grid, aggregated residential customers, and industrial customers.
- Strategies: The hub's owner selects how much energy it is supplying to each customer. Each consumer selects its energy consumption in either a cooperative or a greedy

manner and that is decided based on the type of game they will play, as discussed in the following sections.

- Utility or payoff functions: u_j, where all the players' utilities are shown in equations (6.1)-(6.3).

At this stage, all the information necessary for the game to begin is available. Despite knowing who the players are, their strategies, and their utilities, their behaviors and interactions with one another remain unknown. The outcome would be substantially different if they interacted cooperatively as opposed to acting greedily. Sections 3 and 4 explain two opposing approaches used to model the ESH interactions while section 5 presents the results of applying the two approaches.

6.3 Cooperative Correlated Equilibrium Game Approach

In this approach, the players cooperate and play the game with the goal of achieving the maximum possible social welfare and social fairness. The adaptive learning algorithm utilized here to reach a correlated equilibrium is the regret matching algorithm. There are several steps involved in this iterative approach, the first of which is to adjust the utility functions of all players by adding a global term to every player's utility function. This additional global term is the utility of the most dissatisfied player, meaning the player with the lowest utility value. Each player's utility function represents their satisfaction level and adjusting these functions so they incorporate the aforesaid global term would enhance everyone's overall satisfaction. Rather than every player striving to enhance their own utility (improve their satisfaction), they will now also improve the utility of the least satisfied player. The expected result of this algorithm is that the most selfish player becomes less greedy while all players maintain a reasonable satisfaction level. As proved in [93], the achieved result of the regret matching algorithm will be a correlated equilibrium. A correlated equilibrium describes a probability distribution over a set of strategies and by playing according to this probability distribution, if no other players change their actions, you have no incentive to deviate hence achieving the necessary game results.

6.3.1 Regret Matching Algorithm

At the very beginning of the game, each player randomly chooses an action from their set of strategies and evaluates their utility for that action. The regret matching algorithm consists of a series of steps. First, each player's utility function is normalized as follows:

$$u_j^{norm}(i,j) = \frac{u_j(i,j) - u_j^{min}(i,j)}{u_j^{max}(i,j) - u_j^{min}(i,j)} \tag{6.4}$$

To do this normalization, it is clear that at every iteration of the game, the players' actions must be stored as well as the history of their utility functions. Once this normalization is complete, it is then important to identify the worst-off player within all players. The worst off player is the one with the lowest value utility function, this player is then identified as seen in equation (6.5).

$$F = \min(u_1^{norm}(i,j), u_2^{norm}(i,j), u_3^{norm}(i,j), u_4^{norm}(i,j)) \tag{6.5}$$

Once this player is identified, the utility functions of all players is modified for the very last time to include the worst-off player's utility as seen in (6.6). In this way, social welfare is improved.

$$u_j^{mod}(i,j) = w_1 u_j^{norm}(i,j) + w_2 F \tag{6.6}$$

$$w_1 + w_2 = 1 \tag{6.7}$$

In this work, w_1 and w_2 are chosen to be of equal weight, 0.5 each, to emphasize both each player's own utility as well as the overall welfare of all other players. As soon as all this is done, the game is now ready to be played to achieve a correlated equilibrium. As mentioned earlier, this game is modified at every iteration as the players learn from their previous actions and observe how to improve their own happiness as well as that of others. To achieve this, first, a value called the difference value is calculated. This difference value can be described as such: if player 1 plays action 1, while all other players play their randomly selected actions, player 1 must calculate the difference in their utility if they had played any other action in her action set other than action 1, while all other players did not change their actions, as seen in (6.8). The current iteration is denoted as n, S_j describes player j's chosen action at iteration k, while all other actions that player j did not choose at iteration k are denoted as $S_j^{'}$. Finally, all other player's actions at iteration k are represented as S_{-j}^k.

$$D_j^n(S_j, S_j^{'}) = \frac{1}{n}\sum_{k=1}^{n}(u_j(S_j^{'}, S_{-j}^k) - u_j(S_j, S_{-j}^k)) \tag{6.8}$$

Next, once this difference is calculated it is now easy to calculate regret. This can be seen by the following: if player 1 calculates her difference $D(1,2)$ this means that she is calculating the utility that she would get had she played action 2, less the utility she actually got.

$$R_j^n(S_j, S_j^{'}) = \max(D_j^n(S_j, S_j^{'}), 0) \tag{6.9}$$

If this is positive, it means that she "regrets" not playing action 2, if it is negative, she has no regrets, and regret is stored as 0 as seen in (6.9). Finally, this regret is then transformed into a probability distribution, π, that defines how the player would play her next move at the next iteration as seen in (6.10). This is done by every player at every iteration where μ is a constant that ensures that all probabilities add up to 1.

$$\pi = \begin{cases} p_j^{n+1}(S_j^{'}) = \frac{R_j^n(S_j, S_j^{'})}{\mu}, & \forall S_j^{'} \neq S_j \\ p_j^{n+1}(S_j) = 1 - \sum_{S_j^{'} \neq S_j} p_j^{n+1}(S_j^{'}), & \text{otherwise.} \end{cases} \tag{6.10}$$

Once this is done and each player identifies their new action, and all the utilities are calculated once more, the worst-off utility F at the current iteration is compared to the one at the previous iteration and if it is less (meaning that some player is doing even worse than the worst-off player in the previous iteration), F is found as in (6.5), however, if F is more (all the players are doing better off than the worst-off player before), F is set as 1 to indicate a direction of improvement. This process is then repeated until a correlated equilibrium is reached.

An argument may arise against this approach, since the energy consumers may not care for each other's well-being or each other's satisfaction levels, hence making this approach unreasonable. However, it may be significant to note that this approach can be beneficial because, in reality, all electricity consumers are either directly or indirectly interconnected. Therefore, improving the behavior of one can improve the overall system. For example, if the residential consumer is capable of peak shaving by obtaining energy from the energy hub at the time of peak demand, this means that they would be satisfied because their bills are now decreasing. Moreover, at the same time, this benefits the grid as it reduces the maximum peak, hence reducing the network's peak charges and delaying the need for equipment upgrades. So overall, if one user aims to improve their behavior, all users benefit from those actions. Moreover, to further expand on this thought, one of the major challenges with regards to energy storage systems is the issue of ownership, hence when considering a grid-owned ESH, this cooperative approach is a reasonable methodology. Hence this approach was taken into consideration in this work.

6.4 Non-Cooperative Correlated Equilibrium Game Approach

In this section, the same game setup is modeled as an ascending price clinching auction. It is interesting to note that the following auction framework is based on the concept that each player ends up obtaining what they need at prices that align with their valuations. Moreover, the way that this auction is designed, entails that every player who "clinches" an item pays a price that is not based on his valuation alone, rather it is also based on all other player's valuations, allowing for this auction to be a truthful auction as valuation manipulation or covering would lead to no added benefit, as proved by Ausubel in [94].

6.4.1 Auction Framework

Similar to the previous modeling, the main challenges that this auction tries to tackle are the price selection for the energy resources as well as energy allocation. The ascending price clinching auction mechanism is described in this section to develop answers to the above-posed questions.

As a starting point, all the players in this formulation are limited to integer actions, meaning the price is incremented in integer steps by the ESH owner and users bid on integer items (bundles of energy). Each energy resource is auctioned separately. Note also that since each energy request is independent of the other, a combinatorial auction is not required. The next steps describe a simplified version of this procedure. At the beginning of the auction, the auctioneer announces a starting price, p_i, and once that has been done, every bidder determines the number of units requested at that price. That is done based on their internal marginal valuations: how much they value every incremental unit item received [95]. Once each player determines the number of units to be requested, the auctioneer checks to see if the total demand exceeds or equals the total supply. If there is more demand than supply, the price is incremented by the auctioneer until demand equals or drops below the supply. The final step is to determine which bidders will clinch items and at what price.

To further clarify, consider an instance of the game where the total supply of energy type 1 available is 1000 kWh (10 units of 100 kWh), at a price of 3 \$/kWh. Every bidder then determines how many units of energy of type 1 they should request at this price. Consider the following quantities are obtained: the grid (player 2) requests 600 kWh, the residential customers (player 3) 700 kWh, and the industrial customers (player 4) 300 kWh. The way in which it is determined if anyone is going to clinch any units is as follows. For player j, consider the same game with the same demand levels if j was not participating, the total demand is calculated. If that total demand exceeds supply, then player j does not clinch any units at that price. However, if the total demand excluding player j is less than the supply, player j then clinches the difference between the supply and that demand at the price the auctioneer has at this stage. So, if the above values are observed, it can be determined that player 3 is the only player who clinches at this round. This player clinches 100 kWh of energy at the price of 3 \$/kWh.

Lastly, the auctioneer increases the price by one increment, and the above is repeated. Once the demand becomes less than or equal to the supply, the game is stopped. This is not the only method for conducting auctions; however, this is a simple and reasonable approach for this case. It can be argued that, in this context, the ESH should not be selling the same products or services for different prices. However, this situation is in fact quite reasonable, since an industrial customer, for example, will pay far more than a residential customer to avoid expensive service interruptions, thus the player who values the item most will receive it. For this reason, during the grid's emergency mode of operation, the problem is handled differently. When the grid is in a state of emergency, the entire system (all users included) might be impacted, so when the grid is under emergency, whatever energy they need is given to them. Finally, it is interesting to note that this auction yields the same results as the Vickrey auction.

6.5 Case Study and Results

6.5.1 Cooperative Correlated Equilibrium Approach

To implement both games, $\beta_(j, i)$ was identified for each player and each energy type along with the discrete possible action sets allowable for each player. When the cooperative

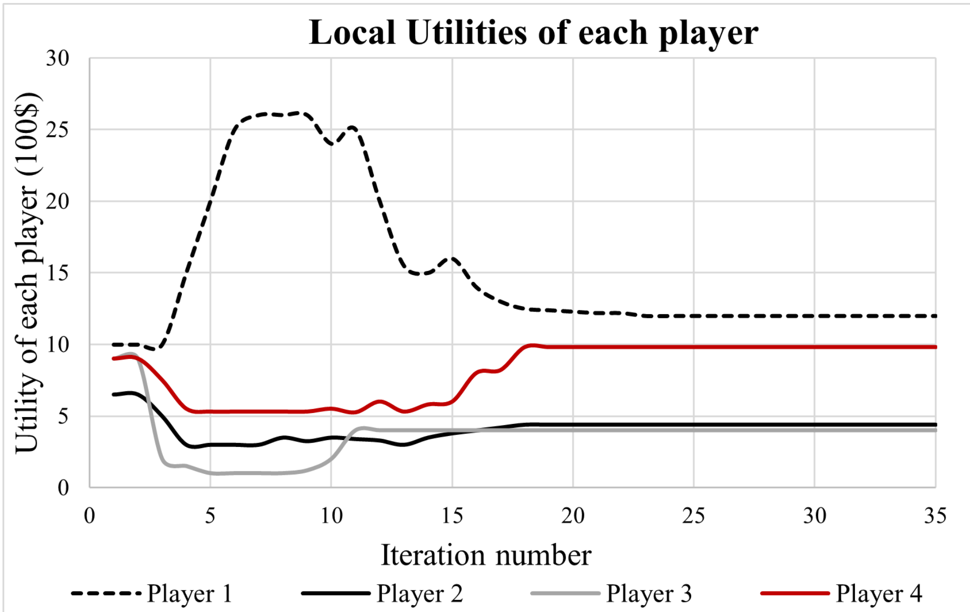


Figure 6.2: Local utilities of each player at every iteration.

correlated equilibrium approach is implemented, the results obtained are displayed in Fig. 6.2 and Fig. 6.3. The individual utilities of each player are cost values calculated in \$, however, due to the normalization, their global utilities are unit-less.

Fig. 6.2 displays the local utilities of each player and how they change with each iteration. As can be seen from the figure above, due to the limited nature of the possible action sets taken by each player, it can be seen that within less than 30 iterations of the game, a correlated equilibrium has been reached, and the players continue to change their actions but only slightly. It is also quite visible that all the utilities are maintained non-negative as per the game specifications. It is significant to note that player 1's local utility, hence profit, started off as the highest and as it decreased, the other player's utility functions improved. This is because player 1 is the hub owner, at first the prices start off exceptionally large to maximize individual utility, however as the game proceeds, it is clear that the most selfish player (player 1) becomes less greedy, and the social welfare of the overall system is improved. Fig. 6.3 shows the global utilities of this same game, the global utilities are the normalized and then modified utilities of each player which include the utility of the worst-off player at every iteration. It can be seen that as the game progresses these global utilities continue to change to reach the correlated equilibrium. Once this equilibrium is reached, no player has the incentive to deviate.

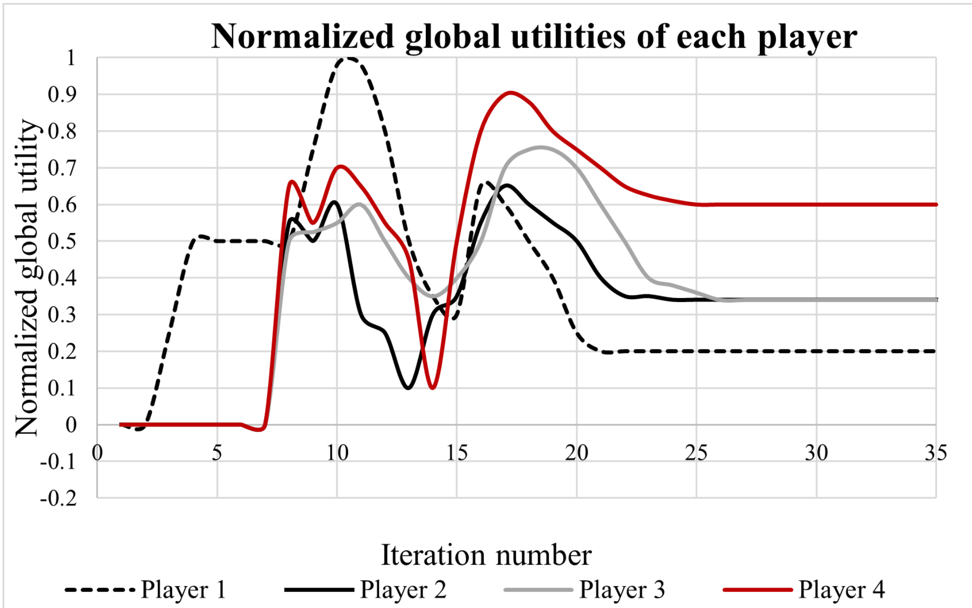


Figure 6.3: Global utilities of each player at every iteration.

6.5.2 Non-cooperative Ascending Price Clinching Auction Approach

In this approach, the auctioneer's energy supply per resource is displayed in Table. 6.2. With a starting price of 0.1 $/kWh, the auction begins. The auction then proceeds in the manner described earlier and the results are displayed in Fig. 6.4. It can be seen that the aggregate demand of each energy type is equal to the supply, which is exactly what this auction should result in.

Table 6.2: Ascending price-clinching auction auctioneer's supply.

Energy Type i	$i = 1$	$i = 2$	$i = 3$
Maximum supply Available (kWh)	40	50	30

A comparison of results obtained from both approaches shows that the hub's revenue is approximately 11% larger using the auction approach, while each player's utilities for the two different approaches vary within ±8% of each other for both approaches. However, the allocations differed in both approaches. This shows that the results are not too different

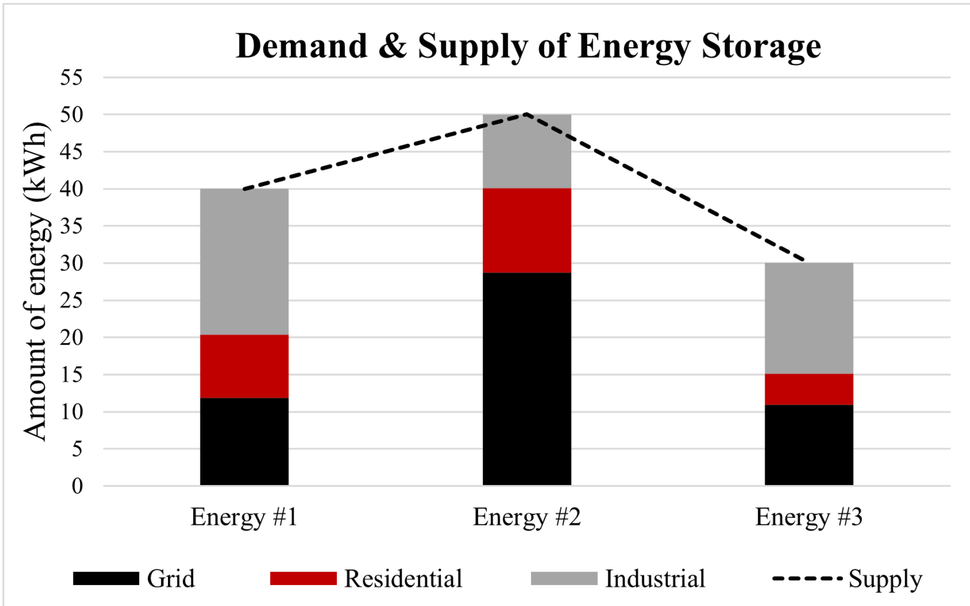


Figure 6.4: Clinching auction results.

from each other, once again this may be due to the small size of the simulated system and the fact that multiple technical and physical constraints were not studied. However, the results produced reasonably describe a real-world scenario in terms of the allocations and the final utilities. Finally, since both approaches used are well established, they have been thoroughly proved and defended in [93] and [94]. Hence the focus of this chapter was on applying these approaches to energy storage and observing their behavior.

6.6 Conclusions

In this chapter, an ESH is modeled to have three categories of customers: the electric grid, residential and industrial customers. The interaction is modeled by using two methods, a cooperative approach, and a non-cooperative approach; the regret matching algorithm and the clinching auction. It should be noted that while both approaches discussed above are well-established, they have never been used to model an energy storage hub or any work related to energy storage trading. In the first approach, the cooperative methodology, the greedy player which is the energy hub owner, reduced their profits, however, the other players were all positively impacted. Despite being independent of each other as entities, these players are still indirectly reliant on each other, especially the grid, so if the grid fails the entire system connected is negatively impacted. Accordingly, it may be beneficial to the hub to work towards improving the grid's behavior and utility even if it means reducing profits. As for the second approach, the non-cooperative methodology, it is readily evident that this is a reasonable model for the energy hub storage system, as it makes the energy available to the player who values the energy the most. There are significant differences between both approaches and they yield distinct results. In the context of a complete system, the comparison will be more comprehensive. As observed through the results, both approaches performed as expected in terms of allocation as well as pricing. As this system continues to be expanded on an electrical basis, and as the number of players and available energy resources expand, more constraints and complexity will arise, so both approaches can be more comprehensively compared. Each approach has the potential to provide meaningful results, hence the goal of this chapter was to show how two conflicting methods of interaction can be implemented and the choice of methodology depends on the application at hand. [1]

The interactions studied in this chapter lay the foundation for the final goal of this thesis. As previously discussed the Public Transportation (PT) system requires a fast, flexible, and holistic solution to tackle the barriers to its electrification. MES presents itself as a very beneficial solution to tackle all these barriers. Once the acquired MES is in smooth operation by the TA, it can be utilized to generate additional revenue by serving external customers outside the transit system. Once again, the TA acts as the energy storage hub owner, where its customers would contract its services to meet their energy needs. The transit agency's goals are clear: maximizing revenue generation without cooperating with their customers. Hence, the non-cooperative clinching auction approach studied in this chapter is deemed the better fit for this application and the interactions between the MES and its customers are modeled in the coming chapter. Adding mobility to the problem increases the complexity as now the ESH incurs costs that were once not there, including but not limited to transportation costs. Additionally, the MES units do not serve these customers exclusively, rather they have to ensure that the TA's needs are served as well. Therefore, the mobility of the MES has an impact on the results, hence, modeling the MES interactions is discussed in depth in the coming chapter.

[1]This work is published in: [96].

Chapter 7

Revenue Stream Generation for Transit-Owned Mobile Energy Storage while Studying Customer Interactions

7.1 Introduction

As stated by the Chair of the Toronto Transit Commission:

> *"By partnering with the IESO, the TTC is pursuing new and innovative approaches to* ***build resiliency and sustainability across our transit network. These projects leverage TTC assets and new technologies to reduce peak energy demand and capture excess energy, allowing the TTC to operate efficiently while also giving back to the power grid."*** [76]

When electrifying the public transportation system, Mobile Energy Storage (MES) presents itself as an excellent holistic solution that tackles numerous Battery Electric Bus (BEB) deployment barriers, allowing for smooth transition and operation of BEB fleets. The addition of the mobility feature onto the well-studied Energy Storage (ES) allows a single MES unit to serve a larger number of energy customers non-simultaneously, hence creating sufficient revenue streams to justify the high initial expense. Although the MES has already proved to be a valuable tool for the transportation system as seen in Chapter 5, there is still room for generating additional revenue from serving external customers in reducing their peaks as mentioned above. Here external customers are those that are not a part of the Transit Agency (TA).

While the MES was sized to optimally provide benefits to the transit system, the following question arises: When will the MES have the available capacity or schedule flexibility to serve additional external customers? MES sizing was done while accounting for the worst-case scenarios in terms of traffic congestion, and weather conditions. Additionally, transit systems are not set in stone with TAs constantly studying their routes, ridership, and fares to determine if any changes are to be made [97]. Several changes to transit systems are possible: seasonal changes that occur periodically as well as one-time permanent or temporary changes [98]. Seasonal changes that depend on other sectors tend to have a significant impact on the transportation sector, for example, reduced ridership of certain lines that serve university towns in the summer season, or increased ridership to tourist spots during certain months of the year, hence leading TAs to decrease or increase their route frequency to match these demands [99]. Additionally, routes that have seen reduced ridership over the years are transformed into "on-demand" routes, where the buses do not run these routes unless requested [100]. All of the above dictate that BEBs do not always run at full frequency, hence allowing for reduced energy requirements from the MES, allowing the MES to have additional energy capacity that can be utilized to benefit numerous customers and also indirectly "give back to the power grid".

Finally, the research done on MES, often assumes that the MES is grid-owned. However, in this research as discussed in previous chapters, the MES is transit-owned, and hence a study of how the MES can interact with its customers and generate revenue streams is crucial. The goal of this chapter can be summarized as follows:

- The development of two novel MES routing and scheduling formulations where the MES is operated to maximize its profits while meeting its own system's needs as well as those of external customers.

7.2 Problem Description

The primary advantage of MES systems is their mobility; they are able to move quickly and frequently to provide services to a variety of customer groups. There are two categories of customers: primary and secondary. Primary customers include entities whose energy needs must be met by the MES, while secondary customers include entities whose needs may or may not be met by the MES. MES owners are usually the primary customers, therefore satisfying their own needs is of paramount importance. After meeting these demands, the MES may then provide services to other consumers from the secondary category to create multiple revenue streams and generate profit. It should be noted that the MES used in this study is owned and operated by the transit system; therefore, their BEBs are the sole primary customer of the MES. Our model includes three secondary customers: owners of Renewable Energy Sources (RESs), Electric Vehicle (EV) parking lots, and residential complexes.

7.3 Problem Formulation

In this section, the formulation of the MES service problem as described above is detailed. The first formulation is an optimization-based approach, while the second is an integrated auction and optimization based approach. It is assumed that any emergency scenario overrides the contracts of any external customers through an agreement with them - emergency situations include natural disasters or hospital emergencies, where the customers served in the case of emergency pay a premium price to have this service. For further clarification, if an emergency were to arise, the MES would stop any ongoing service and travel to the necessary emergency location.

7.3.1 Optimization Based Approach

In this formulation every customer whether internal or external is represented by their location. For elaboration set $N^{'}$ is the set of all locations in this problem where $N^{'} = SD \cup C \cup CS \cup exC \cup exSC$, where set SD represents the starting depot location of the MES, C is a set of all the internal customer locations (the BEBs), set CS is the set of all charging locations that the MES can charge in, set exC is the set of all paying external customers, and finally set $exSC$ is the set of all customers who are energy sellers (customers paid by the MES). It is noteworthy that even if two customers are at the same location, they are still represented as two different locations but with a distance of 0 and travel time of 0 between them. $i \in N^{'}$ represents one of the locations where $j \in N^{'}$ is an alias of i. The set of MES is denoted as M, where each MES $m \in M$ travels to serve its internal and external customers. The binary variable $x_{i,j,m}$ governs the movement of each MES m. This binary variable is 1 if MES m travels from location i to j, to provide a service or to charge at location j, and 0 otherwise.

The research here assumes that the MES is fully charged at the depot at 5 am, ready for daytime operation. On the other hand, daytime charging is accounted for in this formulation. In this optimization based approach, the goal of the MES is to maximize its daily profit while first ensuring the service of its own internal customers, then determining which of its external paying customers if any it will choose to serve during the day and which of its seller customers if any it will choose to purchase energy from and if it will need to stop to charge at any point during the day. This objective function is seen in (7.1a) below where the profit is formulated as a subtraction of the costs incurred from the income generated, IN in (7.1b). This problem is formulated as a Mixed Integer Programming (MIP) problem and the objective function is presented as follows:

$$\max Profit = IN - \left(C^{tr} + C^{chg,g} + C^{chg,s} + C^{labor} + C^{pen} + C^{deg}\right) \tag{7.1a}$$

$$IN = \sum_{i,j \in exC,m} x_{i,j,m} \rho_j Pdc_j \frac{st_j}{60} \tag{7.1b}$$

$$C^{tr} = \sum_{i,j \in exC,m} x_{i,j,m} C_m^{travel} d_{i,j} \tag{7.1c}$$

$$C^{pen} = \sum_{i,j \in C,m} C^{penalty}(1 - x_{i,j,m}) \tag{7.1d}$$

$$C^{chg,g} = \sum_{i,j \in CS,m} x_{i,j,m} C^{grid} Pc_j \frac{ct_j}{60} \tag{7.1e}$$

$$C^{chg,s} = -\sum_{i,j \in exSC,m} x_{i,j,m} C_j^{seller} Pc_j \frac{ct_j}{60} \tag{7.1f}$$

$$C^{labor} = \sum_{i,j \in exC \cup exSC,m} x_{i,j,m} C_m^{labor} \frac{(st_j + t_{i,j}^{tr})}{60} \tag{7.1g}$$

$$C^{deg} = \sum_{i,j \in exC,m} C_m^d x_{i,j,m} Pdc_j \frac{st_j}{60} \tag{7.1h}$$

The MES's income IN is made from serving external customers exC, where ρ_j is the price paid by that customer in \$/kWh, where this price is decided by the customer $Pdch_j$ is the discharging power of the MES, and hence the charging power of the customer and st_j is the service time in minutes. There is no income made from serving internal customers. The costs accounted for are as follows: the cost of traveling to the external customer C^{tr}, the penalty for not serving its own internal customers, C^{pen}, the cost of charging from the grid $C^{chg,g}$, the cost of charging or purchasing energy from energy selling customers, $C^{chg,s}$

and finally the labor costs associated with operating the MES, C^{labor}. The cost of travel C_m^{travel} is a cost in \$/km and accounts for theMES m's driver, and $d_{i,j}$ is the travel distance between two locations in km. The penalty cost comes from the fact that the BEBs will now have to charge from the grid, rather than from the MES and so the MES is penalized to ensure a maximization of the service to its internal customers. The cost of charging from the grid in \$, is the product of C^{grid} in \$/kWh, the charging power Pc_j and the charging time in minutes ct_j. The cost of charging from energy sellers is C_j^{seller} in negative \$/kWh. Next, the cost of labor accounts for the travel and service time to the external customers and energy sellers, where C_m^{labor} is the labor cost in \$/hour of the MES operator. Finally the battery degradation cost is accounted for in C^{deg}, where $C_m^d = \frac{CC_m^{cap,MES}}{eB_m DOD_m LC_m \mu_m^r}$, where $CC_m^{cap,MES}$ is the MES capital costs, DOD_m is its depth of discharge and LC_m and μ_m^r are its cycle life and round-trip efficiency [49, 78]. The objective function in (7.1a) is subject to the following constraints.

Trip constraints

The constraints in this subsection govern the trips made by each MES. Equation (7.2a) ensures that every route from location i to j is traveled by at most one MES. In this formulation, the MES is capable of deciding which of its internal customers it chooses to serve and which of its external customers it chooses to serve as well, no preference is given to any customer. For this reason equations (7.2b) and (7.2c) are formulated as inequalities, setting any of these as an equality equation would enforce service to the internal or external customers respectively. Constraints (7.2e) and (7.2f) ensure that each MES leaves from its starting location SD at most once, while ensuring that the maximum number of MES leaving the depot are the maximum number of available MES, B_{MES}. Finally constraints (7.2g) - (7.2h) account for the flow of the MES between locations.The combination of these equations ensures that each MES moves smoothly from location to location.

$$\sum_{m} x_{i,j,m} \leq 1, \forall i,j \in N^{'} \tag{7.2a}$$

$$\sum_{i,m} x_{i,j,m} \leq 1, \forall j \in C \tag{7.2b}$$

$$\sum_{i,m} x_{i,j,m} \leq 1, \forall j \in exC \tag{7.2c}$$

$$\sum_{i,m} x_{i,j,m} \leq 1, \forall j \in exSC \tag{7.2d}$$

$$\sum_{j} x_{i,j,m} \leq 1, \forall i \in SD, \forall m \in M \tag{7.2e}$$

$$\sum_{j,m} x_{i,j,m} \leq B_{MES}, \forall i \in SD \tag{7.2f}$$

$$\sum_{j} x_{i,j,m} = \sum_{j} x_{j,i,m}, \forall i \in N^{'}, \forall m \in M \tag{7.2g}$$

$$\sum_{m} x_{i,j,m} + \sum_{t} x_{j,i,m} \leq 1, \forall i,j \in N^{'} \tag{7.2h}$$

SOC constraints

In addition to consuming energy or discharging while traveling from one location to another and while serving customers, the MES also needs to be recharged. The MES battery operation is taken care of in this subsection.

The MES State of Charge (SOC) as an energy amount in kilowatt-hours (kWh) is represented as $ec_{i,m}$ which denotes the energy level on board MES m, upon departure from node i. This $ec_{i,m}$ can be converted to a percentage SOC when divided by the total energy capacity of the MES, eB_m. Equations (7.3a) - (7.3d) govern the MES SOC, where the discharging during traveling from one location to the next is taken care of by accounting for the energy required to travel to the customer, $e_{i,j,m}$, while incorporating the driver's behaviour as a factor, df_m. The MES discharges at internal and external customer locations as shown in equation (7.3a) where st_j is the customer service time in minutes, at a power rating of Pdc_j in kilowatt (kW), μ_m^{dc} is the MES discharging efficiency and eB_m is the MES energy rating in kWh. Constraint (7.3b) governs the MES charging at charging stations and external energy selling customers $exSC$, where ct_j is the charging time in minutes, Pc_j is the charging power in kW and μ_m^{c} is the MES charging efficiency. Finally equation (7.3c) ensures that the MES always has sufficient energy to return to its depot and the energy limits are displayed in (7.3d).

$$
\begin{aligned}
&(x_{i,j,m})(df_m e_{i,j,m} + \frac{st_j Pdc_j}{\mu_m^{dc} 60}) - (1 - x_{i,j,m})(eB_m) \\
&\leq ec_{i,m} - ec_{j,m} \leq \\
&(x_{i,j,m})(df_m e_{i,j,m} + \frac{st_j Pdc_j}{\mu_m^{dc} 60}) + (1 - x_{i,j,m})(eB_m), \\
&\forall i \in N', \forall j \in \{C \cup exC\}, \forall m \in M && (7.3a) \\
&(x_{i,j,m})(df_m e_{i,j,m} - \frac{ct_j \mu_m^c Pc_j}{60}) - (1 - x_{i,j,m})(eB_m) \\
&\leq ec_{i,m} - ec_{j,m} \leq \\
&(x_{i,j,m})(df_m e_{i,j,m} - \frac{ct_j \mu_m^c Pc_j}{60}) + (1 - x_{i,j,m})(eB_m), \\
&\forall i \in N', \forall j \in \{CS \cup exSC\}, \forall m \in M && (7.3b) \\
&ec_{i,m} \geq df_m x_{i,j,m} e_{i,j,m}, \forall i \in N', \forall j \in SD, \forall m \in M && (7.3c) \\
&eB_m \frac{SOC^{min}}{100} \leq ec_{i,m} \leq eB_m \frac{SOC^{max}}{100}, \forall i \in N', \forall m \in M && (7.3d)
\end{aligned}
$$

Schedule constraints

Finally, since the MES customers are all time sensitive, the timing and scheduling constraints are displayed in this subsection, where equations (7.4a) - (7.4f) are all designed to determine $t_{i,m}^{arr}$ which is the arrival time of MES m at location i. Equations (7.4a) and (7.4b) ensure that when an MES goes from one location to the next, it accounts for travel time ,$t_{i,j}^{tr}$, and service or charging time depending on the location its headed to. The final term is added to allow for variable continuity, where lt_m^{sd} is a MES's latest return time to its depot. An MES must arrive at a customer's location between the times set by the customer as seen in (7.4c), where st_i^{early} and st_i^{late} are the earliest and latest times at which customers can begin to receive service from a MES. Finally, the MES's operational hours are respected in (7.4d) - (7.4f), where et_m^{sd} is a MES's earliest departure time and lt_m^{sd} is its latest arrival time at the depot.

$$t^{arr}_{j,m} \geq t^{arr}_{i,m} + x_{i,j,m}(t^{tr}_{i,j} + st_i) - (1 - x_{i,j,m})(lt^{sd}_m),$$
$$\forall i \in \{C \cup exC\}, \forall j \in N^{'}, \forall m \in M \tag{7.4a}$$
$$t^{arr}_{j,m} \geq t^{arr}_{i,m} + x_{i,j,m}(t^{tr}_{i,j} + ct_i) - (1 - x_{i,j,m})(lt^{sd}_m),$$
$$\forall i \in \{CS \cup exSC\}, \forall j \in N^{'}, \forall m \in M \tag{7.4b}$$
$$st^{early}_i \leq t^{arr}_{i,m} \leq st^{late}_i, \forall i \in \{C \cup exC\}, \forall m \in M \tag{7.4c}$$
$$t^{arr}_{j,m} - t^{tr}_{i,j} \geq et^{sd}_m, \forall i \in SD, \forall j \in N^{'}, \forall m \in M \tag{7.4d}$$
$$t^{arr}_{i,m} + st_i + t^{tr}_{i,j} \leq lt^{sd}_m, \forall i \in \{C \cup exC\}, \forall j \in SD, \forall m \in M \tag{7.4e}$$
$$t^{arr}_{i,m} + ct_i + t^{tr}_{i,j} \leq lt^{sd}_m, \forall i \in \{CS \cup exSC\}, \forall j \in SD, \forall m \in M \tag{7.4f}$$

With this, the MES routing and scheduling problem formulation comes to an end. When the customer's requests are input into this problem, the formulation determines the selection of customers to serve while maximizing the income received from the external customers as well as minimizing the cost of serving those customers. In this formulation a customer is treated in a binary manner where they either receive their complete energy request or they are not served at all. Additionally, the price is governed by the customer, the MES simply determines whether it is profitable to serve a customer at the price they set. On the other hand, in the auction based formulation discussed in the coming subsection, the price is governed by the MES as well as its customers, and customers can receive fractions of the energy requested.

7.3.2 Integrated Optimization and Auction Based Approach

The iterative approach is based upon the clinching auction mechanism, in which an auctioneer auctions off M units of identical goods. As the auctioneer, the MES owner uses a portion of the MES capacity for internal customers, while the remaining capacity is auctioned off in bundles of a set energy capacity eA in kWh. The mobility of the MES further complicates the problem. Upon completion of the auction, the MES performs an optimality check to determine its optimal schedule and travel and to ensure that the profit made from the auction of energy capacity exceeds the costs of travel and charging.

As a result of mobility, multiple external customers cannot be served at the same time, adding additional complications to the clinching auction. Thus, a customer undergoes multiple screenings. Initially, four inputs are required from each customer: marginal valuations, maximum energy requests, the earliest and latest service time. The marginal valuation of a customer is the amount they value each additional unit, which determines their energy demand at any given price p as shown in Algorithm. 1 [95]. Once a customer has sent in their inputs, they are now considered a potential bidder. In the event that two bidders have overlapping service request windows, the bidder with the lower valuation is contacted to determine whether they are flexible with their timing requests, and if they are not, they are excluded from the final set of bidders. The initial elimination ensures maximum profits for MES without compromising the integrity of the clinching auction.

Algorithm 1 Customer's demand calculation.

Input: Potential bidder's marginal valuations.
Output: Potential bidder's demand at a price p.

Initialization : Set M as the maximum supply to be auctioned by the auctioneer.
for $i = 1 : N$ **do**
    if $V_i(M) \geq p$ **then**
        Bidder i's demand at price p is the maximum supply.
        $D_i(p) = M$
    else
        for $k = M : -1 : 1$ **do**
            if $V_i(k) < p$ **then**
                $D_i(p) = k - 1$
            end if
        end for
    end if
end for

Clinching auction mechanism

A description of the clinching auction mechanism is shown in Algorithm. 2. The auction commences with the auctioneer announcing a starting price, and iterating through Algorithm. 2 while the demand is greater than the supply. As the MES sells energy that has been acquired through charging from the grid, and transports this energy to other locations, the auctioneer begins the auction with a minimum price p^{min} equivalent to the off-peak cost of purchasing energy from the grid plus an additional transportation cost. As soon as the aggregate demand falls below or equals the supply, the auction terminates. At the final iteration of the auction, bidders with positive demand receive supplies; if the aggregate demand equals supply at the final iteration, each player receives exactly their demand. In the event that the aggregate demand falls below the supply at the final iteration, each bidder receives the number of units they requested in the final iteration

Algorithm 2 Clinching auction mechanism.

Input: in

Output: out

1: **Initialization** : Set $p = p^{min}$, $it = 1$.
2: Determine each bidder's demand, $D_i(p)$, at price, p.
3: **while** $\sum_i D_i(p) > M$ **do**
4: **if** $it \geq 2$ **then**
5: Ensure that bidder i has not increased their demand from previous iteration.

$$D_i(p) \leq D_i(p - \varepsilon)$$

If demand increased, bidder i is excluded and auction restarted.

6: **end if**
7: Increase price p by increment ε.

$$p = p + \varepsilon$$

8: Increment iteration it.

$$it = it + 1$$

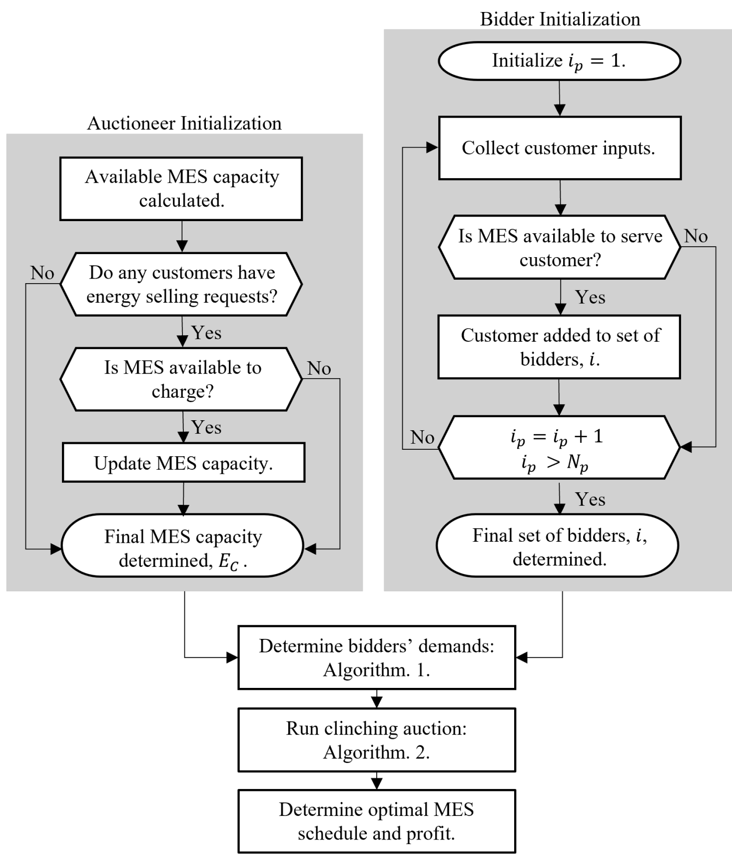
9: **end while**
10: Auction terminated with final price p, proceed to allocation and payments.

and any remaining units are awarded at random to bidders who requested more in the penultimate iteration. Thus, a bidder receives at least their demand in the final iteration and at most its demand in the penultimate iteration. However, the payments are not straightforward, as the clinching auction does not simply sell all units at a single price, rather prices are determined based on the externalities of a bidder, namely the demands of other bidders. Based on Vickrey payments, the payment mechanism utilized in this auction is as shown in equation (7.5). This ensures that bidders are encouraged to submit their true valuations, as they would not benefit in doing otherwise as discussed and proven in [94].

$$P_i^f(j) = -\varepsilon + \min\left\{ q \,\middle|\, \sum_{k \neq i} D_k(q) \leq M - j \right\} \tag{7.5}$$

Schedule and profit determination

Once it is determined which customers are to be served, i, the final units of energy they have clinched, and their final payments ρ_i which is found as the summation of $P_i^f(j)$ over all the units clinched, the MES must now serve these customers while maximizing



Note: i_p refers to potential bidders, where N_p is the total number of customers or potential bidders.

Figure 7.1: Auction framework.

their profits. The objective function shown in (7.1a), is modified as shown in (7.6) where the penalty term is eliminated as all internal customers of the MES must be served, hence constraint (7.2b) is converted to an equality.

$$\max Profit = IN - \left(C^{tr} + C^{chg,g} + C^{chg,s} + C^{labor} + C^{deg}\right) \tag{7.6}$$

s.t. (7.2a) - (7.4f)

7.4 Case Study and Results

For the purpose of this work, the same four short distance routes and the two 1000 kWh MES sized in Chapter 5 were utilized. Since the goal of this chapter is to utilize MES capacity to generate additional revenue, four customers were modeled: two EV parking lots, a residential complex and an RES owner, more specifically, a PV owner. The EV parking lots and the residential complex fall under the category of external customers, exC where they consume energy from the MES, while the PV owner falls under the category of external energy selling customers, $exSC$. The MES utilization and revenue generation is modeled utilizing the two approaches; the optimization based approach and the integrated auction and optimization based approach. The customer requests are as follow: EV parking lot 1 requests 60 minutes of service with an earliest start time of 12:25 and a latest start time of 12:35, EV parking lots 2 requests 60 minutes of service with an earliest start time of 17:10 and a latest start time of 17:20, the residential customer requests 60 minutes of service with an earliest start time of 17:15 and a latest start time of 17:30. In the auction framework, this requested energy is converted to units, where each unit is considered as 25 kWh of service which corresponds to 6 minutes of service at a power rating of 250 kW. The customers also send in their valuations for every additional unit of service. Additionally their valuations are seen in Fig. 7.2. Customers' utilities are seen as downward sloping lines to mimic human behavior of the additional benefit that they would get from one more unit of the requested good. Finally the PV owner requests service at 10:30 am for 60 minutes, where they are willing to sell 250 kWh at a cost of 0.1$/kWh.

7.4.1 Optimization Based Approach Results

When operated using the optimization based approach, customers are selected for full service or no service, customers' needs cannot be partially met. For this reason, based on

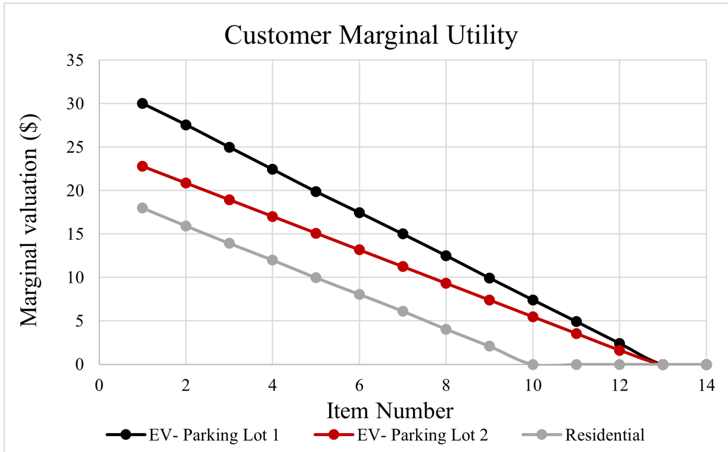


Figure 7.2: Marginal valuations of MES external customers.

Table 7.1: MES 1 schedule and operation - Optimization based approach.

Customer	**Arrival time**	**Service duration (mins)**	**Arrival SOC**	**Departure SOC**
MES 1				
C	09:43	12	94.58%	90.58%
C	11:12	28	89.57%	78.5%
C	11:57	21	77.92%	69.58%
CS	12:30	20	69.2%	78.33%
C	13:00	20	77.92%	70.65%
C	14:10	21	69.58%	61.25%
C	15:42	12	60.83%	56.3%
C	16:09	10	55.83%	52.08%
C	16:45	17	51.67%	45.23%
exC	17:20	60	44.58%	21.34%
C	19:20	25	20.83%	9.83%

Note: C refers to an internal customer, exC external customer, CS charging station, exSC is an energy selling customer.

the scheduling availability of the MES as well as the remaining on-board capacity, only EV parking lot 2 is served, earning the MES $ 122 in revenue for the day, which covers the cost of charging the MES overnight, which amounts to approximately $112 per night. While this may seem like a small financial profit, when scaled and utilized by the entire transit agency at a large scale, the cost savings would be substantial. Of the two MES, MES 1 serves EV parking lot 2 and so its schedule is shown in Table. 7.1. Additionally, it an be seen that the PV customer was not served, this is because the MES was already fully charged at the time the PV service was requested, hence there being no need for the MES to travel for this charging, however in order to serve the EV parking lot, the MES had to recharge for 20 minutes at 12:30 as seen from the schedule.

7.4.2 Integrated Optimization and Auction Based Approach Results

When operated using the integrated approach, customers customers' needs can be partially met, with the objective of ensuring maximum profit for the transit agency and the satisfaction of the customers. Hence, based on the scheduling availability of the MES as well as the remaining on-board capacity, two of the three external customers are partially served while ensuring that the transit system's internal customers are served. The final MES schedules can be see in Table. 7.2, where the final profit earned by the transit agency is $ 126 per day, being very comparable to the above formulation. Using this methodology, EV parking lot 1 is eliminated as a bidder as the MES is not available at the time of its request, hence the clinching auction proceeds between the remaining two consuming customers. Upon completion, EV parking lot one clinches 200 kWh from MES 1 and the residential customer clinches 100 kWh from MES 2.

7.4.3 Opportunities for Further Revenue Stream Generation

While the previous section proved the MES profitability in serving external customers, there exist numerous possibilities for further improving revenue generation, as discussed in this section. To begin with, numerous transit agencies operate different schedules for different times of the year, depending on the locations they serve. For example, large education based routes tend to see reduced ridership and hence reduced frequency in the summer months, whereas routes that serve tourist attractions, large malls or shopping centers tend to see increased ridership and hence frequency during these months. For these reasons, the consideration of reduced frequency operation is a great opportunity for the MES to be further utilized to generate additional revenue. While the MES proved to be profitable while the TA was running its maximum trip frequency, the MES can therefore definitely provide financial benefits at times of reduced trip frequency. The work studied here opens up the possibility for countless solutions. For instance, when operating

Table 7.2: MES 1 and 2 schedule and operation - Integrated approach.

Customer	**Arrival time**	**Service duration (mins)**	**Arrival SOC**	**Departure SOC**
		MES 1		
C	09:43	12	94.58%	90.58%
C	11:12	28	89.57%	78.5%
C	11:57	21	77.92%	69.58%
CS	12:30	10	69.2%	73.75%
C	13:00	20	73.33%	65.42%
C	14:10	21	65%	56.67%
C	15:42	12	56.25%	51.67%
C	16:09	10	51.23%	47.62%
C	16:45	17	47.01%	40.42%
exC	17:20	48	40.0%	20.42%
C	19:20	25	19.83%	10.17%
		MES 2		
C	11:28	12	94.23%	87.57%
C	12:22	28	87.12%	76.25%
C	13:12	21	75.98%	67.92%
C	13:42	20	67.5%	53.75%
C	14:58	21	53.33%	40.42%
C	15:50	12	40.0%	32.08%
C	16:27	10	31.67%	21.25%
exC	17:17	24	20.76%	11.67%

Note: C refers to an internal customer, exC external customer, CS charging station, exSC is an energy selling customer.

at reduced frequency, both MES are still in use by the transit system but less energy is consumed, hence allowing for additional external customers to be served. However, in the case where the transit system completely cancels some lines for a period of time - for example during the holiday season in the winter months, the MES can provide seasonal contracts to other energy storage users that have seasonal demands that coincide with the canceled trips. For example, during the Christmas holiday season, numerous transit routes are canceled, while ski resorts see amplified demand [101]. In such cases, the MES would not be in use be the transit agency, so seasonal contracts can be set up with customers like ski resorts to generate additional revenue, where the utilization of MES by ski resorts is not a foreign concept [84]. The utilization of MES to meet the temporary peak loads in lieu of Stationary Energy Storage (SES) is very beneficial to both the MES owner as well as the ski resort. Additionally, there exists a possibility to charge the MES while generating income by utilizing instances of negative pricing. At times of high generation and low load, three options are available to maintain power balance in the grid: storing excess renewable generation, curtailing excess renewable generation, or ramping down large conventional generators. The last option of ramping down or temporarily shutting down large generators is quite time-consuming and expensive. Thus, these generators bid at negative electricity prices, creating revenue opportunities for energy consumers while avoiding shutdowns [102]. It has been observed over the past several years that instances of negative pricing follow the same trends; their frequency increases in the morning hours (between 9 am and 2 pm) and during the months of low load or low demand (March to May). Some instances of negative pricing also occur in the very early hours of the morning where load is very minimal while wind generation is possibly very high. Negative pricing is quite significant due to its large range (-305 $/MWh), and is not as infrequent as people suspect, for example occurring during one tenth of the time in 2014 and one fifth of the time in 2017. [103–105]. Additionally, their occurrences tend to increase over the years [103]. The MES can utilize these opportunities to charge while generating income rather than paying for consumption. Finally, there exists the opportunity to partner with entities such as the Independent Electricity System Operator (IESO), where they can utilize the flexible MES technology to benefit both the transit system as well as the grid [76].

7.5 Conclusions

The work proposed in this chapter opens up the door for countless revenue streams for MES, and further solidifies MES's position as a fast, and flexible solution. Two formulations for the utilization of MES to serve its external customers are proposed: the first being an optimization based approach that aims to maximize the MES's generated profit, however ensures that if an external customer is selected to be served, its complete energy request will be fulfilled at the price set by the customer. The second approach is the integrated auction and optimization based approach where a customer's energy requests can be met partially, allowing for the service of additional customers as seen above. In this approach the MES energy capacity is auctioned off to customers and upon completion of the auction, a MES routing and scheduling problem is run to ensure that the MES earns a profit when accounting for all expenses. The formulations developed are scalable and adaptable to any application where an MES owner utilizes the MES to meet its internal energy needs as well as to serve external customers. Finally, the presented results display the profitability of the MES when applied to a small scale system, and the discussions provide insight into further possibilities for revenue stream generation.

Chapter 8

Summary, Contributions, and Directions for Future Work

8.1 Summary and Conclusions

The research in this thesis targets transit agencies looking to electrify their Public Transportation (PT) fleets. In the course of the chapters, the reader is provided with a real-world overview of the process adopted by transit agencies as they engage in this electrification. This thesis answers numerous questions in depth; from how many Battery Electric Buses (BEBs) would be needed to electrify a route, to how additional revenue streams can be created after ensuring smooth operation.

The objective of this thesis is to develop a scalable fleet transition plan for public transportation systems, from procurement to the commencement of operations, while addressing the most significant barriers to the adoption of the BEBs. Presented as a comprehensive solution to several deployment barriers, Mobile Energy Storage (MES) enables rapid electrification, improves the resilience of the transportation system, and generates additional revenue streams while having the flexibility to adapt to the ever-changing transportation and power system networks. Following the background and literature review, there are five successive parts to the research that build upon one another. The contents of these chapters and the conclusions drawn from this work are summarized below:

- A methodology for sizing fleets and chargers for electrifying public transportation fleets is developed in the first part of this research. A detailed formulation is provided in *Chapter 3*, where the transit agency gathers and analyzes bids from fleet and charger manufacturers to select the most economically advantageous option. To ensure that fleets are appropriately sized, the operation of fleets and chargers is carefully examined. Two charging methodologies are used to study fleet operation during the day and at night: overnight charging and opportunity charging. In order to simulate realistic transit agencies, the day-time operation of each route is studied separately while modeling detailed route assignment, whereas regarding night-time operation, all routes parked at the same depot are studied together. Through the application of this methodology, four short-distance routes are electrified, resulting in the establishment of an electrified transit system that is the basis of the research done in all the coming chapters. The formulations developed in this chapter are not computationally complex and can be readily applied to the electrification of large fleets.

- As soon as a transit agency has a clear understanding of the size of the electrified transit system they require and the number of assets they need to acquire, they must make decisions about when to purchase these assets. An asset purchase decision is influenced by a number of factors, including annual budgets, government grants, and national and global electrification goals. In this regard, *Chapter 4* presents a transition plan that minimizes the net present value of electrifying a transit system and ensuring that purchase decisions are made in a timely manner while accounting for the smooth operation of the transit system.

- With the electrification of the public transportation system, numerous barriers arise from the several stakeholders involved in the process. The following portions of this thesis explore how MES can be used as a holistic solution to overcome these barriers, with a fast procurement and implementation process, as well as increased flexibility, thereby bringing financial and technical benefits to the system. In *Chapter 5* a comprehensive algorithm for the sizing and operation of MES to support the electrified transit system is presented. The problem is broken down into several stages, which are encompassed within an outer sizing framework, in order to ensure completeness without increasing complexity. A MES routing and scheduling problem as well as an operational feasibility problem are the inner stages. The outcome of this chapter is a planning and operation methodology for MES to aid in the electrification of the PT system. In this study, two systems were analyzed: the first of which consists of four short-distance routes, and the second of which consists of four long-distance routes. Overnight and opportunity charging were used to study each of the systems, with the results showing that employing MES resulted in significant cost savings, increased flexibility in operations, and enhanced resilience in the event of an emergency. Finally, while the benefits of MES were proven for a fully electrified fleet, MES units would also result in significant technical and economic benefits throughout the electrification process as they would ensure smooth transit operations and allow Transit Agencies (TAs) the flexibility to modify their electrified routes without wasting resources.

- Once the transit system acquires the powerful, flexible, and adaptable MES technology, it is critical to determine how it can be utilized to its full potential. As a result, the following sections of this thesis examine how the MES could utilize its unused energy capacity to serve additional customers and generate additional revenue for the transit system. Considering the additional complexity arising from mobility, *Chapter 6* examines the possibility of serving multiple customers using a stationary energy storage system, with the mobility studied in the final chapter. The regret matching algorithm is used to model a scenario in which customers and energy storage owners cooperate, while a clinching auction mechanism is used to model a scenario in which there is no cooperation. The conclusions drawn in this chapter set the stage for the work done in Chapter 7, in which the MES uses clinching auctions to serve external energy customers as the transit agency aims to maximize its own profit.

- The research done in *Chapter 7* brings a conclusion to the electrification of PT while utilizing MES to its full potential. The purpose of this chapter is to use the previously sized MES and modify its routing and scheduling problem in order to determine whether or not it will choose to serve external customers. This is modeled as a profit maximization where two options are presented: determining which customers are served while meeting their full energy needs using an optimization based approach, or serving more partial energy needs by integrating an auction and optimization based approach. The presented formulations proved the profitability of the MES in serving its own internal system while utilizing the unused capacity to serve additional customers. Additionally, the extended work in Chapter 7 allows for this formulation to be applied by any MES owner choosing to serve external customers alongside their internal ones. The formulations developed in this thesis are scalable and adaptable to a wide range of applications.

8.2 Contributions

The main contributions of this work are highlighted below:

- The development of an operational-planning fleet and charger sizing methodology that incorporates detailed Electric Bus Energy Consumption (EBEC) profiles, and optimal route assignment modeling to ensure that the electrified system meets the demands previously met by the conventional transportation system, i.e. the transit system's continuity of service.

- The formulation of an iterative process representative of real life for BEB selection while accounting for interactions with BEB manufacturer in the procurement process.

- The construction of a novel, comprehensive, transition plan for transit agencies interested in electrifying their existing bus fleets considering multiple modes of charging, while integrating the perspectives of the transportation and electrical sectors. The modeled plan can be utilized by any large fleet.

- The introduction of MES as a quick, flexible and holistic solution to overcome the barriers to BEB adoption; addressing technological, financial as well as electrical barriers.

- The development of a novel MES sizing, routing and scheduling approach, that accounts for battery depletion as well as charging. The developed formulation is to be applied when the MES is owned and utilized by the same entity, and the formulation is scalable, and generic, allowing it to be applied by any MES owner and operator.

- The application of cooperative and non-cooperative approaches for modeling realistic interactions between a Stationary Energy Storage (SES) hub's owner and its customers.

- The extension of the novel MESRSP to allow the MES to serve its own internal non-paying customers as well as its external paying customers, while modeling the interaction between the MES and its external customers in two ways: an optimization based approach and an integrated auction and optimization based approach. Once, again the problem is scalable and easily adaptable to many applications.

8.3 Directions for Future Work

In the future, additional studies can be conducted to either build upon the presented work or utilize the methodologies presented in this thesis. The following topics are suggested for further investigation:

- Modeling the public transportation depot as a microgrid, and determining the suitable mix and size of Renewable Energy Sources (RESs) to meet the energy needs of the study location.

- It would be beneficial to apply the methodologies developed in this work to other large fleets that follow set schedules, such as school buses. As they operate for shorter periods of time than PT fleets, their energy requirements are considerably lower, making this problem a simplified version of this study.

- As this thesis focuses on fleet electrification and MES utilization within fleets that have set schedules (PT), it can be applied easily to other fleets with set schedules and service locations. However, there also exists a lot of potential in utilizing MES in serving large fleets with unknown schedules, such as delivery fleets that serve consumers or delivery fleets that service supermarket chains (some examples include FedEx, Amazon, Coca-Cola, etc.). These fleets operate routes that do not necessarily remain the same on a daily basis, however, their routes are predetermined from the previous day and are familiar to their operators, which makes them strong candidates for applying the presented methodologies with slight modifications.

- Finally, utilizing BEBs to perform grid restoration and MES to perform grid restoration have both been extensively studied in the literature as separate projects. However, by combining them both to offer restoration services during times of emergency, substantial results may be achieved.

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